Philip Cash · Tino Stanković
Mario Štorga *Editors*

Experimental Design Research

Approaches, Perspectives, Applications

Springer

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Foreword

That design research is difficult to undertake is a self-evident truism. This book's unique role is to help researchers with this difficult task by giving a theoretical and practical understanding of the key issues. Design research has established that design is an activity or process, whether undertaken individually, in local teams or in widely distributed groups, which can be managed, controlled and supported. However, the detailed understanding that will lead to further insights and innovative support approaches across the process can only be achieved by more extensive and rigorous experimental design research.

It is useful to contrast it with the classical scientific method. The Oxford English Dictionary defines the scientific method as "a method or procedure that has characterized science since the seventeenth century, consisting of systematic observation, measurement, and experiment, and the formulation, testing, and modification of hypotheses." This definition can be extended, albeit in a simplified form, as conceive a hypothesis or generate a theory, in conjunction with undertaking some background contextual investigation or some modelling, construct an experimental approach, perhaps with well-instrumented test rigs and then conduct a series of experiments with a detailed control of key variables and then compare the results with the theory or the analytical models and draw some conclusions. These approaches are recorded, published and crucially are capable or should be capable of being repeated.

The classical scientific method relies on the control of the experimental environment and it relies on the control of key variables. This is very difficult to achieve in design research when the experimental environment might be an engineering design office or meeting room or design studio or even an individual's workspace, and then there are the two key variables. First the engineer or designer or multidisciplinary team being investigated will have varying amounts of experience, training, abilities and so on. The second key variable being the actual task. This creation of the design is undertaken at varying levels of abstraction and detail. Is it on paper, in the computer modelling environment or an actual artefact or machine or system?

Thus when undertaking design research it is not possible to replicate the classical approach and new approaches are required. It may be necessary to incorporate other research approaches that come from psychology, management and other human focused research to create a research method or a variety of methods that work and produce credible and valuable results in this difficult area of design.

Thus this book is a remarkable attempt to bring together a number of key strands in this very challenging area. It is a treasure trove of insights and techniques. It is particularly helpful that it includes some detailed discussions about the theoretical basis for design research and picks up some key themes, such as the interplay between methods and methodology and links together a number of key perspectives.

It also starts the discussion about establishing standards in design research, something that will be very important to increase the levels of rigour in what is effectively a new discipline. It is always important to point out to researchers in the design area that Sir Isaac Newton published *Philosophiæ Naturalis Principia Mathematica* in 1687 and the early work of Taylor on Manufacturing and Management disciplines was first published in 1900!

This book is valuable in that it brings together the state of the art, but the key contribution is the structure and synthesis that the editors have put into the compilation of the work. Thus the four key areas are made clear and explained. These are the foundations, classical approaches, computational approaches and the issues associated with building theories and creating genuine, valuable and useable knowledge. As an aside, the section on computational approaches is particularly interesting and valuable in that it reflects the way that engineers and designers work and anticipates the way that design research will be conducted in future years.

It is through books like this that rigour can continue to increase and standard approaches can be created as it is though rigour and standard approaches that the body of knowledge can increase and be linked together and raw data can be shared. This will give the results of design research real credibility and real traction to practitioners of all sorts. The book thus represents a real contribution and is not only an invaluable basic text for researchers but also an important step on the way to understanding this topic called design.

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Preface

This book's origins lie in the editors' own experiences of developing and reviewing experimental studies of design; and in particular, from our collaborative excitement when combining new methods and disciplinary insights with more traditional experimental design research.

Researchers face ever-growing technical, methodological, and theoretical possibilities and we have found in our own research, as well as that of our students, that getting to grips with these topics can prove somewhat daunting. This book aims to both help researchers share in our enthusiasm for experimental design research, and provide practical support in bringing together the many different perspectives and methods available to develop scientifically robust and impactful experimental studies.

Fundamentally, this book builds on the methodological foundations laid down by many authors in the design research field, as well as our field's long tradition of boundary spanning empirical studies. Without these works this book would not have been possible. In this sense each chapter reflects and builds on key thinking in the design research field in order to provide the reader with chapters that not only constitute distinct research contributions in their own right but also help bring cohesive insight into experimental design research as a whole.

Throughout the writing process our focus has continually been on bringing together insights for researchers both young and established, with the aim to take experimental design research to the next level of scientific development. In particular it is not our aim to lay down a prescriptive set of methodological rules, but rather provide researchers with the concepts, paradigms and means they need to understand, bridge and build on the many research methodologies and methods in this domain. Thus this book forms a bridge between specific methods and wider methodology in order to both develop better methods and also contextualise their work in the wider methodological landscape.

Over the last decades design research has grown as a field in terms of both its scientific and industrial significance. However, with this growth has come with challenges of scientific rigour, integrating diverse empirical and experimental approaches, and building wider scientific impact outside of design research. We see this book as a contribution to this process of scientific and methodological development, and more generally see this process of growth as a necessary and inspiring development taking design research into the future alongside its more fundamental brethren, such as psychology, artificial intelligence or biotechnology. This book reflects our vision of design research as an ever more rigorous and scientifically exciting field, and we think that this is also reflected in the substantial and insightful works provided by each of the chapter authors, without whom this book would have been impossible!

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Part I
The Foundations of Experimental Design Research

Chapters 1–3 lay the foundation for this book's discussion of the varied perspectives on experimental design research. Chapter 1 sets the stage in the experimental design research domain. Chapter 2 then explores how design studies and metrics have evolved in the field. Finally, Chap. 3 closes Part I by discussing the key research principles and methods underpinning human-focused research in this context. Part I both contextualise the importance of experimental design research and serves to highlighting the array of complementary approaches open to the empirical design researcher.

Chapter 1
An Introduction to Experimental Design Research

Philip Cash, Tino Stanković and Mario Štorga

Abstract Design research brings together influences from the whole gamut of social, psychological, and more technical sciences to create a tradition of empirical study stretching back over 50 years (Horvath 2004; Cross 2007). A growing part of this empirical tradition is experimental, which has gained in importance as the field has matured. As in other evolving disciplines, e.g. behavioural psychology, this maturation brings with it ever-greater scientific and methodological demands (Reiser 1939; Dorst 2008). In particular, the experimental paradigm holds distinct and significant challenges for the modern design researcher. Thus, this book brings together leading researchers from across design research in order to provide the reader with a foundation in experimental design research; an appreciation of possible experimental perspectives; and insight into how experiments can be used to build robust and significant scientific knowledge. This chapter sets the stage for these discussions by introducing experimental design research, outlining the various types of experimental approach, and explaining the role of this book in the wider methodological context.

Keywords Design science · Experimental studies · Research methods

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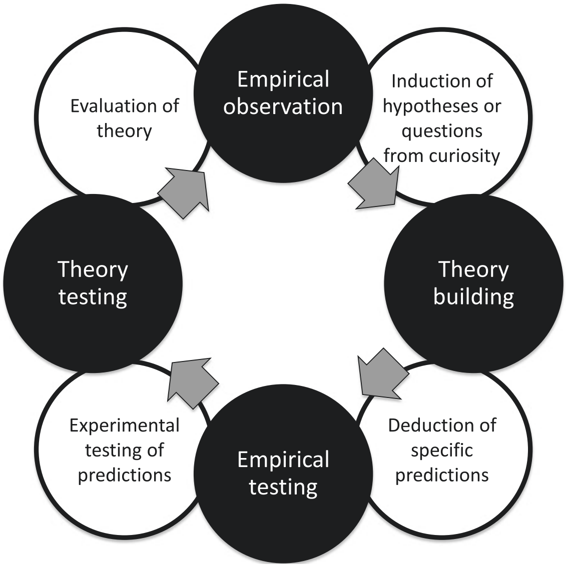
1.1 The Growing Role of Experimentation in Design Research

Over the last 50 years, design research has seen a number of paradigm shifts in its scientific and empirical culture. Starting in the 1960s and 1970s, researchers were concerned with answering what design science actually meant and how scientific practices should be adapted to fit this emerging field where problem-solving and scientific understanding shared priority (Simon 1978; Hubka 1984; Eder 2011). This was the first major effort to adapt and develop methods and processes from the scientific domain into '*design science*', where researchers were also concerned with changing design practice. This effort stemmed from a drive to develop design knowledge and scientific methods that better reflected the fact that although design is concerned with the artefact, designing includes methods, process, and tools not directly embedded in daily practice. In the 1980s, a new paradigm emerged, characterised by the development of '*design studies*'. This was driven by a growing focus on understanding and rationalising the creative design processes of designer behaviour and cognition. This new paradigm was also linked to the emergence of computer-supported design research (see Part III). In the 1990s, there was a move to bring coherence to the field by uniting the *design studies* and *design science* paradigms under the wider label of *design research*, which more fully captured the theoretical, empirical, and pragmatic aspects of research into design. This also reflected a larger effort to unite previously disparate research groups and empirical approaches in a single field, bringing together research and industrial application. This effort has sparked the most recent development since the 2000s: a drive to bring together the varied disciplines in design research and to reinvigorate the arduous process of bringing order and increasing scientific rigour to empirical design research (Brandt and Binder 2007; Dorst 2008). This has been reflected in the renewed focus on the development of field-specific research methods (Ball and Ormerod 2000a), a prioritisation of theoretical and empirical rigour (Dorst 2008), and the emergence of specific design research methodologies (Blessing and Chakrabarti 2009). Thus, the stage is set for our discussion of experimentation in the wider context of empirical design research.

Empirical studies in design research provide the foundation for the development of both scientific knowledge about and impactful guidance for design (see Chap. 2, and Part IV). More formally, empirical studies support the theory building/testing cycle illustrated by the black circles as shown in Fig. 1.1 (Eisenhardt 1989; Eisenhardt and Graebner 2007). Empirical insights are used to derive new perspectives and build explanations, as well as to test those explanations (Carroll and Swatman 2000; Gorard and Cook 2007). Empiricism encapsulates all the varied means of deriving evidence from direct or indirect observation or experience. Experimentation thus forms one part of the wider empirical milieu.

In the context of design research and for the purposes of opening this book, experimentation can be defined as "*a recording of observations, quantitative or qualitative, made by defined and recorded operations and in defined conditions,*

Fig. 1.1 Theory building and testing as an integrated cycle of empiricism, and its link to experimentation



followed by examination of the data, by appropriate statistical and mathematical rules, for the existence of significant relations" (Nesselroade and Cattell 2013, 11:22). This typically follows (although is not limited to) a process of induction, deduction, and testing (Nesselroade and Cattell 2013) in support of the theory building/testing cycle (white circles in Fig. 1.1). Effective experimentation forms a core part of elucidating specific variables, developing and testing relationships/hypotheses, and comparing the predictive power of competing theories (Wacker 1998; Snow and Thomas 2007). It is important to recognise that this perspective limits the focus of our discussion by excluding the observation or instigation of unique and incomparable but observed and manipulated events, which might be referred to as an experiment by an action researcher. For more on the development of experimentation in psychology, see Nesselroade and Cattell (2013), and for a substantially more detailed discussion of how experimentation fits into theory building in design research, see Chap. 12, and Part IV more generally.

Over the last 20 years, the importance of experimentation has steadily grown within design research. For example, in 1990, just 2 % (1 of 43) of papers in Design Studies dealt with experiments, whilst in 2014, that number was 24 % (8 of 33) (ScienceDirect 2015).[1] Experimentation in its various forms is increasingly recognised as a powerful means for carrying out design research (see Part I, Chap. 3). However, this brings increasing demands in terms of how and where experimental techniques can be applied, methodological rigour, and the generation of scientific knowledge (Cash and Culley 2014; Cash and Piirainen 2015). Design

[1]Keyword: *experiment* in *abstract*, *title or keywords* from 1990 to 2015.

research is a comparatively young field and is thus still in the process of developing its own methodological and scientific best practices. This field-specific development is key to building a rigorous body of methods and scientific knowledge within a discipline (see Part I, Chap. 3) (Kitchenham et al. 2002; Blessing and Chakrabarti 2009). Thus, this book seeks to address the need to *develop a tradition of experimentation that is tailored to the specific challenges of design research, whilst also bringing together the lessons learned from the varied fields to which design research is linked*. In order to address this need, it is first necessary to clarify what it is we mean when we talk about experiments in design research.

1.2 Experimental Design Research

The scientific paradigm can be generally characterised as the generation of reliable knowledge about the world (see Chap. 13 for more). Broadly, this has resulted in a tendency, most notable in the natural sciences, to take the production of experimental knowledge for granted and to focus on theory (Radder 2003). However, this perspective can be deceptively one-sided, particularly in the applied context of design research. Here, the development of experimentation is intrinsically linked with the development of technology (Tiles and Oberdiek 1995; Radder 2003). Experimental methods build on (often specifically designed) technologies and technical insights (e.g. see Chap. 6), whilst simultaneously contributing to technological innovations and technical understanding (e.g. see Part III). Thus, there are a number of parallels between the realisation of experimental processes and those processes of technological development that often form the focus of design research. This is particularly important in the social and human sciences, e.g. economics, sociology, medicine, and psychology, where experimental activities form a significant part of the wider scientific endeavour. Problematically in this context, the philosophical discussion surrounding experimental research builds almost exclusively on the natural sciences. Thus, there is a significant need to develop methodological and scientific understanding of experimentation that reflects the unique challenges in the human sciences (see, e.g. Winston and Blais 1996 or Guala 2005), of which design research is a part.

In experimental design research, these discussions are nascent and form a major reason for the development of this book. Core to this endeavour is the realisation that experimental design research concerns human beings and thus faces a set of challenges not fully reflected by discussions of experimentation in the natural sciences (Radder 2003). Specifically, human subjects are often aware of, actively interpret, and react to what is happening in an experiment. Further, this awareness can influence subjects' response to an experiment, often above and beyond the actual intervention response intended by the experimenter. This challenge is reflected by biases such as the John Henry effect, and in methodological techniques such as the placebo control, which are well recognised in, e.g., medical science (Glasgow and Emmons 2007), but are only beginning to be acknowledged and discussed in design research (Dyba and Dingsoyr 2008; Cash and Culley 2014).

More broadly issues of bias and control are only one consideration when dealing with human subjects. From a socio-cultural perspective, science dealing with human subjects must also respect a common-sense perspective on human beings. Here, social and ethical issues are paramount. Radder (2003, 274) states "*who is entitled to define the nature of human beings: the scientists or the people themselves*?" From this, it is possible to draw parallels with the discussions underpinning design practice, i.e. how can designers influence users ethically (Berdichevsky and Neuenschwander 1999; Lilley and Wilson 2013). Thus, just as designers must consider their right to interpret and influence users, design researchers must also consider the implications stemming from their interpretation and influencing of designers. This forms the bedrock on which all discussions of experimental research must build. However, it is not the purpose of this work to discuss these further, and we simply point to the comprehensive ethical guidelines provided by organisations such as the American Psychological Association (2010) and the National Academy of Sciences (2009).

As discussed above, experimental design research encapsulates a wide range of research designs, sharing fundamental design conventions (see Part I, Chap. 3). Table 1.1 gives an overview of the basic types of experimental study, which are further elaborated with respect to design research in Chap. 12. This does not include computer-based simulation studies, which will be dealt with in more detail in Part III. Thus, Table 1.1 describes the types of experimental approach, how each type controls extraneous variables, and what type of evidence each is capable of generating. For example, the recent study by Dong et al. (2015) utilised random assignment and a between-group design, making it a type of true experiment. In contrast, the study by Cash et al. (2012) used a similar type of between-group comparison but used non-random group assignment, making it a type of

Table 1.1 An overview of basic types of experimental design

Type	Summary description
Randomised or true experiment	Participants are randomly assigned to treatment conditions including a control (see also *randomised controlled trial*)
Means of control	Extraneous variables controlled via random assignment and comparison with a *control condition*
Capable of demonstrating	Cause and effect, high quality of evidence
Quasi-experiment (***natural experiment***)	Participants are non-randomly assigned to treatment conditions (participants can also be assigned by forces beyond the experimenters control in the case of *natural experiments*)
Means of control	Extraneous variables controlled via comparison with a *control condition*
Capable of demonstrating	Correlation
Pre-experiment or **pseudo-experiment**	Follows experimental design conventions, but no control condition is used. Sometimes called a *pseudo-experiment*
Means of control	Extraneous variables mitigated via comparison with a no-treatment group (i.e. a group that receives no intervention at all) or using a single group pre-design versus post-design
Capable of demonstrating	Correlation, weak generalisability, low quality of evidence

quasi-experiment. Within each type, there are numerous sub-types. For detailed explanation of these experimental design considerations, e.g. selecting an appropriate sample, see Chap. 3.

Understanding the distinction between the types outlined in Table 1.1 can be critical to assessing the evidence provided by a study and how this can be used to develop rigorous scientific knowledge (see Part IV).

In terms of subject, experiments can be applied at the cognitive or organisational level, utilise classical (Part II) or computational approaches (Part III), and include long or short time frames. Thus, their integration with wider methodology is critical if rigorous evidence and a cohesive body of scientific knowledge is to be developed (Parts I and IV).

In experimental design research, this challenge of integration is more significant than ever due to the growing importance of computer-based experimentation. Building on the pioneering works in artificial intelligence where computers were predominantly used for simulation, which enables the study of various models of human cognition (Weisberg 2006), recent developments in scientific practice highlight the potential for computer-based experimentation. New means for automated analysis, data interpretation and visualisation, and storage and dissemination reflect just a few of the novel approaches opened by computer-based research (Radder 2003). As with previous methodological paradigm shifts (Sect. 1.1), this rapidly expanding research domain faces the challenge of how to define experimental standards and systematic procedures, which ensure both justifiability of the experimental method and the repeatability of the obtained data. However, the potential for design researchers is huge, particularly in the emergent science of complexity and the study of the sociological and psychological roots of designing (see Part III). Thus, this book brings together and confronts the commonalities and conflicts between classical and computational experimental design research in order to distil core methodological insights that underpin all experimental design research, bridging methodology and methods, approaches, perspectives, and applications.

1.3 The Aim of This Book: Linking Methodology, Methods, and Application

From Sects. 1.1 and 1.2, it is evident that experiments are well described at both the methodology level in terms of their role in theory building/testing (Fig. 1.1) and the detailed method-specific level (Table 1.1). At the methodology level, numerous texts offer guidance, for example, Blessing and Chakrabarti (2009), Saunders et al. (2009), or Robson (2002) (also see Part IV). Similarly, at the method-specific level, texts such as that by Kirk (2009) or Shadish et al. (2002)

explore experimental design in detail (also see Part II). Further, there are countless articles discussing specific aspects of experimental methodology or design. Thus, why does a need exist in design research?

An aspect that neither methodology nor method-specific texts deal with is how researchers can adapt or adopt these insights into the specific context of their own field. This need for *field-specific* development and adaption at the interface between methodology and method is highlighted by numerous authors in both design research (Ball and Ormerod 2000b; Blessing and Chakrabarti 2009, 8) and its related fields, where similar efforts have received significant support (Levin and O'Donnell 1999; Kitchenham et al. 2002). The key element that drives field-specific adaption is the integration between specific methods and the wider body of research practice and methodology, i.e. the middle ground between methodology and methods. Thus, it is this middle ground that this book seeks to fill, helping contextualise experiments within design research and exploring how they can be used, adapted to, and developed in the design research context as illustrated in Fig. 1.2. This book explicitly answers the need articulated in Sect. 1.1: *to develop a tradition of experimentation that is both grounded in rigorous methodology and tailored to the specific challenges of design research*; to support design researchers in the following:

- Bringing together methodology and methods for experimental design research.
- Exploring different perspectives on how experimental methods can be successfully adapted to the design research context.
- Discussing approaches to developing greater scientific rigour and best practice in experimental design research.
- Building more robust scientific tools and methods in order to shape a cohesive body of scientific knowledge.

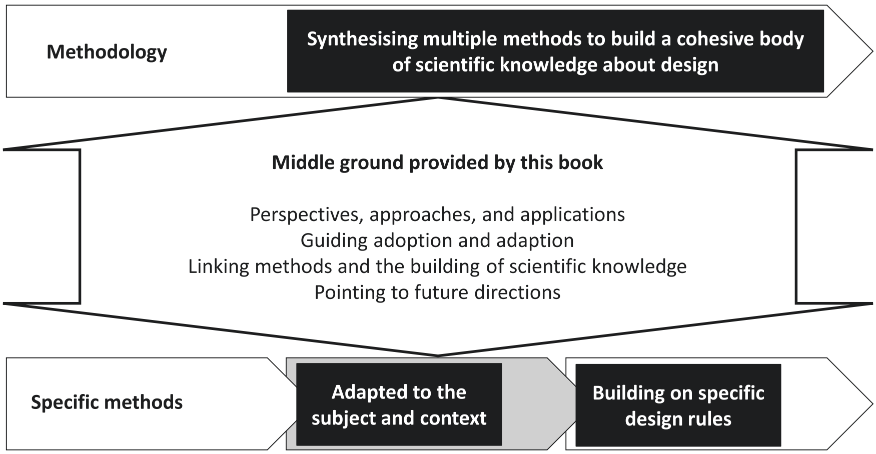


Fig. 1.2 The middle ground between methodology and methods

1.4 The Structure of This Book

Throughout this book, chapter authors draw on a wide range of perspectives in order to provide a multifaceted foundation in the approaches to, and use of, experimental design research in building rigorous scientific knowledge. This is structured in four parts outlined below and illustrated in Fig. 1.3:

Part I ***The foundations of experimental design research*** deals with the development of the experimental design research tradition, its role in the wider scope of design research empiricism, and the fundamentals of experimental design.

Part II ***Classical approaches to experimental design research*** deals with the study of individuals and teams, and the key features of examining these subjects in the design research context.

Part III ***Computation approaches to experimental design research*** deals with the use of computation to complement and extend classical experimental design research, as well as significant developments in this field.

Part IV ***Building on experimental design research*** deals with how to draw all these approaches and perspectives together in order to build meaningful theory, a cohesive body of scientific knowledge, and effective models of design.

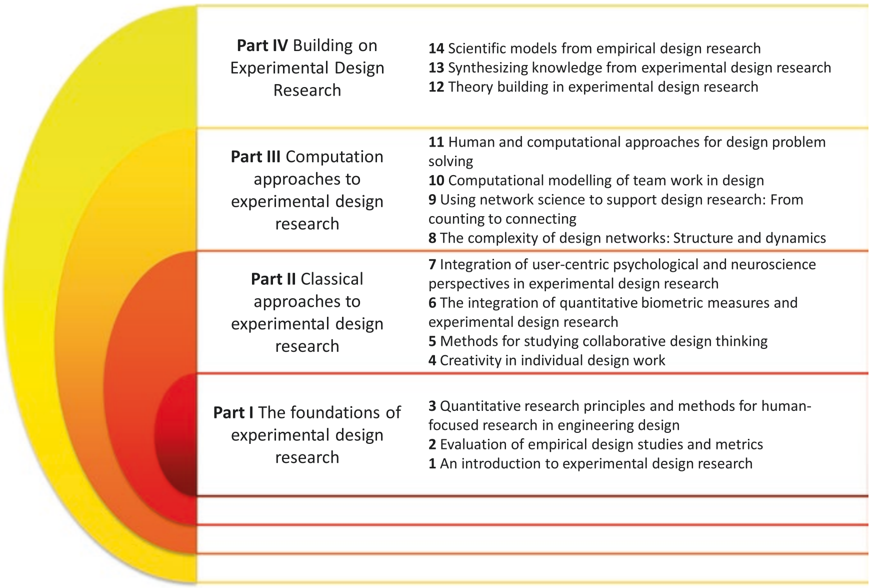


Fig. 1.3 An overview of this book's content and structure

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Chapter 2
Evaluation of Empirical Design Studies and Metrics

Mahmoud Dinar, Joshua D. Summers, Jami Shah and Yong-Seok Park

Abstract Engineering design is a complex multifaceted and knowledge-intensive process. No single theory or model can capture all aspects of such an activity. Various empirical methods have been used by researchers to study particular aspects of design thinking and cognition, design processes, design artefacts, and design strategies. Research methods include think-aloud protocol analysis and its many variants, case studies, controlled experiments of design cognition, and fMRI. The field has gradually progressed from subjective to objective analyses, requiring well-defined metrics since design of experiments (DOE) involves controlling or blocking particular variables. DOE also requires setting experiment variables at particular levels, which means that each variable needs to be characterized and quantified. Without such quantification, statistical analyses cannot be carried out. This chapter focuses on quantifiable characteristics of designers, targeted users, artefacts, and processes.

Keywords Design thinking · Design metrics · Empirical studies

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2.1 Systems View of Design

The aim of most design studies has been to discover strategies and processes that could potentially result in better products, lower development time, and lower cost than the competition. A simplistic model of design is that a designer (or design team) applies design knowledge (internal and external) to a design problem, following a suitable process to obtain design solutions. A systems-level view of design is shown in Fig. 2.1; it contains most major aspects of product design from an engineering point of view. Over the past 50 years, design researchers have conducted empirical studies of virtually all of the aspects of design shown in Fig. 2.1. The objectives of these studies vary from the development of design methods and tools, to enhancing design education and the derivation of design models and theories.

An overwhelming number of design studies have targeted designers: their cognitive processes and search strategies, role of expertise and domain knowledge and characterization of design skills. Studies of design teams have included methods

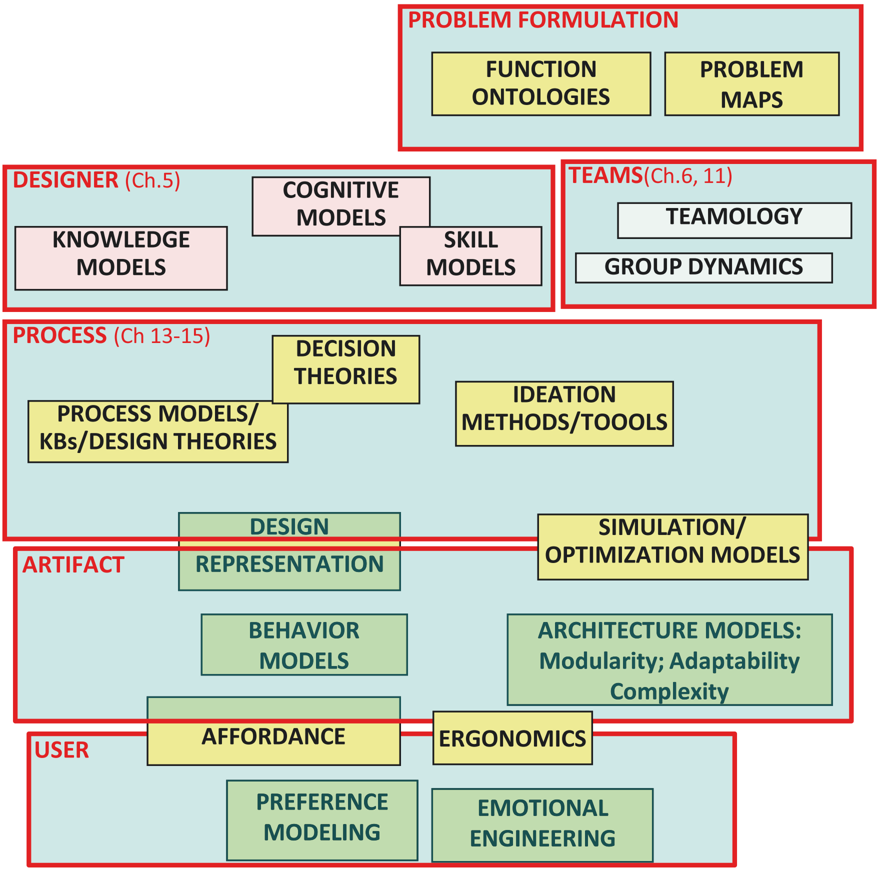

Fig. 2.1 Models of design (later chapters give more details)

for composing effective teams (teamology) and interaction of personalities and communications between team members (group dynamics). More recently, there have been studies in design problem formulation and its impact on quality and efficiency of finding good solutions. Development of function ontologies has been a major effort in this regard, with a few studies looking at broader aspects of problem formulation.

The effectiveness of various methods and tools has also been the subject of studies, from conception generation/evaluation to refinement and optimization. In the USA, there has been a heavy emphasis on utility and decision theory, largely due to heavy personal bias in NSF's design program leadership. Simulation and behaviour models tend to be domain specific and are usually not considered part of design research.

The US government and defence agencies have long been concerned by major cost overruns and schedule delays in the development of complex systems, such as military aircraft and assault vehicles. There is a belief that these systems have become overly complex due to single-minded emphasis on performance factors. There are also some in the government who believe that continuous changes in system requirements and addition of features, unintentionally rewards complexity. This has led to new research in developing metrics for complexity and adaptability, which could potentially be used in system selection process.

A key consideration in product design is an understanding of the user, his/her capabilities (ergonomics), the environment in which the product will be used, and ways in which it can be used or misused (positive and negative affordances). Ergonomics, human factors, and human–machine interfaces have long been disciplines of study in their own right, and we will not attempt to discuss them here.

Driven by mathematicians and design theorists, some popular methods, such as QFD house of quality, Kano model, and popular concept selection methods, have all come under severe criticism. One particular criticism is that these methods implicitly use linear utility, which does not account for user preferences. Another objection is that QFD violates Arrow's impossibility theorem (groups do not have transitive preferences). Yet another issue is that customer preferences collected based on individual attributes could result in products that have attribute combinations for which there may be little demand. Instead, researchers have proposed the use of conjoint analyses in developing product requirements.

One other point of clarification is necessary here. Many of the areas mentioned go across multiple boundaries than depicted in Fig. 2.1. For example, preference modelling and emotional engineering can be just as much part of problem formulation, as they are of artefact behaviour. Similarly, functional ontologies are needed in artefact modelling, as well. To show all these linkages would make Fig. 2.1 much too complicated. Also, in this article, we are leaving out another important aspect: the role of market studies and competitive benchmarking and price point targets.

2.1.1 Research Methods Used in Empirical Studies of Design

The most common method used in design studies is the so-called think-aloud protocol analysis and its many variants. This method is based on the direct observation of designers engaged in design activities. We can classify methods employed in these experiments based on *what* data are collected (verbalized actions, sketches, calculations), *how* it is collected (audio/video recording, computer tool), and *when* it is collected (during or after the design exercise). When viewed in the context of the systems view depicted in Fig. 2.1, we see that protocol analysis (PA) involves a very narrow slice, the study of cognitive processes of designers. Progressive ideation methods, such as C-Sketch and 6-3-5, do not allow direct communication between group members, so this method would not be useful. Instead, we may use an outcome-based method, such as snapshots of sketches/text progression through different key stages of these methods. Another limitation of PA is the short duration of sessions.

In contrast to PA, case studies can be used to collect data from large complex projects and can cover long periods of time. One can analyse an ongoing or past project from project documentation, interviews, meeting minutes, computer simulations, PLM/PDM data, etc. This can give a very comprehensive view of the entire system. Case studies are well suited to collecting and disseminating experiential knowledge, which is a crucial element of engineering design.

While PA is designer centric and case studies largely process centric, an artefact centric method of study is what is termed "product teardown" or reverse engineering. This method can be used for many different objectives such as, students learning how "stuff" works, or companies studying how a competitor's product achieves a particular function, or businesses in developing countries "copying" products from well-established manufacturers. In design research, product teardown by students in design classes led to the development of a function ontology (Tilstra et al. 2009).

It is nearly impossible to simulate real-world design in an academic setting even practicing designers are used as subjects, because we can neither create the motivation, nor rewards or risks, nor the size and complexity of most real engineering design problems. Typically, studies use subjects with limited designer expertise, fictitious problems, and "play" environment with no penalty for failure. Nevertheless, such simulated design experiments have better ecological validity than controlled laboratory experiments at the microscopic level, such as those done by cognitive psychologists on perception, memory, and cognition. However, the latter have higher intrinsic validity due to the smaller number of uncontrolled factors. This leads one in the direction of multilevel, aligned experiments (Vargas-Hernandez et al. 2010) to combine the best of both.

In recent years, several studies have been examining design thinking through physiological phenomenon, such as brain imaging using fMRI apparatus and sensing other internal behaviours, such as pulse rate. They seek to determine the physiological basis for cognitive actions and emotions. This is even lower on the ecological validity scale.

2.1.2 Measurable Characteristics

To put design studies on scientific foundations, it is essential that we clearly identify all variables relevant to the subject of the study, since design of experiments (DOE) involves controlling or blocking particular variables. DOE also requires setting experiment variables at particular levels, which means that each variable needs to be characterized and quantified. Without such quantification, statistical analyses cannot be carried out. Variables may relate to designers (skill levels, creativity), artefacts (complexity, adaptability, modularity), methods (efficiency, effectiveness), design teams (composite personality, skill profile), design ideas, and so on. In the next sections, we review various characterization and quantification methods used in empirical studies.

2.2 Variable Quantification Examples

In this section, we will present examples of characterization, quantification, and measurement methods used in empirical studies in a number of areas related to design. The basis for selecting these studies is that they all involve experiments that use objective measures.

2.2.1 Ideation Metrics

Ideation metrics are needed either to assess the outcome of ideation methods in order to assess their relative effectiveness, or to assess the productivity or creativity of individuals. How should one determine how good a design idea, or a set of ideas, is? One general approach to evaluating ideation is the consensual assessment method of Amabile (1996). It suggests that a subjective assessment by a panel of judges is appropriate as long as each judge is an expert in the domain and the judges evaluate ideas independently of each other. This method has rarely been used with some modifications in ideation assessment. Kudrowitz and Wallace (2013) have defined a set of measures that assigns one of the five labels (creative, clear, novel, useful, and product-worthy) on a three-point scale (2 = yes, 1 = somewhat, and 0 = no) to an idea. An aggregate of scores of 12 random raters per idea from an online crowd is used to score ideas. The authors state that their approach is useful as a first-pass evaluation of a large pool in early ideation stages. Green et al. (2014) have conducted a similar study by crowd-sourcing novice raters. However, they have compared the novices' assessments with experts and devised strategies for selecting a subset of novice raters who have a high agreement with experts. These subjective methods can be difficult to reproduce or validate.

On the other hand, the ideation metrics of Shah et al. (2003) are well established in design research and are objective. They consist of four metrics: quantity, variety, novelty, and quality. Quantity is measured by the total number of generated ideas. Variety is a measure of total unique ideas, taking into account similarity of generated ideas. Novelty is a measure of how rare generated ideas are. It is measured in comparison with ideas generated by a set of participants in a sample or in a historic population. Quality measures the feasibility of an idea and whether it meets the design requirements. All scores are normalized on the same scale (often 1–10).

To calculate these measures, the design is decomposed into its desired key functions. Weights can be assigned to each function. Every generated idea is evaluated with respect to the key functions, and the solution for each function is described. Quantity will be the total number of ideas found by a participant. Variety will be the total number of unique ideas. Quantity and variety can be either the total number of complete solutions or the total number of subsolutions per function. A novelty score for each function is found by determining how rare the idea is, i.e. if all participants have the idea, the novelty score for that idea is the lowest; if only one participant has the idea, the novelty score for that idea is the highest. The novelty score is the sum or weighted sum of the novelty scores of all functions for all solutions. Quality can be assessed by a panel of expert judges who assign a score to each idea generated for each function. The quality score for a design is the sum or weighted sum of the quality scores of all functions.

Modifications on Shah et al.'s metrics have been proposed by others. Oman et al. (2014) propose the expanded creativity assessment method (ECAM) where weights for novelty and quality are not assigned a priori, rather they are assigned based on the rarity or frequency of the ideas in a function; the more the ideas for a function, the lower the assigned weight for it. Oman et al. (2012) conducted a survey of other creativity assessment methods where they also present an earlier version of ECAM called comparative creativity assessment.

2.2.2 Evaluating Fitness of Conceptual Designs with Requirements

Concept selection is a convergent process to evaluate alternative design concepts with respect to customer needs. To conduct concept selection, quantification methods most frequently used are as follows: Pugh matrix (Pugh 1991); quality function deployment (QFD) score (Kogure and Akao 1983); weighted sums (WSM) (Fishburn 1967); and analytic hierarchy process (AHP) score (Saaty 1980). All, except Pugh, use some form of Likert scale (5 or 9 point). The Pugh matrix compares alternative design concepts against customer needs (Pugh 1991). It not only provides quantitative results, but also allows decision makers to generate hybrid candidates. The main drawback to it is in low rating resolution, since only "–", "s", and "+" coding scheme is employed to ratings of each comparison.

Compared to other concept selection methods, however, its strength lies in handling a large number of decision criteria (Pugh 1991; Pugh and Clausing 1996). On the other hand, QFD is a consensus-driven analysis by showing the transformation of customer needs into appropriate technical requirements using house of quality (HoQ) (Kogure and Akao 1983). An advantage of QFD over Pugh matrix is to set weights for these technical parameters. The data from HoQ often combine with Pugh matrix to select a design concept. The weighted-sum model (WSM), presented by Ulrich and Eppinger (1988, 2004), is often applied when decision makers need high resolution for better differentiation among alternative design concepts. After allocating weights to each of the criteria, a decision maker evaluates all of the alternative concepts with respect to one criterion at a time. The total score for each concept can be determined by the summation of the weighted scores. AHP is also a multicriteria decision-making method where decision makers evaluate multiple alternative design concepts by comparing one to another by assigning weights at each level independently in the hierarchical structure. A nine-point Likert scale is used in AHP with cardinal rating via pairwise comparison, spanning from 1 to 9 and their corresponding reciprocals.

Wassenaar and Chen's (2003) study on decision-based design summarized drawbacks of concept selection using multicriteria decision making. First, normalization is inappropriate when attributes have different dimensions. As an alternative, however, the weighted-sum method (WS) and AHP account for assigning weights rather than normalization. Yet it is still quite subjective due to choices of weights and ranks. Hoyle and Chen (2007) highlight that based on Arrow's impossibility theorem (AIT) (Arrow 1950), Hazelrigg's (1996) study shows that QFD utility exists only at the individual level. Consequently, there is a need to overcome current concept selection methods.

2.2.3 Complexity Metrics

Modern products are complex cyber-physical systems; the increasing complexity impacts development time, effort, and cost. According to the US Government Accountability Office (GAO), a major system in the last decade, on average, costs 26 % more than its initial estimated cost (projected to increase and the average delay in delivering the final product was 21 months (United States Government Accountability Office 2008). Aspects of complexity include the product structure, development process, and manufacturing. Many different complexity metrics have been proposed, but few have been verified experimentally.

Complexity is defined as a quality of an object with many interwoven elements and attributes that make the whole object difficult to understand collectively (El-Haik and Yang 1999). Complexity, long studied in computer science, biology, organizational science, and information theory (Du and Ko 2000), has yielded many metrics. In engineering design, these metrics are used to evaluate the complexity of design *problem*, *product*, and *process*. As the complexity of a product increases, the life cycle costs of the product also increase, while a simple product leads to enhanced reliability and quality at lower costs (Braha and Maimon 1998a). Others have used complexity metrics for surrogate modelling to predict assembly time and market price of products (Ameri et al. 2008; Summers and Ameri 2008; Mathieson and Summers 2009, 2010; Summers and Shah 2010). Thus, it is rarely the property of complexity that is of interest, but the property that can be predicted when considering complexity that is truly of interest.

Two views of complexity in design are that it is *the difficulty in solving a problem*, be it manufacturing or design (Braha and Maimon 1998a, b; Holtta and Otto 2005; Hamade 2009), or that *the whole exceeds the sum of the parts* (Boothroyd et al. 2002; Weber 2005). Complexity should include how the parts are assembled; it is not a simple additive property of the components, but rather an emergent property found only collectively in the assembly. This view is predominantly for studying the complexity of the designed product. Of the several developed perspectives on measuring this complexity, some propose that *complexity measures the minimum amount of information* (*bits*) *required to describe the object in a given representation* (Suh 1999, 2001). Such a paradigm ignores the possible interconnectedness of the information and the difficulty of parsing this minimal representation, however. A related perspective entails the concept of *complexity used to measure the phase change between order and randomness* (*entropy*) (El-Haik and Yang 1999). Similarly, through the algorithmic or computational perspective, *complexity is a measure of the tasks required to achieve some function* (*or components*) (Bashir and Thomson 2004) or *a measure of the number of operations required for solving a problem* (Ahn and Crawford 1994). A survey of engineering design complexity metrics (Summers and Shah 2010) classifies complexity into **size** (count of particular elements) (Kolmogorov 1983; Sedgewick 1990; Varma and Trachterberg 1990; Ahn and Crawford 1994; Fitzhorn 1994; Braha and Maimon 1998a; Simon 1998; El-Haik and Yang 1999; Balazs and Brown 2002; Bashir and Thomson 2004; Pahl et al. 2007; Shah and Runger 2011), **coupling** between elements (Dixon et al. 1988; Sedgewick 1990; Ahn and Crawford 1994; Simon 1998; Balazs and Brown 2002; Bashir and Thomson 2004; Pahl et al. 2007; Singh et al. 2012), and **solvability** (if it is possible to predict the design product to satisfy the design problem) (Fitzhorn 1994; El-Haik and Yang 1999; Suh 1999; Sen et al. 2010).

Measuring complexity in engineering design is based upon work from different domains and perspectives, including information modelling, software analysis, and traditional manufacturing and design. From an information perspective, Independence and Information axioms can be used to either reduce or manage the complexity of the design product (Suh 1999, 2001). Similarly, information theory has also been used as a baseline for measuring complexity (Braha and Maimon 1998a, b; El-Haik and Yang 1999). For example, researchers in software development have used complexity measures to determine the “Big-O” difficulty of a problem based on the best possible solution at hand, either implemented or theoretical. Engineers have adapted such complexity measures to model engineering design processes (Harrison and Magel 1981; Varma and Trachterberg 1990; Zuse

1991; Ahn and Crawford 1994; Phukan et al. 2005). Design researchers have long argued that a less complex design is preferable for many reasons (Dixon et al. 1988; Fitzhorn 1994; Simon 1998; Bashir and Thomson 2001; Balazs and Brown 2002; Pahl et al. 2007). For instance, Simon argued that engineering design is related to decomposable systems and that assessing the hierarchical interconnectedness of an engineered artefact enhances the management of such design complexities (Simon 1998). Similarly, others have shown the suitability of complexity measures for predicting assembly times, for elucidating mechanical engineering metrics for DSM and representational directional node link systems, and explored how product complexity varies based on representation (Mathieson et al. 2013; Ameri et al. 2008; Summers and Ameri 2008; Mathieson and Summers 2009, 2010; Summers and Shah 2010; Owensby et al. 2012). Much of the work on measuring complexity has been focused on developing a single holistic value or complexity function (Bashir and Thomson 2001; Shah and Runger 2011; Singh et al. 2012; Sinha and de Weck 2013a, b). Others have attempted to keep the metrics distinct, proposing instead a complexity vector (Namouz and Summers 2014; Owensby and Summers 2014; Summers et al. 2014).

While many metrics of complexity have been proposed in the literature and demonstrated on various examples, few have been experimentally compared for their utility or appropriateness in different application domains. For example, complexity metrics have been correlated with small satellite cost using single representations (Bearden 2003). The function–structure-based metric has been evaluated against large construction projects (Bashir and Thomson 2004). The complexity metric of the level of personnel cross-links in a cross-functional organization has been studied against the project cost and duration (Shafiei-Monfared and Jenab 2012). In each of these, historical data have been fit to develop single, unique complexity metrics for each application. A different series of studies have been conducted to compare different representations and complexity metrics for simple products (sprinkler, seed spreader, and table fan) (Ameri et al. 2008). It was shown that the complexity metrics are not rank-ordered consistently across different representations when comparing products. A similar study explored three types of metrics applied against different representations of products at different scales (simple gearbox and hybrid powertrain) (Singh et al. 2012).

2.2.4 Characterizing and Measuring User Preferences

A part of the design process is modelling preferences, i.e. to define what set of attributes are desired and at what level. Preference models can be a basis for concept selection in later stages. Therefore, developing mathematical models that characterize preferences in a quantifiable way is a key in an efficient design process. An example of such efficiency is the automatic or large-scale comparison of different designs or variants. Absent a mathematical preference model, comparisons are not only resource-consuming but often purely subjective. Yet, even with mathematical models, evaluating preferences exhaustively either can be computationally expensive, or can ignore appropriate suboptimal designs due to some simplified assumptions in building the models. Hunt et al. (2007) noted that in multicriteria design optimization, Pareto efficient designs reduce the problem into a single-criterion problem and often omit unquantifiable criteria. They generalized the Pareto front to a preference cone, whereby the directional trade-off between two criteria is zero on the cone, is infinite in the first quadrant, and is a positive value otherwise. They showed that their method considered the relative importance of criteria in the optimization process and allowed designers to freely explore a set of feasible designs even when they were unfamiliar with their preferences a priori.

In another approach to reducing cost of preference modelling, Moore et al. (2014) proposed value-based global optimization (VGO), which takes into account the cost of analysis and explicitly includes it in the design utility function. They used value of information as a metric for determining the cost of optimization process. If the expected value of information is negative, analyses are terminated. VGO fits a surrogate Gaussian model into a set of existing models, and based on their cost, accuracy, and predictions, another model is selected that maximizes the value of information. Using a case study of a hydraulic hybrid passenger car (with randomly generated test data), they showed that their VGO algorithm converges fast and the cost of analysis is lower compared to the efficient global optimization (EGO) (Jones et al. 1998).

Wassenaar et al. (2005) and Wassenaar and Chen (2003), implemented discrete choice analysis in modelling consumer demands to facilitate decision making in engineering design. They studied a case using the JD Power Consumer survey on passenger vehicles where they identified five customer choice attributes such as engine-to-performance ratio and comfort level, collected data from 2552 consumers, created a choice model, and estimated demand. The model of choice probability was estimated using a binary multinomial logit function (grouped logit) on a Kano utility shape function. The result was the ability to predict change in market share based on changing a design attribute.

Wan and Krishnamurty (2001) proposed a method for learning preferences with dynamic interactive modelling. The method features devise marginal utility functions, dynamic preference information gain, and checking for inconsistencies in preferences among trade-offs. They conducted a case study solving the design of a four-bar mechanism. The design space was populated with each attribute divided into unequal intervals with a finer mesh around values where designer expected the optimum solutions. The advantages were shown to be working with locally optimal sets rather than a globally optimal Pareto front in addition to leading to more accurate and consistent preference models at a lower cognitive load on the designer.

Tovares et al. (2014) conducted a factorial experiment to examine the effect of fidelity in user experience on product preferences. They compared preference models based on virtual reality to 2D sketches and physical prototypes in the design of a long-haul truck. They found that the additional information provided by the experience does not have a negative impact on the predictability of the preference models and that the VR experience is more similar to physical prototypes than 2D sketches.

On the other hand, Orbay et al. (2015) study the relation between 3D shape models and consumer preferences. Deconstructing the shape of a few cars, they generated a hierarchy of volumetric shape abstractions where the final shape of each car is a leaf node. Surveying about 30 participants, they found an abstraction level that made a brand recognizable. The implication is finding a point of debranding in the product shape prior to which designers can make decisions that do not endanger brand recognition. In addition, they also found relations between shape and consumer judgements in terms of attributes (adjectives) such as fast and sophisticated.

Other researches in preference modelling include a few machine learning approaches. Ren and Papalambros (2011) used support vector machines and an EGO algorithm to learn to optimize preferences iteratively based on answers from humans to queries of an interactive computer tool. Tucker and Kim (2011) proposed implementing emerging change mining techniques (e.g., very fast decision trees, or association rule mining while considering several interestingness measures such as the Gini index) to capture trends in emerging customer preferences and facilitate comparison of gain ratios of different attributes over time.

One of the early applications of mathematical modelling in describing preferences is the application of Von Neumann and Morgenstern's utility theory. Alternatively, Dym et al. (2002) propose pairwise comparison charts (PCCs) for ranking designs by designers' votes (or that of consumers), since "comparisons are cheap and require little detailed knowledge". They state that PCC should be used as a discussion tool and not a group decision tool. However, Barzilai (2006) argues that neither utility theory nor voting systems such as PCC encompass multiplication and addition which are pertinent to preference modelling in engineering design; he provides a theoretical foundation using set theory with strong scales in groups and fields.

2.2.5 Characterizing Design Problem Formulation

Not many studies focus on measuring problem formulation characteristics. The problem map (P-maps) ontological framework (Dinar et al. 2015a) is a computational framework which facilitates the representation and quantification of designers' problem formulation. The ontology allows assigning data fragments about problem formulation to one of the six entities: requirements, use scenarios, functions, artefacts, behaviours, and issues. The fragments can be related to each other within each category (entity type) with a hierarchical structure or between categories with links. Different variables can be extracted from P-maps. There are two different ways to define characteristics of problem definition expressed in

P-maps. One is to define characteristics of a state, and the other is to define that of changes across states obeying certain conditions. Both types of characteristics are numerical.

State characteristics can be defined as characteristics of accumulated data fragments over a time period up to a point, the state. An example of a state characteristic is the simple count of requirements. Another example called isolated entities is the count of entities that are not a part of a hierarchy. This characteristic can show how much of the problem is not further decomposed. On the other hand, the number of disconnected entities, i.e. entities without link to other types, can show the inability to recognize relationships among different aspects of the problem. A designer may consider different environmental or usability factors that affect a design problem but fail to identify how these factors situate the requirements.

The second type of characteristic is temporal and process-based, measuring the occurrences of adopting certain strategies. There are characteristics that relate to temporal changes but are not representing a strategy. Consider a sequence of different entity types such as "requirement, function, requirement, artefact, function, function" and a time stamp assigned to them based on their order (1 through 6). A variable can be defined as the median of occurrences of an entity. In the given sequence, requirements are added at times 1 and 3, and functions are added at times 2, 5, and 6, and thus, the median of occurrences of requirements and functions is 2 and 5, respectively. Problem formulation strategies can be formalized in P-maps. A strategy is formalized by a set of conditions that occur across states during the development of P-maps. One strategy is entity depth prevalence. When defining a problem, a designer can add more detail to a fragment or entity before linking it to other categories or link entities at a high level before decomposing each type of entity (Ho 2001). For this strategy, the conditions can be stated as if (a) entity parent of type A added at time t1, (b) entity child of type A added at time t2, (c) entity of type B added at time t3, (d) entity of type B is linked to the type A parent entity at time t4, and (e) t4 > t3 > t2.

The P-maps framework has facilitated a few empirical studies of problem formulation. One study investigates the relation between problem formulation characteristics as independent variables and creativity (Dinar et al. 2015c). Creativity is assessed by the ideation metrics of Shah et al. (2003). Results of linear regression analysis show that: *quantity* and *variety* increase if designers do more abstraction and specify key issues without decomposing them; *novelty* increases if designers specify fewer requirements and use scenarios but more functions, have more functions in hierarchies, and explore each entity in depth rather than in breadth across entity types; *quality* increases if designers specify more behaviours and fewer artefacts, identify more conflicts, and follow a breadth exploration strategy. The quantified problem formulation characteristics and ideation metrics enable determining the statistical significance of inferences made based on the data.

The regression models based on one problem are used to predict the ideation scores of another problem. Compared to scores by an independent panel of judges, the predictions of variety and quality are more accurate. Other studies based on the P-maps framework include the development of a test of problem formulation skills

(Dinar et al. 2015d) and objective assessment of students learning conceptual design through multiple assignments (Dinar and Shah 2014; Dinar et al. 2015b). In both studies, a quantified scoring scheme is suggested by normalizing the number of appropriate responses with respect to data collected from a sample of participants for a specific problem.

2.2.6 Decision-Based Design

Decision theory uses "utility" to quantify the value of an alternative, often expressed in monetary terms. To overcome limitations of multicriteria decision making, various approaches have been proposed (Callaghan and Lewis 2000; Roser 2000; Gu et al. 2002). Chen's analytical techniques include discrete choice analysis (DCA) (Wassenaar and Chen 2003); the product attribute function deployment (Hoyle and Chen 2009) method; and integrated Bayesian hierarchical choice modelling (IBHCM) (Hoyle et al. 2010) approach with quantification aspects.

Various analytical techniques such as multiple discriminant analysis (Johnson 1970), factor analysis (Green and Tull 1970), multidimensional scaling (Green and Carmone 1970), conjoint analysis (Green and Srinivasan 1978, 1990), and discrete choice analysis (DCA) (Wassenaar and Chen 2003; Chen et al. 2012) have been developed to provide a model of customer preference and choice. Among these, discrete choice analysis (DCA) uses individual customers' data represented by a rating scale, in order to model customer choice and ordered logit (OL) (Chen et al. 2012). As the single criterion in alternative selections, in other words, DCA utilizes the economic benefit method to evaluate economic benefit (Wassenaar and Chen 2003; Chen et al. 2012).

The product attribute function deployment (PAFD) method (Hoyle and Chen 2009) is a design tool to guide the product planning phase of a product development. Beyond the framework of quality function deployment (QFD), PAFD method is the quantitative decision-making processes of DBD by removing the need for the user weights and rankings associated with the QFD method (Hoyle and Chen 2009). Additionally, single-objective utility maximization supports decision making under uncertainty and mitigates the difficulties related to weight factors and multicriteria decision making (MCDM) in QFD. This can be feasible by identifying attributes, selecting concepts, and setting targets in the DBD framework. Consequently, quantitative assessments of the PAFD provide better design decisions among alternative concepts.

There is a need to make the connection between quantitative attributes used in engineering design and qualitative attributes that customers might consider. Integrated Bayesian hierarchical choice modelling (IBHCM) approach is a hierarchical demand modelling that addresses this need and captures heterogeneous customer preferences (Hoyle et al. 2010; Chen et al. 2013). The Bayesian estimation methodology is employed to integrate multiple data sources for model estimation and updating. An integrated estimation procedure is applied to alleviate error propagations in hierarchical structure. IBHCM also applies the mixed logit choice and the random-effects ordered logit model for predicting stochastic consumer preferences and modelling consumer evaluations of multilevel design artefacts, respectively (Chen et al. 2013). As a result, IBHCM offers a comprehensive solution procedure and a highly flexible choice modelling for complex design features.

2.2.7 Quantification of Team Dynamics

Prior research on team dynamics has shown that there is a correlation between a variety of factors and team performance. In order to study these correlations, researchers adopted various analytical techniques to get a better understanding of team dynamics (Eris 2002; Wood et al. 2012; Sonalkar et al. 2014). Few have employed quantification methods to form effective teams and globally distributed teams (Wilde 2008; Park 2014). To form creative and effective teams, two studies focused on specific characterizations of designers. Wilde (2008, 2011) developed his teamology formulas by devising a simplified set of 20 questions based on the Myers–Briggs-type indicator (MBTI) personality test. The teamology score is mapped onto two different role maps which are associated with Belbin's role theory (Wilde 2008, 2011). This team role map allows allocating responsibilities, resolving role duplications, and covering low consciousness roles.

To extend the use of teamology in globally distributed and culturally diverse environment, Park (2014) developed a computational method referred to as global design team formation (GDTF) by merging a sociocultural framework (i.e. global leadership and organizational behaviour effectiveness) with the teamology framework. Through the quantitative representation scheme, this method facilitated forming psychologically and culturally cohesive teams from among a diverse population.

On the other hand, to understand the fundamental cognitive mechanism in teams, Eris (2002, 2004) created a taxonomy of questions, i.e. deep reasoning question (DRQ) and generative design question (GDQ). He then measured the ratio of DRQ to GDQ in relation to team performance, indicating that design teams are more likely to ask questions that are divergent in nature in order to produce alternative concepts, over the course (Eris 2002, 2004).

Wood and other colleagues applied latent semantic analysis (LSA) (Deerwester et al. 1990; Landauer et al. 1998) to written descriptions of designers' mental models, in order to quantify team interaction structure and mental model convergence (Fu et al. 2010; Wood et al. 2012). Based on the results from LSA of textual similarity of two documents, they developed a metric that showed differences in individuals' mental models. They identified the relationship between team interaction structure and mental model development.

2.2.8 Characterizing and Measuring Design Skills

A number of cognitive skills relevant to conceptual design have been identified (Shah 2005). They include divergent thinking, visual thinking, spatial reasoning, abstract reasoning, and problem formulation. In order to assess a designer's skill level, a set of standardized tests has been developed for these design skills. This skill evaluation may have potential uses in (1) determination of design strengths/weaknesses of individuals for the purpose of corrective action; (2) matching individuals with complementary strengths on design teams; and (3) continuous improvement and evaluation of course content. Such tests require the characterization and objective measurement of factors relevant to those skills. Divergent thinking skill was characterized in terms of four outcome measures: fluency, flexibility, originality, and quality, and four process measures: abstractability, afixability, detailability, and decomplexability (Shah et al. 2012). Visual thinking was measured using six characteristics: visual comprehension including perceptual speed, visual memory, visual synthesis, mental image manipulation/transformation, spatial reasoning, and graphical expression/elaboration (Shah et al. 2013). Qualitative or abstract reasoning ability was characterized in terms of qualitative deductive reasoning, qualitative inductive reasoning, analogical reasoning, and abductive reasoning (Khorshidi et al. 2014).

2.2.9 Characterizing Patterns and Strategies in Design Processes

With advancements in computing power in recent decades, some empirical studies of design are not only related to quantification but also related to computation. Computational methods, notably machine learning, are used to find patterns from large datasets automatically. Stahovich (2000) created LearnIT, an instance-based learning tool that inducts rules from iterative parametric designs carried out by designers. The goal of the system is to automate documentation and reuse at a low cost.

Some computational approaches focus on text analysis. Dong et al. (2004) used latent semantic analysis (LSA) to understand the relationship of design documentation in teams with successful outcome. LSA is text analysis method that measures the semantic similarity between pieces of documents by creating a high-dimensional word-by-document matrix and drawing patterns by reducing the space with singular value decomposition. A panel of expert faculty and professional designer judges ranked team performance on a set of 13 criteria. Spearman's rank correlation analysis showed significant correlation between semantic coherence in teams' documentation and performance.

Fu et al. (2013a) also used LSA to find semantic similarity in the US patent database and searched for a structure in mapping form to function with a Bayesian algorithm. The goal is to create a tool that aids designers by providing analogical stimuli from a clustered design repository. Based on the created structure which determined a measure for distances among concepts (form and function), Fu et al. (2013b) conducted an experimental study to understand the effect of the distance of an analogue from a problem on designer creativity. They formed three groups of designers who received near, far, and no external stimuli. They found that there is a sweet spot in how effective an analogue can be on designers' outcome.

Glier et al. (2014) used three different classifiers (Naïve Bayes, support vector machine, and k-nearest neighbours) to determine how biology corpora can inspire design. Participants were given a design problem (corn shucker) and text stimuli (biosentences). Instead of asking the participants to generate ideas, they were asked to respond true or false to the question if the sentence gave them any idea for the problem. The stimuli were a few hundred sentences taken from papers in different biology journals. The true or false responses formed the class variable. Tokenization and stemming was used for feature selection in the text, i.e. to reduce the sentences into a set of words more pertinent to biology. They reported precision, recall, and *F* score of each of the three classifiers for a different problem and concluded that the naïve Bayes classifier though having a slightly lower precision score was superior to SVM because of being a simpler model. They also suggested that each function led to a different classifier and planned to develop different classifiers for a function basis.

Dinar et al. (2015a) also used a few machine learning methods in search for patterns in data collected from novice students in the P-maps ontological framework. They used association rule mining with confidence and lift as the evaluation metrics, representing commonness and high correlation, respectively. The rules with higher confidence and lift indicated that designers who had found more implicit requirements also had a deep function hierarchy and designers who had identified more relations between functions and artefacts failed to find implicit requirements. They also used sequence mining among strings of entity types and relations added successively. The evaluation metric is called support which shows how frequently a partial order of the entities appeared among different designers. The subsequences with the highest support were ("requirement", "requirement", "requirement"), ("requirement", "function"), and ("requirement", "parent_of_requirement", "requirement") implying that the novices are problem-oriented; they structured requirements and functions in a more organized way than they did with artefacts and behaviours.

2.3 Contrasting Quantitative Versus Qualitative

One aspect of engineering design research that has been explored for many years is the study of creativity in early stages of design as supported by idea generation. Studies have been undertaken to understand the role that different representations play in idea generation and evaluation (McKoy et al. 2001; Linsey et al. 2008;

Hannah et al. 2011), the role that analogical mapping plays in design (Linsey and Viswanathan 2014), and the effect that different design methods have on concepts generated (Linsey et al. 2011; Chulvi et al. 2012a). In these studies, an important element of the research method employed is the evaluation of the sketch that is generated by the participants. The evaluation might be objective where the results of the evaluation are independent of evaluators or subjective where the analysis results depend on the individuals evaluating the sketches. Often, the degree of inference required to interpret and evaluate the sketch influences the objectivity. Likewise, metrics that are quantitative such as counting the number of lines, features, or renderings can positively influence the objectivity of the metrics. These characteristics of sketch evaluation metrics can be found in (Joshi and Summers 2012).

A brief comparison of sketching and ideation evaluation metrics from 24 studies is illustrated in Table 2.1 (Cross 1997; McGown et al. 1998; McKoy et al. 2001; Yang 2003; Tovey et al. 2003; Cham and Yang 2005; Linsey et al. 2005b, 2008, 2011; van der Lugt 2005; Yang and Cham 2007; Lau et al. 2009; Yang 2009; Chiu and Salustri 2010; Schmidt et al. 2010; Ramachandran et al. 2011; Westmoreland et al. 2011; Chulvi et al. 2012a, b; White et al. 2012; Worinkeng et al. 2013; Cheng et al. 2014; Arrighi et al. 2015; Lee et al. 2015). The goals or the research questions defined by the researchers are illustrated in addition to the data sources that are used for the study. The type of the study is defined as case study (CS), protocol study (PS), or user study (US) as discussed earlier. Half (twelve) of the studies presented can be identified as controlled user studies. Four were protocol studies that captured behaviour or thought explanations while sketching. Finally, eight are classified as case studies with the primary mechanism of study being document analysis. The metric type is coded from four points of view: objective/subjective/subjective with inter-rater reliability testing (O/S/R); explicit/implicit (E/I); qualitative/quantitative (L/N); and manual/automated (M/A). There are no metrics that were automatically coded in the papers reviewed.

The controlled user studies are highlighted in the table. Of the thirty metrics defined for the controlled user studies, twelve (40 %) are objective or were subjective but tested for inter-rater reliability. The others (60 %) were subjective without a clear test for rater objectivity. However, when considering the study overall, half of the studies included objective or inter-rater-tested metrics. Only one study employed both objective (quantity) and non-tested subjective (novelty, variety, and quality) metrics (Schmidt et al. 2010). The three subjective metrics were developed as part of a previous effort (Shah et al. 2000, 2003). Employing previously established metrics is one approach to addressing the objectivity of research as it establishes a distance between the investigator and the object of study (Le Dain et al. 2013). In an attempt to create some objectivity in the evaluation, several researchers have used panels of evaluating judges.

A final observation of the metrics used in the studies is that most of the researchers have chosen to use multiple different metrics in their research. In this way, the researchers have distributed the subjectivity of their analysis and evaluation of the concepts or sketches generated across multiple different dimensions.

Table 2.1 Comparison of research on sketching and ideation based on metrics of evaluation [adapted from Joshi and Summers (2012)]

Ref.	Research goal/questions	Data source	Type of study	Metric	Type of metric
Westmoreland et al. (2011)	Understand the sketching roles in student projects	Visual representation such as sketches, CAD, line drawings, and photographs from senior design reports	CS	Subject matter—system, subsystem, artefact	O-E-L-M
				Part of multiple objects—in same grouping on page but different from one another in type or subject	S-I-L-M
				Motion indicator	O-E-L-M
				Applied forces	O-E-L-M
				Part of set—multiple visuals related to each other	S-I-L-M
				Views—isometric, orthogonal, multiple	O-E-L-M
Linsey et al. (2011)	Understand the relationship between method, representation, and creativity	Sketches from user study	US	Variety	R-I-L-M
				Novelty	R-I-L-M
				Quantity (based on function count)	R-I-N-M
				Quality	R-I-L-M
Schmidt et al. (2010)	Does emphasizing sketching affect ideation?	Design ideas and sketches	US	Novelty	S-I-N-M
				Variety	S-I-N-M
				Quantity	O-E-N-M
				Quality	S-I-N-M
McKoy et al. (2001)	Understand the representation influence on communication	Sketches and textual descriptions of data	US	Quality based on the satisfaction of identified functions	S-I-L-M
				Novelty-using function and sub-function breakdown	S-I-Q-M
				Accuracy of communication	S-I-L-M

(continued)

Table 2.1 (continued)

Ref.	Research goal/questions	Data source	Type of study	Metric	Type of metric
Linsey et al. (2005a)	Understand the role that group ideation plays on ideation	Sketches and textual descriptions, post-session survey	US	Quantity	S-I-N-M
				Quality	S-I-L-M
Linsey et al. (2008)	Understand the influence of analogy on sketched solutions	Sketches	US	Quantity	S-I-L-M
Yang (2003)	Understand the relationship of sketching with project outcome	Student design log books, data from morph charts	CS	Quantity—sketch count, dimensioned sketch counted separately	O-E-N-M
Lau et al. (2009)	Understand the role of sketching in design	Sketches in design journals	CS	Representation—2D or 3D	O-E-L-M
				Annotations	O-E-L-M
				Media—tangible, digital, or mixed	O-E-L-M
Cham and Yang (2005)	Understand the relationship between sketching ability and design outcomes	Data from survey and student design logbooks	CS	Demonstration of grasp of concept	S-I-L-M
				Accuracy of proportions	S-I-L-M
				Correctness of proportions, 3D perspective	S-I-L-M
				Quantity—sketch count	O-E-N-M
Yang and Cham (2007)	Understand the relationship of sketch ability on outcome	Data from survey and student design logbooks	CS	Demonstration of grasp of concept	S-I-L-M
				Accuracy of proportions	S-I-L-M
				Correctness of proportions, 3D perspective	S-I-L-M
				Quantity—sketch count	O-E-N-M
Yang (2009)	Understand the quality of sketch correlation with design outcome	Data from survey and student design logbooks	CS	Quantity—sketch count	O-E-N-M

(continued)

Table 2.1 (continued)

Ref.	Research goal/questions	Data source	Type of study	Metric	Type of metric
Ramachandran et al. (2011)	Understand the relationship between early design seed models and creativity	Sketches from user study	US	Quantity—sketch count	O-E-N-M
				Quality—high, medium, and low based on solutions for requirements	R-I-L-M
Worinkeng et al. (2013)	Understand the effect of presketching on ideation	Sketches	US	Quantity	O-E-N-M
				Novelty	R-I-N-M
White et al. (2012)	Understand the influence of ideation method on quantity and student self-efficacy	Sketches and questionnaires	US	Quantity	O-E-N-M
				Change in self-efficacy	O-E-N-M
McGown et al. (1998)	Understand the sketching behaviour	Sketches from design notebook, observer notes	CS	Complexity based on line shading and annotation	S-I-L-M
				Size scale	O-E-N-M
				Drawing media	O-E-L-M
				Information content	S-I-L-M
van der Lugt (2005)	Understand the sketching through design thinking	Sketches from user study	US	Linkography	R-I-N-M
Chulvi et al. (2012a)	Understand the relationship between logical and intuitive methods and creativity	Sketches	US	Novelty	S-I-L-M
				Quality	S-I-L-M
Cross (1997)	Understand the problem–solution shift in design	Think-aloud transcripts and sketches	PS	Frequency/time	S-I-L-M
Tovey et al. (2003)	Understand the role that different line styles play in concept sketching	Videos of sketching activities	PS	Feature sequence	S-I-L-M

(continued)

Table 2.1 (continued)

Ref.	Research goal/questions	Data source	Type of study	Metric	Type of metric
Chiu and Salustri (2010)	Compare peer evaluation and expert panel assessment of creativity	Project final review presentations	CS	Novelty	S-I-L-M
				Quality	S-I-L-M
				Creativity	S-I-L-M
Chulvi et al. (2012b)	Compare academic creativity methods with expert intuition	Sketches	US	Moss (quality * novelty)	S-I-L-M
				Sarkar (quality * novelty)	S-I-L-M
				EPI (quality * novelty)	S-I-L-M
				Expert (novelty)	S-I-L-M
				Expert (quality)	S-I-L-M
				Expert (creativity)	S-I-L-M
Lee et al. (2015)	Understand the relationship between sketching activities and creativity	Videos of sketching activities	PS	Creativity	S-I-L-M
Arrighi et al. (2015)	Understand how different CAD tools influence quality and creativity of solutions	CAD models	PS	Robustness	S-I-L-M
				Generativeness	S-I-L-M
Cheng et al. (2014)	Understand the influence that partial analogies have on ideation	Sketches	US	Creativity (experts)	S-I-L-M
				Creativity (self)	S-I-L-M

By doing so, the researchers have addressed the subjectivity of the research by segmenting it in much the same way that faculty might use a rubric to increase the objectivity of grading project reports.

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Chapter 3
Quantitative Research Principles and Methods for Human-Focused Research in Engineering Design

Mark A. Robinson

Abstract Engineering design is increasingly recognised as a complex socio-technical process where the human and social aspects of the system require alignment with those focusing on technical product development. Social science research methods are therefore essential to conduct effective and holistic research into such processes. Accordingly, this chapter provides a grounding in the principles and methods of quantitative social science research. First, the measurement of variables in a reliable and valid manner is considered. Second, scientific principles and the nature of variable relationships are examined, including main effects, mediation effects, and moderation effects. Third, experimental and correlational research designs for exploring the relationships between variables are discussed. Fourth, an overview of statistical methods for analysing quantitative data is provided. Finally, participant sampling, ethical issues, and specialist methods are considered.

Keywords Quantitative research · Measurement · Research design

3.1 Introduction

Historically, it was generally thought that engineering design was concerned solely with technical work, much of it solitary, grounded in sciences such as physics, mathematics, and chemistry (Pahl and Beitz 1984). While these foundations are critical to product design, there has been a recognition in recent years

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that the working processes and organisational systems in which such products are developed are quintessential examples of complex socio-technical systems (Baxter and Sommerville 2011). Accordingly, the human and social aspects require alignment with the technical product development processes (Crowder et al. 2012; Davis et al. 2014). Engineering design, as Bucciarelli (1988) noted, is a "social process", one involving "distributed cognition" (Busby 2001) in team-working environments (Dong 2005). It is also a work domain involving complex problem solving (Goldschmidt and Smolkov 2006), creativity (Howard et al. 2008), and complex cognitive visualisation (Demian and Fruchter 2009). It is therefore an ideal domain in which to study human behaviour and cognition. Through my own research, for instance, I have found engineering design to involve socially interactive work some 40 % of the time (Robinson 2012), in complex team environments (Crowder et al. 2012), where the generation, processing, and transfer of information are key (Robinson 2010), and where a range of technical and non-technical competencies underpin effective performance (Robinson et al. 2005).

In recognition of this change of perception, engineering design research is increasingly focusing on the human aspects of work in this field alongside its traditional focus on product development. Much of this research has been conducted by researchers with engineering backgrounds, such as that exploring expertise and task performance (Ahmed et al. 2003), creativity (Howard et al. 2008), problem-solving activities (Cash et al. 2014), information seeking (Aurisicchio et al. 2010), and the evolution of social knowledge networks (Štorga et al. 2013). Other research in this area has been conducted by researchers with social science backgrounds, such as that exploring job design (Lauche 2005), competencies (Robinson et al. 2005), and the role of trust in innovation (Clegg et al. 2002). Part 2 of this book provides examples of the application of psychology, a discipline central to both social and biological sciences, to engineering design research.

However, despite many such examples of excellent, rigorous research, there remains a general lack of awareness of social science research principles in much of the work in this area. This is not due to any lack of ability—indeed, the quantitative methods used by engineering designers to develop and analyse their products are generally more advanced than social science research methods—rather, it is indicative of the lack of social science training in most formal engineering curricula. Thus, in this chapter, I aim to provide a solid grounding in key research principles and methods from social science for those with engineering design backgrounds conducting human-focused research in this area. To do so, I will draw on a hypothetical research study, gradually increasing the complexity of this example to illustrate key research principles. I will provide indicative supporting references for readers to consult, although these research methods are widely covered throughout the social science literature. Finally, I will also include examples from the engineering design literature of the application of such methods in previous research.

3.2 Measurement

A quantitative research study starts by identifying and defining the variables of interest, including how to measure them in a reliable and valid manner. In this section, we will discuss the systematic steps researchers should take to achieve these objectives.

3.2.1 Identifying, Defining, and Measuring Variables

Let us assume, for example, that we wish to study the effects of communication on team performance in an engineering design company (for related research, see Patrashkova-Volzdoska et al. 2003). As both are complex constructs, we must first decide which specific facets to focus on. For instance, communication may encompass frequency, media, recipients, and sources (Patrashkova-Volzdoska et al. 2003; Robinson 2012), while team performance may encompass time, cost, and quality (Atkinson 1999). Guided by the research literature and the nature of the practical problem we are addressing, we will focus here on the facets communication frequency and speed of team work (i.e. performing work in less time) as our research *variables*. Variables are so-called as they exhibit change, across both the unit of analysis (e.g. people, companies) and time, enabling research inferences to be made (Field 2013), as we discuss in Sect. 3.3.

Having established our specific focus, we must now decide how to measure each variable. To do so, we *operationally define* them by specifying the type of data we will use to represent and measure our variables in this research (Foster and Parker 1995). For *quantitative* research, we will be seeking numerical data, preferably of the type that enables us to determine which of the two measurements of a variable is higher (ordinal data), and also the exact distance between these two measurements (interval data), and also using a measurement scale with a true zero (ratio data) (Field 2013). Either such quantitative data can be collected directly by the researcher specifically for the research, so-called *primary data*, or the researcher can use existing data that have been collected for other purposes, so-called *secondary data* (Cowton 1998).

Within quantitative social science research, questionnaires are a popular and effective method for collecting primary data. These involve participants responding to a number of questions or statements ("items") about focal variables, using standardised measurement scales, to indicate the level of a variable in a particular context or scenario (Hinkin 1998). For instance, Peeters et al. (2007) used a 55-item questionnaire to measure three types of design behaviour—creation, planning, and cooperation—in multidisciplinary teams, with a 5-point response scale ranging from "highly disagree" (coded 1) to "highly agree" (coded 5). We could use such an approach in our example, by choosing existing questionnaire items from the research literature. If we were unable to find suitable items to measure our variables, we could develop our own, such as “How many times per week do you e-mail your team leader?” for the variable communication frequency, or “What percentage of your team’s projects are completed on schedule?” for the variable speed of team work.

A further option here would be to use existing secondary data available from the engineering design company to measure our variables. Although such data may not be readily available, they can often be more accurate, as we discuss below, and more efficient to use having already been collected. In our example here, a useful measure of communication frequency may be the number of e-mails that team members send to each other per week, recorded directly from the company’s computer systems, although there may be ethical issues with accessing such data, as we discuss later in Sect. 3.5.2. Indeed, such official e-mail records have previously been used in engineering design research investigating communication content and context (Loftus et al. 2013) and social knowledge networks (Štorga et al. 2013). For speed of team work, a useful measure could be calculated by comparing actual project duration to planned project duration for each team, with relevant dates obtained directly from official company records. Adopting a similar approach, previous research examining the work of electronics design teams used a company’s Gantt chart records to infer whether work was progressing on schedule (Jagodzinski et al. 2000).

3.2.2 Reliability

Having identified potential measures of our variables, communication frequency, and speed of team work, we must now consider their appropriateness and accuracy further before deciding which to use in our example research study. Within social science research, appropriateness and accuracy of measurement are usually jointly considered from the perspective of *reliability* and *validity*. Broadly, reliability refers to whether a measurement method yields consistent results, and we consider it first here because it is a prerequisite of validity (Cook 2009).

The two types of reliability most frequently encountered in social science research are *internal reliability* and *inter-rater reliability*. Internal reliability refers to whether the different components of a measure, where they exist, measure the variable consistently (Gregory 2007). It is most commonly examined in research using questionnaires, where multiple statements or questions are used to measure each variable, such as communication frequency here. To do so, a long-standing and widely used statistical coefficient called *Cronbach*’*s alpha* (α, Cronbach 1951) is calculated, using standard statistical software (see Sect. 3.4), to ascertain the consistency of participants’ numerical responses to each of the statements or questions measuring the same variable. The α statistic ranges from 0 to 1, with higher values indicating greater internal reliability, and a threshold of $\alpha \geq 0.70$ considered sound (Cortina 1993). For instance, Peeters et al. (2007) calculated the internal reliability of their 5 items measuring the variable “reflecting on the design” to be $\alpha = 0.80$ when first developed.

Inter-rater reliability refers to consistency between multiple participants rating the same variable (Gregory 2007). In our example, if all the members of each team rate the speed of their team's work, then there would have to be agreement or consistency between the ratings of each team member for there to be inter-rater reliability. There are several statistical coefficients that can be calculated using standard statistical software (see Sect. 3.4), of which the *intra-class correlation coefficient* (ICC, Shrout and Fleiss 1979) is one prominent example. Ranging from 0 to 1, a value of ICC $\geq$ 0.60 would generally indicate acceptable inter-rater reliability (Shrout 1998), although there are several different versions of this statistic for different purposes (Shrout and Fleiss 1979). For instance, Oman et al. (2013) used this method to assess the inter-rater reliability of judges' ratings of the creativity of engineering design solutions, finding them to have acceptable average reliability of ICC = 0.80.

Most reliability measurements in social science are focused on the ratings of participants involved in studies collecting primary data. However, the principles of calculating reliability can still be applied to secondary data acquired from companies. For instance, multiple measurements of the same variable drawn from the same secondary data source, such as the e-mail frequency data or project durations we have considered here, could also be assessed for reliability using either of the above two methods.

3.2.3 Validity

Validity refers to whether the measure used measures what it claims to (Cook 2009). So, to be valid, the measure of communication frequency in our example would need to truly measure communication frequency rather than another variable. In social science, there are three main methods of establishing the validity of a measure, each linked to a specific type of validity: *content validity*, *criterion validity*, and *construct validity* (Cook 2009). There are two further types of validity that relate to research design rather than measurement—*internal validity* and *external validity* (Campbell 1986)—that we will also discuss in Sect. 3.3.

Content validity concerns whether all components of a variable, and those components alone, are measured (Moskal and Leydens 2000). Put simply, the measure should be both comprehensive and pure. So, to be comprehensive, our measure of communication frequency should address all potential communication modes, including face to face, e-mail, telephone, instant messenger, and other written media (Robinson 2012). Meanwhile, to be pure, our measure should not address work tasks irrelevant to communication frequency. The irrelevance of some tasks, such as travelling, will be obvious, but with other tasks, such as report writing, a judgement has to be made about whether this matches the operational definition of communication frequency used in the study. A common approach to establishing content validity is to consult experts in the domain being researched about the completeness and relevance of the measure, as Dooley et al. (2001) did with their questionnaire measure of design software process maturity and Robinson (2012) did with his measurement categories for engineering design tasks.

Criterion validity refers to whether a measurement of a variable is highly related to the actual level of that variable (Gregory 2007). It is generally measured by a correlation coefficient (see Sect. 3.4), usually Pearson's r, ranging from -1.00 to $+1.00$, with positive values indicating a positive relationship; $r \geq +0.30$ indicates moderate validity and $r \geq +0.50$ high validity (Cohen 1988). It arose in the field of personnel recruitment and so is often conceptualised as the relationship between scores on recruitment tests and subsequent job performance (Cook 2009). Indeed, Shah et al. (2009) used this application in their validation of assessment tests for design skills, finding a correlation of $r = 0.60$ with performance in design contests. However, criterion validity is broader and essentially refers to the relationship between the measurement and an independent objective measurement of the same variable (Moskal and Leydens 2000). So, in our example, criterion validity could be calculated for primary data measures, such as the questionnaire items measuring communication frequency, with reference to equivalent secondary data from the company involved, such as the company's e-mail and telephone records indicating frequency.

Construct validity is most commonly determined by whether the measure is highly related to other measures of the same variable (Gregory 2007). Defined as such, it can overlap with criterion validity somewhat; however, the construct validity of a primary data measure is usually measured with reference to another primary data measure, rather that the objective secondary data that criterion validity is concerned with.

3.3 Research Design

Having identified our research variables and established how to measure them in a reliable and valid manner, we can now examine the relationships between these variables. To do so, we must draw on scientific research principles to collect data systematically using experimental or correlational research designs, as we will discuss in this section.

3.3.1 Scientific Principles

Debates continue about whether social science is truly a science (Winch 1990), and the lack of consensus can be partially attributed to the methodological diversity of its component disciplines. However, social science with a strong quantitative focus—such as most psychology research—is guided by the scientific method and can therefore lay the strongest claims to being a science (Dienes 2008). A key tenet of science is the principle of difference, which states that if two situations are identical except for one difference, and the outcomes of the two situations are different, then the initial difference is the cause of the different outcomes (Hole 2012). This consequential relationship between inputs and outcomes is referred to as *cause and effect*, or *causality* (Field 2013). Researchers can have further confidence in this causality if the cause occurs before the effect, known as *temporal precedence* (Brewer and Crano 2014)—although asymptomatic causes can sometimes obscure this—and the effect either does not occur or is weakened by the absence of the cause (Hole 2012).

In quantitative social science research, a cause is referred to as the *independent variable* or *predictor*, and an effect is referred to as the *dependent variable* or *outcome* (Field 2013). Essentially, then, quantitative social science research examines whether changes in one or more independent variables—such as communication frequency in our example—cause changes in one or more dependent variables—such as speed of team work. Thus, such research is concerned with examining the relationship between two or more variables, and such relationships are often represented using *path diagrams* (Baron and Kenny 1986), such as those shown in Fig. 3.1. Here, variables are represented by boxes and the relationships between variables by connecting arrows.

A prerequisite for the scientific examination of relationships between variables is the reliable and valid measurement of those variables (Cook 2009), as we discussed in Sect. 3.2. Another key tenet of science is that such variable relationships are predicted before the research is conducted, or a priori, in the form of falsifiable statements known as *hypotheses* (Foster and Parker 1995). Hypotheses should be clear and testable, and specify the direction of the relationship, for example "communication frequency is positively related to speed of team work".

When exploring a new research topic, quantitative social science research progresses systematically, building on previous research findings to increase the complexity of the variable relationships it examines (Petty 1997), as shown in Fig. 3.1. Some researchers have referred to this as establishing the *what*, *how*, and *when* of a research topic (Baron and Kenny 1986), and we shall use this framework here. The simplest relationship is between a single independent variable and a single dependent variable, or establishing *what* the *main effect* is (Baron and Kenny 1986). Here, in Fig. 3.1a, we have indicated a positive relationship between communication frequency and speed of team work: as the former increases, so too does the latter and vice versa for decreases. This could also be illustrated graphically, as shown in Fig. 3.2a.

This is an important finding in its own right and a useful starting point. However, in many cases, we may wish to know more detail about this main effect. So, next, we could explore the mechanism through which this effect occurs, or the *how*. It could be the case, for instance, that communication frequency causes speed of team work *indirectly*, by first causing a better common understanding between team members, or what psychologists call shared mental models (Mathieu et al. 2000), which then, in turn, causes speed of team work, as shown in Fig. 3.1b. Such an indirect effect is called *mediation*, and the intervening variable—shared mental models, here—is called a *mediator variable*

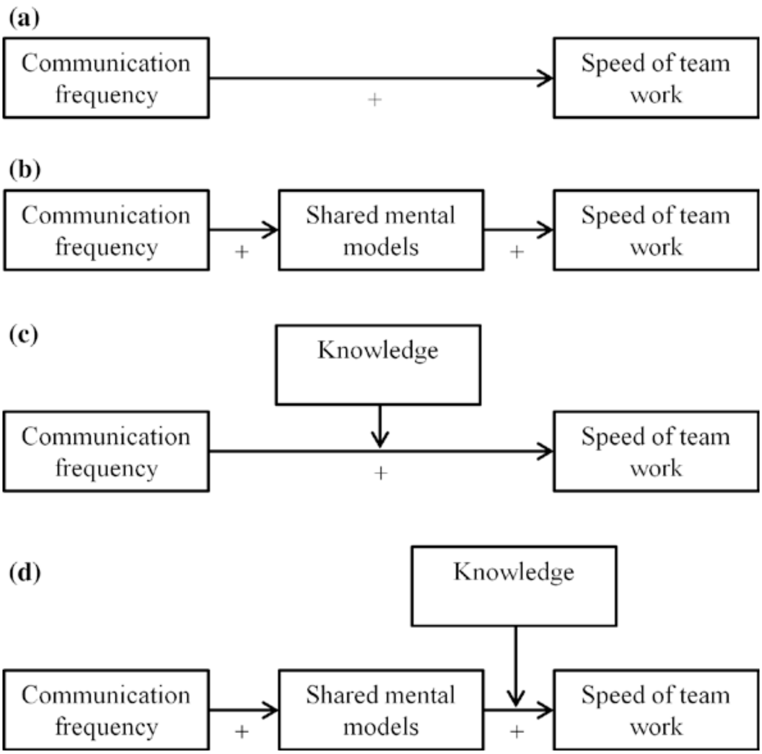


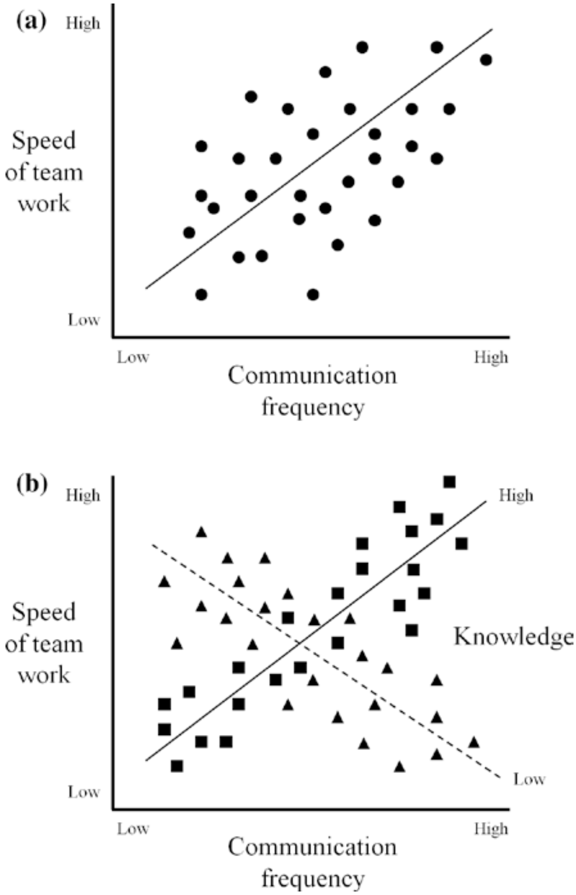
Fig. 3.1 Building a theoretical model by establishing the main effect, mediation effect, and moderation effect (Baron and Kenny 1986) of a research topic. **a** Main effect/"What?". **b** Mediation effect/"How?". **c** Moderation effect/"When?". **d** Theoretical model/"What?", "How?", and "When?"

(or mediator) (Baron and Kenny 1986). For instance, Johnson and Filippini (2013) found that the positive relationship between integration activities and performance in new product development was an indirect one, mediated by integration capabilities; thus, activities led to capabilities, which in turn led to performance.

So, now we have further detail about this main effect and how it happens indirectly via a mediator variable. However, we may wish to know even more detail, so now we could explore the conditions under which the effect is present or strongest, or the *when*. Communication frequency is only likely to increase the speed of team work if that communication is useful in some way, so perhaps this effect only occurs when the knowledge level of those communicating is high (Cross and Sproull 2004), as shown in Fig. 3.1c. If we found this to be the case in our research, then there would be an *interaction* or *moderation effect* occurring, and knowledge would be called a *moderator variable* (or moderator) (Baron and Kenny 1986). For instance, Robinson et al. (2005) found an interaction between engineering designers' ratings of the importance of creativity and innovation to their present and future job roles; in this instance, time (i.e. present or future job) was the moderator variable.

A graphical representation can help clarify the nature of a moderation effect, and Fig. 3.2b provides one such example. Here, there is a positive relationship between communication frequency and speed of team work when knowledge is high (i.e. the solid line and square data points), but the relationship actually becomes negative when knowledge is low (i.e. the dotted line and triangular data points), indicating that non-knowledgeable communication is actually counterproductive. This is an extreme example, with the lines for the different levels of the moderator variable, knowledge, facing in opposite directions to form a cross. In reality, most moderation effects are less dramatic and they are identifiable from converging lines with slightly different gradients.

Fig. 3.2 Graphical representations of a main effect and a moderation effect. **a** Main effect/"What?". **b** Moderation effect/"When?"



In summary then, to understand *what* is happening we must first establish that one variable affects another variable (Fig. 3.1a: a main effect). Then, to understand this main effect in more detail, we can examine *how* it occurs (Fig. 3.1b: a mediation effect), or *when* it occurs (Fig. 3.1c: a moderation effect). These last two questions can be addressed in either order, and their results combined (Fig. 3.1d). By following this systematic research approach, and extending it, it is possible to develop highly complex and nuanced models of causal effects to test, and this is how academic theories are developed in social science (Petty 1997). Part 4 of this book addresses theory and model development specifically in an engineering design context.

3.3.2 Experimental Research Designs

Once we have operationally defined our variables, selected reliable and valid measures, and decided which variable relationships we are examining, we can now design our research study. The purest implementation of the scientific method is the *experiment*. Here, the researcher has full *control* over the independent variables and is able to actively *manipulate* their levels systematically, using different *experimental conditions*, to accurately examine their effect on the dependent variables (Foster and Parker 1995). Often, the dependent variables are measured before and after the administration of the independent variable, known as *pre-measures* and *post-measures*, to gauge the change caused by the independent variable (Liu et al. 2009). Researchers can also include a *control condition* where the independent variable is not administered, and/or a *placebo condition* where the independent variable is administered in the same structure but with inert content (Williams et al. 2002). Structurally, these experimental methods are identical to those used in clinical pharmaceutical trials (Reginster et al. 2001), but applied to human behaviour, cognition, and organisational processes, rather than health.

Figure 3.3 shows the hypothetical results of two experimental research designs. The first, Fig. 3.3a, shows the results of an experiment with three conditions with pre-measures and post-measures of the dependent variable. Here, the control condition shows no change, while the two experimental conditions demonstrate the positive effects of communication frequency, the independent variable, on speed of team work, the dependent variable, with the latter increasing in each case. The second, Fig. 3.3b, shows the results of a quasi-field experiment (see below), in a company for instance. Here, communication frequency has been operationally defined more narrowly as the presence or absence of weekly meetings, as it would be impossible to control all other communication outside of the laboratory. Furthermore, the company wishes to implement weekly meetings throughout the company, so there is no true control condition here. However, to address this, the implementation of weekly meetings could be conducted in two phases (e.g. with a one-month gap between different departments) to effectively create a control condition as shown. Again, the positive effect of weekly meetings, the independent

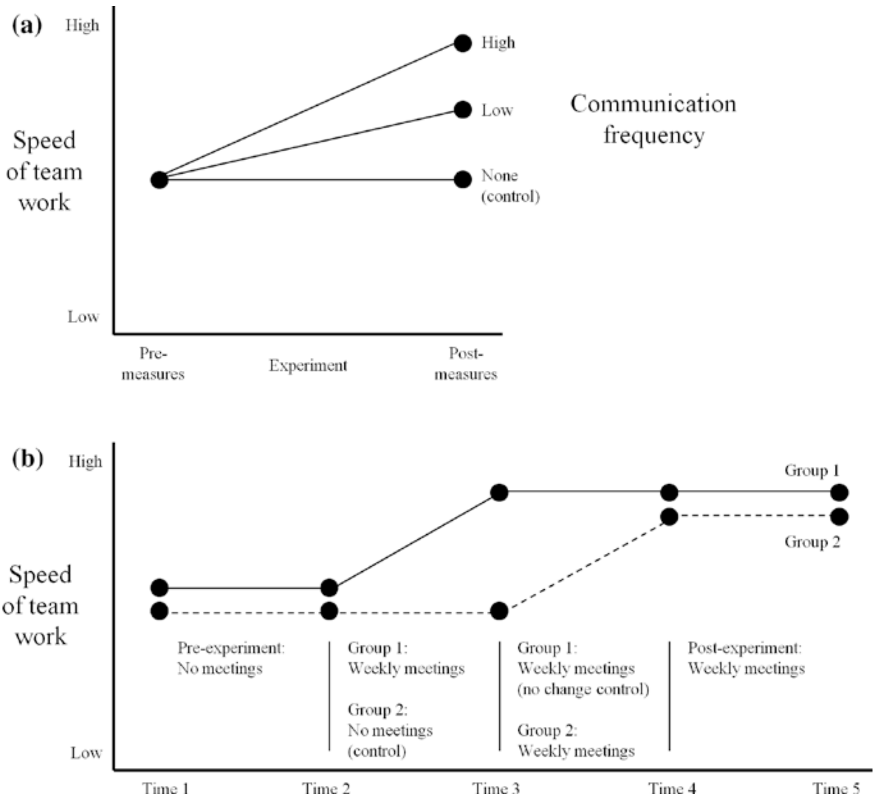


Fig. 3.3 Hypothetical results of two experimental research designs. **a** Hypothetical results of an experiment with pre-measures and post-measures. **b** Hypothetical results of a phased quasi-field experiment to create control groups

variable, on speed of team work, the dependent variable, is demonstrated by the increases in the latter following their implementation.

Participation in experiments occurs in one of two ways. First, different *groups* of participants can be randomly allocated to different conditions, a design known as *between-participants* or *independent measures* (Field 2013). Here, the random allocation of participants helps to randomly distribute their personal differences (e.g. gender, age) between groups, somewhat controlling for them. Second, all participants can be allocated to each of the experimental conditions in turn, a design known as *within-participants* or *repeated measures* (Field 2013). Although this places greater demands on participants, it offers the benefit of ensuring there are no personal differences between participants in different conditions, as they are the same people. However, *order effects*, such as practice or fatigue, must be controlled for by *counterbalancing* the conditions so that equal numbers of participants undertake the conditions in different orders (Reese 1997).

Finally, the researcher also has full control over the experimental environment—very often a laboratory—and so is able to strictly control (i.e. eliminate or reduce) the effects of any other variables unrelated to those the experiment is designed to examine. Some of these *extraneous variables* are randomly distributed and merely reduce the sensitivity of the experiment to detect effects, but others vary systematically with the dependent variable—so-called *confounding variables*—and can substantially bias the experiment unless controlled (Foster and Parker 1995). In experimental research, it is best to control such variables methodologically, by designing them out. Where this is not possible, as in much applied research including correlational designs (see Sect. 3.3.3), such variables can be statistically controlled for (Field 2013).

Having full control over all variables in this way ensures that the relationships between independent variables and dependent variables can be isolated. This gives us confidence that any changes observed in the dependent variables are due solely to changes in the independent variables, which would indicate high *internal validity* (Campbell 1986). Granting the researcher full control of the experiment in these ways is the method's greatest strength. However, this control comes at a price as it also necessitates experiments being conducted in artificial controllable environments, rather than realistic applied settings, making the experiment low in *external validity* or generalisability (Campbell 1986).

We could apply such an experimental approach to our example study. Participants could undertake a standard engineering design task in small teams of four, with time to completion converted to speed (i.e. task per time) as a measure of the dependent variable, speed of team work. For simplicity, we will create two levels of our independent variable, communication frequency, represented by two conditions. In the first condition, high communication frequency, participants are permitted to exchange ten written notes, of ten words or fewer, with the other three team members. In the second condition, low communication frequency, participants are only permitted to exchange two such written notes. If we adopted a within-participants design, we would need two equivalent engineering design tasks of equal difficulty, to ensure that participants encountered a new task each time, presented in a counterbalanced order. We could then run this experiment to see which condition resulted in the fastest speed of team work.

Having established this main effect, we could then introduce the moderator variable, knowledge, into a follow-up experiment. Here, we could manipulate the level of knowledge available in each condition by providing different levels of information. For the high-knowledge condition, we could provide the group with ten recommendations about the engineering design task, and for the low-knowledge condition, we could provide just two recommendations. We could then systematically integrate the independent variable and moderator variable conditions to yield the following four experimental conditions: (1) low communication frequency, low knowledge; (2) low communication frequency, high knowledge; (3) high communication frequency, low knowledge; and (4) high communication frequency, high knowledge. We could then run this second, more complex, experiment to see which conditions resulted in the fastest speed of team work and whether a moderation effect or interaction exists.

Cash et al. (2012) undertook a similar experiment to examine the effect of design information—the independent variable—on the number, originality, and effectiveness of design ideas—the dependent variables. The experiment used a between-participants design with five teams of three participants, each undertaking a standard two-hour design task to develop a new environmentally friendly refrigerator. Each team received a different type of information, representing the five experimental conditions, ranging from no information at all in the control condition through to data pages and videos in the condition with most information. Given the between-participants design, the researchers also sought to control for team role personality types to ensure an equivalent composition for each team. The results indicated that the provision of information was generally positively related to performance in terms of design ideas.

So far, we have discussed pure experiments in artificial environments. However, in many cases, researchers may wish to examine such issues in a more realistic applied setting, such as a company. Sometimes, it is still possible for researchers to retain full control of the independent variables, although it will not be possible to fully eliminate extraneous variables (e.g. background office distractions), so the sensitivity of the experiment to detect effects will be reduced. Such experiments are known as *field experiments* (Dvir et al. 2002) and what they gain in external validity, they lose in internal validity (Campbell 1986). In some such instances, though, it will not be possible to randomly allocate participants to experimental conditions, as the company will have their own strategy for administering the independent variable for business reasons. Experiments without such random allocation are referred to as *quasi-experiments* (Grant and Wall 2009). For instance, Davis (2011) used a quasi-experiment to examine the effects of a change in physical office layouts on communication in an engineering company. However, the company involved was implementing the office changes one department at a time, so it was not possible to randomly allocate participants to conditions. As most field experiments and quasi-experiments are conducted in applied real-world settings, they tend to be longer in duration than laboratory-based experiments, often lasting weeks or months rather than hours.

3.3.3 Correlational Research Designs

In experimental research designs, the researcher actively manipulates the independent variables to examine their effect on the dependent variables (Foster and Parker 1995). However, outside of a controlled laboratory environment, it may not be possible or even desirable to do so. So, in our example, it would essentially be impossible to manipulate the frequency with which engineering designers communicate with each other in a real-world company environment. Furthermore, to increase external validity (Campbell 1986), it would actually be desirable to study realistic levels of communication frequency. So, in such circumstances, as with much applied social science, the research will examine *naturally occurring* levels of independent variables and dependent variables (Tokunaga 2015). Such research is referred to as *correlational research*, to distinguish it from experimental research (Mitchell 1985). Strictly, it is inaccurate to refer to independent variables and dependent variables in correlational research, as no experimental manipulation occurs, so the alternative terms predictor variables (or predictors) and outcome variables (or outcomes) are generally used, respectively (Field 2013). However, these terms are still often used interchangeably, such as in SPSS statistical analysis software (see Sect. 3.4).

As predictor and outcome variables are naturally occurring, and the former are not manipulated in controlled conditions, correlational research has lower internal validity, so the causality of variable relationships is less clear (Campbell 1986). For instance, it may be unclear whether A causes B, B causes A, or both have another cause. Indeed, variants of the phrase "correlation is not causation" are frequently found in the methodological literature (Bleske-Rechek et al. 2015). Nevertheless, well-conducted correlational research does incorporate several key features of experimental research to improve causal inferences, albeit with a lower level of confidence than experimental research. First, researchers still control for extraneous variables (Foster and Parker 1995) where possible, but typically do so statistically rather than methodologically as is done in experiments (Carlson and Wu 2012). Second, correlational research should also be guided in advance by a sound theoretical rationale drawn from the existing research literature and then designed to test hypotheses (Foster and Parker 1995). Third, predictors should be measured earlier in time than outcomes, so that there is temporal precedence (Brewer and Crano 2014). This feature, or its absence, gives rise to two distinct types of correlational research: (1) *longitudinal research*, where predictors are measured earlier than outcomes, and (2) *cross-sectional research*, where predictors and outcomes are measured at the same time (Rindfleisch et al. 2008). Although methodologically superior, longitudinal research is more difficult to conduct due to the practical difficulties of collecting data from the same people repeatedly (e.g. participants may leave the company after the first round of data collection). For this reason, much social science research is of a cross-sectional nature. Fourth, whenever possible, measurements of predictors and outcomes should be collected using different methods to ensure common method bias does not artificially inflate the relationship between them (Podsakoff et al. 2003). This applies equally to experimental research, although it is unusual not to use different measures in these contexts as the experimental tasks usually necessitate it.

So, returning to our example, we will now consider how we could undertake a correlational study. Our predictor variable communication frequency could be measured with a questionnaire, using either existing items, or our own such as "How many times per week do you e-mail your team leader?", as discussed earlier. We could measure our outcome variable speed of team work with reference to official company records about actual project durations and planned project durations. By acquiring predictor and outcome measures from different sources in this way, we could guard against common method bias (Podsakoff et al. 2003). Measuring both variables simultaneously would yield a cross-sectional study, but it would be advantageous to measure communication frequency several months earlier than speed of team work to yield temporal precedence with two *time points* and greater confidence in causality (Brewer and Crano 2014). The questionnaire could be extended to measure shared mental models and knowledge, our respective mediator and moderator variables (Baron and Kenny 1986). For the mediation effect, it would be advantageous to introduce a third time point, between the measurement of predictor and outcome variables, so that there is temporal precedence (Brewer and Crano 2014) for both sequential relationships comprising the mediation effect (see Fig. 3.1b).

One published example of such a longitudinal study was undertaken by Kazanjian and Rao (1999) to examine the development of engineering capability in recently established high-technology firms. First, using a questionnaire, they measured the predictor variables CEO's background, presence of a head of engineering, management team size, and the formality and centrality of decision making. Then, using a second questionnaire 18 months later, they measured the outcome variable engineering capability. Statistical analyses indicated that the presence of a head of engineering and management team size were both significant predictors of subsequent engineering capability, with the former a positive predictor and the latter negative.

Table 3.1 provides a summary of the discussions in Sect. 3.3 concerning the features, advantages, and disadvantages of experimental and correlational research designs.

3.4 Statistical Data Analysis

The statistical analysis of quantitative social science data is a highly specialised field in its own right with accompanying computer software such as Statistical Package for the Social Sciences (SPSS). It is therefore beyond the remit of this chapter to provide detailed guidance in this area; however, we will briefly examine some of the key principles and methods and provide examples of their use in the engineering design literature. Readers seeking detailed guidance should consult some of the excellent books available about conducting statistical analyses using SPSS software, such as Field (2013) or Gray and Kinnear (2012). All of the statistical analysis techniques discussed below can be quickly calculated using SPSS and similar software.

There are two broad types of statistical analyses—*descriptive statistics* and *inferential statistics*—and we shall address each in turn here. Descriptive statistics, as the name implies, are concerned with describing the data collected about a particular variable in terms of its *central tendency* or *average* value and its *variability* or *range* (Foster and Parker 1995). There are three measures of average, namely the *mode*, which is the most frequently occurring value, the *median*, which is the centrally ranked value, and the *mean*, which is calculated by summing all data values and dividing by the number of data values (Field 2013). To examine the

Table 3.1 Comparison of the features, advantages, and disadvantages of experimental and correlational research designs

Methodological criteria	Experimental research designs		Correlational research designs	
	Experiments	Field experiments	Longitudinal	Cross-sectional
Internal validity (i.e. scientific approach)	Very high	High	Moderate	Low
a. Researcher manipulation of independent variables/predictors	Very high	High	None	None
b. Researcher control over extraneous variables	Very high (mainly methodological)	High (mainly methodological)	Moderate (mainly statistical)	Moderate (mainly statistical)
c. Temporal precedence (i.e. independent variable/predictor measured before dependent variable/outcome)	Yes	Yes	Yes	No
d. Random allocation of participants to conditions	Yes (no for quasi-experiments)	Yes (no for quasi-field experiments)	Not applicable	Not applicable
External validity (i.e. generalisable to the real world)	Low	High	Very high	Moderate
a. Realism of environment	Low (often in laboratories)	High (often in companies)	Very high (often in companies with natural data)	Very high (often in companies with natural data)
b. Representativeness of participants	Moderate (often student samples)	High (often company employees)	High (often company employees)	High (often company employees)
c. Realism of study duration	Low (often hours)	High (often months)	Very high (often months or years)	Very low (single time point only)

variability of these data values, we can calculate either the *range* between the lowest and highest values, or the *standard deviation* which is essentially the absolute mean difference between the mean and each data value (Foster and Parker 1995). The mean and standard deviation are the most frequently used of these statistics and the two are usually presented together as measurements of each variable. In many cases, such descriptive statistics are useful in their own right. For instance, Robinson (2012) found in his electronic work sampling study that engineering designers spent a mean of 24.96 % of their time engaged in socially interactive technical work and that the accompanying standard deviation was 9.77 %.

While descriptive statistics provide measurements of each variable, inferential statistics enable us to examine the relationships between variables, to test hypotheses, and to generalise beyond the immediate research (Foster and Parker 1995). A useful although simplistic way of understanding inferential statistics is that they help us test *differences* or *associations* between two or more variables (Gray and Kinnear 2012). Returning to our example, let us assume in our earlier experiment that we wish to test the difference between the speed of team work of those teams in the low communication frequency and high communication frequency experimental conditions. One simple option would be to examine the mean speed of team work in each experimental condition to see which was higher. However, when comparing any data values, there are always variations that occur solely by chance, so we use inferential statistics to establish whether any differences are due to the independent variable rather than chance (Foster and Parker 1995).

By using the relevant inferential statistical test, we can compare the mean values of our dependent variable, speed of team work, in the two experimental conditions to obtain the *probability level* or *p-value* of the difference to determine whether it is *statistically significant* and therefore supports the hypothesis (Gray and Kinnear 2012). *P*-values range from 0 to 1, with a value of $p \leq 0.05$ considered the key threshold for supporting the hypothesis, indicating that there is less than a 5 % probability that the difference was due to chance (Foster and Parker 1995). Although very widely used, several social scientists and statisticians have recently cautioned against complete reliance on *p*-values and suggest calculating *effect sizes* also (Wright 2003; Cohen 1988).

There are many inferential statistical tests covering a wide range of research scenarios, including parametric and nonparametric, and univariate and multivariate (Gray and Kinnear 2012). However, given space constraints, we shall only discuss four of the most frequently used statistical tests briefly here, namely the *t test*, *analysis of variance* (*ANOVA*), *correlation*, and *regression*. *T* tests examine the difference in mean values between two sets of data, either from the same source (e.g. participants, companies) in different scenarios or from different sources (Field 2013). For instance, Robinson et al. (2005) used within-participants *t* tests to compare participants' ratings of the present and future importance of various competencies for engineering design roles. The *t* tests indicated that some of the competencies, such as commercial awareness and innovation, had statistically significantly higher mean importance ratings for the future than the present.

ANOVAs are similar to *t* tests, in that they also measure differences in mean values between sets of data from the same or different sources; however, they extend this capability to multiple sets of data, including interactions between two independent variables (Gray and Kinnear 2012). A key point to be aware of is that *t* tests and ANOVAs both test for differences in dependent variables caused by different *categories* of independent variable (Field 2013). For instance, Robinson (2012) used a two-way within-participants ANOVA to examine the time engineering designers spent engaged in different categories of work, finding that they spent significantly more time in (a) technical than non-technical work and (b) non-socially interactive work than socially interactive work. However, there was no significant interaction between the time spent in these types of work. Given their analysis of data arising from categorical independent variables, both *t* tests and ANOVAs are frequently used to analyse the results of experimental research designs (Gray and Kinnear 2012), although not exclusively so. The ANOVA approach has also been extended into a method called analysis of covariance (ANCOVA) which also enables researchers to control statistically for extraneous variables (Field 2013).

Correlation is a statistical method for examining the association or correlation between two variables, to determine whether it is positive or negative (Gray and Kinnear 2012). With positive correlations, both variables change together in the same direction; so, as one increases, so does the other and vice versa for decreases (e.g. the square data points in Fig. 3.2b and the accompanying solid line). With negative correlations, both variables change together in opposite directions; so, as one increases, the other decreases and vice versa (e.g. the triangular data points in Fig. 3.2b and the accompanying dotted line). Pearson's r (see Sect. 3.2.3 also) is by far the most common statistical correlation coefficient, ranging from -1.00 to $+1.00$, with the valence indicating whether the correlation is positive or negative (Field 2013). The closer the absolute correlation coefficient is to 1, in either direction, the stronger the correlation is, with absolute values of $r \geq |0.30|$ considered medium in size and those of $r \geq |0.50|$ considered high (Cohen 1988). Correlations can be calculated between any two variables, although usually they examine the association between a predictor variable and an outcome variable, despite the earlier caveats we discussed about causality in correlational research (see Sect. 3.3.3). For instance, Birdi et al. (2014) found a correlation of $r = 0.42$ between creativity skills and the implementation of ideas in their study of innovation in an engineering design and manufacturing company.

Regression extends correlation to identify a "line of best fit" through the cloud of plotted data points (e.g. Fig. 3.2a), minimising the overall distances or *residuals* between this line and all the data points in the cloud (Field 2013). Regression coefficients are then calculated for each predictor variable, indicating the gradient of the line, together with where it intercepts the y-axis, from which a regression equation can be generated to predict outcome values from particular values of predictor variables (Gray and Kinnear 2012). Regression analysis also allows researchers to determine the percentage of variance in the outcome variable that is explained by the predictor variables, both for single predictors and for multiple predictors combined (Tabachnick and Fidell 2013). This is essentially an indication of the predictive accuracy of the identified regression result. For instance, Ng et al. (2010) used regression analysis in their research examining performance in a company manufacturing semiconductors. They found that 54 % of the variance in the outcome engineering performance was jointly accounted for by the predictors total quality management, concurrent engineering, and knowledge management. Finally, more complex forms of regression also enable researchers to examine mediation and moderation effects (Baron and Kenny 1986; Fig. 3.1) and to control for extraneous variables (Foster and Parker 1995).

3.5 Further Considerations in Quantitative Research

In this section, we address three further topics of importance to quantitative research. As each is a specialist topic in its own right, only a brief overview is provided here together with references for interested readers to consult for further information.

3.5.1 Participant Sampling

A key contributor to the external validity (Campbell 1986) of a research study is the profile of participants selected by the researchers. Participants represent a smaller *sample* of a larger *population* of people that researchers wish to generalise their results to and should therefore be *representative* of the wider population from which they are drawn (Fife-Schaw 2000). Ideally, to achieve this, we would randomly select participants from the wider population, to obtain a true *random sample* that is unbiased and therefore representative (Field 2013). Where the population are distributed among various categories of importance to the research—such as age groups or departments of a company—we can also choose to randomly sample participants from within these categories (or "strata") by using *stratified random sampling* to ensure accurate proportionality (Foster and Parker 1995). In applied research, however, practical constraints often prevent truly random sampling, in which case simple (i.e. non-random) stratified sampling can help mitigate any resultant biases and lack of representativeness.

Alongside representativeness, *sample size* is a key consideration for ensuring external validity (Campbell 1986) with larger samples generally preferable (Fife-Schaw 2000) for two main reasons. First, larger sample sizes provide more statistical power to detect significant effects (Cohen 1988), and some multivariate statistical methods also require large participant-to-variable ratios (Tabachnick and Fidell 2013). Second, to generalise research results to a population, it is necessary to sample a certain proportion of that population, although this proportion decreases as the population size increases (Bartlett et al. 2001). Many useful sample size calculators are readily available to help researchers calculate the number of participants required in various circumstances (NSS 2015).

3.5.2 Research Ethics

Unlike some technical engineering design research, social science research usually involves *human participants*. Any research with people involves a careful consideration of *ethical issues* to ensure their well-being. Most universities and research institutions have their own formal ethical review procedures that have to be followed to gain clearance for data collection. A number of professional social science organisations—such as the American Psychological Association (APA 2010) and the UK's Economic and Social Research Council (ESRC 2015)—also have their own *ethical research guidelines* that their members must adhere to. All such guidelines have the following key principles in common. First, participation in the research must be *voluntary*, with *informed consent* and the *right to withdraw* at any time. Second, participants' mental and physical *well-being* is paramount, and if the study conceals information from participants—as some experiments do for methodological reasons—then they must be fully *debriefed* afterwards. Third, unless participants agree otherwise, data collected in the research should remain *secure* and *confidential* to the researchers and should only be presented in an *anonymous* manner.

3.5.3 Specialist Quantitative Methods

Finally, there are a number of specialist quantitative research methods based on the principles outlined in this chapter that social scientists are now increasingly using, including longitudinal diary studies (Bolger et al. 2003), the analysis of multilevel, hierarchical, "nested" data (Osborne 2000), social network analysis (Hanneman and Riddle 2005), agent-based simulation (Hughes et al. 2012), and the analysis of "big data" (McAfee et al. 2012). Although coverage of these specialist methods is beyond the remit of this chapter, interested readers should consult these references for further information. Part 3 of this book also addresses social network analysis and agent-based simulation in an engineering design context.

3.6 Conclusion

In this chapter, I have sought to provide engineering design researchers with a grounding in the principles and methods of quantitative social science research. First, we considered how to define variables and measure them in a reliable and valid manner. Second, we considered scientific principles and how to examine the relationships between variables, starting with main effects and progressing to mediation and moderation effects. Third, we discussed experimental and correlational research designs and the trade-off between internal and external validity these entail. Fourth, we considered the statistical methods used to analyse the quantitative data collected. Finally, we considered participant sampling, ethical issues, and specialist quantitative methods. Throughout the chapter, I have illustrated these principles and methods using an example research study together with further examples from the engineering design literature. It is my hope that this chapter will be of use to engineering design researchers, without formal social science training, who wish to undertake research examining the human, social, and organisational aspects of engineering design work.

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Part II
Classical Approaches to Experimental Design Research

Chapters 4–7 explore the major classical approaches to human-focused experimental design research. Chapters 4 and 5 respectively deal with individual and team perspectives on designer's behaviour and cognition. Together these highlight selected methods and key methodological challenges, setting the stage for Chaps. 6 and 7. These then examine the two main perspectives on human-focused measurement—biometric (Chap. 6), and psychological and neuroscience (Chap. 7). Finally, Chap. 7 closes the part by bringing together these varied perspectives on investigation and measurement by emphasising the need for multi-modal research.

Chapter 4
Creativity in Individual Design Work

Yukari Nagai

Abstract In order to answer the questions, "Why can humans design?" and further, "Why are human beings the only species capable of design?" this chapter focuses on individual design work. We discuss the features of creativity in the design process, using experimental studies to observe from the microscopic and macroscopic viewpoints, in order to clarify design creativity as a personal activity. First, the basis of design creativity is discussed, and the character of design creativity is delineated—namely the way in which it relies on different modes of searching for the new concept based on the empathy or consideration for other people. Second, from the microscopic perspective, the concept generation phase in the design process is examined through individual designs. Here, keywords of high dissimilarity were found to advance the originality of creative results. In addition, the role of association—in particular the concept of action—was identified. Third, to identify motivations for engaging in long-term creative activity, this chapter considers designers' process of self-growth to play a role in developing their inner perspective. This chapter also presents a case study of a designer's process of self-growth, which was conducted as part of a long-term experiment. Finally, the internal and external motivations that activate creativity in the cognitive processes involved in individual design work are comprehensively discussed and clarified.

Keywords Creativity · Design process · Drawing

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4.1 Designers' Creativity

Designers are generally expected to have competency in creative problem solving. Designers' cognition is characterized by the engagement, through creative thinking, in exploratory processes that are activated by internal motivations (Nagai 2014).

To enhance the creativity of individual designers, this chapter aims to facilitate an in-depth understanding of human creativity's structure, mechanisms, and nature from multiple viewpoints. Thus, a series of experiments was carried out to extract the cognitive features from design drawings.

4.1.1 Basis of Creativity

In order to attain comprehensive knowledge about human functioning, it is necessary to understand human creativity. Studies on human creativity thus far have argued that creativity is a common interest among various domains, including art, education, business, and engineering. Discussions on creativity are typically unique to each domain.

In art, the creativity of genius artists such as Leonardo da Vinci and Pablo Picasso has attracted considerable interest among researchers (Berger 1989; Shlain 1999; Cremante 2013); many studies have viewed genius as related to a personal talent or gift that enables the production of creative results. Hence, studies of psychological creativity have investigated creative people as subjects (Feldman 1998; Weisberg 2006). To a great extent, the information that elucidates the creative features of an individual artist and the information in an artist's personal biography are coextensive; hence, in elucidating the creativity of a particular artist, reviewing and verifying detailed records are imperative. This enables the particular features of an individual's creativity to be highlighted. Similarly, understanding the relationships between an exceptional artist and society is another challenge. For example, a great artist like van Gogh can be considered an outstanding artist; however, he was never fully understood by society at the time, and he suffered difficulties in life (Naifeh and Smith 2011). In such cases, creativity is not strongly correlated with success. On the other hand, creativity among engineers involves success. Among engineers, creativity is considered to be related to valuable solutions to problems (Cropley and Cropley 2000; Sawyer 2011). For example, a new system of electrical control transformed the traditional mechanical power system into a more rational and reasonable system with improved functionality. It was made possible by a novel technology but at a different level. Nevertheless, an engineer's creativity in applying a novel technology to a different level is related to rationality and applicability. Similarly, from a design perspective, usefulness and desirability are expected from people innovating new products. Thus, creativity in products can be regarded as the integration of engineering and design and is often inclusive of both social and functional value (Yannou 2013; Nagai 2014; Dong 2014).

Needless to say, creativity in art and creativity in engineering have different criteria. However, in both, one common feature is that creativity must change or break the conventional, conservative way or style and produce new meaning. Thus, creativity takes up the challenge of producing new value; this is innovation. In both fields, creativity is a mind-set oriented toward design. The inherent motivation among individuals who seek to "change the world" is also embedded in design.

4.1.2 Design Creativity

Amidst the various studies on creativity, this chapter specifically focuses on creativity in design—that is, "design creativity"—given that design is based on typical human abilities (Taura 2014, Nagai and Taura 2016).

A large number of recent studies have focused on the observation of designers' creativity. These studies have attempted to delineate the specific features of designers' thought in order to enhance not only computer-aided design (CAD) but also computational design methods through artificial intelligence. In terms of basic structure, both CAD and computational design necessitate design processes and methodologies that must be interpreted and described as explicit knowledge (Akin 1986; Archer 1986; Broadbent 1983; Jones 1983).

Actual design work progresses through the participation of multiple people. However, individual design work has gained attention among current researchers; in particular, many studies have attempted to shed light on the thought processes behind the designs of individual designers (Rowe 1987). These studies may be classified by their perspective: the knowledge of expert designers (Lawson 1980; Cross 1982; Candy and Edmonds 1996), and methods of computational design (Mitchell 1992; Brown 2013). Thus, the present study summarizes the extant perspectives on individual designers' creative processes.

The first stage of this study aimed to build a system to help understand expert design based on the activity of expert designers, which was targeted as an ideal model. In this regard, it was necessary to identify the features of expert designers' knowledge of creation. This included decision making, strategy formulation, and problem solving, as well as the creative cognition of the individual designer. To develop the system, many significant models of the design process were referenced (Rosenman et al. 1990; Nagai 2003; Cross 2006). As regards the cognitive features of designs produced by individual experts, experimental methods from social science were adopted, such as the ethnographic approach. These were used to observe the strategic knowledge of outstanding designers as well as to examine design discourses (Margolin 1989).

Other studies have focused on identifying certain mental biases of designers, because such biases must be considered when creating a machine-based support system for human design activities (Viswanathan and Linsey 2014; Taura and Nagai 2012; Yilmaz et al. 2013). In this study, logical design methods were investigated with the aim of creating designs beyond human capacity. Human and machine designs are compared.

4.2 Studying Designers' Creativity

In the previous section, studies of the activities of individual designers were reviewed. In this section, essential issues involved in individual design work but ignored in previous studies are discussed. To this end, the following general but essential research questions are asked.

1. What is design?
2. Why can humans design?
3. Why are humans the only species capable of design?

In regard to the first question, it is necessary to distinguish design and identify the core structure that differentiates design from other activities; to accomplish this, we observed the drawing process.

The second and third questions address the design thinking process from two viewpoints: microscopic and macroscopic. In the microscopic viewpoint, the concept generation phase in the early stages of the design process is highlighted. In contrast, in the macroscopic viewpoint, the focus moves to the intrinsic motivation of an individual designer. This is related to a growing process (self-forming), which was investigated using long-term observation.

4.2.1 Drawings

Drawings are meaningful resources to observe creative processes because they represent designers' thoughts (Lawson 1980; Goldschmidt 1994). Nagai (2003) reported an interesting result obtained from a series of drawing experiments that were conducted in 2002 to identify the creative features of design. The drawing experiments were used to observe designers' drawing processes and behavior. Two of the three participants had received a design education and had professional experience, whereas the remaining participant had no special design experience. They were individually observed at work (see Table 4.1). The first participant was an IT engineer with 10 years of experience in product design. The second was a design educator at a college and had 11 years of experience in graphic design. The third was a research project manager without any design education (hence, referred to as the "non-designer"). The three participants were between 25 and 37 years old.

"Soft boards" were used to record the participants' drawing processes. Each was assigned drawing tasks and then asked to speak about the ideas that had come into their heads while performing the tasks. Positional data were collected on a whiteboard from a drawing pen. The data were digitized and entered into a computer. The data were then plotted in line graphs at 1/100-second interval points. The tasks comprised a set of four sessions. The participants were tasked to draw "a teacup" in the first session. In the second session, they were asked to draw "your teacup" or the teacup they typically used. The assigned task in the third session was to draw "a new teacup" without any mention of the user. Lastly, the assigned

Table 4.1 Participants in the drawing experiments

ID	Job experience	Current specialty	Category
#1	Product designer (10 years)	IT engineer	Designer
#2	Graphic designer (11 years)	Design teacher	Designer
#3	Social worker (3 years), educator (2 years)	Project manager	Non-designer

task in the fourth session was to draw “a teacup for your boyfriend/girlfriend.” The last task was intended to reveal design work.

The participants’ behaviors were recorded using a video camera and the position data for each drawing. Each participant was interviewed immediately after the fourth drawing session and after monitoring the videos of his/her behavior.

The participants’ behavior—in particular, their detailed drawing actions for each task—was observed. Notes on the behavior of all three participants during drawing were collated to find common elements in their drawing processes. The processing times for each drawing task, including the periods before and after the drawing process, were measured. The period before the drawing process referred to the time between the task assignment and beginning of the first line, whereas the period after was the time between the end point of the last line of the drawing and the participants’ “finished” signal.

All participants started drawing immediately after being given the assignment in the first task, without any pondering. In contrast, they pondered the longest before starting to draw the fourth task. The two participants with design experience verbalized their ideas during the third task in particular.

The action of deleting drawn lines many times was observed in the third and fourth tasks. This action was observed frequently; lines were drawn repeatedly in the third task. The results suggest that this deleting action indicated the participant’s thinking mode as part of his/her exploring sequence. This action is also related to the abstract level of thinking. In the third task, the non-designer almost gave up and drew a small-sized sketch with notes. In the interview, the non-designer explained the difficulty of expressing the picture even while having a new idea for maintaining the temperature of tea. The experimental results are summarized in Table 4.2.

Figure 4.1 shows an example of the recorded lines of the participants’ drawings. Data on the x- and y-axes of each drawing were also recorded. The total length of all the lines of each drawing, including the deleted ones, could be calculated. The drawing speed of each line was estimated.

Table 4.2 Drawing experiment results

Task	Drawing time (minutes)	Start time (minutes)	Drawing lines (participants number)
1. Draw a teacup	1–2	Less than 1	Simple (3)
2. Draw your cup	2–4	1–2	Simple (2), decorative (1)
3.Draw a new cup	7–10	4–5	Detailed (2)
4. Draw a cup for your girlfriend/boyfriend	7–14	5–6	Multiple lines, repeated lines, “trial and error”

Fig. 4.1 Examples of the drawings

The results suggest that the participants' drawings differed greatly in the third and fourth tasks compared with the first and second. The participants' drawn sketches in the first task of "draw a teacup" were similar; their sketches were characterized by simple lines and simple representation. Their drawing actions also resembled a reaction to a stimulus. In the second task of "draw your cup," it took time for the participants to remember their own teacup; this resulted in differently drawn sketches. Two participants (a designer and the non-designer) presented detailed patterns of the drawn outline of a teacup. In the interview, all three participants emphatically explained the stories behind their teacups. This process can be equated with the "art" feeling. They looked back at the teacups they used in the past; for example, they remembered the teacup they used in the morning before the experiment or one given as a gift.

As mentioned previously, design perspectives focus on different aspects of engineering products, such as usefulness and desirability. In addition, cultural, ethical, and emotional matters, such as those related to the qualitative values of humans, are integrated in the design of the value system. Cultural, ethical, and emotional matters are related to human beings' cognitive empathy, which is a part of psychological competence. In the next section, we discuss the structure of designers' cognitive features, which are responsible for creativity. It is said that empathy is what ignites creative design work. Thus, activities related to design thinking involve a competence for empathy. This hints at an answer to the third question: "Why are humans the only species capable of design?". Figure 4.2 shows two motivations for the design process that drove "creativity" and "design" throughout the experiments.

4.2.2 *Modes of Thinking*

By examining participants engaged in drawing, this experimental study observed a remarkable thinking process that is deeply related to design; this may be termed the "mode of thinking" in design. To understand individual design work as representative of human creativity, Nagai, the author of this chapter, has, since 1999, investigated particular features of the thinking process in design with the aim of modeling the creative thinking process. Focusing on design creativity, experimental studies were conducted to elicit clues to understanding the mechanisms of innovation in order to formulate a new system and to establish ideal conditions for

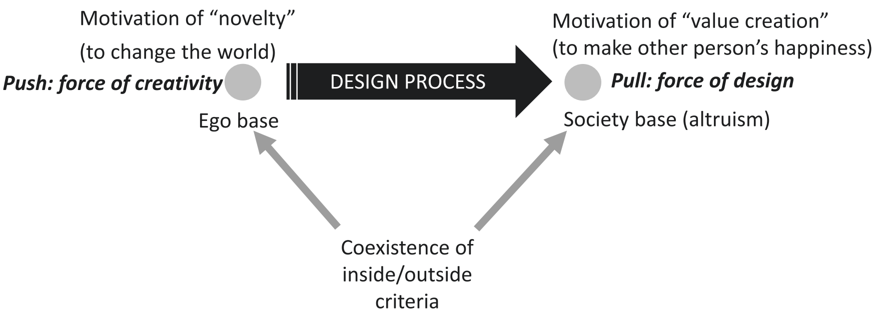

Fig. 4.2 Driving forces of design creativity

an experimental study where a series of design tasks based on creative cognition as a theoretical framework were planned.

One current research challenge has been to elucidate the relationship between creativity and cognitive psychology. Finke, Ward, and Smith proposed the Geneplore Model (Finke et al. 1992), which represents the basic structure of generative and exploratory cycles. The Geneplore Model is useful for understanding individual design work logically; by enabling the behavior of designers to be decoded in a more structured manner, this model can be used to facilitate the development of human creativity. For example, the model specifies that "interpretative constraints should not be too general or too specific." The results of previous experimental studies by the author in 2000–2002 have confirmed this psychological point. In particular, participants who were student designers exhibited higher levels of creativity when they had been given keywords that were rather abstract and difficult to directly connect with a specific form. In general, the experiments indicated that difficult keywords launched the participants on different paths to producing visual images. The results suggested that to stimulate designers, it is important to employ keywords (concepts) that evince, in their hierarchical structure, an adequately abstract level of difficulty.

The first experiment was held in 2000 as an exercise in a university course for basic design training in order to understand the interaction between verbal concepts and visual images in creative thinking during the design process. A transformation process from verbal keywords to images (drawings) was investigated in order to extract modes of thinking. The participants were 80 students majoring in industrial design. They were assigned the task of designing a chair "that evokes a sad feeling." The participants were required to submit their ideas within 60 min and were instructed to append comments to their sketches if necessary. Their final design ideas were presented as color sketches; subsequently, the participants described their impressions of the task in a report.

Terms in the comments that the students had appended to the sketches, as well as their reports, were examined based on the keywords of "sadness" and "chair"; these terms were structured into a conceptual hierarchy based on similarities in meaning. The meaning hierarchy suggested that participants drew their sketches

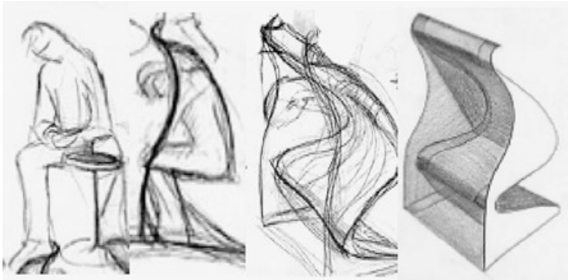

Fig. 4.3 Examples of drawings of "sad" chairs

by associating keywords in the hierarchy, beginning with sadness. We discussed how the participants, by going down the hierarchy of concepts, hit upon changes in form. The frameworks for formal expression within which the participants worked primarily varied according to differences among the keywords in terms of their level of abstraction in the hierarchy. However, in the middle of the hierarchy, there was a point at which greater variation could be seen among the participants in how they conceived of the form of the sad chair. Some participants who used a "posture of sadness" as a metaphor likely drew the forms of their chairs based on their own experiences of feeling sad (Fig. 4.3).

Such a conceptual hierarchy can be said to constitute a structure of meaning; the contents of this structure are representative of the mode of design thinking. Furthermore, retrieving emotional experiences can enable the designer to switch from a search mode based on interpreting the meaning of words (namely the linguistic interpretation mode) to a search mode based on design thinking (namely the design creation mode).

The designer's emotional experience plays an important role in facilitating the switch to the design thinking mode: The designer leaves behind the objective, linguistic mode of searching, which is based on the interpretation of meaning, and comes to embrace the subjective, empathic mode of searching, which is based on the interaction between the self and the sketches. This process can be understood as the basic process of design by emotion. In individual works of design, the designer's own experiences come to constitute intangible assets for producing creative products as well as innovative design ideas.

4.3 Microscopic View of Individual Design

The previous sections introduced examples of the experimental study of drawing in design. All of the tasks described previously were assigned by keywords. For answering the second question—"Why can humans design?"—it is necessary to understand the mechanisms of the idea generation process in design thinking. It has great potential not only for determining the factors involved in developing human ingenuity but also in developing education methods for promoting creativity.

In the process of design, the concept generation phase, which has the strongest relation with design creativity for forming original ideas, is located at a very early stage. The input keywords take the role of driving the design thinking process—of "pushing" it. This is a different mechanism from the problem-solving process in which the goal takes the role of driving, as a "pull"-type power. Keyword pairs, in particular, reveal how concept generation in design is part of a synthesizing process. This has been reported in both empirical examples and scientific research results. Creative processes by way of concept synthesis for design are theoretically explained (Taura and Nagai 2012). Experimental studies of creative cognition using combined words have also revealed this creative process. The invention of the art knife—the first snap-off blade cutter—is a good empirical example. The inspiration for the idea of a knife with a new function came as a synthesized image emerging from the segments of chocolate bars and the sharp edges of broken glass.

4.3.1 Concept Generation in Design

Focusing on the very early stages of design, Taura and Nagai (2012) systematically extracted the nature of concept generation by testing the typical mechanisms of the synthesizing process. It was assumed that the conditions of paired keywords have some effect on the resulting designs. The distance between each keyword is among the significant conditions. Dissimilarity is expressive of the mental distance between each keyword. Highly dissimilar keywords were assumed to drive creativity to a higher level in the concept generation phase. An experimental study to verify this assumption was carried out, and the results showed a weak correlation between the dissimilarity of the initial keywords and the creativity score of the evaluated design idea after the synthesis.

4.3.2 Associative Process

Another study focused on the network structure among concepts (Nagai et al. 2006). Associative concepts can be represented as part of a network structure that surrounds the original keyword. Figure 4.4 shows the case of the association network from a keyword "snow."

Twenty words—comprising both artificial and natural objects—were selected to establish the base concepts in each group to decide on the design tasks. The 20 selected words were "mirror," "glasses," "bag," "letter," "chair," "scissors," "pool," "guitar," "blanket," "thermometer," "flower," "dog," "fish," "bird," "milk," "water," "oil," "egg," "star," and "ice." The number of associations from each word was subsequently calculated by using the Associative Concepts Dictionary (Okamoto and Ishizaki 2001). The Associative Concepts Dictionary is an electronic dictionary that was formed from lists of large numbers of words evoked by the mention

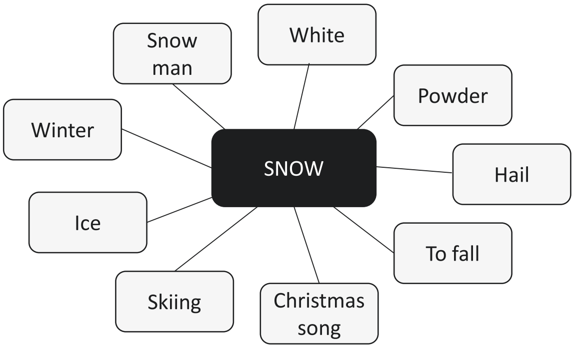

Fig. 4.4 Association network from "snow"

of selected basic words in a fundamental vocabulary in order to extract information pertaining to natural human language. From the list of the number of associations, two sets of keywords were selected. "Egg and blanket" and "flower and mirror" were the two pairs assigned as the design tasks for concept generation. The number of association concepts was 71 for egg, 69 for blanket, 151 for flower, and 114 for mirror.

Five participants performed the design tasks in the experiment. Two were design students, two were art students, and one was a professional industrial designer. Each was asked to create a new product through design sketches evoked by pairs of keywords—"egg and blanket" in Task A and "flower and mirror" in Task B—in a random order. After the design work, each participant was required to answer a questionnaire in a semi-structured interview. The outcomes of the design sessions were evaluated using the method proposed by Finke et al. (1992). The generated concepts were evaluated from two perspectives—sense and originality—with one evaluator for each perspective using a four-point scale.

Nine evaluators (two professional designers and seven design professors) evaluated 10 kinds of design concepts as outcomes of the experiment. Table 4.3 shows the results of the evaluation. In this research, we focused on the differences in the results between Task A and Task B for each participant in order to investigate the influence of the number of associations on creativity. All participants showed a higher creative score for originality in Task B ("flower and mirror") than in Task A ("egg and blanket").

After the design task, the participants were required to verbalize their thoughts during the task and to answer a questionnaire in a semi-structured interview in order to identify the contents of association. All words expressed during the design tasks were classified into associations among the concept types: action, situation, parts, synonym, attribute, abstract concept, concrete concept, and others. The results of a protocol analysis showed that action concepts play a role in creative generation because a higher percentage of action concepts was found in Task B, while a higher percentage of other types of concepts was found in Task A. It is suggested that action concepts play a role in creative design because they are thought to be related to the functions of products, which are understood as more valuable than the shapes of products at the early stage of concept generation.

Table 4.3 Evaluation scores for the design tasks

Participant ID	Significance *n.s.*		Originality[a]	
	Task A	Task B	Task A	Task B
1 (art student)	2.4	2.3	2	2
2 (art student)	1.4	2.4	2	3.1
3 (design student)	2.1	2.3	1.7	2.5
4 (design student)	2.4	2.3	1.7	2.4
5 (professional)	2.1	2.4	2.2	2.3
Average	**2.08**	**2.34**	**1.92**	**2.46**

Two-sided t-test (*n.s.* $p > 0.10$, [a]$p < 0.10$)

Additionally, the cognitive process of recognition between two concepts, based on which similarity or dissimilarity is discerned, as well as the essential cognition for synthesizing concepts, was deeply related in design creativity. In short, the results of synthesizing two dissimilar concepts showed a high potential for producing successful, original design outcomes in the concept generation process. Notably, this kind of cognition was shown equally by all participants regardless of their design experience. Thus, the competency of concept generation for design shows equality (immanent competency), which answers the question of why humans can design.

4.4 Macroscopic Viewpoint of Individual Design Work

We have discussed the concept generation process only at the very early stage. In the experimental situations, all design tasks were completed in the short term, usually between 10 and 60 min. To understand the creativity of individual designers, it is necessary to study their real performance in longer activities. As Fig. 4.2 expressed the inner and outer criteria for design creativity necessarily coexist. Thus, the development of a designer's self (ego) in his/her life is an important factor for design creativity.

For long-term observation to understand the creative process, the art ethnographic approach, developed from the ethnographic method, was proposed in a study (Eguchi and Okada 2010). The study reported that the learning process in car design projects was mastered in four years. It was exploratory trial; however, the results were limited to a certain sketch style—a standard way of car styling was requested—and it was difficult to investigate the nature of design creativity.

Nagai et al. (2010) proposed an integrated first-person and third-person methodology to observe the 5-year process of a designer's creative activity based on "autopoiesis" (Maturana and Varela 1980). They aimed to understand an artist's self-referential record as scientific data. A reason to adopt the first-person method is that it is thought to be advantageous for the observation of the creative process from the inner perspective of real experience. Contrary to the above merit, such an observation is difficult when the person is deeply engaged with the work during the design process. It is therefore necessary to form a new method for self-observation when a designer is engaged in the creative process.

Figure 4.5 shows a basic framework for self-observation methods. To overcome the limitations of each approach—the third-person mode (the third person's voice from an observer's perspective), the second-person mode (the second person's voice from the participant's perspective), and the first-person mode (the first person's voice from his/her own perspective)—it is necessary to modify "autopoiesis." An advanced method for self-reporting the process from an inner perspective is proposed by Nagai et al. (2010). This can subsequently be adopted for investigating creative processes that only the creators recognize, by conducting case studies of design from a macroscopic viewpoint.

The structure of the self-observation is as follows: A designer records real-time creative processes and his/her own daily experiences while engaging in a creative activity, taking down notes in sketchbooks to remember past experiences in the greatest possible detail, which is assumed to be a practice commonly employed by creators. The projects can be long term, and the designer is expected to present and submit his/her records at least once a week to an experimenter who was a collaborator of the designer, who also creates a report. After completing a design, in the first self-report, he/she describes all sources that have been referred to during the process and the final work. An art researcher, who is expected to have professional experience in interpreting artworks, observes the

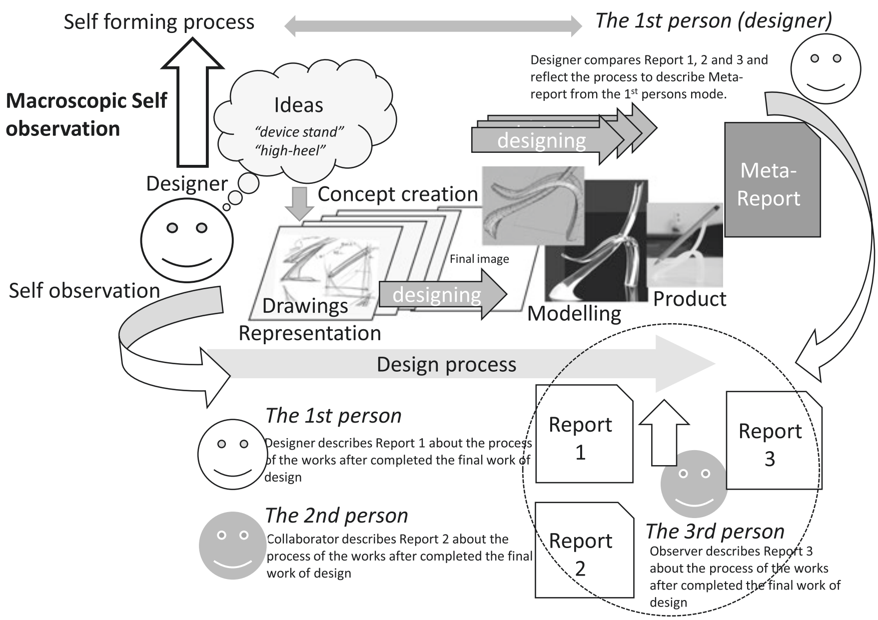

Fig. 4.5 Structure of the long-term observation process in the first person

designer's creative process (drawings, photographs, diary, etc.) and the final work and then writes an observer's report also referring to the report created by the collaborator. The designer then compares his/her own first report, the collaborators' report, and the observer's report to generate a final report (extended reflective report) based on the integration of the three reports. Because the process is complicated, the investigation team should be managed and regular meetings for ethnographic discussion are needed.

After a 5-year case study conducted from 2006, a second case study is now being carried out by the author and a designer (who majored in art and engineering as well as learning design thinking) who have been observing a self-forming process. Two experimenters control the conditions of the case study over the whole duration of this long-term investigation. To cover the missing parts of the designer's self-investigation report, we also developed a method to record the creative activities in the everyday life of the designer.

Csíkszentmihályi (1990) asserted that "flow" is an experience of optimal involvement in an activity and that as people become more skilled in a domain, they search for even more challenging problems in order to continue experiencing this "flow." The "flow" experience has been considered to have a strong connection with intrinsic motivation that contributes to creativity. In addition, intrinsic motivation is thought to contribute to ongoing involvement. Here, the first-person mode is extremely meaningful for investigating the coexistence of inner and outer criteria for design creativity including such flow situations. Thus, we aim to capture the whole atmosphere of design creativity by analyzing drawings and other representations (photographs, diary, etc.) to discover the missing parts (unconsciousness level) of self-observation based on the ethnographic method. An advantage of this method is enabling the capture of in-depth cognition, especially in relation to creative activities in design.

The self-forming process of a designer through the experiences of many design processes reveals a meaning of design that suggests a reason why humans are the only species capable of designing.

4.5 Summary

First, as a prelude to this chapter, the essential features of design were explained. By introducing previous experiments, it was revealed that design is a common competency among humans. In the experiments, the "something new" task activated design creativity; moreover, the "for somebody" task activated deeper and more careful thinking. As a result, it is suggested that *compassion for others* is the essential driver of design. This seems to answer the question "Why can only humans design?"

In humans' cognitive processes, a mode of design thinking can be activated that is related to internal and external stimuli. Based on individual experiences, the drawing process is a meaningful resource that is representative of the design thinking process, which encompasses exploring and generating. Further, we discussed individual design work from different viewpoints: the microscopic and macroscopic.

In order to identify the core mechanism or nature of the design thinking mode in the early stages of design, the concept generation process was focused on from a microscopic viewpoint. As a result, dissimilarities were found with respect to the role of associations and conditions of initial keywords.

On the other hand, from a macroscopic perspective, we confirmed the importance of the designer pursuing, through a long-term design creation process, a self-growth process by finding a subjective theme (namely, motive) that activates individual creativity. Through long-term observations, we discovered that finding a thematic motive for creation in design work and self-growth by changing or shifting previous knowledge are both important for learning innovative processes.

Comprehensively, we found that internal and external motivations act as the sparks that drive the creative process in individual design work. This understanding of individual design work contributes to the in-depth understanding of human creativity where design is a key exemplar. Further, the self-forming process developed through design experiences and the interaction between inner and outer criteria answers the question of why humans are the only species capable of designing.

Finally, we see the next steps in studying design creativity as the discovery of its core motivators, which we aim to explore in future works.

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Chapter 5
Methods for Studying Collaborative Design Thinking

Andy Dong and Maaike Kleinsmann

Abstract When discussing the performance of design teams, researchers repeatedly stress the key role of team cognition, which refers to collective cognitive structures and processes relating to product conceptualization and realization. The perspective taken in this chapter is that individual team member knowledge contributes to team cognition, and the quality of the aggregation of knowledge explains variance in knowledge-intensive activities such a design. We will describe two methods that together assess the structure and processes of team cognition and their impact on design team performance. Taken together, these methods provide a way to assess team cognition over time so as to account for variance in team performance based upon the quality of their knowledge practices.

Keywords Reflective practice · Latent semantic analysis · Team mental models

5.1 Introduction

In a business environment that stresses innovation, the adoption of the cognitive strategies of designers, or "design thinking", is being actively sought by firms to solve problems associated with realizing and capturing innovation. Whereas most of the chapters in this part address research methods associated with studying individual

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designers, this chapter extends the discussion to include experimental investigation of design at the team level. The aim of this chapter is to describe two methods to capture the design thinking processes in innovation-oriented teams and to propose general requirements for the measurement of design thinking at a small group level.

Design thinking supports the creation of novel and radical ideas that are necessary to provide businesses with competitive advantage (Liedtka and Ogilvie 2011; Martin 2009). While the field of design studies lacks a widely accepted construct for design thinking (Johansson-Sköldberg et al. 2013; Kimbell 2011, 2012), in the context of this book chapter, design thinking refers to the set of cognitive strategies (Cross 1999, 2006; Darke 1979; Dorst 2010) to produce novel artefacts, environments, or situations that are intentionally imagined or realized for a certain purpose. In the context of this chapter, by team cognition, we mean the collective knowledge structure at the team level that guides the direction of the design innovation and the innovation process. Some scholars have described this specialization of team cognition as team creative cognition (Shalley and Perry-Smith 2008). For design researchers and management scholars who are interested in design thinking as a vehicle for innovation, it is important to study the way that the collective knowledge structure arises during innovation processes, as the quality of the outcome of the innovation process is highly dependent on these cognitive processes (Dong 2005; Lu 2015). To show the relevance of design thinking to innovation, it is therefore important to investigate the most productive knowledge creation strategies for innovation-oriented teams.

We point out that the underlying assumption of the cognitive approach is that structures and processes of team cognition have causal importance in explaining the performance of design teams (Dong et al. 2013). More specifically, the *shared* cognition perspective hypothesizes that knowledge accounts for more variance in team performance than say interaction as hypothesized by the *interactive* team cognition perspective (Cooke et al. 2013). Given the cognitive paradigm underpinning the methods described in this chapter, the review of methods for measuring collaborative design thinking in the next section will necessarily leave out methods to understand design teams based upon ethnomethodology (Luck 2012), conversation analysis (Matthews and Heinemann 2012), or social interaction (Stumpf and McDonnell 2002). In those approaches, the researcher takes a social route and starts by identifying the context within which work gets done. Given the focus on actions and the environment in which design activities take place, social methods can explain how the structure and conduct of actions and the environment in which these actions take place influence design outcomes. This chapter, and cognitive approaches in general, do not account for the context in which the team members execute the innovation process. Suffice to say, the cognitive approach and social methods make distinctive contributions to understanding how design teams behave. In summary, the perspective taken in this chapter is that individual team member knowledge contributes to team cognition and that the quality of the aggregation of their knowledge explains variance in knowledge-intensive activities such a design.

In this chapter, we will start with an explanation about team mental models and the methodological challenges and limitations in extant methods to measure team mental models. We then present two complementary methods for measuring team cognition in design teams.

5.2 Methodological Challenges and Requirements

Research about design cognition is a topic that researchers have investigated at least since Newell and Simon (1972). The reason researchers are interested in design cognition is that it is believed to be one of the exemplars of intelligent behaviours in humans (Oxman 1996). Design cognition topics in which researchers are interested include the following: (1) cognitive styles of design thinking (see, e.g. Oxman and Oxman 1992), (2) problem solving strategies (see, e.g. Dorst and Cross 2001; Kruger and Cross 2006), (3) creativity and/or fixation (for an overview, see Crilly 2015) and (4) visual reasoning (see, e.g. Goldschmidt 1994; Menezes and Lawson 2006). To extend research from individual cognition to team cognition, we need to adopt a framework that addresses the casual relation between team cognition and team performance. The theory of team mental models (Mohammed et al. 2010) provides a construct to relate team cognition to performance, which we describe in the next section.

5.2.1 Team Mental Models

Research in the field of team cognition has determined the methodological requirements of methods that purport to measure team cognition. The construct of team mental models asserts that the quality of team cognition affects the performance of a team. The research area contains a set of methods for the measurement of team cognition (DeChurch and Mesmer-Magnus 2010) including shared cognition and shared mental models (Klimoski and Mohammed 1994; Langan-Fox et al. 2004; Mohammed and Dumville 2001; Mohammed et al. 2010). It was decided to use this particular area of research because it contains theories that explain how team members draw on their own knowledge to realize actions that are consistent and congruent with their teammates'. Congruent knowledge is linked to effective actions and successful outcomes (Cannon-Bowers and Salas 2001; Klimoski and Mohammed 1994; Mohammed et al. 2000; Orasanu 1990; Rouse et al. 1992). Unfortunately, it is not possible to adopt the *methods* to assess team cognition from the field of team cognition, because the task of a design team differs too much from the tasks[1] of teams that researchers study while investigating team cognition.

5.2.2 Current Methods for Measuring Team Mental Models

In order to understand collaborative design thinking, one must confront research challenges in examining properties of team cognition. A number of methods exist

[1]Researchers within the field of team cognition study teams that have tasks with a well-determined outcome such as flying an airplane.

to study team cognition. For interested readers, Wildman et al. (2014) provide a more complete summary of existing team cognition measurement approaches and critical summaries of those methods. They vary along two key dimensions:

- Source of data
  - Predefined concepts described on cards (Smith-Jentsch et al. 2001).
  - Self-reported concepts obtained through direct elicitation (Harper et al. 2003).
  - Concepts extracted by automated analyses of essays about mental model content (Carley 1997).
- Method of analysis
  - Network relations between concepts such as pathfinder (Lim and Klein 2006; Schvaneveldt 1990).
  - Centrality and sharedness of concepts in mental models (Mathieu et al. 2000, 2005).

One of the key barriers to progress in this area is the lack of appropriate research methods to measure cognition at the group level of designers *while* engaging in creative activities rather than *after* they have completed their activities.

5.2.3 Challenges in Collaborative Design Thinking

Studying team cognition in design teams introduces methodological challenges not previously encountered. Extant research on team cognition in general does not provide a similar context because the task oriented teams normally studied in the literature on team mental models work on directed, highly coordinated, and highly focused tasks. These tasks are not comparable to a design task. Designing is not like the task of flying an airplane, for which the mission is clear, the knowledge that is needed to achieve the task is known a priori, and the success factors for achieving the flight mission are fixed and predetermined. Creative design teams work on “wicked” problems that lack a well-described set of “permissible operations” or enumerable set of solutions (Rittel and Webber 1973). The need for a novel solution precludes simple repetition of past behaviour and creates uncertainty about what needs to be done (Hoopes and Postrel 1999). Design is an activity subject to conditions of dynamic and incomplete knowledge. Instead of acting upon relatively certain knowledge (Badke-Schaub et al. 2007), designers make decisions based on unstable, dynamic, uncertain and inaccurate knowledge (Hazelrigg 1998). These important differences introduce challenges in assessing the content and structure of knowledge within teams since the relevant knowledge for a particular design task would not be known in advance.

Second, the act of design is about producing things that do not (yet) exist, the consequence of which is that design teams would not have a stable, unchanging cognitive model that refers to or are about objects. This makes studying team cognition challenging since the knowledge generated is new and not predetermined. Part of the instability of the mental states stems from the necessity of design teams being comprised of individuals having multiknowledge (Park et al. 2009) and the requirement to create highly integrated knowledge structures (Berends et al. 2007) to solve problems that demand more knowledge than any one individual possesses. The effectiveness of the design team depends on the richness of the team members' knowledge and the quality of their knowledge sharing, since knowledge is applied and generated over the course of the process (Mohrman et al. 2003). Since the knowledge integration is dynamic, getting to grips with team mental models as a team-level construct of team cognition necessarily entails understandings how the team mental model changes over a given period of time. Neither the team members' knowledge structures nor the team mental model are static.

Third, when executing a design project, knowledge is often dispersed between team members from various disciplines due to the complexity of the project. Diverse knowledge is a requisite for the novelty of the product idea (Hirunyawipada and Paswan 2013). Consequently, each team member will have different cognitive structures—due to their different knowledge bases—that need to be shared and aligned in order to make sense of the available knowledge (Weick 1995). Often, a design problem has no practicable solution and the problem must be recast before a solution can be found, or each of the stakeholder's conceptions of the problem must be changed, or both. Social (as in interpersonal) agreement on how problems should be definitively formulated and by what criteria solutions should be evaluated are preconditions to the effective formulation of those problems for formal, rational solutions to be obtained. As a result, managing a design project demands the alignment of different individual belief structures that shape and frame how individual team members make sense of their work (Dougherty 1992), a process that varies with the design brief. Combining the knowledge of the different team members into a successful design is not so much a coordination or cooperation problem as it is with flying an airplane; it generally is a knowledge integration problem (Hoopes and Postrel 1999). Team members all have their own *belief structures* as to what the designed work should be and have domain knowledge over only a particular aspect of the entire project (Dougherty 1992). Whether the belief structures will prove to be "valid" or "true" is impossible to know before, for instance, a product is launched. As such, what matters more is whether the belief structures are "acted" out in the design process and provide a direction for the team, i.e. provide a way of "seeing" the world that informs their design actions.

To sum up, two broad sets of issues, *dynamic team mental models* that refer to or about objects and *transforming knowledge into directed action*, introduce methodological challenges for understanding team cognition using the team mental model construct. A team mental model is generally assessed in terms of two measures: similarity and quality. The *similarity* of team members' mental models concerns the alignment of the mental models of the different team members to the actions and knowledge of the team. Similarity is generally assessed in terms of the overlap of mental models among team members (Cannon-Bowers et al. 1995; Klimoski and Mohammed 1994). However, in design, it makes no sense to measure similarity *post facto* once the design has already been realized. We need instruments that can measure similarity as the designers are working and developing their team mental model. Second, the *quality* of the team mental model addresses the requirement that the team mental model actually contains the relevant content to achieve the team's aims. The problem that design teams face is that the referent model cannot be known a priori because the only suitable referent model is the design that is being constructed during the teamwork.

Given the previous discussion, we summarize the main requirements of any experimental research method to assess design team cognition using the team mental models construct. The method should be able to:

1. Identify the content and structure of an individual and the team mental model dynamically (changing over time),
2. Define and measure the quality of the team mental model,
3. Characterize the change in team mental model as activities occur, and
4. Show the relation between a quality team mental model and goal-directed action.

5.3 Computational Approaches

To date, the latent semantic approach (Dong 2005) remains the only computational method to understand design team cognition published in the design research literature (Dong 2005; Dong et al. 2004, 2013). Like computational approaches described in Part 3 of this book, the latent semantic approach was developed to deal with verbal and textual complexity encountered in empirical and experimental settings. While originally developed to study the performance of design teams based upon their written documentation (Dong et al. 2004), the method has been extended to study team mental models (Dong et al. 2013) by assuming that words are prima facie evidence of cognition (c.f. Matthews 2009). The main problem addressed by the latent semantic approach is to ascertain to what extent an individual team member's knowledge is synchronized and coherent with team knowledge. Mental models are represented in a multidimensional space in which each dimension represents a unit of knowledge about the designed object, such as its shape, function, use, affordance, but without any a priori determination of what the knowledge is. The distance along any axis represents the importance (Smith-Jentsch et al. 2005) of a unit of knowledge in an individual designer's mental model. For example, to one designer, its function has more import than the object's intended end-user in the designer's mental model of the object. Knowledge components of individual mental models are mapped onto the multidimensional space, and the team's combined knowledge (representation of the designed object) is represented by the union of the individual mental models. This combined team knowledge is not the team mental model; it is simply what the team knows, or more accurately, what it has expressed as its knowledge. To identify the team mental model, a lower-dimensional space of the combined knowledge is computed using singular value decomposition. This lower-dimensional Cartesian space represents the knowledge axes of the team mental model, or, more formally, the orthonormal basis of the union of the individual mental models.

Mathematically, this space is represented by the matrix **X**, consisting of n rows representing the units of knowledge, such as a word or short phrase, and m columns representing instances in which the unit of knowledge is realized, such as in a document or a verbalization. The value $\mathbf{X}_{ij}$ describes "how much" of the unit of knowledge is realized in an instance. The lower-dimensional space permits a projection of individual mental models onto the team mental model. A projection of an individual mental model onto the lower-dimensional space analytically describes "how much" of an individual's mental model is comprised of the units of knowledge that make up the team mental model. The details of this calculation are outlined elsewhere (Dong 2005; Dong et al. 2013).

The quality of the team mental model is assessed through various metrics, summarized in Table 5.2 (Dong et al. 2013). The semantic space of the team is calculated as the mean of the column vectors of **X** by row, resulting in an $n \times 1$ vector. The semantic space of each team member is calculated similarly taking only those columns from **X** attributable to team member k. Semantic coherence is used to assess similarity between the semantic spaces of the team and each team member. Semantic coherence has been shown to be a reliable predictor of performance in knowledge-oriented activities. Martin and Foltz (2004) were able to predict the performance of a flight team by comparing the semantic coherence of the transcript for a given flight team with the transcript of another team with a known level of performance. Similarly, latent semantic analysis has been shown to reliably score essays of varying levels of quality without human intervention (Landauer and Laham 2000). Similarity is calculated by the total root mean square (RMS) error between each team member's mental model and the geometric mean of the individual mental models projected onto the lower-dimensional team mental model space. A lower value of RMS indicates greater semantic coherence between each team member and the team. The rate and duration of semantic coherence, which we name semantic consonance, is calculated by finding the area under the curves representing the semantic coherence for a team member or for the team.

5.4 Content-Coding Based Approach

In design research, many paradigms exist regarding the process of designing, the designer and the design task including design as rational problem solving (Simon 1996), design as a social process (Bucciarelli 1994) and design as experiential learning (Schön 1983). For studying knowledge processes in design teams, the experiential learning paradigm is the predominant paradigm, since it stresses the dynamic, unique, cyclic and unfolding characteristics of design (Stumpf and McDonnell 2002) and emphasizes how reflective practice is a characteristic property of expertise formation in professions (Schön 1983). The reflective practice consists of three alternating activities—*naming, moving, reflecting*—and a coordinating cognitive activity *framing*, which leads to the construction of frames.

Frames—enclosing both the problem and solution space—guide and direct the team's design activities. During naming, team members identify important elements that need the team's explicit attention. Team members are moving when they are developing the design concept, for example, when they are generating ideas, exploring problems, or looking at the consequences of design decisions. Moves often contribute to the development of new frames or to changes in a frame. Moves help designers redefine the design problem at hand. There are two types of moves. Moves *inside* frames are guided towards a (sub) goal whereas moves *outside* frames are unguided actions. The fourth activity is *reflecting,* in which team members turn their thoughts towards their current actions or what has been done so far on a macroscopic level. During reflection, they question where their actions are taking them. Reflecting provides insight into both the project's progress and quality and can lead to reframing the design problem or new moves.

The activities naming, moving and reflecting can occur either within or outside a frame. The extent to which they occur within or outside a frame has important consequences on the productivity and efficacy of their collaborative design thinking. According to Schön (1983), framing occurs during a *conversation with the situation*. Through framing, the parameters of the design problem are established, which function as a context for further activities (Gray 1996). When designers set the problem, they select what they treat as the elements to take into account and where they set their boundaries of their attention (Weick 1995). When studying the individual designer, framing is an internal, cognitive process. However, team framing is a collective activity that is performed through communication between team members. Sensemaking is devoted in part to the development of socially shared beliefs which define the relevant set of rivals and guide strategic choices about how to compete within this set (Porac et al. 1989). Therefore, while framing, team members create *shared belief structures*.

While designing, team members contribute to the activities by adding their individual knowledge to the team's knowledge. Through this integration of knowledge, team members align their actions and make their mental models congruent. If the team succeeds in doing this, a frame will be constructed; otherwise, the moves remain unguided, and no frames will be constructed. All frames that are developed during the course of a design project together form the team mental model. Therefore, for studying team mental models, framing and moving are the most interesting activities. When the function, structure and behaviour of a design are discussed *within a frame*, this implies that team members have a shared rationality about the design activity. In other words, they have a productive team mental model at that point in time.

The reflective practice coding scheme developed by Valkenburg and Dorst (1998) introduced a means to identify team framing and the collective actions that are directed towards a common goal when the team is operating within a frame. The coding scheme identifies the shared belief structures of the design team in the transcript by characterizing the team members' expression of attributes, inferences and goals—the elements of a belief structure (Mohammed et al. 2000). Attributes are operationalized by names, since they both contain meaningful features. Inferences are moves since they can be seen as elaborations on the design problem and its solution. Frames can be seen as (sub) goals since they guide the design

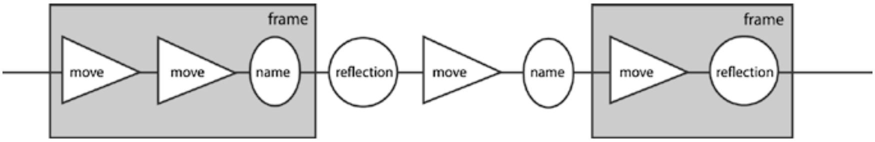

Fig. 5.1 Design as a reflective practice in which four activities alternate

process towards a desired state or end. Aside from the content of the team mental model, the reflective practice coding scheme captures the process of creating a team mental model over time—by showing what frames were developed when—and identifies the relationships between the elements of the team mental model.

Figure 5.1 shows the graphical representations as developed by Valkenburg and Dorst (1998). The grey rectangles, ellipses, triangles and circles represent the frames, names, moves and reflections, respectively.

5.5 Methodological Integration

This section provides an integration of the techniques presented by considering how the two methods in tandem deal with accounting for team mental models in design teams. As a brief synopsis of the methods, recall that the latent semantic approach is a quantitative technique that applies a computational distributed semantics calculation to the verbalizations of the design team. The reflective practice coding scheme codes the activities, as expressed through the team members' dialogue that take place during the course of the design process. Both the methods of Valkenburg and Dorst (1998) and Dong (2005) are accepted methods in the design research community. The combination of the two methods allows us to evince semantic coherence with goal-directed behaviour as antecedents of and indicators for the existence of a quality team mental model. Table 5.1 summarizes the discussion of Sects. 5.3 and 5.4 to present how the methods measure mental models with respect to the criteria set by Mohammed et al. (2000) and Sect. 5.2.3.

Table 5.1 Metrics of semantic coherence and team mental model quality (Dong et al. 2013)

Measure	Symbol	Method
Group's semantic space	γ	Row mean of the columns of **X**
Team member k's semantic space	ψ_k	Row mean of the columns of **X** corresponding to knowledge contributions by team member k
Semantic coherence of member k to the team	$\chi(\gamma, \psi_k)$	$\mathrm{M}_\mathrm{o}^5\mathrm{X}$
Semantic similarity	$\lambda(\gamma, \psi_k)$	$\mathrm{M}_\mathrm{o}^5\mathrm{X}$
Semantic consonance	$\kappa(\gamma, \psi_k)$	Trapezoidal rule integration of the area under the curve $\chi(\gamma, \psi_k)$ for all knowledge contributions in the design process

Table 5.2 How the methods address the criteria for measuring mental models

Criteria	Latent semantic approach	Reflective practice coding
Content	The content is represented by the lexicalized concepts, and their distributed patterns of co-occurrence, expressed by a team during collaborative activity. The activity may be synchronous or asynchronous	The reflective practice coding scheme captures content by analysing and coding the team's activities—that are displayed through verbal communication—that take place during the course of the design process
Structure	The structure is described by the distributed relations between the units of knowledge, generally words. It is abstractly represented in a high-dimensional vector	The method provides insight into the complete structure of the process of creating a team mental model since it captures the knowledge processes chronologically and the relationships between the four reflective practice activities
Quality	The metrics in Table 5.2 describe ways to assess the quality of a team mental model	The quality of team cognition is related to activities that happen within a frame
Change over time	The measurement of semantic coherence is explicitly time-based, as it takes into account new knowledge added by each individual throughout the process and calculates the resulting team mental model dynamically	The reflective practice coding technique captures the generation of frames throughout the design process. Each of the codes in the reflective practice coding scheme represent a design activity
Accepted approach	Latent semantic analysis is a text analysis method that is now widely available through open source software tools	A detailed description of the use of the method (Valkenburg 2000) and a sample video to train researchers using the method are available
Reliability	The use of software eliminates human coder error and has been tested on benchmark data and team communication in different languages	Multiple interrater reliability tests showed sufficient results (Cohen's Kappa between 0.67 and 0.72)
Team-level analysis	Semantic coherence is a property of the collective activity of the team rather than a mere average of each team member's contribution	The reflective practice framework applies to collective activity, wherein designing is a product of the team members' behaviour within a design situation

The latent semantic approach calculates semantic coherence; the degree to which a mental model of one team member is integrated to become part of the team mental model is calculated by the global relations of the units of knowledge expressed (generally in verbal or written communication) by all of the team members. By doing this calculation, the method provides insight into the degree of semantic coherence among team members and between an individual team member and the team. Because the calculation is dynamic in that it calculates the semantic coherence as each team member contributes new knowledge, the method can show the rate of formation of semantic coherence, the degree of semantic coherence formed at a point in time, and the interrelatedness of each team member to the team. The latent semantic approach shows which of the team members share the most semantic coherence and which ones do not share semantic coherence with the team. In the reflective practice coding and subsequent relational analysis, frames serve as a way to capture periods in which the team member's mental models are congruent, since frames only exist when a coherent team mental model exists. Within frames, the activities naming, moving and reflecting provide insight into what knowledge was deployed during a task and what knowledge preceded the tasks. Outside a frame, the method provides insight into what is going on and to the question why the team is not able to create a frame.

Thus, whereas the reflective practice chronologically captures activities and the knowledge going into the activities as patterns in the relationships between codes, the latent semantic approach provides insight into the degree of semantic coherence occurring "in parallel" to the tasks being performed. Detecting frames and frame shifts with the use of associations and dissociations provides insight into the relationships between frames to show a comprehensive view of the design process as executed by the design team. How semantic coherence is ultimately deployed into goal-directed behaviour is addressed by the reflective practice coding scheme. The actions that the team performs are not purposeless. They have the consequence of enacting their team mental model at a point in time. Yet it is clear that the enactment of the team mental model is fruitful, that is, exhibiting the benefit of a quality mental model, only when the team mental model shows a high degree of semantic coherence *and* of goal-directed behaviour. As such, the two methods mutually complement each other as both are needed to identify these characteristics, respectively.

5.6 Conclusions

The aim of the chapter was to describe two methods for capturing team cognition in innovation-oriented teams. To address this aim, we needed an understanding of the methodological challenges associated with measuring team mental models. Therefore, the chapter addresses the problem of understanding whether innovation-oriented teams such as design teams have the "right" mental model. In these professions, talking about facts is not a sufficient basis to characterize the team as having a quality team mental model *for designing*. In other words, it is not the same situation as a flight crew, in which we can assume that if the team members are discussing known facts about flying, then they have a quality mental model. If the communication between the flight crew is coherent and matches the knowledge needed to operate the flight, then they are likely to have a quality team mental model. For the design team, it must be shown that a team mental model is forming *and* that it is enacted as goal-directed behaviour that leads to the knowledge being embodied in the design. It is possible for the design team to have a team mental model, but to have a team mental model that is purposeless does not lead to a well-formed design.

Design has been characterized as a process of creating new representations (Visser 2006). Given this definition, it is the interrelationship between the quality of the team mental model and goal-directed behaviour leading to new representations that is of interest. This chapter started by framing design thinking as a set of cognitive strategies. The chapter presented methods to assess collaborative design thinking from the perspective of team cognition. In collaborative teams, where individuals may have competing interests and alternative ways of framing problematic situations, their collaborative design thinking must be focused towards goal-directed behaviour. While these teams may not be flying an airplane, and they may have different or even contradictory frames for an aerial transport system, heading towards a creative leap will require them to find a unifying team mental model.

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Chapter 6
The Integration of Quantitative Biometric Measures and Experimental Design Research

Quentin Lohmeyer and Mirko Meboldt

Abstract In design research, recently an increasing number of experiments have been conducted that successfully applied quantitative biometric measurement methods to investigate design-related research questions. These methods are heart rate variability (HRV), skin conductance response (SCR), electroencephalography (EEG), functional magnetic resonance imaging (fMRI) as well as remote and mobile eye tracking (ET). Within the scope of these experiments, a variety of different biometric measurement systems have been used, each able to record specific raw data and each using characteristic measures to detect and specify particular patterns of human behaviour. This chapter explores how these biometrical measurement systems work, what exactly they measure, and in which ways collected raw data can be analysed to obtain meaningful results. By using the example of selected design studies, the benefits as well as the limitation of the aforementioned biometric measurement methods are discussed and reflected in regard to their present and future role in experimental design research.

Keyword Biosignals · Neuroimaging · Eye tracking

6.1 Introduction

In experimental design research, collecting and analysing quantitative data are already well-established. In particular, in the context of investigating human behaviour in design, traditional research methods such as surveys, interviews,

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observations, document analyses, and protocol analyses are widely used (see Chaps. 4 and 5). However, the use of such methods may be associated with limitations since interview and survey data, for example, are often subjective and possibly influenced by hidden intentions of the informants (vom Brocke et al. 2014).

Quantitative biometric measures instead are known to be an objective source of information about a person's condition. Indeed, biometric measurement has a long history in the field of medical diagnostics. Starting from monitoring basic vital signs, such as pulse or breathing rate, medicine nowadays can take advantage of multiple bioelectrical signals (Kaniusas 2012) and imaging technologies (Haidekker 2013) to examine physical as well as cognitive conditions in order to make evidence-based decisions on treatment options.

Integrating quantitative biometric measures and experimental design research is based on the idea to record physiological data of participants in order to establish a more objective basis for analysing behavioural patterns of designers and users (Meboldt et al. 2014). Since there are specific biometric measures that are valid indicators for, amongst others, mental stress, emotional arousal, cognitive activity, and visual attention, biometric measurement provides the opportunity to substantially enlarge the body of experimental design research methodology and to improve the validity and reliability of design studies.

This chapter gives an overview of selected biometric measurement methods that have been successfully transferred into the field of experimental design research. These methods are heart rate variability (HRV), skin conductance response (SCR), electroencephalography (EEG), functional magnetic resonance imaging (fMRI) as well as remote and mobile eye tracking (see Table 6.1).

Each biometric measurement method is described by using the following structure. First it is briefly stated which aspect of human behaviour can be analysed by using the specific method. Then, the associated measurement system and its basic working principle are shortly explained. In doing so, it is clarified what exactly is recorded by the measurement system and which biometric measures are included in the resulting raw data. Based on this, it is described how the raw data are processed to compute characteristic values allowing the detection of corresponding

Table 6.1 Biometric measurement methods applied in design research

Measurement method	Abbreviations	Biometric measurement	Scope of research
Heart rate variability	HRV	Variation in time between consecutive heartbeats	Mental stress
Skin conductance response	SCR	Changes in the electrical conductance of the skin	Emotional arousal
Electroencephalography	EEG	Electrical fluctuations in the cortex of brain	Cognitive activity
Functional magnetic resonance imaging	fMRI	Changes in blood oxygenation inside the brain	Cognitive activity
Eye tracking	ET	Angular displacements of corneal light reflection	Visual attention

behavioural patterns. Finally, for each method an experiment conducted in the context of design is presented to exemplarily demonstrate the particular integration of quantitative biometric measures and experimental design research.

6.2 Biosignal Monitoring

Biosignals usually refer to changes in the electrical current across specific organs or tissues. Although in medicine the number of monitored biosignals is very large, other disciplines investigating human behaviour have especially adapted the measurement of heart rate variability (HRV) and skin conductance response (SCR).

6.2.1 Heart Rate Variability (HRV)

Heart rate variability (HRV) is a biometric measurement method that allows drawing conclusions regarding mental stress of a participant based on the variation in time intervals between his or her consecutive heartbeats.

HRV is based on data gained by electrocardiography (ECG), a procedure recording the electrical activity of the heart. Suitable measurement systems are conventional ECG systems using three electrodes placed on the skin between heart and limbs (limb leads) or chest strap systems using multiple aligned electrodes near the heart (chest leads). Simplified pulse monitoring systems worn on the wrist or finger are not capable of recording ECG data.

A typical ECG signal of a heartbeat is composed of five waves denoted by P, Q, R, S, and T, at which the R-wave represents the highest peak. Based on ECG data, the central HRV measure referred to as RR interval can be determined. The RR interval gives the time between consecutive heartbeats. It is defined as the time between two R waves and it is measured in milliseconds (ms). There is a reciprocal relation between RR interval and heart rate. Thus, a series of short RR intervals is equivalent to a high heart rate and a series of long RR intervals implies a low heart rate.

Although mean RR interval (mRR) and mean heart rate (mHR) themselves can be indicators for mental stress, these measures provide little information about the heart rate's variability. Research indeed found several heart rate variability measures (Ernst 2014). However, most studies investigating stress especially refer to the LF/HF value, which is the ratio of the power spectrum of low frequency (LF) and high frequency (HF). To calculate the LF/HF ratio, first a power spectral density estimation has to be processed based on the RR intervals (Ramshur 2010). The resulting frequency spectrum is then subdivided into the low frequency band from 0.04 to 0.15 Hz and the high frequency band from 0.15 to 0.4 Hz. Due to this classification, the percentages of LF and HF as well as their ratio can be calculated. Nowadays, several software tools are available that support researchers in the analysis of ECG data and the computation of relevant HRV measures.

The measures of LF and HF are known to be indicators for the activity of the two main divisions of the human autonomic nervous system: the sympathetic and the parasympathetic system. In a stressful situation, the sympathetic system becomes dominant, which causes immediate stress responses such as pupil dilation, increased sweating, elevated blood pressure and increased heart rate. The domination of the sympathetic system over the parasympathetic system comes along with an increase of the LF value and/or a decrease of the HF value. In consequence, an event of mental stress can be well detected by a significant increase of the LF/HF ratio.

Experimental design research using heart rate variability was presented by Nguyen et al. (2013). Their experiment aimed to investigate the distribution of mental stress during conceptual design activities. Eleven graduate students with engineering background participated in the study. The participants were asked to work on a small, open-ended design task while ECG data were recorded by a chest strap measuring system. The data were first segmented based on the observed designer's activities (write, pause, scroll, etc.). Then for each segment, the LF/HF ratio was computed and finally the segments were clustered into seven levels of stress. Data analysis showed that solving the assigned design task was basically performed under low levels of mental stress. Consequently, no correlation between the observed designer's activities and mental stress could be found.

This experiment exemplarily demonstrates that heart rate variability can be easily applied in the context of design research. HRV measurement systems are relatively cheap and easy to use. However, this measurement method is best applied in situations where stressful events actually might come up. This requires challenging time limits as well as well-defined success criteria. Since pressure of time and pressure of success play a major role in everyday design practice, HRV might support establishing a deeper understanding of the impact of stress on design performance.

Furthermore, HRV might be especially suitable to analyse user–product interaction expecting a significant increase of LF/HF ratio, when the design of a product is not sufficiently intuitive. Since HRV measurement systems are non-invasive and are also available as wireless devices, future experiments might be even conducted in the natural environments of product applications.

6.2.2 Skin Conductance Response (SCR)

Skin conductance response (SCR), also Galvanic Skin Response (GSR), is a biometric measurement method that allows drawing conclusions regarding emotional arousal of a participant based on changes in the electrical conductance of his or her skin.

Fig. 6.1 Example of a skin conductance response measurement system (reproduced with permission of NeuLog, Rochester, NY)

Skin conductance is usually measured from the inner skin surfaces of the fingers. Most SCR measurement systems are using two electrodes, which are attached to the index finger and the middle finger of the non-dominant hand (see Fig. 6.1). These measurement systems work by applying a small voltage (typically 0.5 V) to the electrodes and then tracking the amount of current that passes between them. Based on this measure, electrical conductance can be computed and recorded over a specific period of time. Skin conductance is usually expressed in microsiemens (μS).

In situations of emotional arousal, the human body reacts with an increased activity of the perspiratory glands. Since sweat is an electrolyte solution, the more sweat is secreted between the electrodes, the more current passes and thus, the more the skin conductance value rises. In this context, it is essential to consider that skin conductance is a time-lagged signal. There is a latency of 1–3 s between the moment of emotional arousal and the resulting SCR.

The most common skin conductance measure is SCR amplitude (SCR.amp), which is defined as the difference between the peak value of a specific response and the trough value preceding this peak. SCR amplitude is a central characteristic value representing the intensity of emotional arousal, and thus, it is most useful for comparisons across participants and across stimuli.

Several recent SCR studies additionally measured the area under the curve (SCR.auc) within a defined measurement window of typically 5 s time (usually beginning 1 s after the stimulus onset). In contrast to SCR amplitude, the area under the curve also takes into account the rise and fall of a response and thus represents a more valid SCR measure. However, the area under the curve cannot be measured directly from SCR raw data. Its computation requires preprocessing that can be realized by using either a moving-difference function (Naqvi and Bechara 2006) or a high-pass filter (Figner and Murphy 2010).

Experimental design research using skin conductance response was presented by Kim et al. (2010). Their experiment aimed to investigate relations between semantic and emotional responses to bio-inspired designs. Six master degree product designers participated in the study. They were subdivided into two groups.

Participants of the first group were successively confronted with six images showing inspirational animal postures, participants of the second group with six images of matching car designs. During the experiment, SCR data of all participants were recorded with a sampling rate of 200 Hz by a finger straps measuring system. In data analysis, for each image a segment of 11 s was analysed consisting of a 5 s preparation phase (before showing the stimulus) and a 1 + 5 s measurement window (after having shown the stimulus). In order to facilitate comparing responses across stimuli, the measurements were normalized and time-averaged. As one result, data analysis showed that in most cases, the car images caused responses with considerably higher SCR amplitudes than the animal images.

This experiment exemplarily demonstrates that biometric measures such as skin conductance can be well combined with traditional design research methods (e.g. questionnaires) in order to strengthen the validity of a study's results. In particular, for research investigating relations between design and emotion, SCR is a promising measurement method to robustly quantify emotional responses. However, SCR experiments are usually conducted in controlled laboratory environments. Due to the signal's time lag, stimuli have to be released separately with adequate waiting periods in between. In natural environments, participants are exposed to multiple stimuli instead and this complicates the assignment of stimuli to responses.

6.3 Neuroimaging

Neuroimaging includes a set of imaging technologies used to non-invasively investigate structural or functional aspects of the human brain. In research on cognitive activity, electroencephalography (EEG) is a well-established measurement method, but especially functional magnetic resonance imaging (fMRI) is increasingly used in corresponding experiments.

6.3.1 Electroencephalography (EEG)

Electroencephalography (EEG) is a biometric measurement method that allows drawing conclusions regarding cognitive activities of a participant based on electrical fluctuations in the cortex of his or her brain.

Cognitive activity means that specific regions of the brain are activated. This activity is generated by thousands of neurons that locally synchronize in emitting electrical impulses and thus in sum generate electrical potentials that can be detected, amplified, and recorded over time. The resulting EEG signal is an oscillating curve, whose amplitudes are within the range of microvolts (μV).

EEG data are recorded by using multiple electrodes placed on the participant's scalp. Basic measurement systems come with 2–19 recording electrodes (plus ground and reference electrodes), which nowadays are often embedded in a net or

Fig. 6.2 Example of an electroencephalography measurement system (reproduced with permission of Emotiv, San Francisco, CA)

a cap (see Fig. 6.2). To reach higher spatial resolutions, high-density measurement systems with 32–256 electrodes can be applied.

The placement of the electrodes on the scalp is specified by the international standard 10–20 system. Each placement location is defined and tagged by an ID composed of two parts. The first part refers to the specific cortex region of the electrode location: *F* (frontal), *C* (central), *T* (temporal), *P* (parietal), and *O* (occipital). The second part is either the letter z (zero), which indicates a location on the line of symmetry, or a number. Even numbers refer to electrode positions on the right cortex side, whereas odd numbers refer to those on the left side.

Research found that the regions of the human cortex are related to different cognitive functions (Teplan 2002). Electrodes placed at frontal regions are located near the centres for rational activities (*F*7), near the intentional and motivational centres (*F*z), and close to sources of emotional impulses (*F*8). Analogously, electrode locations on central cortex regions are related to sensory and motor functions (*C*3, *C*4, *C*z), those on parietal regions to activity of perception and differentiation (*P*3, *P*4, *P*z). Locations on temporal regions are associated with emotional processors (*T*3, *T*4), memory functions (*T*5, *T*6), and those on occipital regions with visual processing (*O*1, *O*2).

However, due to limitations caused by the non-homogeneous properties of the skull, different orientation of the cortex sources, and coherences between the sources, EEG data may not reflect the exact location of cognitive activity (Teplan 2002). This limitation in spatial resolution is usually referred to as the major drawback of EEG measurement.

Results of EEG experiments are usually based on spectral analysis. Therefore, EEG raw data have to be preprocessed by applying both a high-pass and a low-pass filter, before in a next step, the power spectrum is computed (Adjouadi et al. 2004). The resulting frequency spectrum is subdivided into four frequency bands: delta waves (<4 Hz), theta waves (4–8 Hz), alpha waves (8–13 Hz), and beta waves (>13 Hz). This classification allows to track changes in the power distribution within each frequency band. For example, several studies found an increase in the theta band and a decrease in the alpha band as task difficulty increases (Nguyen and Zeng 2014). Power spectrum is usually computed for each electrode placed on the scalp.

In order to integrate these results, most EEG software tools use coloured scalp maps to visualize power distribution within a frequency band across all cortex regions.

Experimental design research using electroencephalography was presented by Seitamaa-Hakkarainen et al. (2014). Their experiment aimed to investigate the question of whether brain responses working with visual (drawing) or material (mould clay) representation would differ between tasks of copying, creating novel designs or freely improvising. Eight first-year and eight master design students participated in the study. While solving the tasks, EEG data of all participants was recorded by a measurement system with 32 channels.

This experiment exemplarily demonstrates that EEG data can be analysed regarding multiple research questions. Indeed, in context of the presented study, it was expected to find differences (1) between more visual and more motor activities, (2) between more creative and less creative activities, and (3) between more experienced and less experienced participants. The experiment showed that EEG can be applied quite flexibly, which, for example, allows researchers to investigate the analytical as well as the creative design activities during the development of two-dimensional and three-dimensional design representations.

6.3.2 Functional Magnetic Resonance Imaging (FMRI)

Functional magnetic resonance imaging (fMRI) is a biometric measurement method that allows drawing conclusions regarding cognitive activities of a participant based on changes in blood oxygenation in his or her brain.

fMRI is based on magnetic resonance imaging (MRI), a procedure at which internal organs (such as the brain) are scanned in slices. The central component of a MRI scanner is an extremely heavy, ring-shaped magnet that provides a strong and homogenous magnetic field at its centre. Since the spatial resolution of a scanner is strongly related to the maximum magnetic flux density of its magnet, MRI scanners are grouped in Tesla (T) classes. Presently, most clinical MRI scanners are 1.5 T systems, while in research usually 3 T or 7 T systems are used. However, a conventional MRI scan reveals the individual anatomy of a participant's brain, but it provides no information regarding cognitive activity.

Cognitive activity comes along with an increased blood flow to the corresponding brain regions. In this process, deoxygenated blood is locally replaced by oxygenated blood within a few seconds time. fMRI uses the effect that blood saturated with oxygen behaves as a diamagnetic, while blood depleted of oxygen behaves as a paramagnetic substance. This difference allows improved MRI scanners to detect changes in blood oxygenation for every volume element of the brain. Regions with higher concentration of oxygen give a stronger BOLD (blood oxygenation level dependent) signal (Amaro and Barker 2006), which in turn indicates a higher cognitive activity in these regions.

fMRI data are acquired in slices. Smaller distances between these slices result in more accurate data, while larger distances result in faster data acquisition. In order to allow fMRI systems to survey the whole brain every 2 s, spatial resolution is usually reduced (compared to anatomical imaging). As a result, a fMRI measurement of 10 min generates only 300 full brain images (volumes), but each image represents BOLD data of more than 100,000 volume elements (voxels). This fMRI raw data can be analysed in multiple ways. fMRI research indeed developed a rich body of methodology including well-established methods such as general linear model (GLM) or multivoxel pattern analysis (MVPA) (Poldrack et al. 2011).

Since fMRI data allows a researcher to detect accurately to a millimetre, which brain regions are activated by a stimulus or a task, several fMRI projects are keen to localize specific cognitive functions. Proponents of functional specificity suggest that the human brain is composed of regions that are selectively engaged in a specific cognitive function and indeed brain regions have been identified that are specialized for basic sensory and motor processes or for perception of faces (Kanwisher 2010). However, recent research results also indicate functional connectivity, i.e. a rather functionally integrated relationship between spatially separated brain regions (Friston 2011).

Experimental design research using functional magnetic resonance imaging was presented by Alexiou et al. (2009). Their experiment aimed to explore the neurological basis of design cognition. Eighteen volunteers (all having some experience in design) participated in the study. The participants were confronted with 8 problem-solving tasks and 8 design tasks while fMRI data were recorded by a 1.5 T MRI scanner. The results of their data analysis indicate that there is a more extensive neural network involved in the activity of understanding and resolving design tasks than in problem-solving tasks.

This experiment exemplarily demonstrates that fMRI studies can be performed in the context of design even though assigned design tasks have to be accomplished without extensive movements (including drawing or modelling). It also shows that fMRI data can confirm central hypotheses of design research and thus may contribute to a deeper understand of design thinking.

6.4 Eye Tracking

Eye tracking (ET) is a biometric measurement method that allows drawing conclusions regarding visual attention of a participant based on the movements of his or her eyes.

6.4.1 Remote Eye Tracking

In remote eye tracking, the measurement system is located below a computer monitor that displays a digital stimulus like a picture or a website. The eye tracking system emits infrared light onto the eyes of the participant and measures the location of the resulting corneal reflection relative to the location of the pupil centre (Duchowski 2007). Based on this measure (and the known distance between eyes and screen), the coordinates of the present gaze point on the stimulus can be calculated and recorded over time. Remote eye tracking systems are able to record this raw data with sampling rates in the range from 30 to 500 Hz.

Eye tracking raw data are usually processed to detect the basic eye tracking events: fixations and saccades. A fixation is an event, in which the gaze point remains at a specific location of the stimulus (e.g. within 100 pixels) over a certain period of time (e.g. 80 ms). A fixation indicates that a participant gives special attention to the presently gazed location in order to perceive information from it. The central characteristic of a fixation is its duration, which is measured in milliseconds (ms).

A saccade is an eye tracking event that describes the eye movement from one fixation location to another. Since these movements are very fast, humans are not able to perceive any information during a saccade. However, saccades present the path of the gaze point on the stimulus and thus provide valuable information about attentional guidance and attentional shifts. The central characteristic of a saccade is its amplitude, which is measured in degree (°) or in pixel (px).

Fixations and saccades are often visualized by a scan path representation, which is overlaid onto the stimulus. In a scan path, fixations are visualized by circles and saccades by connecting lines. Here, the diameter of each circle represents the duration of a particular fixation and the length of each connecting line displays the amplitude of a corresponding saccade.

Advanced analysis of eye tracking data is usually based on the definition of areas of interest (AOIs). Most eye tracking software tools supply AOI editors, which allow researchers to geometrically define those areas of the stimulus that are characterized by homogeneous semantics. In doing so, specific AOI measures like number of fixations on AOI, mean fixation duration on AOI and dwell time on AOI can by computed. Furthermore, AOI-based analysis methods such as sequence analysis or transition matrix analysis can be applied (Holmqvist et al. 2011).

Experimental design research using remote eye tracking was presented by Lohmeyer and Meboldt (2015). Their experiment aimed to investigate the visual behaviour of engineers while trying to understand an engineering drawing of a machine system. Twenty-six mechanical engineering master students participated in the study. The participants were confronted with a sectional drawing of an axial piston pump and were asked to identify its pressure and its suction side depending on a given rotation direction. Eye tracking data were recorded by a remote eye tracking system using a sampling rate of 250 Hz. In data analysis, first fixations and saccades were computed. Based on the definition of four AOIs, in the following steps a combination of skimming and scrutinizing sequencing and transition matrix analysis were applied. Due to this, three behavioural patterns were found, which in the context of understanding engineering drawings are indicators for the cognitive processes of orientation, comprehension, and conclusion. A key finding was that in general all three patterns are required to knowingly choose the correct answer.

This experiment exemplarily demonstrates that remote eye tracking is particularly well suited to investigate how designers interact with two-dimensional design representations. Based on remote eye tracking data, visual as well as cognitive strategies of novice and expert designers can be revealed and compared regarding their effectivity and efficiency. However, remote eye tracking is not limited to static stimuli. It further allows to investigate the interaction with video records or software applications. Thus, future experimental design research may focus on evaluating performance and usability aspects of new computer-aided design tools developed to support designers in ideation, creation or evaluation processes.

6.4.2 Mobile Eye Tracking

In mobile eye tracking, the measurement system is integrated into a pair of glasses that is worn by the participant during the experiment (see Fig. 6.3). These eye tracking glasses contain the infrared emitters, the cameras capturing the eye movements, and an additional camera recording the scene from the participant's first-person view. Since the distance between eyes and measurement system remains invariant, the point of gaze can be computed and directly overlaid onto the scene video. Currently, mobile eye tracking measurement systems are using sampling rates of either 50 or 60 Hz.

Fig. 6.3 Example of a mobile eye tracking system (reproduced with permission of SensoMotoric Instruments, Teltow, Germany)

The key advantage of mobile eye tracking is that participants are allowed to move freely while data are collected. Due to this, eye tracking studies are no longer limited to laboratory environments. Instead, modern eye tracking glasses provide the opportunity to investigate the participants' natural behaviour in real-world environments. However, this benefit comes at the price of a considerably complicated data analysis.

The analysis of mobile eye tracking data is usually based on the definition of AOIs. In contrast to remote eye tracking, where AOIs are static areas of a picture stimulus, AOIs in mobile eye tracking are dynamically changing regions of a scene video. If, for example, a glass on a table is the object of interest to a participant, the AOI framing this glass, changes in shape and size as soon as the glass is tipped over. Furthermore, the location of the AOI changes every time the participant moves the head. Nevertheless, in order to compute AOI measures (number of fixations on AOI, mean fixation duration on AOI, and dwell time on AOI), it has to be known for each measurement point whether the gaze hits a certain AOI or not.

Several methods can be applied to deal with dynamic AOIs (Bojko 2013). In a manual frame-by-frame analysis, for instance, the researcher has to check each frame of each scene video and note at which frame which AOI was hit. The assignment can be facilitated by using a static reference view (Ruckpaul et al. 2014). Due to the fact that manual analysis of mobile eye tracking data is highly time-consuming, several researchers aim to develop semi-automated (Papenmeier and Huff 2010) and fully automated (De Beugher et al. 2014) methods that are capable of computing or detecting the changes in shape, size, and location of dynamic AOIs over time.

Experimental design research using mobile eye tracking was presented by Mussgnug et al. (2015). Their experiment aimed to investigate the question to what extent mobile eye tracking data (recorded from a user's point of view during product application) can support designers in identifying unfulfilled user needs. Twenty graduate students and six PhD students participated in the study. The participants were asked to analyse two videos showing different scenes of a person using a powder-actuated fastening tool. One of the videos was recorded by a 50 Hz mobile eye tracking system (first-person perspective with gaze point), the other by a stationary digital camera (third-person perspective without gaze point). Their results showed that during the analysis of mobile eye tracking videos more details of the scene and more causes of problems were described than during the analysis of scene videos from a third-person perspective.

This experiment exemplarily demonstrates that mobile eye tracking is especially suitable to investigate interactions between users and products in real applications. It further shows that data recorded by eye tracking glasses allow an improved evaluation of designs regarding aspects of user experience and user needs. Beyond that, mobile eye tracking seems to be a promising method to explore design creativity. Studies on visual cognition indicate a measurable correlation of analogical forming and fixation on AOIs. This research approach may easily be transferable into the field of design research.

6.5 Limitations of Biometric Measurement

Research on human behaviour in design includes studying designers' behaviour during product development as well as users' behaviour during product application. The former is often characterized by interaction between the members of design teams (see Chap. 5), the later by interaction between users and products (see Chap. 7). This high level of interaction in both scenarios requires that in experimental design research the persons involved have to be minimally constrained by biometric measurement systems and thus allowed to behave as naturally as possible. However, most biometric measurement methods presented in this chapter come with limitations regarding the participants' freedom to move (see Table 6.2). Skin conductance measurement, for instance, only constrains the movement of the hand, at which the electrodes are attached. Instead, remote eye tracking basically requires that head and body of the participants are not moved during the whole data acquisition. Here, interaction can only be realized by using the mouse cursor.

In order to overcome these limitations and to allow data acquisition in real environments without influencing the participant's behaviour, biometric measurement systems continuously become smaller and more comfortable to wear. Due to the major technological progresses in microelectronics, modern biometric measurement systems are characterized by a compact and lightweight design. These measurement systems are usually wearable devices using either a portable recording unit or a wireless data transmission. Due to this, mobile measurement systems,

Table 6.2 Limitations of biometric measurement methods

Measurement method	Abbreviations	Limitations regarding freedom to move	Limitations regarding resolution of data
Heart rate variability	HRV	None (free movement)	None (high resolution)
Skin conductance response	SCR	Hand movements are restricted due to electrodes attached to the fingers	Time-lagged signal due to latency of perspiratory reaction
Electroencephalography	EEG	Head and body movements are restricted due to wires and electrodes	Low spatial resolution due to non-homogeneous skull and scalp properties
Functional magnetic resonance imaging	fMRI	Method allows no head or body movements; noise affects behaviour	Low temporal resolution since data are acquired in thin slices
Remote eye tracking	ET	Method allows no head or body movements; gaze has to be on the screen	None (high resolution)
Mobile eye tracking	ET	None (free movement)	Temporal resolution limited since scene video has to be recorded simultaneously

such as eye tracking glasses, are most suitable to be applied in investigating interactions in design teams or between users and products.

Further limitations originate in the limited temporal and spatial resolution the specific biometric measurement method can reach (see Table 6.2). In neuroimaging, for instance, EEG allows a very high temporal resolution, but due to measuring through skull and scalp the spatial resolution is rather low. In contrast, fMRI allows much higher spatial resolution than EEG, but since the brain is scanned in thin slices, it takes at least a few seconds time before a point of measurement can be updated.

Differences in data resolution also complicates the combined application of biometric measurement methods. Though data can be recorded independently during the experiment, in data analysis the different data sets have to be merged, which means they have to be aligned to a consolidated timescale. In particular, in the multifaceted field of design research, such combined analyses of biometric data are promising to gain valid research results. For example, a combination of eye tracking and EEG might reveal correlations between patterns of visual attention and corresponding cognitive activities.

6.6 Conclusion and Outlook

The intention of this chapter was to point out that quantitative biometric measurement already is an inherent part of experimental design research. Even though until now, biometric measurement methods were mostly applied only in small design studies, their results indicate that biometric measures are most suitable to also investigate design-related research questions.

As highlighted in this chapter, each biometric measurement method is related only to specific aspects of human behaviour. Thus, a purposeful application of these methods requires a basic understanding of the associated physiological processes and the corresponding measurement procedure including its limitations. This knowledge is key to design proper experimental set-ups and to capture valid data.

In this context, it is also essential to consider which measurement values are really measured and which are computed from raw data. Data processing often includes steps of normalization, transformation or classification, in which parts of raw data can get lost. Consequently, to guarantee reproducibility and thus, to enable comparability across different studies, it is highly important to clearly describe the analysis methods applied and to explicitly specify the thresholds used.

In future design studies, quantitative biometric measurement itself will almost certainly gain deeper insights into the cognitive processes and behavioural patterns of designers and users. However, its full potential will not be unlocked until it is effectively combined with traditional design research methods such as interview techniques or protocol analyses.

Quantitative biometric measurement provides an excellent basis of empirical data to corroborate research hypotheses that until now have only been supported by rather subjective data. In turn, analysing data collected by traditional research methods strongly facilitates the interpretation of biometric measures since they provide valuable semantic and contextual information. In both ways, the integration of quantitative biometric measurement and experimental design research allows researchers to substantially improve the level of validity and reliability in upcoming design studies.

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Chapter 7
Integration of User-Centric Psychological and Neuroscience Perspectives in Experimental Design Research

Claus-Christian Carbon

Abstract This chapter deals with the experimental investigation of user-centred, rather than technology-centred, perspectives on engineering design. It explores how experimental approaches can be used to assess and capture the cognitive as well as emotional mechanisms that underlie the perception of human–product interaction and other facets of design cognition. The focus of the chapter is on the experimental research of product design, exploring key features of methods based on applied psychological and neuroscientific theories, concepts, methods and data.

7.1 The Human Behind the Product

When most people think of design research for technological products, they limit their associations to technology-based issues, especially which kind of material was used, which technology was employed and how functional the product is. This is simply astonishing when we merely try to imagine *why* such products have been spontaneously invented, developed, designed and manufactured—obviously consumer products are "consumed" or at least "used", calling for a perspective towards the consumer, the user. This rather self-evident insight necessarily leads to the so-called user-centred perspective of engineering design. As soon as we have identified the user as the centre and origin of the design

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process, we need a theoretical as well as methodological framework to gain insights into essential questions as follows:

1. What does the user want?
2. Does the user understand the product?
3. Can the user handle the product?
4. Does the user accept the product?
5. Is the user interested in the product?
6. Has the product the potential to extend the user's perspective?

In the following sections, we will learn how these questions can adequately be addressed by means of user-centred research that logically leads to psychological methods (including psychological as well as neuroscientific testing). In other words, to think of design without taking a psychological perspective does not make sense at all as it neglects the main agent that will consume, use and buy the designed product (cf. Pelletier et al. 2013). This essential psychological view on the design process is also in accord with the ISO standard for "Human-centred design for interactive systems" (ISO (International Organization for Standardization) 2010), which explicitly calls for the understanding and analysis of the user—this goal can be achieved not only by asking the user for evaluations but by directly involving the user during the design process. To capture the user's experiences while being involved in the process, we need a multidisciplinary approach. And to capture the full range of the user's experience supports the major aim of designers to create usable, intuitively usable, everyday usable and long-term usable products. Such products have the capability of assisting the user's everyday demands, of activating and inspiring the user for taking on fresh challenges and, last but not least, to enjoy the product.

7.2 What Does the User Want and Like?

Before any design process can be started, the essential question of "what the user really wants?" has to be addressed (see Kujala 2008). To get an idea of user requirements and needs, the typical user herself has to be identified. For highly specific products such as goods explicitly dedicated to relative circumscribed and homogeneous groups (e.g. toys for toddlers, assistive systems for blind persons), this initial step is relatively easy to execute. However, the user is often not well understood or is not very specifically defined at all. If this is the case, the next step, the identification of requirements and needs is unavoidably based on general and unspecific rules and recommendations, making true user-centred design in the deeper sense of the word impossible. To be placed in the centre, the user must be known, and to be known means to have at least a good idea what features she needs, which skills she already has and which constraints are important for her. To concretely investigate typical users, the issue of who is a good representative of a user group is essential; this step thus calls for effective methods to identify such representatives—for a deeper understanding of this specific problem, I would like to refer to specialised literature (e.g. Damodaran 1996).

But even if we succeed in identifying such "representatives", we have to further balance conflicting interests of complementary user perspectives to gain reliable but still informative statements (Planinc et al. 2013). Such a process of balancing is rather difficult as on the one hand, individual and concrete information is very precious but also on the other hand, a general approach to a product has to be defined. As there is a great variety of methods to following this goal, I would like to refer again to other, specialised, sources (see Kaplan and Norton 1992).

Despite all efforts put into these concerns to identify target users and agents associated with a product (e.g. elderly people who use an ambient assistant living device vs. caretakers vs. relatives), these can only be the first steps towards an understanding of what the user wants. The next consequent step must be to find out what requirements and needs the identified user groups have. This task is a major challenge for psychological research. In actual fact most people, especially those originating from the engineering sector, underestimate the range of difficulties that may be faced when trying to address this task—this underestimation of difficulties seems to be rather independent of how strongly the user is involved, e.g. by just "informative" or "consultative" or by "participative" involvement (Damodaran 1996; Kujala 2008). One major difficulty is in getting information about "real" requirements and "actual" needs—usually people are asked in situations which are socially relevant, and so any given answer is susceptible to bias due to social desirability (Paulhus 1991). We can generally follow two different methods to gaining knowledge about requirements and needs, and neither is fully free of bias: (1) asking users in an explicit way and (2) using implicit methods to gain such knowledge (see Sect. 7.2.3).

7.2.1 Overview Over Some Methods

The main path to investigating the user is still by employing *explicit* measures, mainly questionnaires, focus groups (e.g. dual moderator focus group, two-way focus group) or (in-)depth interviews (e.g. semi-structured format, open-ended)—see elsewhere for details (Harding 2013; Nachmais and Nachmais 2008). Questionnaires in particular are often established ad hoc or derive items and topics from established instruments such as a needs assessment survey (see Kaufman 2006; Witkin 1994). They all face two essential problems: first of all, they are prone to bias, e.g. towards social desirability, as the aim is hardly concealable; second, most users cannot imagine how a new product may change their behaviour, so they are generally fixated on familiar and ordinary concepts (Carbon and Leder 2005)—due to their inability to abstract from their knowledge, they mostly base their requirements and needs on known products, strongly neglecting their genuine interests.

7.2.2 Techniques to Reduce Social Desirability

Self-reports often reflect the tendency of people to provide socially desirable answers. Therefore, research has developed a series of procedures to increase the validity of reports by effectively reducing the social desirability bias (see Gosen 2014 for an overview), for example, by applying a "private setting" situation (e.g. sealed envelopes, clear privacy declarations) (see Tourangeau and Yan 2007), by avoiding interview-administered questionnaires which are particularly prone to desirability biases (cf. Krumpal 2012) and by rephrasing questions on sensitive and critical topics (Krumpal 2013). Although trained interviewers might reduce such biases in an effective way, they cannot prevent the biases in general. Therefore, research has also developed further measures that change the logic of how information gain is assured. We call these measures "implicit" as they do not rely on *explicit* questions but on variables, which are implicitly changed by specific processes or attitudes.

7.2.3 Indirect and Implicit Measures

Implicit testing, often also labelled "indirect testing", can actually be a very effective means of reducing social desirability biases (c.f. specific information on experimental research designs in Chap. 3 and typical methods used in this realm, e.g. eyetracking, described in Chap. 6). While most of the techniques which can be subsumed under indirect testing do have the considerable appeal of being cognitively impenetrable, or at least less cognitively penetrable than explicit testing (see Langner et al. 2010; Fiedler and Bluemke 2005), and also show less tendencies towards desirability biases, they are meanwhile rather limited in their complexity and show only a very narrow possible application. For instance, the Implicit Association Test (IAT, Greenwald et al. 1998) is interpreted as a tool for providing valid information (Cunningham et al. 2001; Nosek et al. 2005) on implicit "attitudes" (e.g. Maison et al. 2001) or "associations" (Bar-Anan et al. 2006) or at least providing indications for automatic processing (Dasgupta and Greenwald 2001). The IAT has, besides a series of logical as well as psychometric problems (Fiedler et al. 2006), one specific constraint making it applicable only to a limited extent to the engineering design process: usually the IAT is only capable of measuring valence associations of a visual design, so any inferences are restricted to positive versus negative associations of visual exemplars. Although this valence check might at least give initial indications towards the acceptance of a product, findings on such a raw level are not indicative enough to evaluate the product in a reasonable way. It is also not satisfactory to know that one product is preferred over another (e.g. Apple vs. Microsoft, see Brunel et al. 2004) when insight into the basis of such a preference is not obtainable.

To get deeper insights into such a preference pattern, Gattol et al. (2011) extended the IAT with a multidimensional perspective. This procedural extension allows for indirect measurement of the strength of associations on multiple dimensions. A typical multidimensional IAT (also known as *md-IAT*) comprises from four to six dimensions which are tested for in separate blocks yielding test times of below 30 min, thereby remaining useful and applicable in applied contexts. With the resulting multidimensional pattern of results offered by the md-IAT, differentiated brand-related as well as consumer product-related profiles can be created.

7.2.4 Emotional Aspects of Design Appreciation

Over the last two decades, it has become increasingly clear that emotions are not only important for our autobiographical traces and that they help to elaborate experiences and memory, but that they also guide us through life and help us to differentiate between important and less important entities (Cacioppo et al. 2001). This makes the consideration of emotional factors in design research promising (see for instance Demir et al. 2009), especially as soon as haptic factors play a role in the interaction with the product (Jakesch and Carbon 2012). Modern design theories do not only try to address emotional factors but even aim to establish them as the core principle of design efforts. The concept of "emotional design", most prominently propagated by Donald Norman (e.g. Norman 2004), explicitly bases its design principles on psychological dimensions of learning, appreciation and understanding. Importantly, extending design research with emotional research not only means adding positive emotional factors but also comprises negative emotions as well (for instance Fokkinga and Desmet 2013), because emotional processing independent of its valence has the capability to *enrich* the overall product experience (Fokkinga and Desmet 2012). Rich experiences might also refer to so-called mixed emotions which consist of different emotional states (Fokkinga and Desmet 2013; Muth et al. 2015a)—a finding which reflects typical emotional "states", episodes or experiences in everyday life (see Russell and Barrett 1999), meaning experiences we all share day by day. Actually, a mixture of emotions including negative ones can ensure that people add depth and significance to the experience in question and thus the product itself (Fokkinga and Desmet 2013) which increases the chance of getting insight and extra deep elaboration (Muth et al. 2015a, b; Muth and Carbon 2013).

Desmet and Hekkert (2007) introduced a framework of product experience where three distinct levels of product experience are supposed to be interrelated: besides an *aesthetic level* and a *level for meaning*, they explicitly propose an *emotional level* which involves experiences that are related to the appraised relational meaning of products. The framework is based on Russell's (1980, 2003) circumplex model of core affect and has two major axes: The horizontal axis represents *valence* (i.e. from "unpleasant" to "pleasant") and the vertical axis represents arousal (from "clam" to "activated").

Besides this theoretical framework, design researcher Pieter Desmet provided a product emotion measurement for capturing the characteristic low intensities and intermixed qualities of typical affective everyday life experiences which he calls *PrEmo* (abbreviation for Product Emotion Measurement Tool) (Desmet 2002). *PrEmo* is assumed to work quasi-cultural independently as the users have to report their emotions (called "consumer emotions") by assigning prefabricated expressive cartoon animations instead of typical verbal scales; whether this really can hold true is an important question of future intercultural research. The whole set of emotions comprises 14 affective reactions that were selected to represent the typical "emotions" elicited by consumer products. Half of these 14 affective reactions are called by the author *pleasant* (desire, pleasant surprise, inspiration, amusement, admiration, satisfaction, fascination), and the other half are called *unpleasant* (indignation, contempt, disgust, unpleasant surprise, dissatisfaction, disappointment, boredom).

7.2.5 Techniques to Increase Familiarity and Consciousness

Despite all efforts to establish reliable and valid measurements for getting insights into how users evaluate product design, we generally face one problem which is mostly neglected as many researchers focus on the side of measurement tools: the further away a product design is from the visual habits of the beholder, the more difficult it gets to evaluate it validly (Carbon 2012). Humans as such show a tendency to reject excessively novel and innovative ideas at first glance as they always tend to compare them with given items with which they have experience (Carbon and Leder 2007; Hekkert et al. 2003). To circumvent this universal problem, people need to first become familiarised with the to-be-assessed product design before having to finally evaluate it. To establish a standard routine for such a familiarisation and elaboration, Carbon and colleagues (e.g. Faerber et al. 2010; Carbon 2006; Carbon and Leder 2005, 2007; Carbon et al. 2006; Carbon et al. 2008) have developed the so-called *Repeated Evaluation Technique* (RET), where people are forced to elaborate on new concepts yielding much more valid assessments than when asked without such a step of elaboration. The core idea behind RET is the method of "elaboration via evaluation": when people have to think about product design, they cannot prevent getting familiar with and elaborating the design and processing it deeply (see Fig. 7.1)—we can even deliberately try

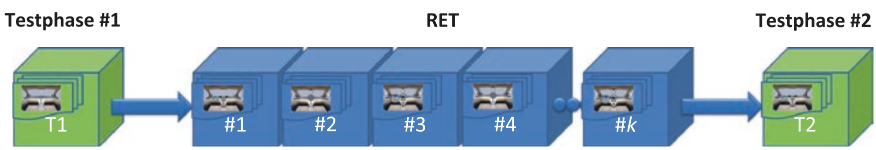

Fig. 7.1 Visual illustration of the typical procedure of the Repeated Evaluation Technique (RET) by Carbon and Leder (2005)

to prevent such a type of elaboration, but we will be affected by the mere processing of the material anyhow (see Carbon 2011a, 2012). Importantly, findings from the field of neuroscience (e.g. Biederman and Vessel 2006) revealed that elaboration as such can lead to increased pleasure due to the deeper level of processing when assessing elaborated items, and such deep processing potentially leads to more evocation of endorphins; this neuronal mechanism might be the explanation for why elaboration, at least from a specific point of view, lets people feel joy and fun: the deeper people know their stuff the more pleasure they get by evaluating it—this is a positive requisite for employing an extensive RET, because elaborated material will also increase the possibility that people will really take care in evaluating the material on a valid basis because doing so is relatively rewarding.

There are now several empirical documentations suggesting that deep elaboration leads to more stable, valid and plausible assessments of a product (e.g. Carbon and Schoormans 2012). Deep elaboration via evaluation as executed by RET very much resembles everyday life experience with novel products. Actually, what RET primarily does is to accelerate the familiarisation and elaboration process in order to provide valid information on the liking of specific designs even under very restricted time constraints (see Fig. 7.2 illustrating everyday life elaboration in comparison with the elaboration via RET in terms of an "accelerated elaboration"). This mechanism of saving a lot of time for elaboration makes RET

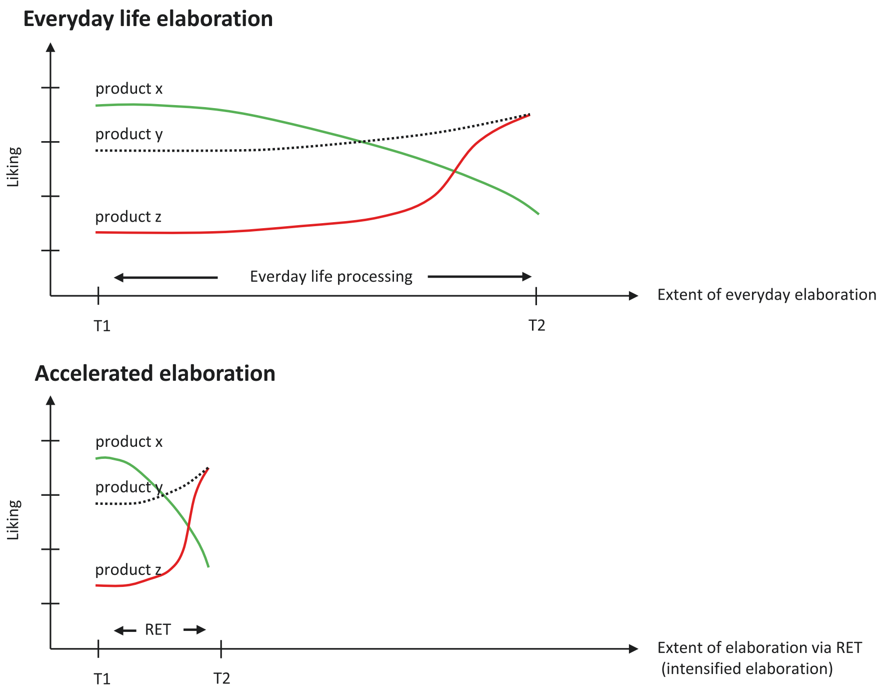

Fig. 7.2 Illustration of the time-lapse effect caused by deep familiarisation elaboration via the Repeated Evaluation Technique (RET) according to Carbon and Leder (2007) and Carbon (2015)

an ideal tool for assessing the design's quality long before a product comes into the world—but the RET is also useful for intermediate design evaluations and subsequent decisions on design modifications or variants.

Deep elaboration also adds additional value to the processing of a product. With deep elaboration, understanding often emerges which has positive effects on the appreciation of a product (Leder et al. 2006). Even if a riddle is not fully able to be solved, the process towards the solving of it is already pleasurable, sometimes even particularly pleasurable when a potential solution of the riddle cannot be found, but the feeling that it could be solved as such is available (Muth et al. 2015b).

7.3 Can the User Handle and Understand the Product?

The next big challenge is to find out whether a design is understandable and whether users can handle the product adequately. This kind of evaluation refers especially to the field of usability—the ease of usage, but also the ease of being able to learn and understand the usage of a consumer product. To test usability, we can generally follow two major approaches: (1) relying on expert statements and (2) basing our conclusions on typical or potential users. Both approaches show clear caveats.

Experts are most often very deeply involved in the development of the products and so can be very specific and clear on the evaluation of the target; however, they also face certain cognitive and motivational limitations as they can barely abstract from brand aspects and they cannot cut the ties of brand loyalty; furthermore, they often show rigid approaches to the products which means that they use products in a very particular way which might not be congruent with typical naïve users. Typically, experts also show "expert strategies", which means that they know from the beginning how to use certain functions in an effective way, while at the same time being blind to new functions, concepts and design opportunities (cf. Kotze and Renaud 2008). Furthermore, expert processing is also susceptible to mainly top-down oriented processing towards a specific evaluation scheme (Ball and Ormerod 1995), neglecting further points which would be highly important in everyday life contexts where the consumer product is utilised by laymen.

Another way of gaining knowledge on the handling of consumer design is to directly involve the typical user, but here, we face the problem that most users cannot articulate their opinions, follow very idiosyncratic strategies and interests or do not understand the product. As already mentioned before, the *Repeated Evaluation Technique* (RET) can be a tool to reduce such problems, but still we have to analyse and gather together data from different users and from different strategies and perspectives. Here, a mere aggregation of data in terms of mean values can prove to be fatal in finding concrete cues for evaluating the product design as the users' answers might be too diverse. Deep analysis of single cases can therefore be very beneficial, especially when design flaws have to be identified (Lewis and Norman 1986; Norman 1988).

One typical problem of design is that the product in question cannot be unambiguously identified. Especially, in areas where safety issues are important to address, e.g. design of control instruments in aviation systems (see Badke-Schaub et al. 2008), ambiguity presents a particular danger. To understand the entire process of identifying and processing a product on a haptic basis, Carbon and Jakesch (2013) have proposed a functional model for haptic aesthetic processing and discussed its implications for design (see Fig. 7.3).

The functional model for haptic aesthetic processing by Carbon and Jakesch (2013) is also a potential advocate for integrating the haptic sense into any design consideration. In fact, the haptic quality as a major source of information is often responsible for enjoying or rejecting a product. A reason for this strong affective component of haptic aesthetics is its linkage to so-called gut feelings and such haptic experiences can be hardly expressed on a complex verbal and sophisticated way: we feel it or not, it feels good or not and it has a good or bad feel—that's all, nothing to be added. Still, we trust such simple gut feelings; according to the theory of bounded rationality (Simon 1959; Gigerenzer 2007), we might try to justify it on a complex verbal and cognitive way *afterwards* when the decision has already been arrived long ago (Gigerenzer and Goldstein 1996)—but actually we base our real decision, not the rationalisation of this decision, on such gut feelings.

The establishment of this functional model has the major aim to assist researchers as well as design practitioners in systematically assessing and addressing haptic design properties. The main idea is that haptic aesthetics is a "microgenetic" (Bachmann 2000; Carbon 2011b), i.e. multi-stage, process with different experiences being possible during the overall three phases. From one phase to the other, the haptic experiences are increasingly elaborated accumulating and integrating the information that have been processed at earlier phases (see Fig. 7.3). The whole process starts with a haptically unidentified object with the goal to identify this object at the end of the process and to assign meaning to it. During the first phase, low-level analyses are employed with unspecific exploration of the haptic entity. After this exploration phase where local haptic aspects are processed, more elaborate processing takes place, which integrates the local aspects into more global qualities. The last phase is characterised by deep cognitive and emotional evaluations strongly associated with individual memory representations and personal experiences activated and modulated by these evaluations. By continuously increasing the specificity and complexity of the processes, the material properties are increasingly integrated and elaborated: the haptically inspecting person gains knowledge and understanding of the object and creates an emotional episode while processing it. Despite the strict feed-forward logic of processing for the three main phases (1) *exploration*, (2) *assessment* and (3) *evaluation*, additional recursive feedback loops for each phase (i.e. (1) *expectation*, (2) *integration* and (3) *familiarity*, respectively) modulate and refine the phase-specific process. Furthermore, the embedment of the unspecified object provides helpful context information to assist the subsequent processes in categorising the object. In the end, the successful identification of the object is the prerequisite of effective handling and to provide a useful product.

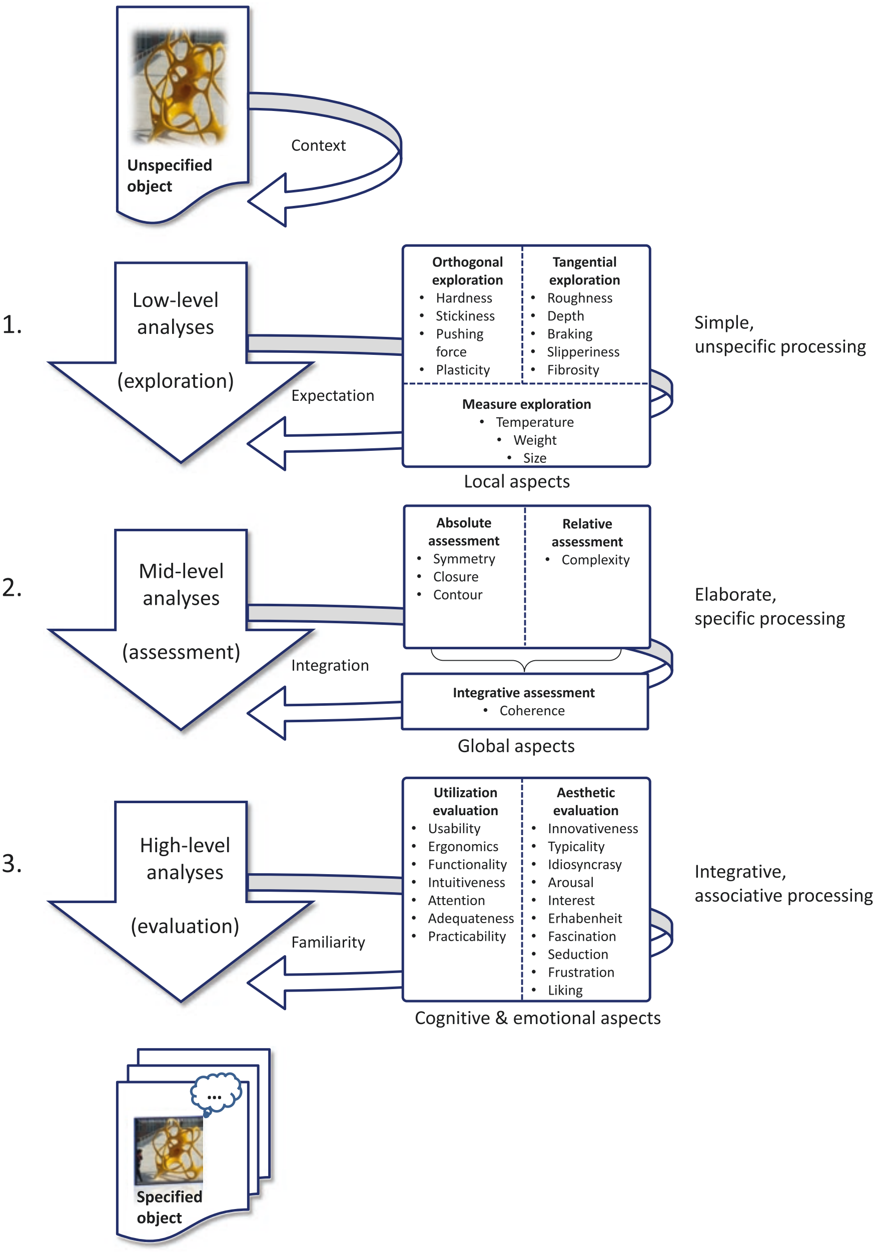

Fig. 7.3 Functional model for haptic aesthetic processing by Carbon and Jakesch (2013)

7.4 Does the Product Extend the User's Perspective?

Some last words should address a further point mostly neglected with engineering design: even when we have identified our users, have understood our users and have provided the most adequate and appealing product, we have not fully exhausted the full range of possibilities a product can develop. It might be rather rare, but we should definitely try to follow a design way that not only fulfils all requirements and needs but extends the perspective of the user. When, for instance, the text message system (Short Message System, SMS) for mobile phones was developed as part of the Global System for Mobile communications (GSM) in the early 1980s and finally established in 1992, it was just designed as a mere additional to enhance communication possibilities. Despite all (extreme) limitations—very short message size, i.e. 160 characters, and very limited character set (just 2^7 different characters)—and low usability by complex key assignments, text messaging became a new standard way of communication. In fact, SMS changed the entire communication behaviour by reducing contents, developing new ways of fast responses and establishing emoticons, a very efficient way of transmitting affective states in a very sparse way—typically with just combining three or less characters to one new information chunk. Such an extension of the user's perspective, which creates new opportunities, might be the most thrilling and interesting phase instead of face of product design, because this can lead to highly dynamic societal changes.

7.5 Conclusion

This chapter aims to make clear that user-centred design always includes the general perspective that the user is the most wanted person in the entire design process. To understand the user, we need expertise from research areas linked with psychology, mostly from the so-called affective and cognitive sciences. However, there is no *one standard* technique to capture what a human really thinks of a product, but every research question needs specific methods to compile valid data. One way to address this complex problem of employing the most adequate method for evaluating design is to provide a multifaceted toolbox equipped with multidimensional measuring routines that can capture dynamic design experiences. Just recently we have provided such a framework toolbox which we call M_o^5X (Multi-Methodal Multi-Modal Measurement of eXperience, see Raab et al. 2013)—see also Chap. 6. The M_o^5X toolbox is based on the following key layers of design experience, or more generally on *any* kind of experience:

1. Design experience is inherently a dynamic phenomenon, so it must be investigated as a multi-stage process;
2. Experience is a complex phenomenon, so it must be investigated by means of multi-methodical analyses;

3. Experience is a multi-sensory phenomenon, so it must be investigated on a multi-modal basis.

The toolbox is not a convenience product fully developed and ready for every design requirement, but will be expanded and enriched on demand in a continuous way. So it will increase its power and complexity with the processed tasks over time. We hope to provide an open access platform where M_o^5X is presented and offered for design research issues very soon.

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Part III
Computation Approaches to Experimental Design Research

Chapters 8–11 explore the emerging area of computational approaches to human-focused experimental design research. Chapters 8 and 9 set the scene by discussing the use of complex network visualisation and analysis in the design research domain. Chapter 8 outlines the key principles and methods underpinning network statistical properties and dynamics. Subsequently, Chap. 9 provides accessible and concrete guidance for design researchers seeking to use network approaches in their research. Finally, Chaps. 10 and 11 respectively deal with the simulation of design teams and individual designers. Part III brings together exciting new approaches in the experimental design research domain and provides a foundation for their understanding and application.

Chapter 8
The Complexity of Design Networks: Structure and Dynamics

Dan Braha

Abstract Why was the $6 billion FAA air traffic control project scrapped? How could the 1977 New York City blackout occur? Why do large-scale engineering systems or technology projects fail? How do engineering changes and errors propagate, and how is that related to epidemics and earthquakes? In this chapter, we demonstrate how the emerging science of complex networks provides answers to these intriguing questions.

Keywords Complex engineering networks · Error and failure propagation · Robustness and fragility

8.1 Introduction: The Road to Networks in Engineering Design

There are two critical questions in design theory: the characterization of design forms, and the design processes used to create them. These issues were studied over the years by the design theory and methodology community who developed theoretical and algorithmic frameworks for engineering design (Braha et al. 2013). One of the earliest design theories was called the Formal Design Theory (FDT, see Maimon and Braha 1996; Braha and Maimon 1998; Braha and Reich 2003;

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Braha and Maimon 2013). According to FDT, the first question was addressed by introducing algebra for design representation, which is based on three constructs: 'modules', 'relationships', and the rules of combining them to create complex design representations (akin to a network representation of 'nodes' and 'links'). The second question was addressed by establishing an analogy between the design process and biological evolution. According to this approach, evolving design solutions 'adapt' to design specifications, which in turn evolve based on new information generated by emerging design solutions. Mathematically, this evolving coupled process of specification refinement and design solution generation was cast in the framework of general topology, logic and finite automata, information theory, adaptive learning, constraint-based design, and geometric reasoning. This theory was put to practical use by developing effective knowledge-based design systems with applications to a wide variety of engineering domains (Braha and Maimon 2013). The question of quantifying the complexity of engineering design was addressed by FDT utilizing the 'module-relationship' representation of design combined with information-theoretic methods and computational complexity analysis to measure the amount of information and inherent difficulty embedded in design products and design processes (Maimon and Braha 1996; Braha and Maimon 1998, 2013).

While the efforts leading to the formation of a formal design theory were off to a good start, the theory dealt mostly with design processes from the perspective of a single designer. Large-scale product design and development is often a distributed process, which involves an intricate set of interconnected tasks carried out by hundreds of designers (see Fig. 8.1), and is fundamental to the creation of complex man-made systems (Yassine et al. 2003; Yassine and Braha 2003; Braha and Bar-Yam 2004a, b; Braha et al. 2006; Braha and Bar-Yam 2007). This complex network of interactions and coupling is at the heart of large-scale project failures as well as of large-scale engineering and software system failures (see Table 8.1). A new approach, which takes into account the complex interdependencies characterizing product design and development, is needed in order to understand the relationship between network architectures (topologies) and network dynamics—a critical step towards the management of complex design products and projects, and the prevention of engineering failures.

This chapter presents recent discoveries related to the structure and dynamics of complex product design and development networks (Braha 2003; Braha and Bar-Yam 2004a, b; Braha and Bar-Yam 2007). Social networks analysis and complex networks theory are applied to analyse the statistical properties of very large-scale design products and engineering products and projects, which are represented as networks of 'nodes' that are connected by 'links'. The nodes could represent people, tasks, subroutines, or logic gates, which communicate via links representing engineering change orders, parameters, specifications, or signals. The findings to be presented are grounded in empirical observations of very large design systems, including forward logic chips with 23,843 logic gates and 33,661 signal links, open-source software systems with 5420 subroutines and 11,460 calling relationships among subroutines, or a product development process with

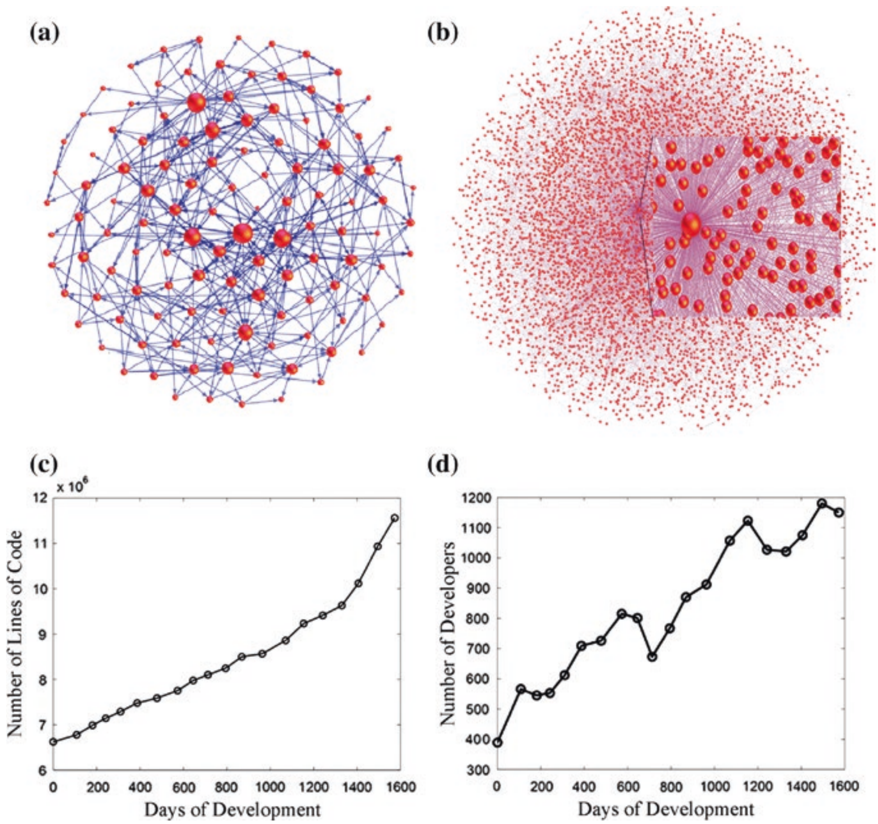


Fig. 8.1 Complex product design and development networks. **a** Network of information flows between main tasks of a vehicle large-scale design (Braha and Bar-Yam 2004a, b, 2007). This task network consists of 417 directed information flows between 120 development tasks. Each task is assigned to one or more actors (design teams, engineers, or scientists) who are responsible for it. Here, the information links are directed—each task consumes information from others and generates information to others. **b** Open-source software system (Braha and Bar-Yam 2007, Online Supplements). The software system network was generated from the call graphs of the Linux operating system kernel (version 2.4.19). A call graph is a directed graph that represents calling relationship among subroutines. This software network consists of 11,460 directed information flows between 5420 subroutines. In both networks, the degree of a node (i.e. the number of nodes adjacent to a node) is represented by the size of the node. The design networks were visualized using Gephi 0.8.2. **c** Linux kernel development: size of source code. The Linux kernel keeps growing in size over time as more hardware is supported and new features are added (Kroah-Hartman et al. 2009). Software size is measured as lines of code. Each data point represents a different Linux version (beginning with version 2.6.11 and ending with version 2.6.30; see Kroah-Hartman et al. 2009). **d** Linux kernel development: the number of different developers. The number of Linux developers (and likely interaction among them) shows an increasing trend over the different Linux kernel versions

Table 8.1 Large-scale product design and project failures

System	Failure
Columbia Space Shuttle, 2003	Damage to thermal protection tiles, leading to left wing structural failure
The New York blackout of 1977	Multiple lightning strikes at Buchanan South substation, tripping two circuit breakers
Mars Climate Orbiters, 1999	Mixture of pounds and kilograms, leading to the failure of the software controlling the orbiter's thrusters
Pentium II and Pentium Pro FPU bug, 1994	Incomplete entries in a look-up table used by the floating-point division circuitry, returning incorrect decimal results
Gulf of Mexico oil spill, 2010	Sea-floor oil gusher followed by the explosion and sinking of the Deepwater Horizon oil rig
US Federal Aviation Administration Advanced Automation System, 1982–1994	Project was abandoned in 1994 with an estimated cost of \$6B
London Stock Exchange Taurus Paperless Stock Trading System, 1990–1993	Project was abandoned in 1993 with an estimated cost of \$600 M
US Air Force Advanced Logistics System, 1968–1975	Project was abandoned in 1975 with an estimated cost of \$250 M

889 tasks and 8,178 information flows. The study of such engineering and software networks has led to many surprising results. It is shown that these networks have structural (architectural) properties that are like those of other biological, social, and technological networks. The dynamics of engineering and software networks can be understood to be due to processes propagating through the network of connections, including the propagation of changes, errors, and defects in complex product design and development projects. This interplay between structure and dynamics is illustrated by presenting a generic model of error dynamics embodying interactions through the network. Remarkably, it is shown that the reported network structural properties provide key information about the characteristics of error and defect propagation, both whether and how rapidly it occurs. Moreover, these architectural properties are shown to have implications for the functional utility of engineering systems including their sensitivity and robustness (error tolerance) properties.

8.2 The Universality of Complex Networks

Networks have become a standard model for a wealth of complex systems, from physics to social sciences to biology (Albert and Barabási 2002; Boccaletti et al. 2006). A large body of work has investigated topological properties (Albert and Barabási 2002) including changes due to node removal (Albert et al. 2000; Cohen et al. 2000; Buldyrev et al. 2010). The main objective, though, of complex network

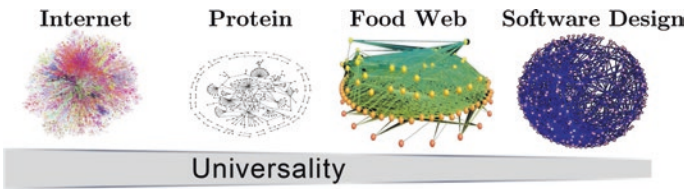


Fig. 8.2 The universality of complex networks. Network patterns are found to be the same in a wide variety of technological, biological, and social systems. This chapter demonstrates that engineering design networks can be put in the same class as complex networks in other domains

studies is to understand the relationship between structure and dynamics (Barrat et al. 2008)—from disease spreading and social influence (Pastor-Satorras and Vespignani 2001; Barahona and Pecora 2002; Laguna et al. 2003; Moreno et al. 2004) to search (Guimerà and Diaz-Guilera 2002) and time-dependent networks (Braha and Bar-Yam 2006; Hill and Braha 2010). Complex networks theory has also contributed to organizational, managerial, and engineering environments, where new theoretical approaches and useful insights from application to real data have been obtained (Braha and Bar-Yam 2004a, b; Braha and Bar-Yam 2007). Most importantly, these structural patterns and dynamical properties were found to be universal—that is, the same or very similar in a wide variety of complex systems (see Fig. 8.2). Basic definitions and notations of networks pertinent to this chapter are described in the Appendix. (The reader is recommended to read it first.)

Of particular interest are scale-free networks where the degree (i.e. the number of nodes adjacent to a node) is distributed according to a power law or a long right tail distribution (see Appendix). Such networks have characteristic structural features like ‘hubs’, highly connected nodes (Albert and Barabási 2002), features which cause them to exhibit super-robustness against failures (Albert et al. 2000; Cohen et al. 2000; Buldyrev et al. 2010) on the one hand and super-vulnerability to deliberate attacks and epidemic spreading (Pastor-Satorras and Vespignani 2001; Barahona and Pecora 2002; Laguna et al. 2003; Moreno et al. 2004) on the other. Here, we find that the framework of complex networks, mainly applied to natural, social, and biological systems, can be usefully applied and extended to understand the relationship between the structure and dynamics of large-scale engineering and product design and development networks.

Regular networks, where all the degrees of all the nodes are equal (such as circles, grids, and fully connected graphs), have been traditionally employed in modelling physical systems of atoms (Strogatz 2001). On the other hand, many ‘real-world’ social, biological, and technological networks appear more random than regular (Albert and Barabási 2002; Boccaletti et al. 2006). With the scarcity of large-scale empirical data on one hand and the lack of computing power on the other hand, scientists have been led to model real-world networks as completely random graphs using the probabilistic graph models of Erdős and Rényi (1959).

In their seminal paper on random graphs, Erdős and Rényi (1959) considered a model where N nodes are randomly connected with probability p. In this model, the average degree of the nodes in the network is $\langle k\rangle \cong pN$, and a Poisson distribution approximates the distribution of the nodal degree. In a Poisson random network, the probability of nodes with at least k edges decays rapidly for large values of k. Consequently, a typical Poisson random network is rather homogenous, where most of the nodal degrees are concentrated around the mean. In particular, the average distance between any pair of nodes (the 'characteristic path length', see Appendix) scales with the number of nodes as $d_{\text{random}} \sim \ln(N)/\ln(\langle k\rangle)$. This feature of having a relatively short path between any two nodes, despite the often large graph size, is known as the small-world effect. In a Poisson random graph, the clustering coefficient (see Appendix) is $C_{\text{random}} = p \cong \langle k\rangle/N$. Thus, while the average distance between any pair of nodes grows only logarithmically with N, the Poisson random graph is poorly clustered.

Regular networks and random graphs serve as useful models for complex systems; yet, many real networks are neither completely ordered nor completely random. It has been found that social, technological, and biological networks are much more highly clustered than a random graph with the same number of nodes and edges (i.e. $C_{\text{real}} \gg C_{\text{random}}$), while the characteristic path length d_{real} is close to the theoretically minimum distance obtained for a random graph with the same average connectivity (Albert and Barabási 2002; Boccaletti et al. 2006). Small-world networks are a class of graphs that are highly clustered like regular graphs ($C_{\text{real}} \gg C_{\text{random}}$), but with a small characteristic path length like a random graph ($d_{\text{real}} \approx d_{\text{random}}$). Many real-world complex systems have been shown to be small-world networks, including power-line grids, neuronal networks, social networks, the World Wide Web, the Internet, food webs, and chemical reaction networks.

Another important characteristic of real-world networks is related to their node degree distribution (see Appendix). Unlike the bell-shaped Poisson distribution of random graphs, the degree distribution of many real-world networks has been documented to follow a power law:

$$p(k) \sim k^{-\gamma} \tag{8.1}$$

where $p(k)$ is the probability that a node has k edges (or neighbours). Networks with power law distributions are often referred to as scale-free networks (Albert and Barabási 2002; Boccaletti et al. 2006). A power law distribution is an example of an uneven node degree distribution, which is characterized by a long right tail—some nodes are very highly connected ('hubs'), while most have small degrees. These heavy-tailed distributions are characterized by 'wild' variability and right skewness of the connectivity distributions. The term 'wild' variability means that the second moment $\langle k^2\rangle$ (equivalently the variance) of the degree distributions is extremely large (and sometimes diverges) relative to the average degree of the nodes in the network. This is in contrast to the fast decaying tail of a Poisson distribution, which results in a small second moment or variance. Power law distributions of both the in-degree and out-degree of a node have also been observed in a variety of directed real-world networks (Albert and Barabási 2002; Boccaletti et al. 2006) including the World Wide Web, metabolic networks, networks of citations of scientific papers, and telephone call graphs. Although scale-free networks are prevalent, the power law distribution is not universal. Empirical work shows that the node degree distribution of a variety of real networks often has a scale-free regime with an exponential cut-off, i.e. $p(k) \sim k^{-\gamma} e^{-\left(\frac{k}{k^*}\right)}$, where the parameter k^* is the cut-off of the degree distribution (Erdős and Rényi 1959). The existence of a cut-off has been attributed to physical costs of adding links or limited capacity of a vertex (Amaral and Scala 2000). In some networks, the power law regime is not even present and the node degree distribution is characterized by a distribution with a fast decaying tail. Moreover, studies of the dynamics of link utilization in complex networks offer a radical alternative to the static-based view of complex networks (Braha and Bar-Yam 2006; Hill and Braha 2010). In such time-dependent networks, there is hardly any continuity in degree centrality of nodes over time (i.e. hubs rarely stay hubs for any length of time), even though cross-sectional snapshots are scale-free networks.

8.3 Complex Engineering Networks: Structural Properties

The goal of the present section is to investigate the statistical properties of large-scale engineering systems with emphasis on distributed product design and development networks. We show that large-scale engineering networks, although of a different nature, have general properties that are shared by other social, technological, and biological networks. First, it is found that complex engineering networks are highly sparse; that is, they have only a small fraction of the possible number of links (i.e. have low density; see Appendix). The low sparseness of engineering networks (see Table 8.2) implies that the functionality of these networks (e.g. effective information flow between designers) is not related to the sheer

Table 8.2 Density of real-world engineering networks. Complex engineering networks are highly sparse

	Network	Type	# Nodes	# Links	Density
Open-source software	Linux kernel	Directed	5420	11,460	3.9×10^{-4}
	MySQL	Directed	1501	4245	19×10^{-4}
Forward logic chip	s38417 electronic circuit	Directed	23,843	33,661	5.9×10^{-5}
	s38584 electronic circuit	Directed	20,717	34,204	7.9×10^{-5}
Product development	Vehicle	Directed	120	417	2.9×10^{-2}
	Operating software	Directed	466	1245	5.7×10^{-3}
	Pharma facility	Directed	582	4123	1.2×10^{-2}
	16 Story hospital facility	Directed	889	8178	10^{-2}
Technological	Internet	Undirected	10,697	31,992	2.8×10^{-4}
	Power grid	Undirected	4941	6594	2.7×10^{-4}

Table 8.3 The 'small-world' property of complex engineering systems

	Network	d_{real}	d_{rand}	C_{real}	C_{rand}
Open-source software	Linux kernel	4.66	5.87	0.14	0.001
	MySQL	5.47	4.20	0.21	0.004
Forward logic chip	s38417 electronic circuit	20.66	23.48	0.016	0.0001
	s38584 electronic circuit	13.39	17.32	0.012	0.00003
Product development	Vehicle	2.88	2.70	0.21	0.07
	Operating software	3.70	3.45	0.33	0.02
	Pharma facility	2.63	2.77	0.45	0.02
	16 Story hospital facility	3.12	2.58	0.27	0.02
Technological	Internet	3.31	2.86	0.39	0.001
	Power grid	18.7	12.4	0.08	0.005

While the random graphs are not modular (low clustering coefficients), engineering networks exhibit the 'small-world' property of high degree of modularity (high clustering coefficients) and fast information transfer (short average path lengths between any two nodes)

number of information links in the system but to the way those information flows are patterned in the network. We will substantiate this observation more formally in Sect. 8.4. Moreover, complex engineering networks are 'small-world' networks; that is, despite being primarily locally connected and modular, such engineering networks exhibit short average path lengths between any two nodes. This is shown in Table 8.3 where we compare the clustering coefficients and characteristic path lengths of the real engineering networks with the corresponding characteristics computed from a random ensemble of random graphs with the same number of nodes and links. We see that the clustering coefficients of the real networks are much higher than the clustering coefficients of the random graphs ($C_{\text{real}} \gg C_{\text{random}}$), but with similar characteristic path lengths ($d_{\text{real}} \approx d_{\text{random}}$). A high clustering coefficient is consistent with a modular organization, that is the organization of the system (project or product design) in clusters that contain most, if not all, of the interactions internally, while minimizing the interactions or links between separate clusters. However, while 'modularity' is intuitively perceived as inversely related to the rate of information transfer throughout the network, here we show that 'small-world' engineering networks have the capacity of fast information transfer, which results in immediate response to signals propagated from other components of the product design, or rework created by other tasks in a product development network (see Sect. 8.4).

In Sect. 8.2, we considered two typical network topologies: Poisson random networks and scale-free networks. Statistical analysis of the data reveals an asymmetric pattern of node degree distributions related to the information flowing into and out of nodes (product design components or product development tasks). More specifically, both the degree distributions of incoming and outgoing information flows show a power law regime with a decaying tail. However, the degree distributions related to the incoming information flows seem to exhibit a faster decaying tail (much like a Poisson distribution), whereas the degree distributions related

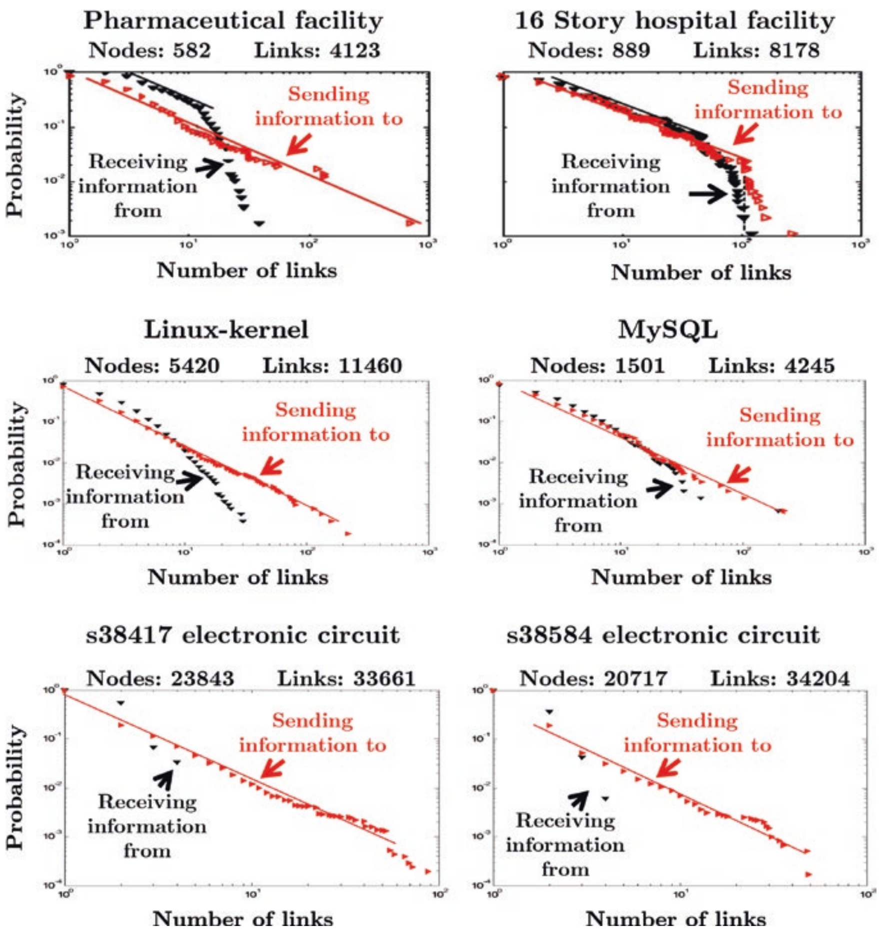
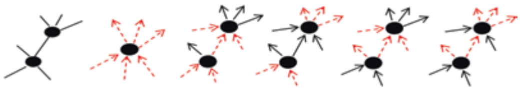


Fig. 8.3 Degree distributions of complex engineering networks. While both the incoming (*receiving information from*) and outgoing (*sending information to*) connections of nodes show a power law regime (*straight-line* on logarithmic scale) with a decaying tail, the incoming link distributions have sharp cut-offs that are substantially lower than those of the outgoing link distributions

to the outgoing information flows seem to be highly heterogeneous (much like a power law distribution (see Fig. 8.3). The noticeable asymmetry between the distributions of incoming and outgoing information flows shown by large-scale engineering networks suggests that the incoming capacities of nodes (e.g. the ability to integrate and process information) are much more limited than their counterpart outgoing capacities. The power law behaviour of the incoming and outgoing distributions suggests that nodes play distinct roles in processing information flows. More specifically, it implies that the dynamics of directed engineering networks is dominated by a few highly connected hubs, which either consume and/

or generate a lot of information through network links. These are the 'information bottlenecks' of the engineering network. The functional significance of the power law behaviour of the incoming and outgoing distributions is intimately linked to two important characteristics of engineering systems: 'ultra-robustness' and 'ultra-leverage'. Ultra-robustness is the ability of an engineering network to be resilient and error tolerant when unexpected and negative design changes occur over time, while ultra-leverage is the ability to influence the performance of engineering systems (measured, for example, in terms of defects or product development time) by taking advantage of the 'wild' variability and right-skewness properties of the incoming and outgoing connectivity distributions. More specifically, a remarkable improvement in the performance of engineering systems can be achieved by focusing engineering and management efforts on central 'information-consuming' and 'information-generating' nodes. We further elaborate on these issues in Sect. 8.5.

We conclude this section by introducing two concepts that are important in understanding the dynamics of complex engineering systems: assortativity and dissortativity. Assortativity (or assortative mixing) refers to the tendency of nodes in a network to connect to other nodes with similar properties. Here, we focus on assortativity in terms of a node's degree. That is, a network is assortative if it is likely that low- or high-degree nodes of the network connect to nodes with similar degree. Assortative mixing by degree is observed in networks that exhibit positive correlations between nodes of similar degree. On the other hand, a network is disassortative if it is likely that high-degree nodes connect to low-degree nodes. Disassortative mixing by degree is observed in networks that exhibit negative correlations in their degree connectivity patterns. The concept of assortativity (or dissortativity) in the context of directed networks (typical for engineering systems) can be extended by considering several mixing patterns in the network (see Fig. 8.4). Moreover, assortative (or disassortative) mixing can also be observed at the level of individual nodes. In this case, we check whether low or high in-degree nodes of the network also have similar out-degree, that is whether the network exhibits a positive correlation between the in-degree and out-degree of nodes. If the network is uncorrelated (neither assortative nor disassortative), the only relevant information for the structure of the network is the node degree distribution $p(k)$ or the corresponding degree distributions for directed networks $p_{\text{in}}(k)$ and $p_{\text{out}}(k)$. The presence and the extent of mixing patterns in a network have a profound effect on the topological properties of the network as it affects the detailed wiring of links among nodes. It is also closely related to the dynamics of error and change propagation in large-scale engineering systems as discussed in Sect. 8.4. For example, assortative mixing (positive correlations) leads to complex structural properties including cycles, loops, and the emergence of a single connected component (referred to as the giant component, see Appendix) that contains most of the nodes in the network (and thus many cycles and loops). These structural features tend to amplify the propagation of design changes and errors through the engineering network. It is thus expected that engineering networks show negative (or no) correlations in their degree connectivity patterns. This is, indeed, empirically observed as shown in Fig. 8.4. In Sect. 8.4, we provide a theoretical explanation of this empirical fact.



	Degree-Degree	Fan In-Fan Out	In-In	In-Out	Out-In	Out-Out
Internet	-0.189***					
Power Grid	-0.003					
Vehicle		0.17	0.094	-0.217***	-0.073	0.004
Pharmaceutical		0.1*	0.245***	0.016	-0.011	-0.010
Hospital		0.11**	-0.075***	-0.131***	-0.064***	0.016
Linux-kernel		-0.01	0.013	-0.098***	-0.009	-0.004
MySQL		-0.03	0.179***	-0.101***	-0.067***	0.113***
s38417 Electronic Circuit		-0.085***	0.134***	-0.015**	-0.112***	-0.039***

Fig. 8.4 Degree correlations in engineering networks. The reported numbers are the Pearson correlation coefficients for various mixing patterns in the network. Notice that for directed networks, several different mixing patterns can exist depending on the directionality of links. We also denote whether the reported correlations are statistically different from zero at the *5 %, **1 %, or ***0.1 % level. Overall, the results provide support for the hypothesis that complex engineering networks exhibit negative (or no) correlations in their degree connectivity patterns, a finding explained in terms of network dynamics (see Sect. 8.4)

8.4 Error and Change Propagation in Complex Engineering Networks

In this section, we present a model for the dynamics of errors, rework, or change propagation in complex engineering networks. Here, we outline basic results; a detailed account of the dynamic network model is given by Braha and Bar-Yam (2007). Think about a scenario of designing an engineering system, which involves a large number of development teams (e.g. airplane, car, software). As shown in Fig. 8.5a, we consider a network representing development tasks carried out by teams who work to resolve various open design problems. The network includes N nodes taking only the values 0 (coloured red in Fig. 8.5) or 1 (coloured blue in Fig. 8.5), representing 'open' or 'resolved' state of a particular task, respectively. At each time step, a node is selected at random. If the node is in a 'resolved' state (Fig. 8.5b, top), its state can be modified depending on the 'open' nodes connected to it through incoming links. These 'open' nodes send out change order information that might lead to the reopening of the 'resolved' task. More specifically, each incoming 'open' task causes the 'resolved' task to reopen its state with probability β (the 'coupling coefficient'). If the node is in an 'open' state (Fig. 8.5b, bottom), its state can be modified depending on two conditions: (1) it is not affected by any of its incoming 'open' tasks (each with probability $1-\beta$), and

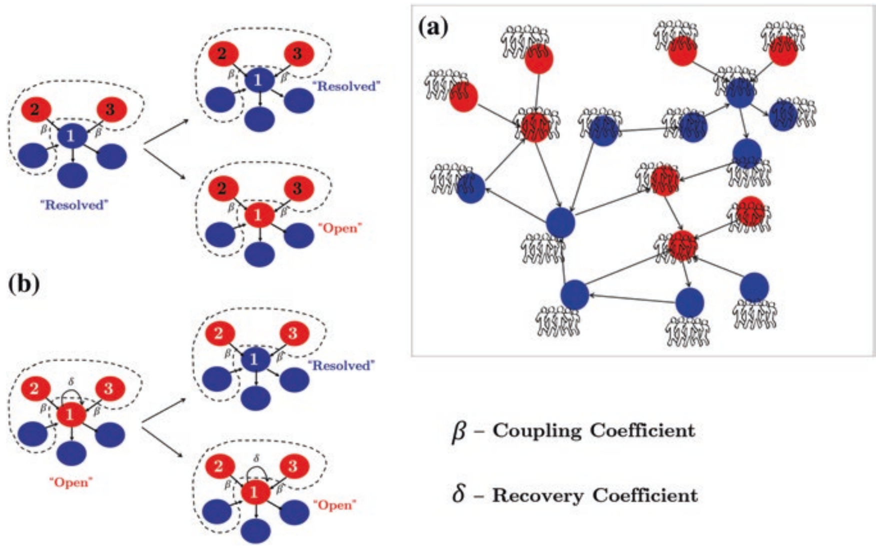


Fig. 8.5 A dynamic network model of error propagation in complex engineering networks. **a** The engineering network consists of nodes representing development tasks carried out by teams who work to resolve various open design problems. The teams interact with one another via communication links. In the diagram, blue and red nodes represent 'resolved' and 'open' tasks, respectively. **b** The stochastic rules that govern the dynamics of the system. The model involves two parameters, which measure the coupling strength between neighbouring nodes, β, and the rate by which development teams resolve open problems autonomously, δ

(2) it becomes 'resolved' with probability δ (the 'recovery coefficient'). The latter condition captures the idea that development teams can resolve the open problems autonomously, regardless of the states of incoming nodes. Though not an essential assumption, in order to gain insight into the model, we assume that $\beta_i = \beta$ and $\delta_i = \delta$ for all nodes in the network—considered as typical average values.

As the project unfolds, open tasks are resolved autonomously. Later in time resolved tasks might be reopened in light of influence of unresolved tasks (via their associated 'open issues') that are propagated to neighbouring tasks in the network, thus generating additional rework and revision. This process continues either until all tasks become 'resolved' or until the network settles into an equilibrium state of nonzero fraction of 'open' tasks. The latter outcome is an undesirable result from a project management perspective. To illustrate this dynamical behaviour, we show in Fig. 8.6a two typical simulation runs of the dynamic network model. The underlying network in this case is the real-world pharmaceutical product development network, which includes 582 nodes (tasks) and 4213 links (see Table 8.2). The bottom graph (Fig. 8.6a, circle marker type) shows the time evolution of the percentage of open nodes, leading to a converging network where there are no open tasks in the network. Increasing the coupling between neighbouring nodes in the network leads to a different qualitative behaviour as shown in the top

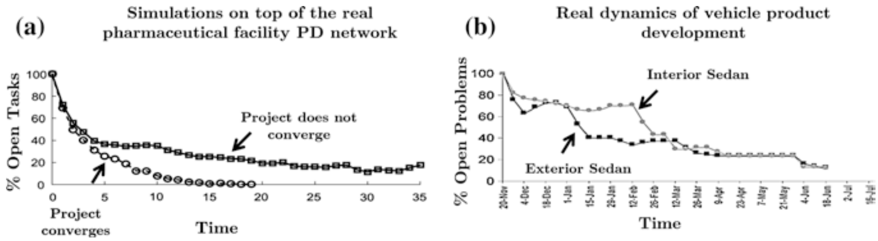


Fig. 8.6 The percentage of open problems in simulated and real product development systems. **a** A typical simulation run of the dynamic network model on a real-world pharmaceutical product development network (see Table 8.2) with 582 nodes (tasks). The average number of incoming arcs connected to a node is 7.08. The bottom graph (*circle* marker type) shows the time evolution of the percentage of open nodes when the coupling and recovery coefficients are $\beta = 0.065$ and $\delta = 0.5$, respectively. In this case, the simulation run converges to the fully resolved state where there are no open tasks in the project. The top graph (*square* marker type) shows the time evolution when the coupling and recovery coefficients are $\beta = 0.09$ and $\delta = 0.5$, respectively. In this case, the increase in coupling between neighbouring nodes (from $\beta = 0.065$ to $\beta = 0.09$) leads to a project that spirals out of control with open problems remaining indefinitely in the project network. Both of these outcomes can be predicted by our theory. **b** The dynamics of open problems observed in a family of vehicle programmes based on real-world data collected at a large automotive company (Yassine et al. 2003)

graph of Fig. 8.6a (square marker type). In this case, the project spirals out of control with open problems remaining indefinitely in the network. These two different types of behaviours will be explained by the theory presented below. It is instructive to compare the simulation results to the dynamics of open problems observed in real product development projects. In Fig. 8.6b, we show the dynamics of open problems surveyed in a family of vehicle programmes (interior and exterior subsystem design) at a large automotive company (Yassine et al. 2003). The similarity in dynamical behaviour between the model and real-world data is appealing.

The dynamic network model can represent a variety of real engineering systems. An example is the propagation of failures in complex engineered systems such as power grids, communication systems, computer networks, or mechanical structures. In this case, the state of a node (e.g. a power substation) could represent its maximum working capacity. When a node in the network fails, it transfers its load to neighbouring nodes in the network. Those neighbouring nodes then become overloaded and transfer their load to other nodes, triggering cascading failures throughout the system.

Next, we address the following key question: given the coupling strength between neighbouring nodes β, the recovery coefficient of self-directed problem solving δ, the initial number of 'open' tasks, and the underlying network structure, how will the fraction of 'open' tasks develop with time? and crucially will the system converge to the globally resolved state, where the fraction of 'open' tasks becomes zero? or perhaps, over the long run, will there always be a fraction of 'open' nodes and open problems present in the network? Remarkably, it is shown that the structural properties of the underlying network provide key information about the characteristics of error and defect dynamics. Here, we represent network structure by considering the various correlations in the degree connectivity patterns of the network as shown in Fig. 8.4.

We begin our analysis by investigating the effect of an Erdős–Rényi random network (see Sect. 8.2) on the dynamics of error propagation. For a random network, the degree correlations corresponding to the mixing patterns shown in Fig. 8.4 are absent. Although real engineering networks are different from random networks, the analysis of this special case will be useful for understanding the dynamics of error propagation on general networks. The main result is summarized in Fig. 8.7a. The long-term behaviour of the system is determined by whether $\delta \geq \beta\langle k\rangle$ or $\delta < \beta\langle k\rangle$, regardless of the initial number of 'open' tasks. In the former case, the project converges to the globally resolved state, where the fraction of 'open' tasks becomes zero; otherwise, the project spirals out of control with persistent 'open' tasks in the network. We thus have a threshold phenomenon. This threshold behaviour is further illustrated by the phase diagram shown in Fig. 8.7b. The phase diagram shows the conditions at which distinct phases can occur at equilibrium. Here, the x-axis shows the coupling strength between neighbouring nodes β, and the y-axis shows the recovery coefficient of self-directed problem solving δ. The two phases in the diagram are separated by the line $\delta = \beta\langle k\rangle$. So, imagine a project corresponding to point 1 in Fig. 8.7b. The conditions specified by point 1 imply that the project will converge to the globally resolved state. Increasing the coupling between tasks (point 2 in Fig. 8.7b) will still lead to project convergence, though the time to complete the project may be longer.

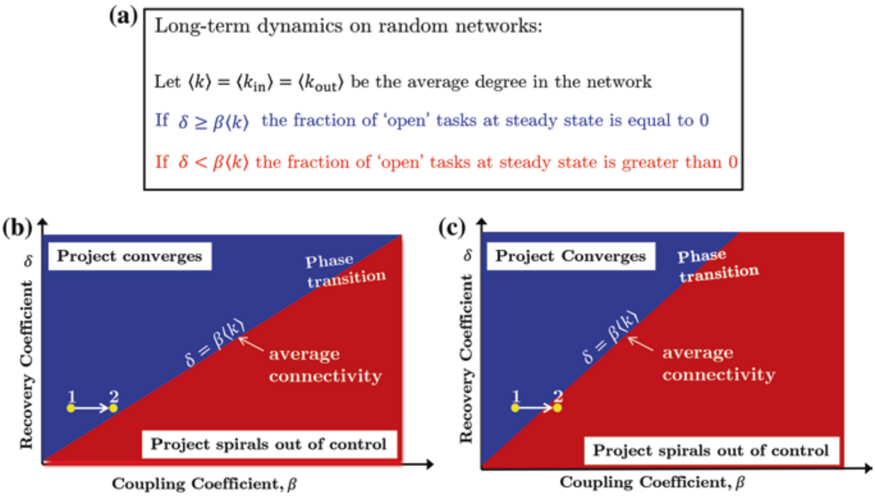


Fig. 8.7 The dynamics of error propagation on Erdős–Rényi random networks. **a** The long-term dynamics of the network is determined by a threshold that depends on the coupling coefficient, recovery coefficient, and the average connectivity in the network. **b** and **c** Demonstrating the threshold behaviour by using phase diagrams, which show the conditions at which the two distinct phases can occur at equilibrium

Increasing the average connectivity $\langle k\rangle$ of the network will increase the slope of the line that separates the two phases in the diagram (Fig. 8.7c). In this case, starting at point 1 (corresponding to a convergent project) and increasing the coupling between tasks may lead to a project that spirals out of control (point 2). Thus, for a given β and δ, adding more links (and thus more complexity) to a project network can hinder the project's convergence.

We next analyse the dynamics of error propagation for correlated networks (for which the random network is a special case). In general, it can be shown (Braha and Bar-Yam 2007) that the dynamics is determined by the degree correlations corresponding to the various mixing patterns in the directed engineering network (top row in Fig. 8.4). In this chapter, however, we focus on a special class of correlated networks where the only relevant information is related to the correlation between the in-degree and out-degree of individual nodes (the fan-in/fan-out mixing pattern in Fig. 8.4). This approximation is fully justified in engineering systems where the observed correlations between neighbouring nodes are very small, as shown in Fig. 8.4. The main result is summarized in Fig. 8.8a. The long-term behaviour of the system is now determined by whether $\delta \geq \beta\frac{\langle k_{\text{in}}k_{\text{out}}\rangle}{\langle k\rangle}$ or $\delta < \beta\frac{\langle k_{\text{in}}k_{\text{out}}\rangle}{\langle k\rangle}$, regardless of the initial number of 'open' tasks. We thus have a threshold phenomenon, which is further illustrated by the phase diagram shown in Fig. 8.8b. The two phases in the diagram are now separated by the line $\delta = \beta\frac{\langle k_{\text{in}}k_{\text{out}}\rangle}{\langle k\rangle}$. This critical line can be interpreted as follows. Using the fact that the covariance between the in- and out-degree of a node is $\text{cov}(k_{\text{in}},k_{\text{out}}) = \langle k_{\text{in}}k_{\text{out}}\rangle - \langle k\rangle^2$, the critical line can also be written as follows:

$$\delta = \beta\frac{\langle k_{\text{in}}k_{\text{out}}\rangle}{\langle k\rangle} = \beta\left(\langle k\rangle + \frac{\text{cov}(k_{\text{in}},k_{\text{out}})}{\langle k\rangle}\right) = \beta\langle k\rangle + \text{"correlations"} \quad (8.2)$$

We thus see that the critical line is shifted by the amount of correlation (essentially related to covariance) between k_{in} and k_{out} in the network—an example of a network effect. If k_{in} and k_{out} are positively correlated (i.e. the network is assortative), the critical line is shifted upward relative to the critical line corresponding to an uncorrelated random network, $\delta = \beta\langle k\rangle$. This upward shift has negative effect on projects; it shrinks the region corresponding to a convergent project (see Fig. 8.8b), thereby reducing the number of available degrees of freedom and increasing the likelihood that the project spirals out of control. To illustrate, consider the convergent project corresponding to point 1 in Fig. 8.8b. Increasing the coupling between tasks (perhaps due to product redesign), even slightly, may lead to a project that spirals out of control (point 2). We note that for uncorrelated random networks, $\langle k_{\text{in}}k_{\text{out}}\rangle = \langle k_{\text{in}}\rangle\langle k_{\text{out}}\rangle = \langle k\rangle^2$, or equivalently $\text{cov}(k_{\text{in}},k_{\text{out}}) = 0$. Plugging into Eq. 8.2 gives the critical threshold for Erdős–Rényi random networks $\delta = \beta\langle k\rangle$. The critical line in Fig. 8.8b can also be interpreted in the following way:

$$\delta = \beta\frac{\langle k_{\text{in}}k_{\text{out}}\rangle}{\langle k\rangle} = \beta\frac{\langle k_{\text{in}}k_{\text{out}}\rangle}{\langle k\rangle^2}\langle k\rangle = \beta'\langle k\rangle \quad (8.3)$$

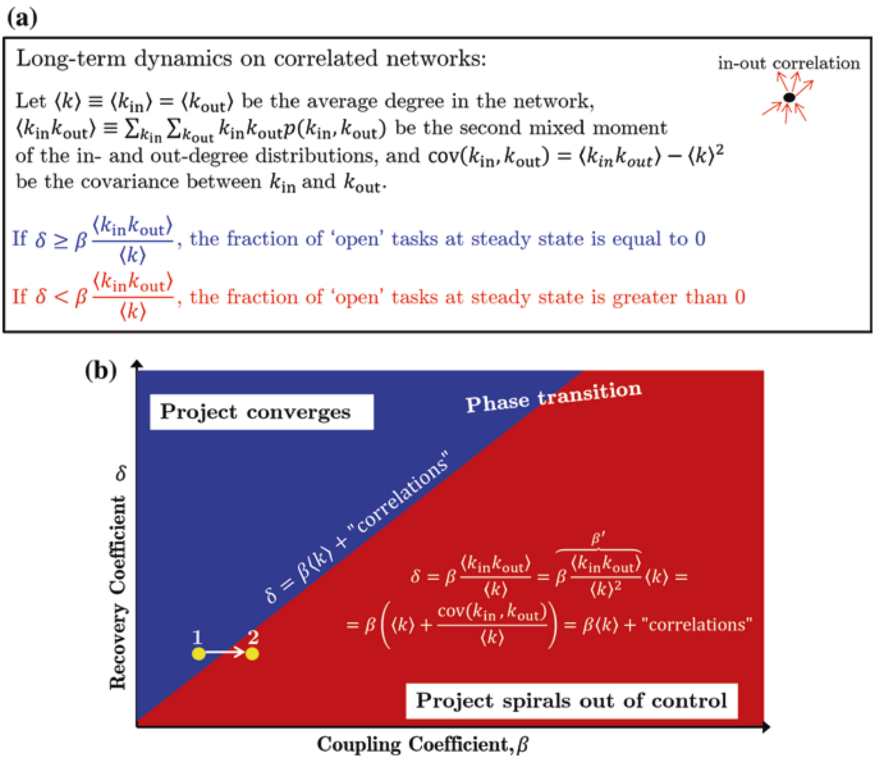


Fig. 8.8 The dynamics of error propagation on correlated networks. Here, we assume that the correlations between neighbouring nodes are very small, and the only relevant correlation is the one between the in-degree and out-degree of individual nodes. **a** The long-term dynamics of the network is determined by a threshold that depends on the coupling coefficient, recovery coefficient, and the in–out correlation in the network. **b** The two phases in the diagram are separated by a critical line, which is shifted upward—by the amount of positive correlation in the network—relative to the critical line $\delta = \beta \langle k \rangle$ corresponding to an uncorrelated random network

where $\beta' = \beta \frac{\langle k_{in} k_{out} \rangle}{\langle k \rangle^2}$ is the 'effective coupling'. Thus, we see that the correlated network has the same effect as a random network with average degree $\langle k \rangle$, recovery coefficient δ, and effective coupling β'. If k_{in} and k_{out} are positively correlated, $\langle k_{in} k_{out} \rangle > \langle k \rangle^2$ and $\beta' > \beta$. In other words, the faster propagation of errors resulting from positive correlations in the network is equivalent to increasing the effective level of coupling and dependency between nodes in the associated random network.

The above analysis provides an explanation for the empirical results reported in Fig. 8.4. There, it was shown that complex engineering networks tend to be uncorrelated or disassortative; that is, complex engineering networks exhibit no (or negative) correlations in their degree connectivity patterns. In the light of our model, a negative (or no) correlation between k_{in} and k_{out} has the effect of shifting the critical line downward relative to the critical line corresponding to an uncorrelated random network. This will increase the number of available degrees of freedom and decrease the likelihood that the project spirals out of control.

In summary, we presented a model of error dynamics and change propagation in complex engineering networks and most importantly have demonstrated the deep relationship between the structure of networks and the resulting dynamics. We next apply the model to study two key properties of complex engineering networks: robustness and sensitivity.

8.5 Robustness and Leverage of Complex Engineering Networks

In this section, we discuss the functional role of the right skewness and 'wild' variability characteristics of the connectivity distributions observed in complex engineering systems (see Fig. 8.3). The first functional property—robustness—is the ability of a network to maintain its performance despite extreme, often unanticipated, events that affect the individual nodes in the network. The second functional property—leverage—is the ability to improve remarkably the performance of the network by preferentially allocating engineering resources to certain parts of the network. This is often achieved by prioritizing the efforts towards the highly connected nodes in the network (hubs). We demonstrate these two functional properties by simulating the dynamic network model presented in Sect. 8.5 on real-world engineering networks.

8.5.1 Robustness and Vulnerability

We illustrate the concept of robustness in the context of product development networks. We measure the performance of the network in terms of the time it takes for the project to converge to the globally resolved state, where the fraction of 'open' tasks becomes zero [assuming the conditions for convergence are satisfied (see Sect. 8.5)]. We start with a 'normally running' project network where $\beta_i = \beta$ and $\delta_i = \delta$ for all nodes. To emulate extreme events that could occur over time, we select a fraction of nodes in the network and impair their characteristic parameters so that $\beta_i^{\text{new}} > \beta$ or $\delta_i^{\text{new}} < \delta$. The former modification reflects, for example, changes in product design that lead to increased dependence between tasks in the project network. The latter case reflects, for example, changes in project resources that lead to development tasks that require longer autonomous development times. We consider several rules of selecting the nodes that will be impaired in the network. The first rule is to select the nodes randomly, regardless of their structural position in the network. We can also prioritize the nodes according to some rule that takes into account their structural position in the network. Here, we consider

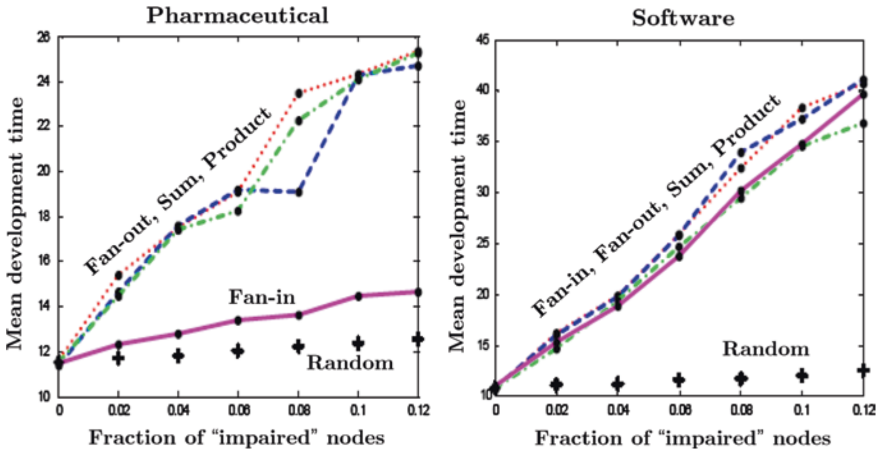


Fig. 8.9 Robustness and vulnerability of complex engineering systems. We compare the five priority rules: **Random** (+), **Fan-in** (*magenta solid line*), **Fan-out** (*green dash-dot line*), **Sum** (*blue dashed line*), and Product (*red dotted line*). The figure presents the network performance (project duration) versus the fraction of impaired tasks in the network for which their coupling coefficients are modified. For the non-random priority rules, each data point is the average of 1000 realizations. For the **Random** rule, each point is the average of 30 different task selections, performed for 100 independent runs. The model parameters, before and after the change, are as follows: software: $\delta = 0.75$, $\beta = 0.05$, $\beta^{\text{new}} = 0.1$; pharmaceutical: $\delta = 0.75$, $\beta = 0.05$, $\beta^{\text{new}} = 0.1$

four priority rules: **Fan-in**, select tasks in decreasing order of their in-degrees; **Fan-out**, select tasks in decreasing order of their out-degrees; **Sum**, select tasks in decreasing order of their total degree (sum of in- and out-degrees); **Product**, select tasks in decreasing order of the product of their in-degree and out-degrees. Starting with a 'normally running' project network and impairing a percentage of nodes in the network will clearly impair the performance of the network (in our case, prolonging the duration of the project). The question that we ask here is whether or not the above rules affect the network performance to the same extent. Remarkably, as shown in Fig. 8.9, we find that the network performance is extremely robust if nodes are impaired in a random order; that is, the duration of the project goes up very slowly as increasingly more nodes of the network are impaired. However, a completely different behaviour is observed if nodes are impaired according to the above priority rules. As increasingly more nodes of the network are impaired, the duration of the project is increased rapidly and dramatically, becoming about twice longer as its original value even if only 6 % of the tasks are impaired (see Fig. 8.9). Thus, the network performance becomes highly sensitive to changes targeted at highly connected nodes. These findings apply to all of the engineering systems included in Table 8.2. We can sum up these observations as follows. The dynamics of engineering systems is ultra-robust and error tolerant when negative design changes occur at randomly selected nodes, yet highly vulnerable and fragile when unwanted changes are targeted at highly central nodes.

8.5.2 Leverage and Control

The robustness characteristics deal mostly with unexpected adverse changes that could occur in the network. The dual concept of leverage deals with deliberate network changes that aim at improving and controlling the performance of the engineering network. More specifically, the sensitivity of the network to changes directed at highly connected nodes can be utilized by designers to influence the performance of the network. The structure of our analysis is similar to that of the previous section; the only difference is that now we select a fraction of nodes in the network and improve (rather than impair) their characteristic parameters so that $\beta_i^{\text{new}} < \beta$ or $\delta_i^{\text{new}} > \delta$. The former modification reflects, for example, changes in product design that lead to modular architectures and reduced dependence between tasks in the project network. The latter case reflects, for example, allocation of additional project resources that lead to development tasks that require shorter development times. The results are presented in Fig. 8.10. When nodes in the network are selected in a random order, we find that the performance is improved very slowly; that is, the duration of the project goes down gradually as more nodes of the network are increasingly modified. However, a drastically different behaviour is observed when tasks are selected based on a preferential policy that takes into account their connectivity in the network (i.e. Fan-in, Fan-out, Sum, or Product). In this case, as increasingly more nodes of the network

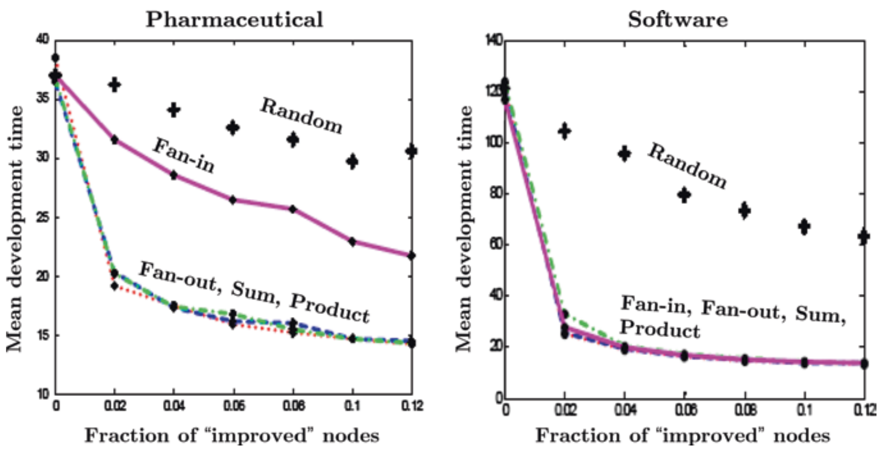


Fig. 8.10 Leverage and control of complex engineering systems. We compare the five priority rules: Random (+), Fan-in (*magenta solid line*), Fan-out (*green dash-dot line*), Sum (*blue dashed line*), and Product (*red dotted line*). The figure presents the network performance (project duration) versus the fraction of improved tasks in the network for which their coupling coefficients are modified. For the non-random priority rules, each data point is the average of 1000 realizations. For the Random rule, each point is the average of 30 different task selections, performed for 100 independent runs. The model parameters, before and after the change, are as follows: software: $\delta = 0.75$, $\beta = 0.1$, $\beta^{\text{new}} = 0.05$; Pharmaceutical: $\delta = 0.75$, $\beta = 0.1$, $\beta^{\text{new}} = 0.05$

are improved, the duration of the project is decreased rapidly and dramatically, becoming about twice shorter as its original value even if only 6 % of the tasks are impaired (see Fig. 8.10). This remarkable behaviour is observed in all of the engineering systems included in Table 8.2.

In sum, the heavy-tailed degree distributions and the characteristic feature of 'hubs' (highly connected nodes) offer a strategy for exploiting complex engineering networks—a remarkable improvement in the performance of engineering systems can be achieved by focusing engineering and management efforts on central nodes in the network. Simultaneously, the long right tail of the degree distributions also leads to robustness under the circumstances that unanticipated negative changes affect nodes in a random fashion. On the one hand, the long right tail also makes the network more fragile and vulnerable to unanticipated negative changes that occur at highly connected nodes, a condition that could lead to failure and spiralling out of control. This 'no free lunch' principle lies at the heart of complex engineering networks.

8.6 Summary

Large-scale engineering systems often involve hundreds or thousands of designers that self-organize to develop, tweak, and tinker architectural designs, which are locally optimized to be integrated in the larger system. The remarkable thing is that this tinkering process leads to large-scale universal patterns and system properties that were not written in the initial specification sheet or anticipated from the outset. Here, we analysed a wide variety of large-scale engineering systems—including open-source software, electronic circuits, product development, power grids, and the Internet. These systems share common structural properties of networks such as sparseness, heavy-tailed degree distributions, high clustering coefficients, short average path lengths between any two nodes, and negative (or no) correlations in their degree connectivity patterns (disassortative mixing by degree).

We presented and analysed a model for the dynamics of errors, rework, or change propagation in complex engineering networks. The model is based on the idea that non-trivial, large-scale behaviour can be produced by simple processes involving interactions between the nodes in the network. The key result of our model is that the network structure provides direct information about the characteristics of error dynamics. For example, in the context of product design and development, the dynamics is characterized by a phase transition from convergence to the globally resolved state, where the fraction of 'open' tasks becomes zero, to the state where the project spirals out of control with persistent 'open' tasks in the network. The threshold separating the two phases was found to be closely related to the extent of degree correlations in the network; in particular, positively correlated networks tend to impede the convergence of the product development process. The heavy-tailed degree distributions and the existence of hubs affect the functionality of engineering networks in intricate ways. First, the dynamic behaviour of complex engineering networks is highly robust to uncontrolled changes occurring at random nodes, yet vulnerable to changes that are targeted at central nodes. At the same time, changes that are directed at highly connected nodes can significantly boost the performance and efficiency of the network.

The emerging discipline of complex networks research offers a new and potentially powerful perspective on managing large-scale engineering systems. By mapping the information flows underlying large-scale systems, supported by network visualization tools, engineers could gain better understanding on the relationships between structure and dynamics. We anticipate that the theoretical and practical insights gained by modelling large-scale engineering systems as self-organizing complex networks will turn out to be highly relevant to the science of design.

Appendix: Measuring Complex Networks

Complex networks can be defined formally in terms of a graph $G = (V,E)$, which is a set of nodes $V = \{1,2,\ldots,N\}$ and a set of lines $E = \{e_1,e_2,\ldots,e_L\}$ between pairs of nodes. If the line between two nodes is non-directional, then the network is called undirected; otherwise, the network is called directed. A network is usually represented by a diagram, where the nodes are drawn as points, undirected lines are drawn as edges, and directed lines are drawn as arcs connecting the corresponding two nodes. Several properties have been used to characterize 'real-world' complex networks:

Density: The density D of a network is defined as the ratio between the number of edges (arcs) L to the number of possible edges (arcs) in the network:

$$D = \frac{2L}{N(N-1)} \text{ (undirected networks) } D = \frac{L}{N(N-1)} \text{ (directed networks)} \tag{8.4}$$

Characteristic Path Length: The average distance (geodesic) $d(i,j)$ between two nodes i and j is defined as the number of edges along the shortest path connecting them. The characteristic path length d is the average distance between any two vertices:

$$d = \frac{1}{N(N-1)} \sum_{i \neq j} d(i,j) \tag{8.5}$$

Clustering Coefficient: The clustering coefficient measures the tendency of nodes to be locally interconnected or to cluster in dense modules. Let node i be connected to k_i neighbours. The total number of edges between these neighbours is at most $k_i(k_i-1)/2$. If the actual number of edges between these k_i neighbours is n_i, then the clustering coefficient C_i of a node i is the ratio:

$$C_i = \frac{2n_i}{k_i(k_i-1)} \tag{8.6}$$

The clustering coefficient of the graph, which is a measure of the network's potential modularity, is the average over all nodes:

$$C = \frac{\sum_{i=1}^{N} C_i}{N} \tag{8.7}$$

Degree Centrality: The degree of a vertex, denoted by k_i, is the number of nodes adjacent to it. The mean node degree (the first moment of the degree distribution) is the average degree of the nodes in the network:

$$\langle k \rangle = \frac{\sum_{i=1}^{N} k_i}{N} = \frac{2L}{N} \tag{8.8}$$

If the network is directed, a distinction is made between the in-degree of a node and its out-degree. The in-degree of a node, $k_{\text{in}}(i)$, is the number of nodes that are adjacent to i. The out-degree of a node, $k_{\text{out}}(i)$, is the number of nodes adjacent from i. For directed networks, $\langle k_{\text{in}} \rangle = \langle k_{\text{out}} \rangle = \langle k \rangle$. Other node centrality indices were established, including closeness centrality, betweenness centrality, and eigenvector centrality (Braha and Bar-Yam 2004a).

Degree Distribution: The node degree distribution $p(k)$ is the probability that a node has k edges. The corresponding degree distributions for directed networks are $p_{\text{in}}(k)$ and $p_{\text{out}}(k)$.

Connected Components: A weakly (strongly) connected component is a set of nodes in which there exists an undirected (directed) path from any node to any other. The single connected component that contains most of the nodes in the network (and thus many cycles) is referred to as the giant component. For a certain class of networks in which degrees of nearest neighbour nodes are not correlated, the critical threshold for the giant component is found by the following criteria:

$$\frac{\langle k^2 \rangle}{\langle k \rangle} = 2 \text{ (undirected networks) } \frac{\langle k_{\text{in}} k_{\text{out}} \rangle}{\langle k \rangle} = 1 \text{ (directed networks)} \tag{8.9}$$

where $\langle k^2 \rangle$ and $\langle k_{\text{in}} k_{\text{out}} \rangle$ are the second moment and joint moment of the in- and out-degree distributions, respectively. We notice that, for undirected networks, higher variability of the degree distribution leads to a giant component. For directed networks, higher correlation between the in-degree and out-degree of nodes leads to a giant component, and this could lead to significant number of network cycles and further degradation and instability of the system as shown in Fig. 8.8.

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Chapter 9
Using Network Science to Support Design Research: From Counting to Connecting

Pedro Parraguez and Anja Maier

Abstract A network-based perspective on designing permits research on the complexity of product, process, and people interactions. Strengthened by the latest advances in information technologies and accessibility of data, a network-based perspective and use of appropriate network analysis metrics, theories, and tools allow us to explore new data-driven research approaches in design. These approaches allow us to move from counting to connecting, meaning to explicitly link disconnected pieces of data, information, and knowledge, and thus to answer far-reaching research questions with strong industrial and societal impact. This chapter contributes to the use of network science in empirical studies of design organisations. It focuses on introducing a network-based perspective on the design process and in particular on making use of network science to support design research and practice. The main contribution of this chapter is an overview of the methodological challenges and core decision points when embarking on network-based design research, namely defining the overall research purpose and selecting network features. We furthermore highlight the potential for using archival data, the opportunities for navigating different levels of the design process that network analysis permits, what we here call zooming in and out, and the use of network visualisations. We illustrate the main points with a case from our own research on engineering communication networks. In this case, we have used more than three years of archival data, including design activity logs and work-related email exchanges from a recently completed large-scale engineering systems project of designing and developing a renewable power plant.

Keywords Network Analysis · Complexity · Design Process

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9.1 Introduction: A Network-Based Perspective on the Engineering Design Process

With the increased availability of empirical data and advanced analytical methods to acquire and analyse such data, experimental and observational design research has grown in volume and importance. This has meant that bridging and interpreting results obtained from different methodological approaches (e.g. qualitative and quantitative) and levels of analysis (from human behaviour to industrial ecosystems) is a pressing need in order to strengthen the scientific development of our discipline. Furthermore, the growing socio-technical complexity of the design process in engineering systems has led researchers increasingly to adopt a systemic view for studying design. One question that has emerged in this context is, how can we navigate and integrate results obtained at different levels of analysis and with different methodological approaches? Or in other words, how can we go from counting fragmented empirical findings to connecting and integrating them?

One way of answering this question is through a networked perspective of the design process; a perspective focused on how the myriad elements that play a role in the collective act of designing are connected. Following such a perspective, the design process can be modelled as a network of interactions between and within, for example, design engineers, project stakeholders, design activities, or product components. It is through this network-based perspective of design that we can go from counting to connecting and explicitly link otherwise disconnected data fragments. As a result of applying this networked perspective, we enable the generation of new insights about the mechanisms driving and affecting the design process (Parraguez 2015).

However, the path from a research mode focused on counting, embodied in the form of tabular data and charts, to one focused on connecting, embodied in the form of relational data and network graphs, is not simple. Such a transition requires means for data acquisition, analysis, and interpretation, which until recently were new and mostly unexplored territory for the design research community. Some of the challenges of this transition include integrating, analysing, and visualising the vast amount of interactions between and within the process, organisation, and product domains, as well as navigating and integrating different levels of analysis. The objective of this chapter is to help translate the (growing) apparatus of methods and tools generated by the multiorigin and multidisciplinary field of network science for design researchers. The key result is an empirically grounded reflection about, and a guide to, important decision points regarding the selection of network features relevant for all those using network science in their design research studies.

9.1.1 Network Science and Its Application in Design Research

Network science allows for integrative and multilevel analyses that explicitly consider interaction effects and non-linear relations between inputs and outputs. Such nonlinearity and interconnectedness is a core characteristic of complex systems (e.g. Strogatz 2001). As a result, network representations of systems in all kinds of fields have allowed us to gain access to new and valuable practical and theoretical insights. Insights that would have been otherwise out of reach hidden underneath a wealth of disconnected data pieces.

Due to the strengths and wide applicability of network-based approaches, researchers are increasingly modelling and analysing complex systems as networks. For example, network science principles and tools have been used to understand a variety of biological, social, technical, and socio-technical systems and, in particular, the relation between structure and behaviour (Albert and Barabási 2002; Newman 2003). Furthermore, there is growing evidence about the existence of network properties common to a range of different complex systems with direct effect on the behaviour and performance of those systems (e.g. Ahn et al. 2010 and Braha in this book).

Consequently, the impact of the emergent science of networks is rapidly spreading through different fields and application areas, ranging from the study of intricate chains of protein–protein interactions to large-scale social networks that include millions of individuals (e.g. Vespignani 2009; Christakis and Fowler 2011). Hence, we have arrived at a point where understanding how a complex structure of interactions can generate useful (or harmful) behaviours has become crucial to managing the complexity of design, production, and management of human-made engineered systems (Calvano and John 2004; Storga et al. 2013).

Network studies of complex systems are not unknown in the context of design research, dating back to pioneering works of authors such as Simon (1962), Allen (1977), and Steward (1981). However, design research has not yet reached the maturity that fields such as computer science, physics, and sociology have, where there is a longer tradition and a stream of theoretical and methodological contributions to network science. It is for this reason that a grounded and contextualised support for the future use of network science in engineering design seems timely and appropriate.

Although the use and development of network science in design research are still far from mature compared to other research fields, in recent years we have seen an increase in the use of network analysis to support both theory building and theory testing while also enriching design management practice. Examples of this include researchers that have modelled and studied the architectures of process, organisational, and product domains as networks (Eppinger and Browning 2012; Eppinger and Salminen 2001). In the process domain, different variants of activity networks in matrix form (e.g. the Design Structure Matrix) and graph form have been applied to understand and analyse information dependencies between activities to optimise the logical sequence of activities and the impact of the process architecture on variables such as cost and time (Browning and Eppinger 2002; Steward 1981). In the organisational domain, traditional social network analysis with roots in sociology and organisational studies have influenced the analysis of networks of design engineers, focusing on aspects such as formal and informal relationships and communication exchanges (e.g. Allen 1977; Maier et al. 2008), creative interactions (e.g. Sosa 2010), and the analysis of organisational roles (e.g. Sonnenwald 1996). Finally, in the product domain, the interconnected architecture of components has also been analysed (Baldwin et al. 2013; Sosa et al. 2007) to explore issues such as product quality (e.g. Gokpinar et al. 2010; Sosa et al. 2011), the characterisation of modularity, and other complex product architectures (e.g. Sharman and Yassine 2004).

Further, a diverse set of network methods (Kreimeyer and Lindemann 2011; Lindemann et al. 2009) have been used to model aspects such as the temporal evolution of information across the design and development stages of an energy plant (Parraguez 2015); to explore how information flows through design activities and is exchanged between designers in the organisation (e.g. Batallas and Yassine 2006; Parraguez et al. 2015a); or to analyse the propagation of changes and errors in the design process (e.g. Braha and Bar-Yam 2007; Giffin et al. 2009; Wynn et al. 2014). While this recent body of research has advanced our theoretical understanding and analytical methods to analyse networks in a design context, it has also highlighted the need for a more cohesive, systematic, and reflective revision of the many network features that have been and can be analysed, as well as the methodological steps followed in their analysis and their consequences. Such a reflection is essential for the consolidation of disciplinary knowledge, the building of a common language, and the understanding of different methodological decisions.

In summary, we see strong evidence for the usefulness and benefits of network science to support design research and increasing uptake in engineering design studies. However, alongside compelling reasons to conduct network-based analyses, there are also conceptual and methodological challenges. Such challenges need to be understood and addressed in an engineering design field-specific manner, so as to conduct rigorous research and to capitalise on the benefits of applying a network-based perspective to the study of the design process. We will sketch the core decision points below and illustrate them with study examples focused on the engineering design process.

The remainder of the chapter is structured as follows: Sect. 9.2 introduces the main methodological challenges and decision points a researcher faces when using network science to support design research. In Sect. 9.3, we provide specific case examples to illustrate core decision points a researcher needs to address and, in particular, we highlight three distinctive characteristics of network approaches: data-driven analyses, a multilevel perspective, and result interpretation facilitated by interactive visualisations. Section 9.4 pinpoints the opportunities for using network science and discusses the core points raised in this chapter, and Sect. 9.5 concludes by providing a summary and outlook.

9.2 Methodological Challenges and Decision Points

Well-established and generic methodological guidance in the field of network science exists, including fundamentals on graph theory and network analysis (e.g. Barabási 2012; Diestel 2005). However, despite the emergent use of network analysis in engineering design, the field still lacks cohesive field-specific methodological support. Support of the sort that already exists for social sciences such as sociology and organisational studies (e.g. Borgatti et al. 2013; Carrington et al. 2005) and for natural sciences such as physics and biology (e.g. Estrada 2013; Ma'ayan 2012). This support is needed to build and share common terminology and tools, and to further develop research methods that respond to the distinctive characteristics of our field. Some of the **characteristics and methodological challenges of engineering design** that impact network-based research include the following:

1. The diversity of research questions, units, and levels of analysis. This often requires an understanding of multilevel network analysis methods.
2. The inherent dynamic and socio-technical nature of the design domain. This generates the need for a robust understanding and study of heterogeneous (multimodal and multiplex) dynamic networks that can simultaneously combine multiple elements, including people, activities, documents, and engineering components.
3. The often unknown or unclear direction of causality between network structure and performance. This lack of clarity increases the difficulties of data interpretation, which are in part the results of difficult experimental conditions and the limited possibilities to implement control variables when studying design processes 'in the wild'.

In order to respond to design's distinctive characteristics and methodological challenges when applying network science, we started by examining previous classifications of network studies (e.g. Borgatti and Foster 2003; Parraguez 2015). From those classifications, we can distinguish two key aspects that affect network research within and beyond the design field: (A) the overall research purpose (exploratory and explanatory), including assumptions about the direction of causality (network structure affecting behaviour and performance or vice versa), and (B) network features including main units and levels of analysis. See Fig. 9.1 for an illustration of the key decision points.

9.2.1 Define Overall Research Purpose

While design studies often attempt to move from an exploratory and descriptive mode to a hypothesis- and theory-testing one, limitations in available data (sample size, contingency, level of detail, etc.) and the somewhat embryonic state of network theories and methods specific to the design context complicate extrapolation of results. So far, most network studies in design research are primarily exploratory, are theory-generating, and portray case-specific patterns that allow for theory development (e.g. Collins et al. 2010). However, we are also beginning to see examples of network studies moving into explanatory, hypothesis-testing mode (e.g. Sosa et al. 2011).

With respect to **direction of causality**, research in design and most other fields has generally examined how network structure affects behaviour and not vice versa (Borgatti and Halgin 2011). In design research, this can be explained by the fact that most dependent variables are associated with performance measures of sort, either related to the designer (e.g. speed, creativity), the activity (e.g. on time, on budget),

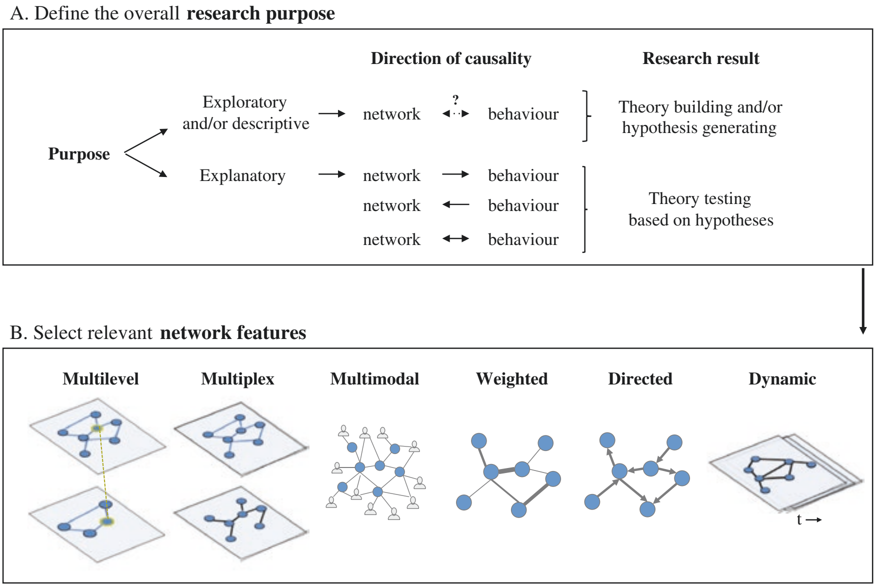


Fig. 9.1 Using network science in design research: decision points. **a** Define the overall **research purpose**. **b** Select relevant **network features**

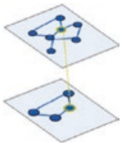
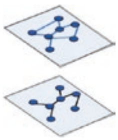
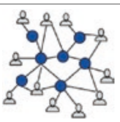
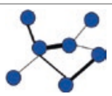
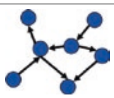
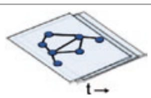
or to what is being designed (e.g. quality, meeting specifications, novelty). Therefore, network properties and measures (such as network size, density, centrality, and clustering) have mostly been used as predictors or independent variables in the analysis. This reinforces the trend of causality direction of the type 'network structure affects behaviour'. While this logic is sound, it is important to note that in complex systems, causality is rarely unidirectional, and feedback loops are common. For this reason, exploring how the behaviour and attributes of designers and performance outcomes shape the network structure of the design process would also be of value to design research. In summary, if the purpose is exploratory, the causal relationship is not predefined and research is part of theory building and/or hypothesis generation. If the purpose is explanatory, then a causal relationship should be hypothesised upfront and tested.

9.2.2 Select Relevant Network Features

Having considered the type of network studies to be undertaken, the researcher wishing to analyse networks needs also to be aware of common network features that affect the methodological design and reach of his/her study. A network conceptualisation of complex systems can be **multilevel**, **multiplex**, **multimodal**, **weighted**, **directed** and/or **dynamic**. However, for analytical reasons and practical purposes, a network may instead be conceptualised and studied from a simpler perspective, i.e. unilevel, non-multiplex, unimodal, unweighted (binary), undirected, and/or static. In any case, we need to address the theoretical and analytical consequences and limitations of selecting certain features and not others. We exemplify each feature listed above focusing on the design process. Table 9.1 provides references to generic conceptualisations of each network feature and offers references to the application of each network feature in design-related research.

The **units and levels of analysis** in network-based design research can vary widely. For example, if the unit of analysis is defined as individual designers, activities, or components, the level of analysis would be nodes in a network. At this node-level, the idea is to quantify the effect of the whole network (or part of it) on each node. In contrast, if the unit of analysis is defined as information exchanges and/or information flows between people or activities, the level of analysis would be edges in a network. At the edge level, the idea is typically to quantify the characteristics of each connection between two nodes, e.g. a set of two

Table 9.1 Network features and exemplary references

Network feature		Conceptualisation	Application in design research
Multilevel (also known as nested networks)		The network is studied at different levels shedding light on the architecture of nodes, edges/interfaces and the whole network or parts of it (e.g. Brass et al. 2004; Moliterno and Mahony 2011)	Eppinger et al. (2014), Johnson (2005), Parraguez (2015)
Multiplex (also known as multilayer)		The same system of interconnected elements/nodes is studied through different network layers. Each layer defines a different type of relationship between the elements/nodes (e.g. Kivelä et al. 2013)	Parraguez (2015), Pasqual and de Weck (2011)
Multimodal (also known as heterogeneous networks)		The network under study contains heterogeneous elements/nodes (e.g. Wasserman and Faust 1994: 29)	Durugbo et al. (2011), Morelli et al. (1995), Parraguez (2015)
Weighted (also known as valued networks)		The edges/relations between elements/nodes are valued to quantify the strength of the edge/relation (e.g. Wasserman and Faust 1994)	Browning and Eppinger (2002), Parraguez and Maier (2015), Parraguez (2015), Sosa (2014)
Directed (also known as directional networks)		The edge/relation between elements/nodes in the network has an explicit directionality (e.g. Wasserman and Faust 1994)	Meier et al. (2007), Smith and Eppinger (1997)
Dynamic (also known as temporal or evolving networks)		The elements/nodes and or relations/edges change over time. This includes adding, removing and/or reweighting nodes and/or edges (e.g. Holme and Saramäki 2012)	Braha and Bar-Yam (2007), Collins et al. (2010), Parraguez (2015), Parraguez et al. (2015a)

(dyads) or three nodes (triads) and their connections. Finally, if the unit of analysis is the whole design process, organisation, or project, the level of analysis would be the whole network or at least subsections thereof.

Multilevel: The network structure of the design process can be analysed from multiple levels, including individual activities (nodes), information flows between activities (edges), and the entire process architecture (whole network). The intrinsically multilevel nature of networks allows design researchers using network science to integrate findings and more fluently move between micro- and macro-levels, maintaining analytical consistency across the examined levels. This is the equivalent of being able to zoom in and zoom out as required by the research question at hand.

Multiplex: A multiplex view of the process architecture means that different types of relationships or interactions between activities are explicitly considered and analysed as different 'network layers'. This could be used to analyse and compare the network structure of the actual and planned process under a consistent framework, or to map and compare (actual) information exchanges between people with the (required) information dependencies between tasks.

Multimodal: A multimodal network of the design process would in the same network layer simultaneously include two or more different entities, for example people and activities. While multimodality significantly increases the complexity of the model, it also allows bridging different domains and allows integrating different domains, such as the organisation and process domains.

Weighted: An edge between two nodes in the network may be weighted. This might refer to the intensity or amount of information flowing between two activities. Weighting can be essential to distinguish patterns in the network structure that might otherwise be hidden underneath the homogeneity that a binary (unweighted) relationship between two nodes suggests.

Directed: A relationship between two entities may or may not be directed. That is, energy or material usually flows in a particular direction. Likewise, information exchanges may or may not be reciprocated. As a result, networks are classified as directed or undirected.

Dynamic: The network structure may change over time as nodes and edges appear or disappear over time, due to reweighting of edges and/or changes in relationship types. When analysing a system's structure over long periods of time, the temporal and potentially dynamic evolution of the system can be the key to understanding its structure. This is particularly true when studying complex and evolving processes such as designing, where changes in the emergent behaviours are not only expected but needed to fulfil envisioned objectives.

9.3 Case Study

Here, we highlight and exemplify the key decision points detailed previously in this chapter. We illustrate some of the decision points with snapshots from one case example of a renewable energy plant as a large-scale engineering system where we used archival data (activity log and email data) spanning three years of design and development.

The focal company has designed, developed, and built steam-generating plants for over 150 years. It has done this in coordination with a partner company and a network of more than 50 external national and international organisations, including a range of suppliers, manufacturers, building contractors, consultants, and regulatory agencies. While their engineering design process works well and complies with the highest industry standards for process and project management, the company has come to realise that to move forward, they require additional support. For example, the complexity of the technology they develop, in conjunction with the fast-paced and competitive market they operate in, has stretched to the limits their organisational set-up and the traditional approaches they use to plan, execute, control, and improve the design process. They have therefore been seeking a systemic overview of their information flow and design activities in order to streamline their process of designing and developing biomass power plants.

For this, they needed a way to view, understand, and monitor their actual design process by way of integrating both the technical (information dependencies between activities in the design process) and social (work-related communications between people in the organisation) dimensions of how they organise their design work. They needed to move beyond counting incidences separately in the product, process, and organisation domains, to connecting the data, so that they could identify the actual information flows between activities. These flows can only be modelled and understood in the context of information exchanges between people, hence the need for connecting cross-domain data. Further, they needed an objective way of 'measuring' their patterns of information flows.

9.3.1 Illustration of Methodological Challenges and Decision Points

(A) ***Defining the overall research purpose***: Due to the company need for a broad and deep overview of their interaction patterns, we set the research purpose as primarily descriptive, seeking to study the actual design process through a systemic, multilevel, socio-technical, and data-driven network approach. We choose not to assume a direction for the causal relationship between the analysed network architectures and observed design process performance. The reason for this was that we needed to first build an appropriate theoretical frame for linking network architecture to performance. Only after the theory-building process was considered appropriate, could we move to an explanatory, hypothesis-testing mode.

(B) ***Selecting relevant network features***: Our descriptive research purpose required a set of network features consistent with a multilevel socio-technical focus. With these requirements in mind, and given the availability of suitable digital data traces, we selected the most comprehensive set of network features possible that were analytically compatible with a study that combines people and activities (process and organisation domains). As a result, this case illustrates the analysis of a wide range of network features through the study of just one design process.

The selected network features included: a **multilevel** characterisation of the design process to describe the network architecture of design activities, interfaces between activities, and the design process at the whole network level. To study the degree of alignment and influence between the actual and planned design processes, we adopted a **multiplex** network approach where actual and planned processes represent different network layers which could then be mapped. To capture the socio-technical nature of the design process, we needed to combine people and activities. To achieve this, we opted for a **multimodal** network approach, combining the process and organisation domains. To capture the natural spectrum of intensities that occurs in information exchanges between people as well as the variation in the amount of participation in activities, we conducted all our analyses using **weighted** networks. Even though email exchanges show direction, we decided to use **undirected** instead of directed networks in our analyses, as most email exchanges were reciprocated and affiliation to activities are naturally modelled as undirected networks, and because many centrality metrics are not yet refined for directed networks. Finally, we selected a **dynamic** approach for the level of the whole process in order to explore evolving information centralisation patterns through different stages of the design process.

For more detailed information on specific aspects of this case study, see the following: The overall research approach, named The Networked Process Framework, was developed in Parraguez (2015), the dynamic network analysis of the whole process was published in Parraguez et al. (2014, 2015a), the interface level analysis in Parraguez et al. (2015b), and the activity-level network analysis in Parraguez and Maier (2015).

9.3.2 Case Snapshots

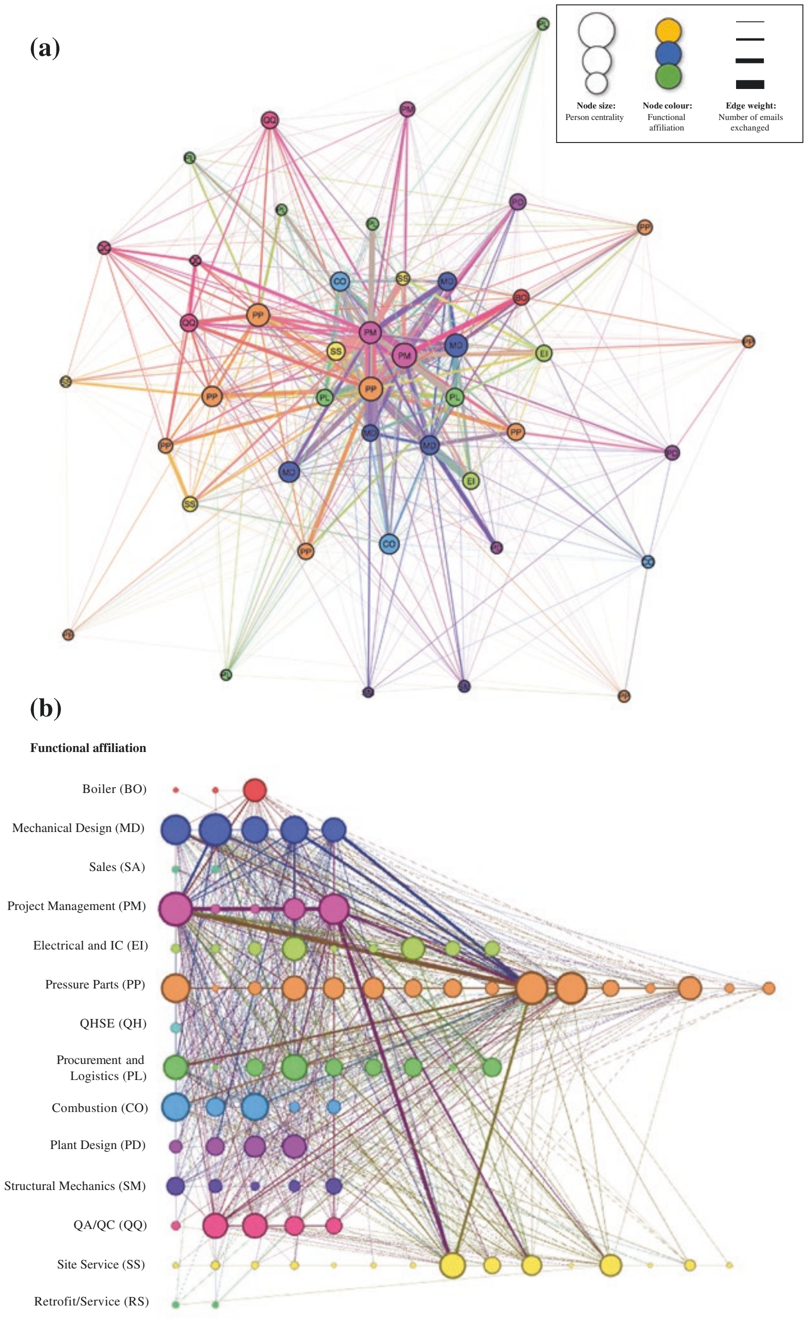
The snapshots presented here are the result of applying the proposed network science approach and following the prescribed decision points in our own case study. The objective is to provide an empirical overview and reflection about the outcomes of its application, combining data from the process and organisation domains. These snapshots show the effect of the approach on data acquisition, gathering, and interpretation, highlighting the relevance of network visualisations and the multilevel nature of the analysis. The network analysis was conducted combining network visualisation produced with Gephi (Bastian et al. 2009) and network analyses performed with UCINET (Borgatti et al. 2002).

Mapping the actual organisation network: Following the tradition of social network analysis and organisational network studies, we modelled the network of actual communications (organisation domain) by mapping the email exchanges between people from the case company as an engineering communication network. We drew from a repository that includes more than 10,000 emails between several hundred people in a period of more than three years (September 2009 and August 2013). Figure 9.2a, b shows the analysis including the formal functional affiliation of people within the company. The figures differ in terms of the graphical layout applied to visualise the network and show how different visual representations can lead to different network insights. Figure 9.2a emphasises the natural distribution of people based on their email communications. Figure 9.2b arranges the position of each person based on his/her formal functional affiliation, which allows identifying key communication lines between groups.

At this level of detail, we can see individual people inside the focal company, their email communications, and the formal organisational groups they are affiliated with (shown in node colour and label). This aggregated view of the information exchanges allows us to identify key players such as the project manager and the leader of on-site integration, and also some unexpectedly central people. Here, it is also possible to analyse the degree of information exchange between the formal organisational groups within the company and other interesting insights for traditional organisational studies. One way of connecting such information exchanges with the design process is by using the simplifying assumption that formal organisational groups can be mapped directly and in a one-to-one fashion onto design activities. However, such an assumption is problematic for complex projects where each activity requires inputs from different technical specialities, and assigning people to activities is more dynamic than assignment of people to formal organisational groups. For example, it is not uncommon for people to be iteratively working on different activities and therefore switching back and forth between activities. Furthermore, our analysis shows that, for this particular case, that assumption would be inadequate because people do not tend to cluster communications within their own formal organisational groups. One reason for this is that communication is being clustered around design activities instead of functional groups (as Fig. 9.3 reveals).

Mapping of organisation (communications) and process (activities) networks: The bridge between organisation and process was generated by a weighted and multimodal network of people and activities that we built through the use of more than 10,000 activity logs (see Fig. 9.3).

Figure 9.3 shows how people indeed tend to cluster around activities rather than formal functional groups. It also shows the relative diversity of each activity in terms of the number of individuals from different functional groups participating in the activity. The limitation here is that we have no proxy for the direct communication between people, which we know is at least as important as the coparticipation in activities to determine the information flow between activities. To incorporate this, we need to integrate the previous information about email


(a)
Node size:
Person centrality
Node colour:
Functional affiliation
Edge weight:
Number of emails exchanged
(b)
Functional affiliation
Boiler (BO)
Mechanical Design (MD)
Sales (SA)
Project Management (PM)
Electrical and IC (EI)
Pressure Parts (PP)
QHSE (QH)
Procurement and Logistics (PL)
Combustion (CO)
Plant Design (PD)
Structural Mechanics (SM)
QA/QC (QQ)
Site Service (SS)
Retrofit/Service (RS)

◂ **Fig. 9.2** **a** Internal project-level communication. Weighted and undirected simplified network graph showing key people within the design process of the focal company. Force-directed layout highlights the organic distribution of people based on their email communication. Nodes represent people, and edges represent the sum of email exchanges between two individuals. The network analysed includes 85 people and 10,700 emails. Functional affiliations are coloured and labelled, e.g. pressure parts (PP) and project management (PM). See Fig. 9.2b for details. **b** Internal project-level communication using the same data set as in Fig. 9.2a. Weighted and undirected network graph showing key people within the design process of the focal company. Fixed attributional layout highlights organisational affiliation and cross-group communications

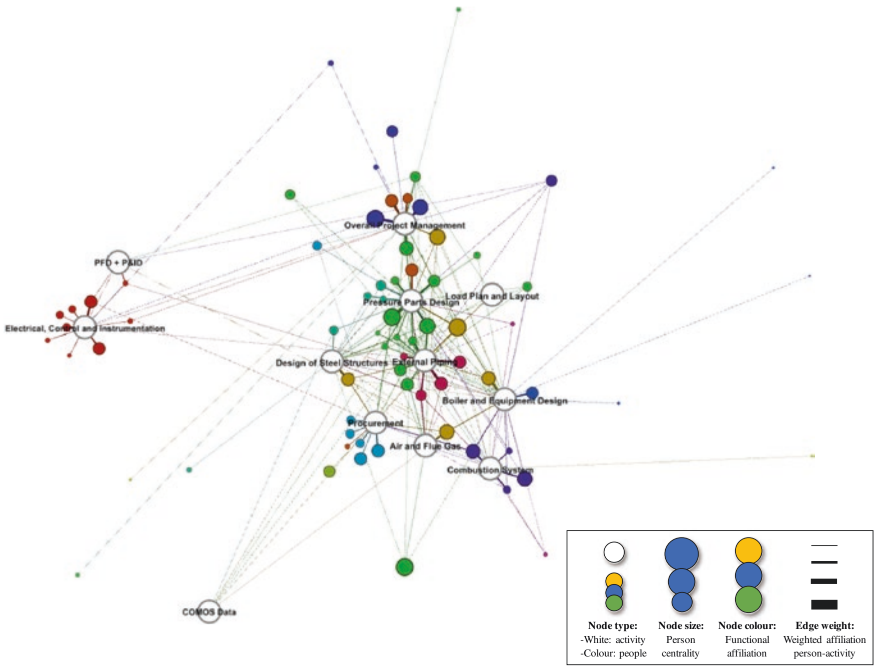


Fig. 9.3 Mapping of 85 people (*colour nodes*) to 12 activity groups (*white nodes*) as obtained from archival data. Activity names are based on company codes. Edges show the sum of 10,505 activity records connecting people with activities

exchanges between individuals to the network of people performing activities. Figure 9.4 provides such an integrated view.

Figure 9.4 depicts a compact and rich visualisation of the entire design process in terms of aggregated information flows between activities. Here, we can estimate closeness between activities based on the actual information flow between them, identify central and peripheral activities and people, and calculate a full set of network architecture metrics at different levels of analysis.

Multilevel zooming in and out: In order to exemplify multilevel movements as described above and analogous to zooming in and zooming out in the network, Fig. 9.5 shows a sequence of visualisations that takes us from the whole process level to the activity and interface levels.

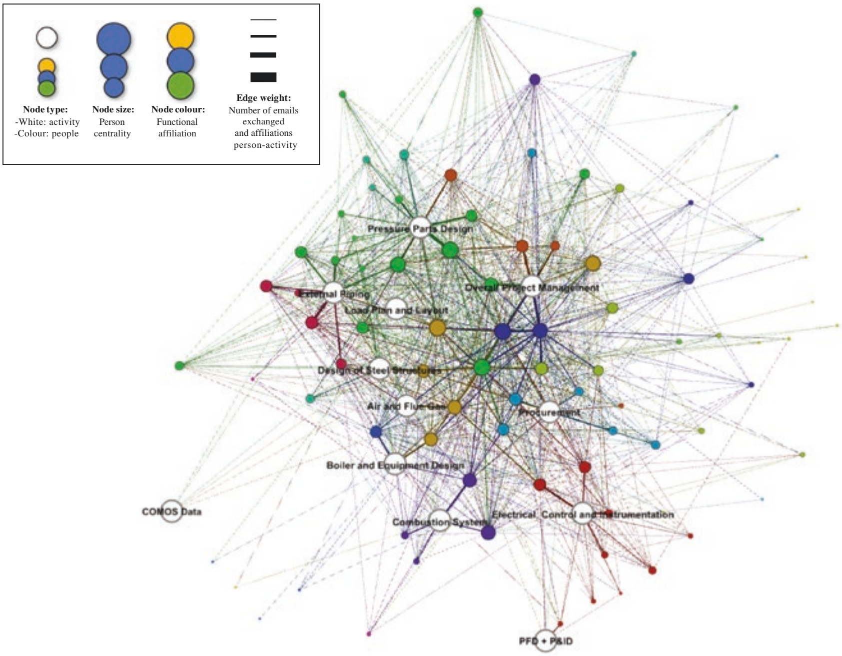


Fig. 9.4 Mapping of people (*colour nodes*) to activity groups (*white nodes*) as obtained from archival data. Activity names are based on company codes

Figure 9.5 shows an example of a multilevel network visualisation. In this figure, based on the overall process architecture, we can select two information interdependent activities, for instance, *pressure parts design* and *electrical control and instrumentation*. These two design activities are located at opposite ends of the graph and have distinctly different network structures and compositions in terms of network size, diversity, and density. Zooming in from the whole process, in which *pressure parts design* is embedded, to the level where we can examine *pressure parts design* as a single activity, we gain an additional level of understanding with more detail. At the activity level, we can quantify the characteristics of this activity and compare it with other activities in the network. We can also identify specific information roles and subgroups of people, and we can perform a full social network analysis on the engineering communication network associated with the 'inner workings' of this activity. Moving from the study of *pressure parts design* in isolation to the interface level, and in particular the interface with *electrical control and instrumentation*, we can now observe the joint network that enables the information transformation and information exchange between these two activities. At this interface level, it is possible to quantitatively characterise each interface network as well as to identify key individuals working at each interface.

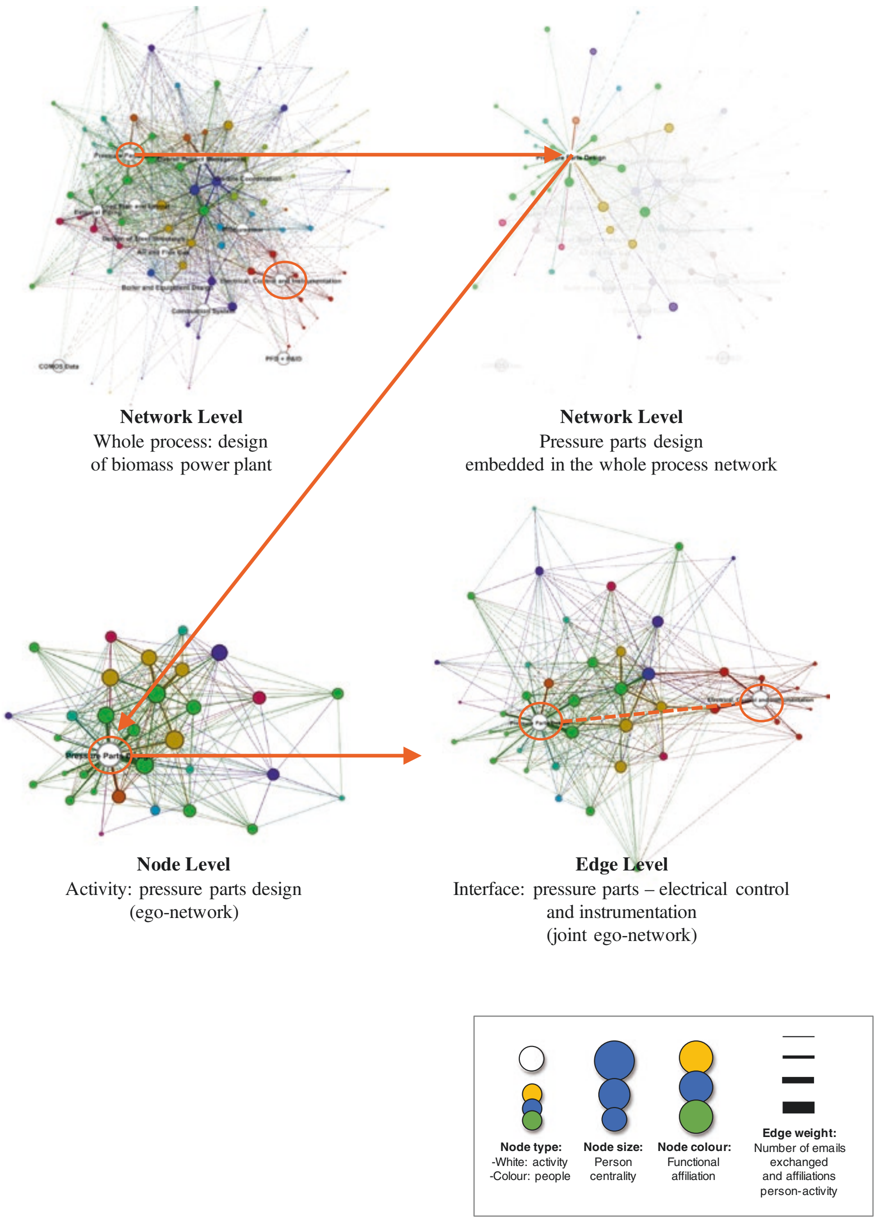


Fig. 9.5 Multilevel network visualisation combining all the previous analysis. Figure illustrates the idea of zooming in and out between network levels

9.4 Discussion

Based on the results of our own studies and previous network science research applied to engineering design (e.g. see Chap. 8), three opportunities for using network science in design research stand out:

(1) Studying the nature of the interactions that occur in the network. This includes how the behaviour of nodes (such as people, activities, or components) is affected by their location in the network; or how the qualities or attributes of the nodes (e.g. functional affiliation to departments, activities types, or categories) influence the structure of the network.

(2) Studying how network structure (e.g. centrality, connectivity, clustering, degree distribution, density, path length, size) influences processes that develop over the network, e.g. spread or propagation effects, such as spread of information or the propagation of changes; with the core idea of how network structure influences a (stochastic) process of spread. For example, the way in which information flows through design activities and is exchanged between designers in the organisation, or the propagation of changes and errors in the design process.

(3) Knowledge of network properties allows us to use network models to test the effect of interventions. One of the core motivations for developing network models is to come up with a virtual laboratory representing (socio-technical) systems with (mathematical) representations, for example, to generate answers to what-if scenarios. To illustrate, we may test for resilience, robustness, and vulnerability of the design process and design organisation when facing disruptions such as the loss of key designers or staff changes following an organisational restructuring. More generally, we may probe for patterns of how relationships or information spread, or how we may encourage or inhibit the spread of information.

It is often argued that an holistic and systemic perspective is necessary to understand patterns of designing (Eckert et al. 2005). This requires moving between qualitative and quantitative research modes as well as between detailed microanalyses of design activities and designer behaviour and macro-analyses of the whole design process.

Network-based research, due to its inherently multilevel and system-oriented nature, plays a key role in responding to this need. Through the snapshots of our case study, we have shown how applied network science may be used to integrate large amounts of process data with qualitative case study interpretations, providing a quantitative multilevel platform from which to examine the design process and from which to gain new insights. Through such a network perspective, we can connect otherwise disconnected data and generate knowledge ranging from individual activities and people to whole process-level dynamics. We thereby facilitate connecting the dots between what design researchers have learned through in-depth studies at different levels of the design process. Furthermore, researchers exploring computational modelling of teamwork in design (see Chap. 10) and other types of computer simulations (see Chap. 11) can use the empirical results of network analyses to support modelling and parameterisation of their computer models. We thereby gain precision and allow for the integration of empirical data produced by other researchers. In the same way, design researchers working with qualitative case studies can complement their analyses and interpretations of the case with quantitative analyses and visualisations produced by network-based approaches.

9.5 Conclusions

We have in the last three decades seen a growing number of studies applying different variants of network analyses to the design process. However, despite this increasing interest, so far there has been little convergence and reflection about the challenges, methods, and key decisions surrounding the implementation of network-based research in design. Furthermore, as Cash and Culley (2014) write on ‘the role of experimental studies in design research’, so too do we take liberty to say that there is a lack of field-specific guidance for using network approaches in design research.

In this chapter, we contribute to this field-specific guidance providing a summary of core decision points that design researchers can use as a reference when planning and implementing their studies. We illustrate these decision points through a case study, examining the structure and dynamics of a real engineering design process. Our emphasis is on multilevel analyses and on the importance of visualisations. These visualisations serve as tools for eliciting (qualitative) feedback, for validating results, and for collaboratively interpreting findings, e.g. in a case study setting.

With this contribution, we aim to facilitate the fruitful integration of network science into the toolbox of both qualitative and quantitative design researchers, in particular those with an interest in multilevel design research. Similarly, and in connection with the next chapter in this book on simulations, the results of empirical network analyses of the design process provide key inputs for the development of more detailed simulation-based approaches of designing. Such inputs provide researchers using simulations with quantitative parameters and process topologies that feed their models and test their simulations.

As noted in the chapter, there are many significant works on applied network science. It is hoped that design researchers also turn to these works for inspiration and further guidance on ways of using network analysis to support and further design research and design management practice.

Encouraged by several discussions with colleagues in the growing field of network science, we would also like to point out that design practice provides a unique and wonderfully rich socio-technical fabric of interactions that researchers from other fields are eager to get their hands on and heads around. This offers interesting interdisciplinary research opportunities for mapping, understanding, and predicting relationships between network architecture, observed socio-technical behaviours, and performance.

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Chapter 10
Computational Modelling of Teamwork in Design

Ricardo Sosa

Abstract Computational simulation has been long established across research areas for modelling the behaviour of complex, multivariable and socio-technical systems. In the computational study of teamwork in design, the focus is set on capturing dynamic interactions between the individual team members within their environment using multi-agent systems. Agent-based simulation (ABS) provides a platform to inductively develop and examine theories on human behaviour in design that have the potential to inform experimental research. This chapter aims to outline the role of agent-based simulation in design drawing from a multidimensional framework for computational modelling. This research approach is applied to examine group support at the time of creative breakthroughs. The chapter concludes with guidelines for the use of agent-based simulation in design research.

Keywords Creativity · Simulation · Collaboration

10.1 Group Agency in Design

Teamwork plays a central role in design practice. However, research on creative collaboration in design teams remains marginal in comparison with studies that examine the design process with an individualistic focus. This chapter presents computational simulations as an inductive research approach for the study of group processes in design. By group or team processes in design, we mean more than the simple sum of individual behaviour. Group phenomena of interest are those that take place when designers interact, generating collaborative results

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such as agreement, unanimity, coordination, dissent, antagonism, or support. Such processes do not result simply from aggregating the behaviour of independent (*autonomous*, in computational parlance) units, but are *emergent results*, i.e. group outcomes that are observable at the scale of the group, rather than at the individual units. The importance of creative synergies in dyads, and groups in general, has received increasing attention in design and creativity research (Csikszentmihalyi 2014; Glaveanu et al. 2014), but much remains to be understood.

Examining group processes by experimental methods is challenging, yet the insights that can result from an evidence-based approach to creative collaboration are valuable for managerial and pedagogical practices. This chapter shows one way in which computational models, particularly agent-based simulations (ABS), offer a good platform to examine closely such questions, primarily to aid in the examination of some key ideas that can guide future experimental research. As a way to structure a research programme using agent-based simulations, we adopt a framework for multilevel modelling of creativity (Sosa and Gero 2015).

10.1.1 Individuals, Groups, and Societies

The multidimensional creativity (MDC) framework builds on a triad model of creativity that focuses on the interactions between epistemological, individual, and social dimensions (Sosa et al. 2009). In various influential theories aimed at explaining change, three dimensions are identified, for example, Fleck referred to *exemplars*, *proponents*, and *communities* (Fleck 2012); Schumpeter identified *innovations*, *entrepreneurs,* and *markets* (Schumpeter 1947); Morin systems include *noosphere*, *strong spirit,* and *culture* (Morin 1991); Csikszentmihalyi viewed *domain*, *individual,* and *field* interacting (Csikszentmihalyi 2014); and finally, Simonton explains creativity by *logic*, *genius,* and *zeitgeist* (Simonton 2004). Drawing from these influential theories of change, three intrinsic processes and six directed interaction processes are used to support multidimensional modelling of creativity (Sosa et al. 2009; Sosa and Gero 2015). Temporal and functional relationships are defined in five scales of analysis: culture (MDC-C); society (MDC-S); group (MDC-G); individual (MDC-I); and brain (MDC-B).

Relationships across MDC dimensions are defined in the computational study of creativity either as independent or interdependent; that is, the former are processes that occur in isolation within a scale, whilst the latter are those that occur between scales. Figure 10.1 shows the MDC framework as applied in this chapter. A radial arrangement shows that rather than subsumption of lower levels, scale-specific factors exist at each MDC level that are not decomposable to smaller units.

Definitions and representative studies across these scales are presented here; details on the MDC framework including the role of time across scales are given elsewhere (Sosa and Gero 2015). Culture, MDC-C, refers to the macroepistemological scale of creativity and addresses questions such as ‘How do systems

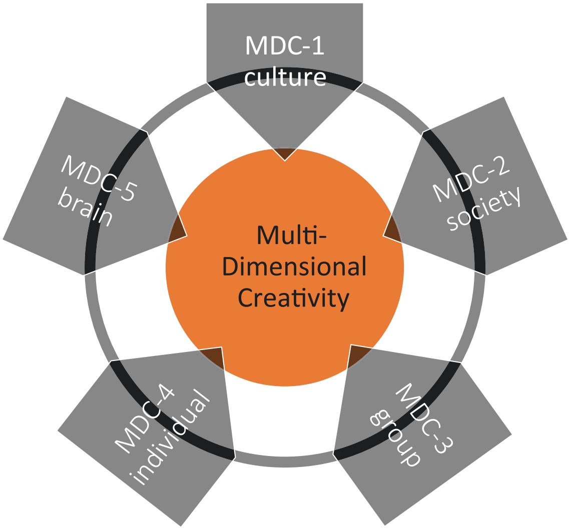

Fig. 10.1 Multilevel framework to support computational simulations of creativity at five scales: culture, society, group, individual, and brain

of beliefs, language or taste change over time?'. Research at the MDC-C scale includes cultural dimensions of creativity (Lubart 2010) and how the built environment shapes creative activity (McCoy and Evans 2002).

MDC-S refers to the macrosocial scale of agency. It captures processes that account for the influence of—or seek to grow effects on—demographics, networks, and migration, such as 'How do societies regulate dissent?'. Cultural psychology (Glăveanu et al. 2014), the impact of migration in creativity and innovation (Hansen and Niedomysl 2009), and the social capital of creativity (Huysman and Wulf 2004) constitute research approaches of societal issues that can be modelled.

MDC-G looks at creativity phenomena that occurs at the scale of small to large groups of people. This includes team ideation, communities of practice, family and peer support, cocreation, artist collectives, art commission, change management and leadership, and collaboration/competition strategies. Studies of team diversity (Bassett-Jones 2005) and group brainstorming (Paulus and Dzindolet 1993) illustrate issues that can be examined at this level of inquiry.

MDC-I is the most common scale of study spanning cognitive science and psychology research, broadly identified as 'creative cognition' (Smith et al. 1995). MDC-B includes all creativity-related processes at the neural scale including neuroanatomy (Dietrich and Kanso 2010) and neural network (NN) models of creative reasoning (Iyer et al. 2009).

In this chapter, we focus on the computational study of creative groups. In particular, agent-based simulation is used to examine the principles in the interaction between group members in the context of ideation. Research on group brainstorming has a long tradition of comparing individual and group performance (Isaksen and Gaulin 2005), called 'nominal' and 'real' groups, respectively. The literature in this area often claims that nominal groups are more creative than real groups.

However, disagreements exist over precise definitions and the assessment of creativity, i.e. to what extent does the number, quality, novelty, or diversity of ideas constitute appropriate indicators. Another reason to challenge such claims is the extent to which laboratory research methods may capture the team dynamics in the workplace (Sutton and Hargadon 1996). The challenges behind idea evaluation and selection can also be considered in the framing and interpretation of individual versus group performance. Lastly, some of the underlying premises and conditions used in this area of research remain problematic; that is, time limits for real groups are allocated by adding up the time given to nominal groups. This practice goes against evidence from studies of design teams such as the ‘2/3 rule’ showing that groups use only two-thirds of the time working on content, with the rest being used for coordination (Stempfle and Badke-Schaub 2002).

Therefore, the decision on what constitutes ‘the same amount of time’ to complete an idea generation challenge for design teams and for designers working individually is not straightforward. Across the literature, time allocation is justified by a notion of equivalence between individual and group work: ‘the two treatments, given the same number of people working for the same amount of time’ (Girotra et al. 2010). This is sensible from a managerial planning of resources and time. However, when working in isolated conditions, the subjects are fully engaged in idea generation reasoning, whilst working in a group requires additional time to listen and talk to others, to manage non-verbal communication, to coordinate turn-taking, and to deal with issues of power, interpretation, persuasion, vocabulary, etc.

Rather than relying on rhetoric to define such crucial factors in experimental studies, we adopt an agent-based modelling approach to examine these issues and support our reasoning about the complex interactions at the group scale. Rather than replicating a specific outcome, the role of these simulations is to inform key decisions in the planning of future experimental studies.

10.2 Agent-Based Simulation

Agent-based simulation (ABS) is a modelling strategy that consists of building computational systems where multiple ‘agents’ or independent programmes are fully specified, as well as their attributes, rules of interaction, and initial conditions. What makes ABS more relevant to the study of individual and group behaviour is that in such systems of multiple interacting agents, emergent outcomes ‘grow’, enabling experimentation with the model’s variables, and informed reasoning about the target system. ABS has been used for some years to study a variety of topics related to social dynamics (Gilbert 1998).

In recent years, ABS starts to be used to inform challenging questions of creativity and innovation (Watts and Gilbert 2014). The model presented here belongs to a class of ABS used to gain qualitative understanding of human and social behaviour, and it is also one of the simplest to code (Axelrod 1997). Such 'small-scale systems' are advantageous because they are easily communicated, implemented, understood, and modified (Montfort and Fedorova 2012).

10.2.1 Model of Culture Dissemination

The model of culture dissemination is a type of two-dimensional cellular automata where a population of agents interacts in a shared environment guided by simple representations and behaviours (Axelrod 1997). Agents hold an 'opinion' or 'idea', which is encoded as a chain of numerical values; ideas are collections of *features* with *traits*. The core function in this model is to communicate with neighbouring agents to exchange and influence ideas. These local interactions create emergent outcomes that help the researchers better understand the assumptions behind the model and the type of processes that are possible in such systems.

In the initial state, agents are instantiated with a unique location in a two-dimensional space and with random values assigned for ideas. A torus grid and neighbourhood type 'Von Neumann' (adjacent neighbours to the north, south, east, and west) are customary in these models. On every simulation step, each agent becomes *active* and adopts a feature from one of its neighbours. Over time, from these local exchanges, the population reaches consensus on an idea shared by all agents. Experimentation is possible with the factors that lead to such ergodic outcomes, for example the effects of limiting local exchanges to an existing condition of similarity (Axelrod 1997).

Figure 10.2a shows a sample case at initial state with 100 agents in a torus square grid—four features shown as concentric circles for each agent. A graph shows in Fig. 10.2b the process of convergence over time from maximum diversity of ideas to all agents sharing the same idea, or *diffIdeas* = 1. The final state where all agents display the same dominant idea is shown in Fig. 10.2c.

The variable *diffIdeas* refers to the number of different ideas across the population at a particular time. The variable *ideasBreadth* refers to how many variables

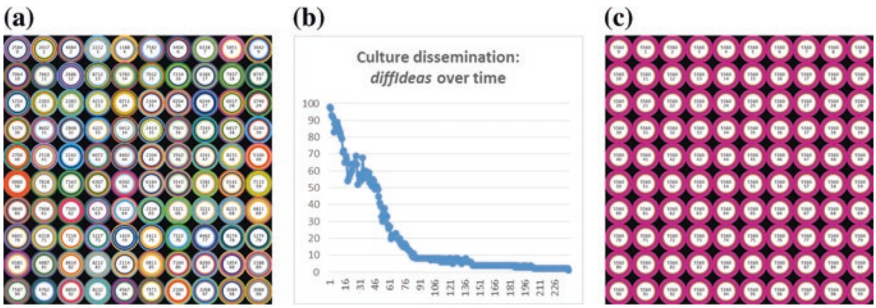

Fig. 10.2 **a** Initial state of a simulation showing all agents with unique random ideas shown in concentric rings; **b** process of group convergence over time showing idea diversity in the group; **c** final state showing all agents with a common idea set

are used to represent ideas and *ideasDepth* the possible values for each variable. In other words, the former captures how many issues are being discussed in the group, whilst the latter captures how varied are each of those issues. The settings used in this chapter are as follows: 100 agents, *ideasBreadth* $= 4$, and *ideasDepth* $= 9$, and all results are calculated by running 10,000 cases.

In the original model of culture dissemination, all processes belong to the MDC-I level, since all behaviour is defined at the microlevel of individual agency. The dependent variable *diffIdeas* defined above is an MDC-G indicator, as it is derived by comparing all ideas held by all group members. Other measurements of interest are also MDC-G, such as similarity between ideas of neighbours based on the number of shared features.

Understanding group convergence is important when reasoning about creativity because novel ideas are considered creative by groups growing agreement upon their novelty and usefulness (Kaufman and Beghetto 2009). However, for these systems to be more relevant as reasoning aids in the study of creativity, they need to support divergence. One way to capture divergence in these models is to include a threshold inspired by classic studies of the human bias to avoid monotonous, homogeneous stimuli. With a mechanism of *dissent*, as agents become exposed to a dominant idea, their probability of introducing a new value to the group increases.

10.2.2 Model of Culture Revolutions

We extend the model of culture dissemination to study 'culture revolutions', the reverse process from convergence: rather than maximum *diffIdeas* at initial time, the model is initialized in full consensus (*cns*) with all agents in the population sharing the same idea. As simulation time progresses, when *diffIdeas* $= 1$, agents have a very small chance of introducing a new idea to the group. Even when a nonconformist agent manages to introduce a new idea, the group still operates with the same rules of the model of culture dissemination; therefore, in most instances, new ideas are overcome by the group convergence and the population goes back to the dominant idea previously challenged due to the influence of neighbours. This result favours incumbency is called here redominance, or *rdm*. In some cases, the new idea introduced by the nonconformist agent spreads to all agents and replaces the previously dominant idea. This is what we identify as a culture revolution, or *rev.* By introducing divergence in this model, reasoning about change cycles is supported. Figure 10.3a shows a segment of a fully converged group (all agents with value 0000, represented by four concentric rings of the same colour), Fig. 10.3b shows agent #77 introducing a new value (0080), and Fig. 10.3c shows the group reaching consensus on that new value.

This model of culture revolutions enables experimentation with factors that shape cycles of divergence and convergence in groups, thus capturing at an abstract level the behaviour of groups in ideation sessions where new ideas are generated, evaluated, and selected (Isaksen and Gaulin 2005). The experimental

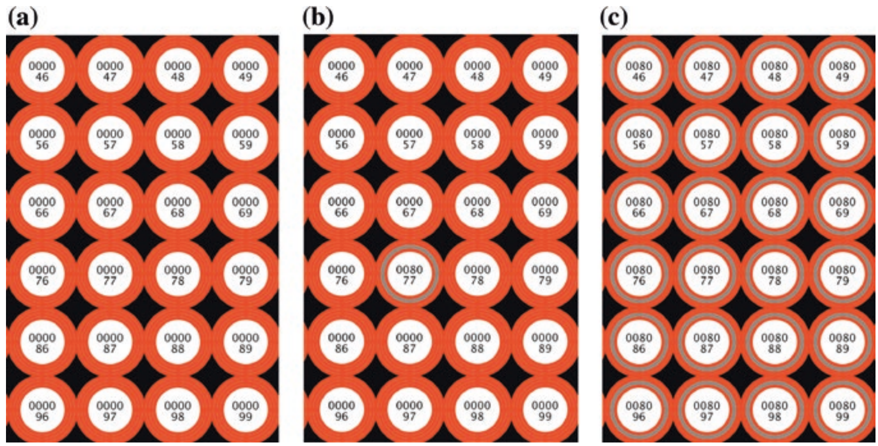

Fig. 10.3 A 'culture revolution' shown in a segment of a group: **a** all agents have value '0000'; **b** agent #77 introduces value '0080'; **c** all agents reach consensus on the new value

variables include the same used in the model of culture dissemination, plus *dissentProb*, a probability of an agent being able to introduce a new value when *diffIdeas* $= 1$, and *changeScope*, the number of features that a dissenting agent is able to modify. The additional dependent variables include number of redominance (*rdm*) instances, number of revolutions (*rev*), and length of revolutions (*rev_l*), i.e. the span in simulation steps from the introduction of a new value by a dissenting agent to its adoption by the entire group.

Although we discuss here a model of culture revolutions with no specific evaluation function, nothing prevents the researcher from introducing mechanisms to measure the fitness of certain types of ideas in this model. For example, as shown in Figs. 10.2 and 10.3, the values can be mapped onto colour spaces; therefore, in one application, agents can generate colour palettes searching for monochromatic, complementary, split complementary, double complementary, analogous, and triad colour compositions. The overall goal in such systems would be to find as many permutations in ascending or alternating order, or combinations that add to an ideal value range. In order to simplify things, we limit our analysis here to a model with no evaluation function, where ideas compete based on randomness alone.

These variables allow the researcher to experiment with factors that shape what we call here 'creative group capacity', defined by the likelihood of a model to support cycles of divergence and convergence, or revolutions. Beyond average cases, we suggest that comparisons across model conditions include the top percentile of cases, based on the observation that in the study and practice of creativity and innovation, the interest is on outcomes that are out of the ordinary (Sutton and Hargadon 1996; Girotra et al. 2010). As with the model of culture dissemination, all processes in the model of culture revolutions are MDC-I, or rules of microbehaviour. In the next section, MDC-G processes are added to the model of culture revolutions to show the potential of agent-based simulations to support reasoning about group dynamics.

10.3 The Revolutionary Effect of Local Support

'Culture revolutions' can be modelled in several ways, many of them by experimenting with individual attributes (MDC-I level). For example, agents in the population can be assigned roles of 'idea taking' or 'idea giving', inspired by qualitative research where different idea sharing behaviours are identified in professional teams (Elsbach and Flynn 2013). Or, agents can be initiated with individualized capabilities such as differentiated mutation rates resulting in varying probabilities of introducing new values in dissent mode. Individual thresholds can also be assigned to define the scope of change by dissenting agents as a way to account for personality traits such as openness to experience. Also, agents can have non-uniform neighbourhood sizes reflecting their network position or social capital. When evaluation functions are incorporated, agents can have an individual bias to certain regions of the solution space.

Revolutions can also be modelled by defining group-level (MDC-G) processes. This section presents an illustrative case of this approach inspired by Howard Gardner's biographical study of seven accomplished creators in *Creating Minds* (1993). Gardner describes an unexpected and 'surprising discovery' of the 'intensive social and affective forces that surround creative breakthroughs'. As he explains, 'support is needed *at this time*, more so than at any other time in life (…) it is precisely at these times that our creators needed, and *were fortunate enough* to be able to secure, *strong support* from other individuals'. Our emphasis here is on three key aspects of support and its role in the lives of creative figures: time, luck, and behaviour of other (close) individuals. We argue here that to model such critical factors behind creativity (Gardner identified common themes across the lives of the seven creators that he analysed), it is necessary to model extra-individual factors in social simulations.

Group support is a construct that can be experimentally analysed in agent-based simulations of creativity. It has a situational character, as it occurs beyond the control of any single agent, and is caused by an alignment of conditions jointly defined by multiple agents (that who receives support, those who give support), and is time-bound. The effects of group support can be examined in such simulations to understand its criticality, scale, and scope of influence by modifying multiple group conditions. The next section presents how group support can be studied in our model of culture revolutions.

10.3.1 Set-up

To implement group support in the above-described model of culture revolutions, a variable is defined in the system (*changeAgentId*) to record the identifier of a dissenting agent at the time that it manages to introduce a new value to the group, i.e. Gardner's 'creative breakthrough' time. The time stamp associated with this act of dissent is also stored. Change agents are assigned a value (*support_steps*) that is visible to its neighbours and serves as a counter to control a decay function of support measured in simulation steps. This enables experimentation with the effects of the duration of support given by neighbouring agents.

At every simulation step, when an agent interacts with its immediate adjacent neighbours, it performs an additional check to see whether these include an agent identified by *changeAgentId*, i.e. as one that has recently introduced a new value to the group. In such case, the neighbours display a supportive role by adopting the change agent's value, and the counter *support_steps* is decreased one step. Once *support_steps* reaches a zero value, the entry in *changeAgentId* is reset; i.e., the change agent is stripped from the 'fortune of strong support from other individuals' (Gardner 1993). To reiterate, this is a group-level (MDC-G) process since it is beyond the control of any agent alone, but occurs in coordination between a dissenting agent and its neighbours within a narrow window of opportunity.

A number of research questions can be formulated with this model, starting with 'What degree of support from surrounding neighbours is needed to make a long-term impact on the number of revolutions in a group?'. This is precisely the experimental scenario examined here: the effects of length of support (*support_steps*) on the creative capacity of a group. Simulations are run with *support_steps* = 0–10 in increments of 1 and from 10 to 100 in increments of 10. To examine neighbourhood effects, we run the simulations using Von Neumann neighbourhoods and the following model parameters: torus grid of 10×10 (100 agents), *ideasBreadth* 4, *ideasDepth* 9, dissent probability 0.001, change scope 1 trait, initial convergent state, 10^5 steps or iterations, and 10^3 cases. The experimental variable here is *support_steps*, from 0 (where agents *changeAgentId* receive no support from their neighbours as the control or baseline) to 10 steps in single increments, and 10–100 steps in increments of 10.

Four dependent variables are registered: consensus (*cns*); redominance (*rdm*); revolutions (*rev*); and revolution length (*rev_l*). To reiterate, *cns* shows the number of times in a case when agents reach convergence, or *diffIdeas* = 1; *rdm* shows the number of times in a case when a population returns to the preceding dominant value after being challenged by a new idea introduced by a dissenting agent; *rev* shows the number of times when a population reaches convergence on a new value; and *rev_l* stands for the number of simulation steps taken by a new value to produce a revolution, when such is the case.

10.3.2 Results

With no local support (*support_steps* 0), the average outputs are as follows: *cns* = 444.6; *rdm* = 437.4; *rev* = 6.2; and *rev_l* = 181. This shows how difficult it is for dissenting agents to trigger a revolution in this model, as only 6 revolutions on average take place in 10^5 steps or iterations. Two out of 10^3 cases reach the highest number *rev*(*max*) = 15 and the top 1 % percentile *rev* = 12.

Table 10.1 Effects of *support_steps* in revolutions

support_steps	*cns*	*rdm*	*rev*(*mean*)	*rev*(*max*)	*rev*(0.99)	*rev_l*
0	444.6	437.4	6.2	15	12	181
1	321.1	311.6	8.5	19	15	179.7
2	261.4	250.6	9.8	21	16	179.2
3	226.6	214.9	10.8	22	17	178.9
4	216.5	204.4	11.1	22	18	178.7
5	211.8	199.5	11.3	24	18	179
10	194.8	181.7	12.2	24	19	176.8
20	184.0	170.0	13.0	26	20	175.9
30	179.8	165.4	13.4	26	21	175
40	177.7	162.8	13.8	28	21	174.4
50	176.8	161.9	14.0	27	22	173.4
100	174.7	159.2	14.6	27	22	171.4

Results show that local support even for a single step (*support_steps* 1) has a significant effect on how a group reaches revolutions, with an increase of over 30 % on average. As support extends, the number of revolutions continues to increase but gradually decelerates to a point where local support that extends beyond 10 steps has only minimal effect in how likely revolutions are in a group. Table 10.1 shows all values extracted from 10^3 cases.

Results show that local support plays an important role in augmenting the impact of change agents in this model. Figure 10.4 shows the increase in revolutions with extending *support_steps* (bars). It also shows (line) a measure of 'efficiency' dividing revolutions (*rev*) by the total consensus (*cns*), showing an increase from 1.4 % to 8.3 % with *support_steps* = 0 and 100, respectively.

Another way of visualizing the effect of local support is to measure the number of cases with an equal or higher number of revolutions compared to the maximum value for cases without any local support (*rev*(*max*) >= 15). Figure 10.5 shows a significant increase from two cases when no local support occurs (*support_steps* = 0) to 5015 cases when *support_steps* = 100, i.e. an increase from 0.02 % to over 50 % of cases when support lasts one hundred steps—a seemingly inconsequential period compared to the total simulation length of 10^5 steps.

These results show that local support has the potential to play a significant role in creative groups. Under baseline conditions, a single agent in this model has a very marginal chance of triggering a collective change, or revolution. Everything else being equal, the slightest support from its surrounding neighbours plays a key role with the largest effects occurring in small doses of local support (lasting only a few steps) and with diminishing returns as support extends to long periods.

We find remarkable that a simple agent model can capture Gardner's unexpected insight shared by prominent creators. This enables a large number of questions to be addressed in the future: (a) the effects of neighbourhood size (Von Neumann, Moore types); (b) effects of novelty in dissent (incremental to radical

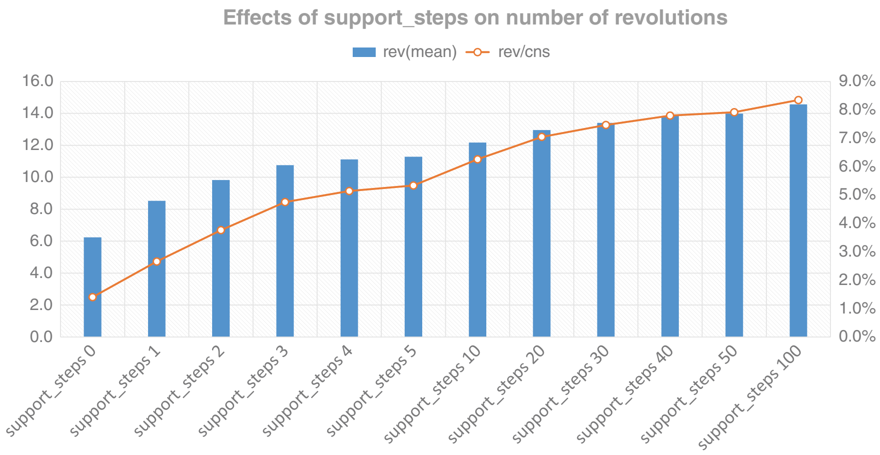

Fig. 10.4 Introducing short instances of local support for change agents increases the creative capacity of groups, but this effect decreases as support is extended over longer periods

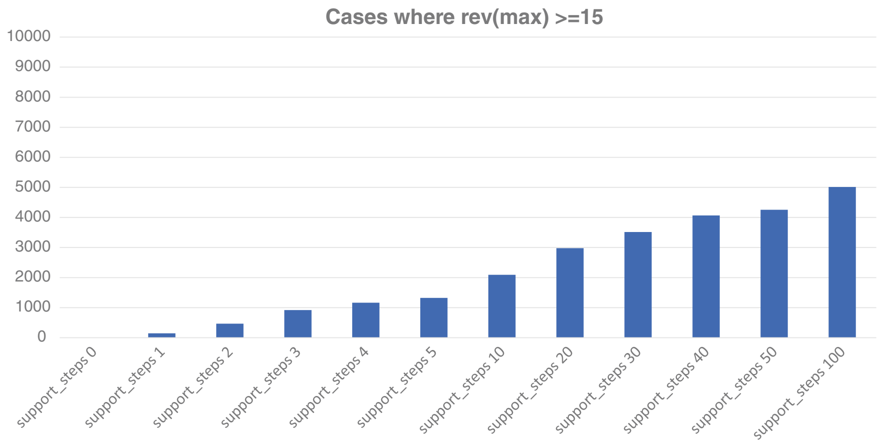

Fig. 10.5 Benchmark of cases where 15 or more revolutions occur, the *rev*(*max*) value when no local support is given to a change agent. Having local support even for one hundred steps means that one in two cases will reach a number of revolutions viewed only exceptionally in baseline conditions

changes); (c) differences between support from adjacent neighbours compared to support from distant group members (idea champions in the same department versus a remote department in the organization); and (d) effects of antagonistic neighbours, i.e. 'reverse-support', would brief instances of opposition play a significant role in 'sabotaging' new ideas and impeding revolutions?

10.4 Discussion

As with other types of inductive research, social simulations are valuable in new lines of enquiry where limited knowledge is insufficient to deduce testable propositions. Such models are not expected to replicate observed situations, or provide conclusive evidence to assess current theoretical constructs. Their role is exploratory, their value is to aid reasoning, and they constitute an inductive approach to the study of creativity: these models help demonstrate what is possible, with the advantage of explicitly representing the mechanisms and dynamics at work.

In order to guide multidimensional computational modelling, the following guidelines are formulated extending the work by Jordanous (2012) inspired by the need for more methodical approaches to computational creativity. These guidelines aim to be flexible to support a wide range of modelling scenarios, yet support clearer specification and communication across studies including a more objective definition of assumptions and agent behaviour.

- **Guideline #1: Scales to be included within the model**
  - Define primary target scales in the model. Whilst empirical validation may not be possible across levels, computational explorations support modelling creative agency at different scales.
  - Identify level variables (experimental and dependent) that represent observable behaviours or patterns of interest. Background literature from several disciplines may inform the formulation of contextual conditions.
  - Define inputs and outputs at target levels, establishing the bootstrapping strategies of the model. Spell out the modelling assumptions at each scale.
- **Guideline #2: Processes and links between scales**
  - Establish explicit connections above/below primary levels in the model.
  - Define irreducible factors, causal links, and whether the model is being used for holistic or reductionist purposes.
  - Identify internal/exogenous factors to the system. Justify the use of randomness at each scale.
- **Guideline #3: Processes and links across time**
  - Establish time-based conditions, processes, and variables of interest.
  - Ensure that the targeted time series are reproducible to allow for experimental treatment.
- **Guideline #4: Define system outputs**
  - Define type and range of outputs, identifying extreme points such as non-creative to creative artefacts.
  - Specify parameter ranges, identifying idealized conditions when relevant.
  - Capture and analyse aggregate data, model tuning, and refinement.

- **Guideline #5: Evaluation metrics**
  - Validity may be achievable in models where relevant empirical data exist at the primary level(s) of interest, but this may be inaccessible and even undesirable for inductive, exploratory models.

10.5 Conclusions

This chapter aims to present computational social simulation as a way to inductively study the dynamic interactions in creative teams. Agent-based simulation is introduced based on a framework for the computational modelling of creative agency at multiple scales. Through a systematic examination of convergent and divergent group dynamics, the chapter focuses on the effect of local group support as initially described by Gardner (1993) in his biographical study of prominent creators. The model confirms the critical importance of local support and further suggests that even temporary local support may significantly increase the creative capacity of a group. Moreover, the results of this model show that local support may be subject to a gradual process of diminishing returns, suggesting future research directions to better understand and manage creative teams.

The usefulness of computational models of group creativity is defined by their capacity to aid as reasoning tools, to explore hypotheses, to identify and connect issues across scales, and to articulate informed conversations between disciplines.

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Chapter 11
Human and Computational Approaches for Design Problem-Solving

Paul Egan and Jonathan Cagan

Abstract Human and computational approaches are both commonly used to solve design problems, and each offers unique advantages. Human designers may draw upon their expertise, intuition, and creativity, while computational approaches are used to algorithmically configure and evaluate design alternatives quickly. It is possible to leverage the advantages of each with a human-in-the-loop design approach, which relies on human designers guiding computational processes; empirical design research for better understanding human designers' strengths and limitations can inform the development human-in-the-loop design approaches. In this chapter, the advantages of human and computational design processes are outlined, in addition to how they are researched. An empirical research example is provided for conducting human participant experiments and simulating human design problem-solving strategies with software agent simulations that are used to develop improved strategies. The chapter concludes by discussing general considerations in human and computational research, and their role in developing new human-in-the-loop design processes for complex engineering applications.

Keywords Problem-solving · Complexity · Human-in-the-loop

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11.1 Human and Computational Design Approaches

Although many design methodologies are presented as a concise series of steps to follow, in practice, design is typically anything but formulaic. Successful human designers draw upon years of experience and use non-sequential approaches to solve problems with deductive, inductive, and abductive reasoning processes (Dorst 2011). Empirical design research approaches have begun forming a foundation of scientific evidence to describe human design reasoning, but there is still much to learn (Dinar et al. 2015). Basic design reasoning, such as logically evaluating quantitative design trade-offs, is often easier to measure and scientifically describe than blurrier processes such as creative thinking. Current research endeavours have begun simulating basic design reasoning with computational approaches, which could lead to automated approaches for solving design problems at a much faster rate than human designers may accomplish. Findings may also provide insights for better understanding human design reasoning processes (Egan et al. 2015a; McComb et al. 2015; Yu et al. 2015).

The vision of computers perfectly mimicking human reasoning processes has long sparked the imagination of researchers, but there have been many roadblocks in creating an artificial intelligence that fully emulates intelligent human behaviours (French 2012). Although major advances have been made in artificial intelligence fields, it is likely that highly complicated reasoning processes, such as design, will not be fully recreated by computational approaches in the immediate future. In the meantime, computational design approaches are useful for efficiently making algorithmic design decision-making processes that support human design process. When deployed effectively, computational automation can improve the pace of a design project by rapidly generating, evaluating, and selecting design concepts. To effectively use computational processes to support human designers, it is important to understand the advantages and differences amongst human and computational design approaches (Fig. 11.1).

Design problems are typically ill-defined initially which makes them difficult to formalize for computational processes. Human designers, however, are capable of redefining a design problem towards a more manageable representation (Björklund 2013). Once better defined, a designer can use creative processes to propose solutions that draw from their experiences beyond the design problem itself. These are generally qualitative processes that are difficult to translate into algorithmic logic

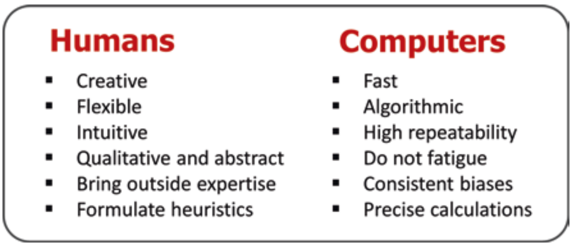

Fig. 11.1 Advantages of human and computational design processes

for computational processes. However, a designer has a limited cognitive capacity for reasoning about the many variables that may be found in a design problem; depending on the situation, a designer may use their intuition (Pretz 2008) or formulate heuristics (Daly et al. 2012) to quickly propose a good solution that works, rather than exhaustively searching a design space to find an absolute best solution.

Computational design processes, in contrast, tend to work best when they extensively search a design space according to a set of rules. These rules remove many biases from the design process that humans are likely to carry from past design experiences. Computers can store a large number of variable relationships simultaneously and are not subject to fatigue like human designers that only work effectively for a limited duration of time. Computational processes also offer a high degree of repeatability when solving problems, whereas humans may be inconsistent. When repeatable deterministic approaches for solving a design problem are found to limit a computational search's ability to find high-performing alternative design solutions, computers may be programmed with stochastic or probabilistic decision-making strategies (Cooper 1990). Stochasticity is often necessary to encourage a computational process to explore a diversity of solutions before converging on its best considered solution. Due to computational approaches being advantageous for algorithmically finding solutions to a design problem, they are commonly used once a design problem has already been framed by a human user, such as optimizing an already parameterized design.

Because there are both advantages and disadvantages to human and computational design approaches, it is important to carefully consider the characteristics of a design problem prior to selecting a process. An approach that considers both human and computational processes can leverage the benefits of each and is particularly helpful for engineering complex systems (Ottino 2004; Simpson and Martins 2011). Complex systems are notoriously difficult for humans to understand (Hmelo-Silver et al. 2007; Chi et al. 2012) due to their large number of variables and emergent behaviours. Computational processes can be used to quickly evaluate variable relationships and provide analytical output describing a complex system for a human designer to interpret. A human designer may then steer computational processes with a "human-in-the-loop" design approach by making high-level decisions that guide the computational processes towards more beneficial solutions (Simpson et al. 2011). In this framework, a human designer could potentially steer computational processes based on knowledge of multilevel parameter interactions that influence qualitatively distinct emergent system behaviours (Egan et al. 2015c) and could potentially be difficult to formalize computationally. Empirical research studies can play a role in scientifically determining the most effective way to interface human and computational decision-making processes for solving such design problems.

The aim of this chapter is to investigate the use of human and computational approaches for solving design problems and how to empirically study them. Research methods and findings concerning human and computational processes are covered next in Sect. 11.2. In Sect. 11.3, an empirical research approach for developing new design strategies with human participant experiments and computational simulations is provided as an example for conducting a controlled scientific investigation for empirically researching design problem-solving. Further considerations for using human and computational processes in empirical design research and for human-in-the-loop applications are discussed in Sect. 11.4 prior to concluding the chapter.

11.2 Human and Computational Design Research

This section covers a few of the many research approaches and findings for empirically studying human design reasoning processes and conducting computational design research. The use of graphical user interface (GUI) experiments is introduced as a basis for bridging human and computational processes in empirical design research.

11.2.1 Human Participant Experiments

There are a large number of approaches used by researchers for empirically studying human designers, which include verbal protocols, case studies, and controlled experiments (Dinar et al. 2015). Controlled experiments are particularly useful because they enable precise study of specific design processes with rigorous statistical comparisons, rather than case studies and verbal protocols that may contain more conflating variables that obscure the validity of conclusions. Experimental comparisons of novices and experts are common in design research (Björklund 2013) and particularly useful because they can reveal key attributes of expert designers that novice designers do not possess, but could learn. However, even expert designers are subject to cognitive limitations (Linsey et al. 2010) and could benefit from computational support, especially when considering the fundamental limits of human cognitive processes.

Numerous experiments have demonstrated that humans have limited working memory and are subject to cognitive load. Three types of cognitive load that may influence a designer's reasoning processes are: intrinsic, extrinsic, and germane (Van Merriënboer and Sweller 2010). Intrinsic load is caused by a design problem itself, extrinsic load is related to other information presented to a designer not directly related to solving the design problem, and germane load is proportional to the effort a designer places into solving a problem. Designers are more successful when all types of load do not surpass a particular threshold that is dependent on the cognitive capabilities of the designer. Germane load can aid in design problem-solving if it is not too large, since the effort placed into solving a design problem can result in learned knowledge that helps enable the designer to make better decisions while solving a problem. There are a number of techniques used to measure cognitive load (Hart and Staveland 1988; Paas et al. 2003; DeLeeuw and Mayer 2008) that are typically conducted by exposing human designers to increasingly difficult problems and measuring their performance and/or considering self-reports from designers.

The amount of information humans may consider at a time is limited to a few pieces of information (Miller 1956), which can impede human design problem-solving performance. Such limitations have been observed as humans solve increasingly difficult parametric design problems (Hirschi and Frey 2002) with experiments showing that as the number of considered variables increases human problem-solving performance declines significantly. These findings are related to design since each parameter could theoretically be tied to a real-world design variable. This decline in human performance occurs because it is difficult for human problem solvers to retain information concerning all parameter relationships while also making decisions for solving a problem. Due to these limitations, problem-solving strategies that enable humans to change only one variable at a time are beneficial (Kuhn et al. 2008; Chen and Klahr 1999), in part because they enable learning how each variable works in isolation rather than reasoning about multiple parameter interactions simultaneously.

11.2.2 Computational Design Research

Unlike human designers, computers are not subject to the same limitations in working memory and cognitive load. Computational design approaches are particularly well-suited for solving optimization design problems, since computational approaches perform quantitative operations at a much faster rate than any human. A difficulty in using computational approaches emerges when selecting the best algorithmic strategy for solving design problems. There is a diversity of strategies for solving design problems (Belegundu and Chandrupatla 2011), and the most effective strategy depends on the nature of a design space. Common computational search strategies range from being deterministic and reaching the same answer every time they solve a design problem to being highly stochastic (Du Pont and Cagan 2012; Yin and Cagan 2000). Stochastic searches are necessary when a design space has many locally optimal designs since a deterministic approach is more likely to converge on a final design that underperforms in comparison with the best possible solution.

The use of software agents is common in computational design research to solve a wide variety of design problems, with the potential for software agents to work together through using a diversity of strategies (Campbell et al. 1999). Software agents are computational objects with varied capabilities in perceiving, manipulating, and learning about a virtual environment. Both stochastic and deterministic search approaches may be used by agents in addition to agents adapting their strategies during a design space search (Hanna 2009; Landry and Cagan 2011). Agents can use processes that mimic human reasoning, learn during problem-solving (Buczak et al. 2006; Junges and Klügl 2012), and may be tuned with varied strategical preferences suited to different design problems. In addition to strategical preferences, agents may possess knowledge that emulates human experts (Schiaffino and Amandi 2009). These qualities of agents make them highly amenable to simulating human design reasoning processes and could provide insights for new ways that humans could solve design problems (Egan et al. 2015a).

11.2.3 Graphical User Interface Experiments

Graphical user interfaces (GUIs) are interfaces that enable human users to interact with electronic devices or software programs using graphical icons or visual indicators. They are commonly used in psychology studies to gain data that enable inferences of human reasoning processes. In design contexts, a GUI can present a user a set of design inputs and then evaluate the performance of a user-configured design. Engineering design experiments have demonstrated that information presented to a user via a GUI can influence their design decision-making choices, with participants having higher design optimization success when information is provided in real-time in comparison with a delayed response (Simpson et al. 2007).

Some GUI studies have investigated human understanding of complex systems (Vattam et al. 2011), which can inform design approaches where humans guide computational routines with a GUI (Parasuraman et al. 2000). A key consideration in constructing a GUI is the tuning of cognitive load a designer experiences (Hollender et al. 2010). Extrinsic cognitive load may be minimized by only presenting information relevant to solving a design problem, which is demonstrated in a screen capture of a design GUI in Fig. 11.2 for optimization problems.

The GUI in Fig. 11.2 presents an optimization problem prompt in the top left of the screen and enables users to manipulate design inputs via sliders on the left

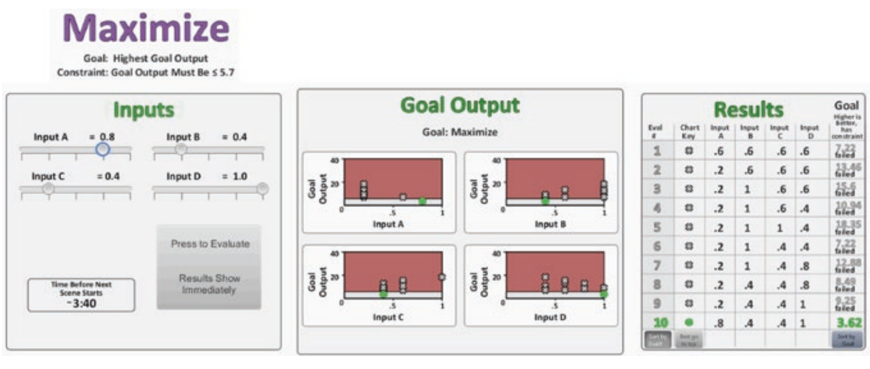

Fig. 11.2 Screen capture of a GUI for tracking human design searches

side of the screen and evaluate designs with a large button. Constraints in the problem statement are represented by red areas in charts in the middle of the screen. In the charts, evaluated design inputs are plotted as independent variables and the goal output is plotted as a dependent variable which provides a visualization of the design space (Kollat and Reed 2007). Due to the difficulties humans have in interpreting multivariable plots (Zhang et al. 2012), a table on the right of the screen presents results in a second format. Buttons along the bottom of the table enable automated design sorting to aid users in quickly comparing design evaluations.

Figure 11.2 GUI is only one possible way of presenting information visually to a designer and is particularly well-suited for conducting experiments concerning designers' decision-making processes. GUIs for other experiments, such as tracking a user's creative thought processes, may look very different and could include input areas for designers to write about their thought processes or sketch designs.

11.3 Example: Empirical Human-Agent Research Approach

Our goal in this section is to communicate core techniques and processes required to conduct empirical design research with humans and computational process, where human participant data are tracked with a design GUI and computational processes are carried out by software agents. An example is illustrated with abridged findings from an empirical human-agent research approach (Egan et al. 2015a), which we refer the reader to for a more thorough explanation of experimental techniques and findings. In brief, the example is motivated by recent advancements in the understanding of cognitive approaches that now make it feasible to understand a human design search strategy, model that strategy computationally, and then computationally optimize refined search strategies that humans can apply to more effectively and efficiently solve future design problems of similar ilk.

11.3.1 Defining an Experiment

The first step in carrying out an empirical design research study requires clearly defining the experimental goal. For our design problem, a complex muscle biosystem was considered across scales, with a particular emphasis placed on the mechanical design of nanoscale motor proteins (Howard 2001; Egan et al. 2013). Due to the complexity of the design problem, human-in-the-loop approaches (Simpson and Martins 2011) were identified as a potential design strategy that motivates the need for human participant experiments for empirical testing and validation (Egan et al. 2015b). A specific research goal was formulated to isolate a highly successful and empirically validated search strategy for human designers.

Table 11.1 Testable cognitive-based design search strategies

Design search strategy	Human reasoning process	Software agent rules
Near	Designs are improved through small changes	One or more design inputs for current best design are perturbed
Univariate	Manipulating one variable at a time enables controlled changes for finding better designs	One design input for current best design is perturbed
Learn and Apply	Learning how each variable influences a design can inform search decisions	One design input for current best is perturbed; findings direct future design perturbations

A sample set of search strategies amongst the diversity of existing optimization strategies (Belegundu and Chandrupatla 2011) were identified as potentially useful for humans to use and inform which search behaviours of human designers should be tracked in the experiment. A restriction is made in this study to only consider designs that are algorithmic, so strategies may be implemented and refined by software agents. Three cognitive-based strategies informed by the literature were proposed and are presented in Table 11.1.

The Near strategy in Table 11.1 is proposed by considering a human designer's limited cognitive capacity, meaning search decisions should require low effort (Hirschi and Frey 2002), which could be facilitated by making small changes to an existing best design. The approach was also used in engineering strategies such as the extended pattern search (Yin and Cagan 2000) that uses information based on the current best designs to inform choices in selecting new designs. The Univariate strategy (Chen 1999; Kuhn 2008) in Table 11.1, where only one design input is changed when modifying a design, is proposed since it requires a low cognitive effort in human decision-making while also reducing the effects of parameter coupling from an engineering perspective. The Learn and Apply strategy in Table 11.1 is proposed since humans may learn parametric relationships that are stored initially in short-term memory (Hirschi and Frey 2002) and apply knowledge of relationships towards improving a design. The application of knowledge during a search could promote fast convergence on a high-quality design from an engineering perspective. These strategies are only a portion of the possible strategies that could be investigated and are chosen as feasible strategies for initially testing and implementing the empirical research approach.

11.3.2 Experimental Method

Once potential strategies are identified for testing, an experimental methodology is developed to measure human design behaviours in an effort to empirically determine which strategies humans may use and are most effective. Our approach

Fig. 11.3 Empirical human-agent research method. *1* Humans search with no provided strategy. *2* Agents refine most successful human-derived search strategies. *3* Humans search with best agent-refined strategy

consists of human participant experiments and software agent simulations with steps for the following: (1) collecting human search data and identifying the most successful search trends related to proposed cognitive-based strategies, (2) refining the best human-derived search strategies through exploration with software agents solving the same design tasks, and (3) validating the usefulness of the agent-refined strategies with a final human subject experiment. Participants using the agent-refined strategy should, on average, find significantly better designs than designers in the initial human subject experiment (Fig. 11.3). The best strategy found is representative of an empirically validated approach for human designers to use to support a human-in-the-loop design approach.

The numbers in Fig. 11.3 reflect the growth of design scores across steps when designs are rated on a scale of 0–1. Design ratings are expected to improve through each phase, but do so according to a statistical distribution since there is typically a stochastic element in human decision-making and all participants in an experiment are likely to search the design space uniquely. Software agents are also programmed to make design decisions stochastically. Due to the stochastic nature of searches, there is a need to collect large samples of data to find meaningful averages for statistical comparisons.

The method uses only two human subject experiments since they are typically resource expensive. The first human subject experiment is necessary for deriving initial cognitive-based search strategies, such that agents only refine strategies that a human designer could conceivably understand and implement, rather than search strategies that are computationally efficient but are potentially impractical for humans to use efficiently. It is possible to use the initial set of human searches as a control for validating the best agent-refined strategy in the second human subject experiment and to determine whether humans have greater search success when provided the agent-refined strategy.

11.3.3 Human Participant Experiment with no Provided Strategy

The first human participant experiment aims to determine whether successful human search behaviours agree with the proposed cognitive-based strategies in Table 11.1. 31 mechanical engineering students participated. Optimization problems with constraints on a goal/objective output and/or other performance outputs were used as design optimization tasks. An easy design task was created by adding a goal output constraint while a difficult task had an additional constraint on a secondary output variable.

Participants used a design GUI (Fig. 11.2) to manipulate 3 design inputs for configuring a single motor protein and 1 design input to determine how many proteins are in a system (Egan et al. 2013). Participants were allowed ten design evaluations and four minutes for each task. Once experiments were completed, data were separated by the 25 % most and 25 % least successful searches for each task, named the "best" and "worst" designer populations, respectively. Trends were assessed for each task separately and analysed to determine how often search rules were used by human participants that reflect each of the strategies explained in Table 11.1; results are plotted in Fig. 11.4 and search success was determined by rating a designer's best found design on a scale of 0–1 relative to the objective function value of the global optimal design for a given problem.

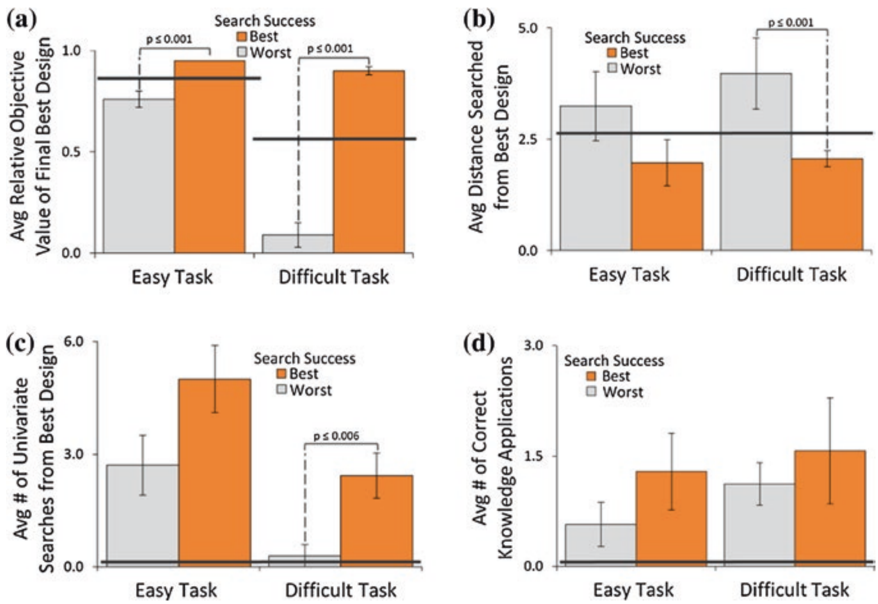

Fig. 11.4 Empirical results of initial human participant experiment

Figure 11.4a demonstrates that the best population found significantly better designs on average than the worst population on each task, so any search trends of the best population that significantly differ from those of the worst population may account for the differences in each group's success. A comparison of results with a random solver (black lines in plots) suggests that participants made deliberate decisions that may represent strategies used. Random solvers are useful as a basis of comparison since they can act as a form of experimental control when no other empirical data are available for comparison.

Figure 11.4b shows that the average distance searched was much lower for the best population on the difficult problem, suggesting that small changes to a good design can lead to higher search success. Figure 11.4c demonstrates that univariate searches were used by the best population much more often than the worst population on the difficult task. There are no significant trends in Fig. 11.4d to show evidence that one population used a Learn and Apply strategy more often; however, there is also no evidence to refute the strategy as beneficial.

11.3.4 Agent Simulations to Refine Human-Derived Search Strategies

Since cognitive-based strategies proposed in Table 11.1 are shown to correspond to how the best population searched in Fig. 11.4, it is promising to propose slight variations in each strategy and rapidly test and refine them with software agent simulations to find highly successful search strategies. Agents can explore strategical variations and test their influence on design search success at a much faster rate than further human studies. Additionally, agents have greater comparative power since simulations may run until there is little error.

Each software agent has access to the same information as human designers, which includes the design inputs and output values provided by the GUI. Agents assess the current state of a design search and input a new design based on a set of rules reflecting an agent's preferred strategy. Agent rules reflect the three cognitive-based strategies presented in Table 11.1. Differences in agent preferences reflect how far they search away from a previous best design or how they select design inputs initially. All agents with a particular strategy repeatedly solved a task and results are aggregated until error is negligible.

The average best relative objective function value found by agents for each cognitive-based strategy is plotted in Fig. 11.5. For all agent strategies, selecting a random set of design inputs was found as the most beneficial initial input.

Results demonstrate that the Near strategy performed worst for each task and the Learn and Apply strategy performed best. The Learn and Apply strategy marginally improved search success on the easy task compared to both other strategies and greatly improved search success on the difficult task. A black line that represents the findings of a random solver in Fig. 11.5 suggests that only the Learn and Apply strategy offers a large improvement over a random search. This finding is

Fig. 11.5 Best performance achieved by each agent-refined strategy

important, since when viewing the human data in isolation from Fig. 11.4, it is not possible to determine which differences in the best and worst populations' search trends may cause higher design search success.

11.3.5 Human Participant Experiment with Agent-Refined Strategy

A second human participant experiment was conducted to determine whether the Learn and Apply strategy improves human search success in comparison with the first experiment when no strategy is provided. A participant population of 30 students from a master's level engineering course was selected to closely match the first experimental population.

All aspects of the second human participant experimental protocol were identical to the protocol used for the first human participant experiments, except for a modification to the GUI to guide participants in making choices restricted to the same strategic rules as followed by the best agent-refined strategy. The results for the average best relative objective found by the humans in the first and second experiments and agents using the Learn and Apply strategy are presented in Fig. 11.6, with black horizontal lines reflecting random solver results.

Results demonstrate that on both tasks humans with guidance performed significantly better than humans with no guidance from the first experiment. These findings suggest that the introduction of the agent-refined strategy is beneficial for human searches and demonstrates the merits in implementing an empirical human-agent approach to discover and refine cognitive-based search strategies. These results illustrate how synergistically using human and computational approaches in research can reveal key insights concerning the design process, namely that human designers benefit from using control of variables strategies when solving complex system design problems. These findings are also informative for how to present a design problem for humans to solve when guiding automated processes in a human-in-the-loop design approach.

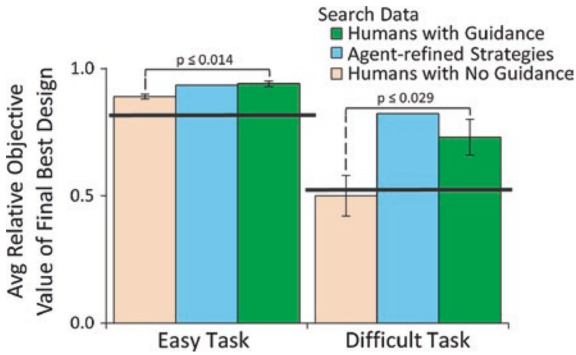

Fig. 11.6 Comparison of human search data with no guidance, agent-refined strategies, and human search data with guidance

11.4 Discussion of Human and Computational Design Processes

The need for further empirical research endeavours opens many new questions for discussion, including possibilities for extending experimental approaches with humans and agents and the potential to study diverse cognitive phenomena relevant to design. Studies of human designers can directly inform the set-up of human-in-the-loop design approaches for varied design applications and there is a great need for continued empirical design research for both understanding designers and establishing effective design approaches.

11.4.1 Human and Agent Experimental Approaches

There are many potential approaches for extending the example approach for simulating human designers with computational processes presented in Sect. 11.3, which may be accomplished by embedding different programming logic or assumptions in design problem-solving simulations. Software agents are particularly amenable for testing how varied assumptions influence design problem-solving outcomes since they provide a modular platform for implementing varied logic circuits. Agents also have autonomous decision-making capabilities that resemble human designers. Some possibilities include providing agents design heuristics used by human designers or with a priori knowledge of a design domain so agents can emulate human experts familiar with a domain. Findings of agents embedded with expert knowledge have demonstrated faster convergence for finding design solutions (Egan et al. 2015a). However, sometimes fast convergence is detrimental if it encourages the selection of a locally optimal design that underperforms in comparison with many other potential solutions. Introducing stochastic search logic (Du Pont and Cagan 2012; Yin and Cagan 2000) can encourage early design exploration for these types of design problems by enabling convergent searches to potentially begin from a more fortuitous starting point.

Recent studies have considered the simulation of entire teams for investigating cognitive phenomena by using similar agent simulation approaches. One approach has sought to recreate non-obvious human design behaviours with agent simulations paired with simulated annealing optimization approaches (McComb et al. 2015). This model investigates how designers work in teams to configure a complex truss structure and was validated with human participant experiments. By using the simulated annealing approach, a number of different cognitive phenomena were modelled, which demonstrates the robustness of using computational processes to recreate and explore human designer behaviour. Another study that used a simulated annealing approach has found that the most successful designers in a human participant experiment used search process that resemble a well-tuned simulated annealing optimization algorithm (Yu et al. 2015). The worst designers in the study tended to use pseudorandom approaches.

11.4.2 Potential Cognitive Phenomenon to Investigate

There are many reasoning processes designers use that could inform new empirical research investigations. Basic cognitive phenomena related to design are typically characterized initially in the psychology literature and require further investigation from a design perspective. There is a need to follow-up on fundamental psychologically studies with more specific design oriented experiments since design research seeks to answer questions that typically are not investigated in basic psychology research. For instance, human understanding of complexity has been studied psychologically (Hmelo-Silver et al. 2007; Chi et al. 2012), but there are fewer efforts to determine how understanding of complexity influences a designer's capabilities for making decisions.

One of our recent human participant experiments demonstrated that human understanding of qualitative behaviours across complex system scales improves human design decision-making performance (Egan et al. 2015c). However, a precise cognitive mechanism for how designers translate such understanding towards better design decision-making was not identified. This lack of explanation may be attributed to the small number of participants in the study and the large number of different strategies a designer may employ to use learned knowledge effectively. Therefore, the study has opened doors for new scientific investigations with alternate experimental designs that could specifically investigate potential cognitive mechanisms. Because experiments must be designed to target specific phenomenon, many empirical research endeavours pursue incremental advances based on unanswered questions from previous studies. Further cognitive phenomenon that may be of interest to design researchers are qualitative reasoning (Kuipers 1986) and spatial intelligence (Bhatt and Freksa 2015), which are both core cognitive processes that human designers use but are difficult to simulate computationally.

11.4.3 Empirical Findings for Human-in-the-Loop Approaches

Empirical research can inform design approaches by providing a scientific basis for how to design effectively. The research example provided in this chapter forms a basis for experimentally determining which human search strategies are potentially effective for aiding human-in-the-loop design approaches for complex systems design (Simpson and Martins 2011). In human-in-the-loop approaches, humans can use intuitive and qualitative reasoning processes that are difficult to automate, but crucial for generating novel concepts and quickly removing bad designs when solving a design problem. Computational processes are necessary to support design space searches when the number of considered variables surpasses human cognitive capabilities, since computational processes can quickly traverse a space and suggest design alternatives.

Empirical research can provide a basis for determining how well a human designer can understand a design space and form effective decisions. In the Sect. 11.3 example, empirical results showed that human designers could effectively reason about complex system design if they learned and applied knowledge using a control of variables approach when design optimization problems consisted of 4 design inputs and up to 2 performance outputs. The inclusion of a second performance output in a difficult problem significantly reduced human search success when compared to easy problem results (Fig. 11.4a), which suggests computational processes are increasingly needed as design tasks become more difficult.

These findings have now been used to form the basis of a human-guided system that includes computationally automated processes for discovery, description, and development of complex biological system designs (Egan et al. 2015b). In this approach, computational optimization is used to search a complex design space and find high-performing biolibraries. A biolibrary is considered a catalogue of biological parts used for forming a set of nanotechnologies similar to a product family. The human-in-the-loop approach is effective for this type of problem because a computational process can use stochastic search processes to find a generally high-performing set of nanotechnologies constructed from the biolibrary, with each individual nanotechnology being represented by 4 design inputs and evaluated with up to 2 design outputs that are suitable for humans to refine. The initial optimization problem solved by computational processes includes the optimization of many nanotechnologies that require simultaneous consideration of a much larger number of design inputs and outputs. Therefore, humans can make high-level decisions to improve the overall design of a biolibrary and developed nanotechnologies by making small changes to initial designs found during a computational search. The use of empirical design research has provided a basis for tuning the complexity of representations for human searches that would otherwise be difficult to determine, and how humans may best make strategic decisions for tuning designs suggested by initial computational searches.

11.4.4 Future Considerations for Empirical Design Research

Controlled scientific investigations are crucial for building a body of knowledge for design research, but there are limitations. Scientific investigations relying on statistical analyses tend to place a higher emphasis on studying successful processes that are favoured significantly by a majority of designers. It is possible that some successful design processes go unnoticed, which could be a problem in studies with low participant numbers. For instance, if the theoretically best possible design process was used by only one human participant, it would be difficult to identify the process used amongst other measured design behaviours more commonly used. Secondly, the process would likely not appear as significantly better than others when statistical tests are employed. Due to the logistics of experiments, it is not possible to empirically explore with human participants all possible influences on design search processes; design researchers must carefully consider the research goals they wish to explore prior to conducting a study. These limitations are an inherent part of the scientific process and also push experiments towards pragmatically investigating phenomena that are measurable since all scientific experiments must be conducted within the confines of time and resources available.

It is particularly important for design researchers to differentiate between the knowledge they hope to gain from scientific studies, and the knowledge that is feasible to gain from scientific studies. Although the introduction of computer simulations to mimic human designers can significantly enhance the rate of discoveries in design research, there are always roadblocks in setting up experimental controls and correctly validating studies with scientific rigour. These considerations can significantly influence the future outlook in empirical design research since rigorous research must constrict each new study to only measuring a small number of design phenomena. These limitations encourage the creation of new methods and empirical approaches that build upon one another to facilitate future research discoveries. These established findings may form a foundation for repeatable and controlled scientific investigations and act as anchors in empirical design research for continued discoveries with increasingly mature findings.

11.5 Concluding Remarks

In this chapter, an overview was provided for human and computational design processes and the need for empirical studies to better characterize human design reasoning, particularly for developing human-in-the-loop design approaches. Human reasoning processes tend to be creative, intuitive, and qualitative while computational approaches are fast, algorithmic, and quantitative. Human-in-the-loop approaches are advantageous since they can benefit from advantages offered by both human and computational design approaches. Empirical design research can play a large role in determining how to best tune a human-in-the-loop approach so human designers can effectively make decisions to guide computational processes.

Processes for empirical design research were demonstrated that include defining an experiment, developing a method for carrying out an experiment, measuring human design behaviour, and analysing data. An example empirical research approach was summarized that used human participant experiments and software agent simulations. Software agents are a particularly helpful approach since they may simulate human designers' reasoning processes and test human design problem-solving strategies at a much faster rate than extensive human participant experiments would allow. Continued research in this area has great potential in reaching new insights in how designers design through simulating their reasoning processes computationally, and using those findings for developing integrated human and computational processes for designing diverse systems.

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Part IV
Building on Experimental Design Research

Chapters 12–14 bring the previous parts together in order to explore how researchers can use experimental design research to build rigorous scientific knowledge. Chapter 12 discusses the foundations of theory building in the design research domain. This sets the stage for Chap. 13, which discusses how varied empirical approaches and theory can be synthesised into meaningful scientific knowledge. Finally, Chap. 14 explores the scientific models that can be produced from empirically-grounded data, and brings together the varied perspectives explored throughout the book linking back to the opening chapters in Part I. Part IV brings together the key elements of theory, methodology, and scientific modelling to provide a foundation for design researchers seeking to build compelling, theoretically grounded scientific knowledge.

Chapter 12
Theory Building in Experimental Design Research

Imre Horváth

Abstract As an introduction, a brief overview of the types and process of experimental research is provided and the concept of research phenomenon is discussed. Then, various kinds of theories, such as: (i) explorative, (ii) descriptive, (iii) explanatory, (iv) predictive, and (v) regulative theories, are considered as milestones of progression of knowing, and some philosophical stances and approaches of scientific theorizing are deliberated. Historically, there has been a move from empiricist and positivist approaches to pragmatist, interpretivist, and instrumentalist approaches of theorizing, which recognized the socially constructed nature of scientific knowledge. These approaches are concisely reviewed and, after that, a systematic procedure of theory building and testing is proposed, which harmonizes with the epistemological and methodological objectives of experimental research. It consists of an exploratory part, which includes knowledge aggregation, assumptions on conducting data generation, and deriving a specific theory, and a confirmative part, which includes justification, validation and consolidation of the proposed theory. As an exemplification, the differences of probabilistic theory building in various manifestations of experimental research are summarized. Finally, some propositions are made.

Keyword Theory building · Experimental design research · Natural and created phenomena · Milestones of knowing · Philosophical stances · Testing of theories · Statistics supported theorizing

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12.1 On the Objectives of This Chapter

Experimentation is one of the engaging practices of research. As its title communicates, the intention of this chapter is to cast light on the fundamentals of theory building and testing in experimental design research (EDR). The previous chapters have shown that EDR has huge potential for a greater utilization in design research, but also that it is very broad and the ways of arriving at tested theories are somewhat vague and uncertain. These all are correct observations because EDR can be conducted according to different research designs and, depending on the progression in knowing, different kind of theories can be sought for. Furthermore, not only obtaining intelligence for and construction of candidate theories are part of the endeavor, but also justification, validation, and consolidation of the proposed theory (Hughes et al. 1986). The rest of this chapter addresses many of these issues—as much as it is possible due to its limited extent. As a first step, Fig. 12.1 sketches up the so-called landscape of experimental work. It identifies three fundamental categories of experiments, namely: (i) thought experiments, (ii) computational experiments, and (iii) physical experiments. Individually or in combination, each of these plays a role in design research.

While thought experiments rely on cognitive capabilities and critical reasoning, computational experiments are virtual simulations based on mathematical models, computational algorithms, and contextualized data. Considering the environment of conducting experiments, we can talk about (i) field experiments, (ii) laboratory experiments, and (iii) mixed-placed experiments. Laboratory experiments, which can be conducted in both real and virtual laboratories (hence with local or remote instrumentation), offer high scientific control at testing hypotheses, but often suffer from the influence of the artificially created setting. Field experiments are conducted by applying various observational and intervening methods in naturally occurring environments in order to empirically examine various interventions in the real world. The specific objectives of field experiments can be: (i) measurement,

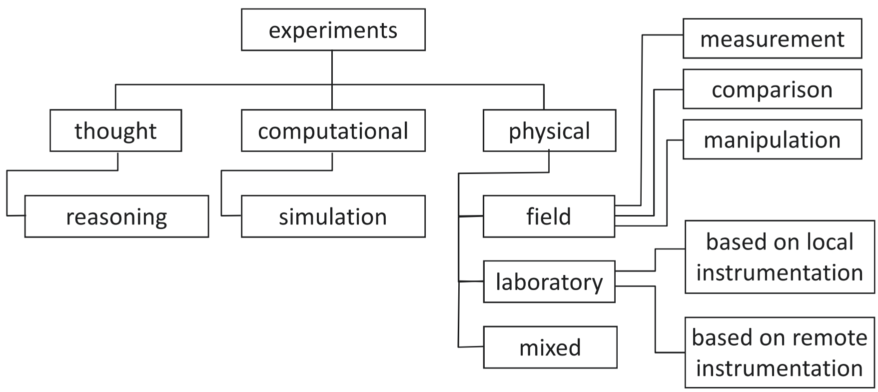

Fig. 12.1 Landscape of experimental work

(ii) comparison, and (iii) manipulation. In general, the sampling units of subjects and specimen are randomized in both field and laboratory experiments, and experimental and control groups are formed with the aim of comparing the outcomes between these groups. From the perspective of theory building and testing in EDR, the above three fundamental categories make no real difference. They can serve the purpose of data generation and aggregation equally well.

It seemed to be necessary to devise a consistent terminology for this chapter since there are at least as many interpretations of the notions and key terms in the related literature as authors, if not more. For this reason, let us continue here with some basic concepts and definitions of theorizing.

EDR intends to explore, describe, and/or explain various phenomena, which exist or are supposed to exist in the studied local world, based on tested facts and theories. A theory is expected to have implications in some contexts of knowing and is deemed to be a cohesive construct formed by logically coherent and semantically meaningful chunks of knowledge. Theory building may happen on a philosophical level, working with widely founded speculations, and on a practical level, involving work on experimentation. Since the stance of speculative deductionism contradicts to a large extent with the very essence of experimentation, theory building in EDR gives preference to other stances, such as inductive, abductive, and retrospective, instead. Finding facts and meanings is an important prerequisite and the first step of theorizing, no matter if expressed, embedded, or implied theories are concerned.

As indicated above, different types of experimental studies can be designed depending on: (i) the manner of sampling units of subjects and specimen, (ii) the environment of conducting the studies, and (iii) the extent of intervention taken into consideration in the study. Typically, four research designs are distinguished based on these factors: (i) true-experimental, (ii) quasi-experimental, (iii) pseudo-experimental, and (iv) non-experimental. Figure 12.2 shows the logic of differentiating the mentioned approaches. Quasi-experimental research designs differ from true-experimental ones in that they do not use random selection and assignment and they typically take less time and require less logistical support than truly experimental ones. The environment where an experimental research is conducted and the means used in experimentation (in particular, if they are not specifically developed for this purpose) also influence the type of experiment. If a true- or quasi-experimental research is conducted in laboratory environment, it is referred to as laboratory experiment.

As shown in Fig. 12.3, the root of theory development concerning a studied phenomenon is either curiosity (expressed by research questions) or assumption (expressed by research hypotheses). A hypothesis specifies an expectation about how a particular phenomenon is, works, and/or impacts. In this context, an experiment is a procedure carried out to verify, refute, or establish the validity of a hypothesis, or a set of related hypotheses. By means of a systematic manipulation of the factors determining a phenomenon, experiments provide insight into both the input factors (influences) and the output factors (implications), as well as the input–output correlations and cause-and-effect relations. Experimental design

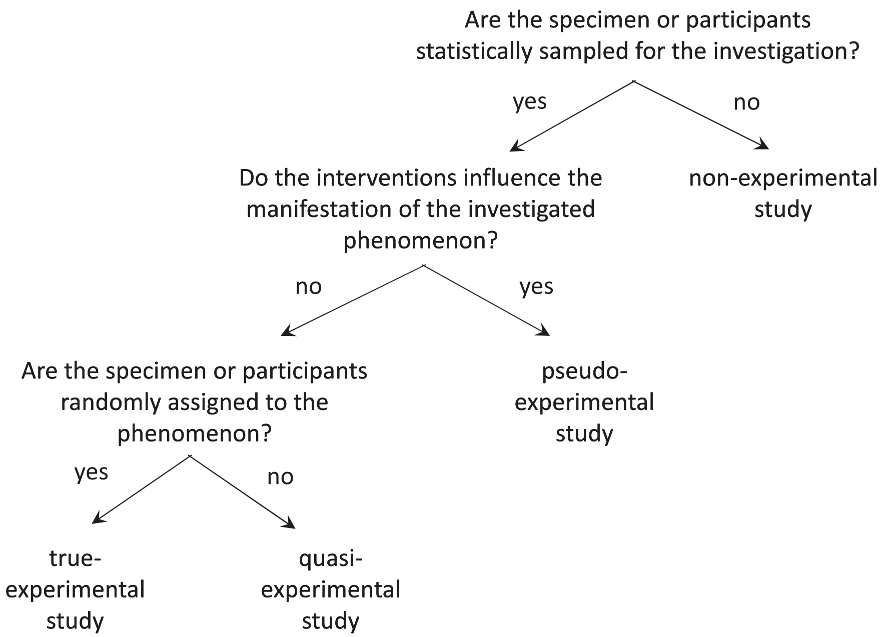

Fig. 12.2 Logic of reasoning about the types of experimental designs

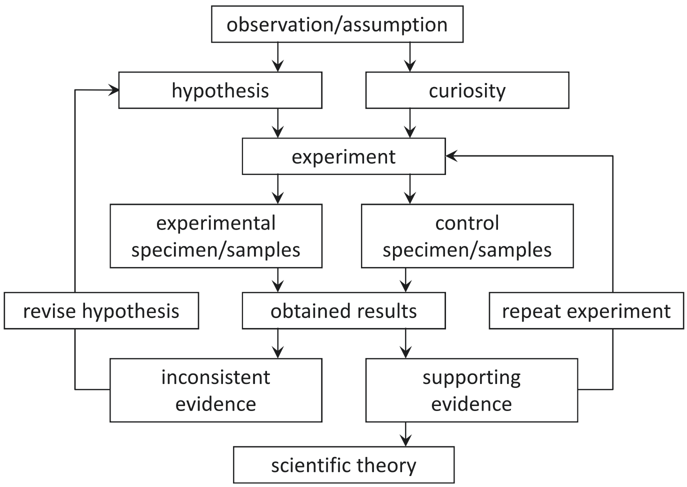

Fig. 12.3 The general process of theory development by experimentation

refers to the conceptual framework within which the experiment is conducted. It is a blueprint of the procedure that enables the researcher to test a hypothesis by reaching valid conclusions about relationships between independent and dependent variables. Schindler (2013) elaborated on the role of theory-driven data reliability judgments, according to which theories which are sought to be tested with a particular set of data guide reliability judgments about those very same data. This is of double relevance and importance in the case of experimentation is design research, which is driven by specific objectives and done in specific contexts.

In a higher resolution, twenty steps can be identified in the process of conducting experimental research: (i) identification and specification of the phenomenon, (ii) definition and operationalization of the research problem and objectives, (iii) formulation of overall research questions and/or hypotheses and conjecturing their consequences, (iv) making decision on the type of experimental research design, (v) construction of an experimental design that represents all related factors, conditions, and relations, (vi) determining the place, time, and duration of the experiment, (vii) estimation of minimal sample size and selecting the sample elements (e.g., subjects and specimen), (viii) construction (or selecting) and validation of the instruments to measure outcomes, (ix) identification and control of non-experimental factors, (x) conducting pilot studies to validate the research design, (xi) conducting the full-scale experiment (focused studies), (xii) compilation, filtering, and coding of raw research data, (xiii) quantitative, qualitative, and/or hybrid processing of research data, (xiv) application of appropriate tests of significance, (xv) critical analysis and interpretation of the findings to explore facts and relations for a proper theory, (xvi) documentation of the synthesized theory, (xvii) justification of the logical properness of the derived theory, (xviii) internal and external validation of the derived theory, (xix) internal and external consolidation of the derived theory, and (xx) making decisions of possible enhancements by an improved research design.

12.2 Phenomena as Target of Theory Building

Researchers study phenomena of the world around us and generate and test theories that describe, explain, and forecast them (Schwarz and Stensaker 2014). What is a phenomenon? Anything that is observed to exist or happen and is experienced as given (Bunge 1977). Phenomena are usually classified as natural or artificial (Falkenburg 2011). Wikipedia mentions several examples for natural phenomena such as sunrise, weather, fog, rainbow, thunder, tornadoes, decomposition, germination, wave propagation, erosion, tidal flow, electromagnetic pulses, volcanic eruptions, and earthquakes. On the other side, innumerous artificial phenomena have been identified or created by the various design disciplines, such as product experience, appreciation, attachment, metaphors, complexity, transparency, creativeness, design concept, stress, customization, paradigms, innovativeness, collaboration, tools, computer-support, simulation, and optimization. These, and lots of others, are already empirically known, but an infinite number of other existent or emerging phenomena are still undisclosed, or not subject of extensive investigations.

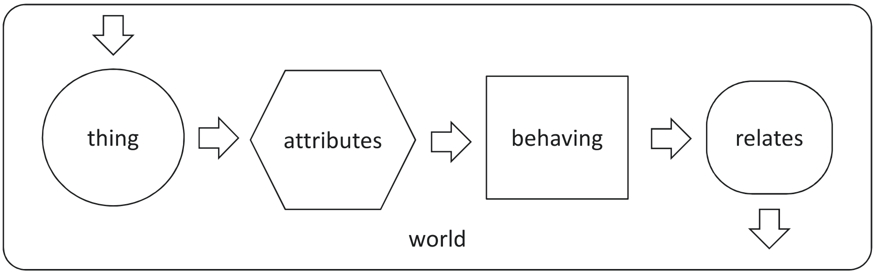

Fig. 12.4 Definition of a phenomenon as a compound cognitive concept

As the above examples indicate, a phenomenon may concern an object, fact, situation, case, occurrence, event, happening, circumstance, experience, change, impression, opinion, relationship, appearance, and so forth, especially those ones whose characteristics, manifestation, explanation, or effects are still in question. From the perspective of EDR, a phenomenon needs to be discernable and directly accessible to observation or intervention in real life, or reproducible under controlled circumstances in the local world of investigation. As shown in Fig. 12.4, it can be represented by a compound cognitive construct having either physical or intellectual origin. The cognitive construct identifies the thing that manifests itself in a local world and captures it through the attributes that characterize it. The way the thing manifests itself in the phenomenon is the discernable and accessible behaving of the phenomenon. This behavior establishes relations with other things and phenomena. The things, attributes, behavior, and relations can be the objectives of experimental investigation of the phenomenon by adequate methods and means.

In the literature of philosophy of science, there is a tendency to regard phenomena as images of reality. Notwithstanding, there is an intense debate about the relationships between data, phenomena, and theories, and concerning observable and non-observable phenomena (Glymour 2000). Stated by Woodward (2011), data are public records produced by experiments and measurements that serve as evidence for the existence or features of a phenomenon. It is also proposed that one should better distinguish between phenomena that are explained and predicted by theories, and data that are the observed outcomes of measurements. For instance, Bogen and Woodward (1988) argued that phenomena have to be inferred from data, and that data provide evidence for the existence of phenomena. Schindler (2011) took a position against this view by arguing that the reliability of data, which constitutes the precondition for data-to-phenomena inferences, can be secured without the theory one seeks to test. Apel (2011) scrutinized how exactly the distinction between data and phenomena has to be understood and what its philosophical impact is. From an empiricist perspective, observable phenomena are those, which human beings are able to sense and recognize by the natural sensory apparatus. Because these apparatus have inherent limitations, human observations involve uncertainty and human beings must use purposeful instruments to aid empirical observations of phenomena.

Many phenomena remain, however, unobserved even if the natural sensory apparatus is extended with sophisticated instrumentation. Recognition of phenomena in real life is often accompanied by commonsensical and/or critical reasoning. Unobservable phenomena can be pseudo-unobservable or not-at-all observable (Massimi 2007). Evidence for perceptually not-at-all observable phenomena comes from data that have been selected, regimented, and laboriously organized in a data model. Reasoning about their existence can be supported by thought experiments (speculations) and computational experiments (simulations). How phenomena manifest themselves in data models and how theoretical models able to save them are still topics of philosophical debates (Thagard and Litt 2008). Recognition of phenomena in real life is often also associated with and is the result of informed commonsensical and/or critical reasoning (Weick 1989, 1999).

If its attributes, behaviors, and relationships are accessible or attainable in the local world of study, then the phenomenon in question can be described directly. Otherwise, the whole of the phenomenon can only be described by indicators. An indicator is a research construct conceptualized to provide evidence on the existence, state, behaving, or condition of something. An indicator introduces research variables that may provide information about the attributes, behaviors, and relationships of a phenomenon. Evidently, research data provided by experiments are pure quantities or qualities (tokens), which need interpretation and transformation in order to be functionally meaningful in the context of attributes, behaviors, and relationships of a phenomenon. Their interpretation is normally enabled by existing theories or commonsensical reasoning.

Other issues to be considered are simplicity and complexity of phenomena, and their permanent or emergent nature. A phenomenon is said to be complex if it is a composition of multiple constituting phenomenon, rather than if it is influenced by a multitude of interacting factors. The distinction between simplicity and complexity has raised considerable philosophical difficulties when applied to statements. Hayek (1967) proposed a relatively easy and adequate way to measure the degree of complexity of a phenomenon through abstract patterns. Namely, the measure he proposed is the minimum number of elements of which an instance of a pattern must consist in order to exhibit all the characteristic attributes of the class of patterns investigated. He also argued that in the case of complex phenomenon it is more obvious that we must have our theory first before we can ascertain whether the things do in fact behave according to this theory. This entails that in order to be able to deal with complex phenomena, we shall first invent some pattern before we can discover its presence in the phenomenon. This needs a holistic view on it. Thus, a complex phenomenon is against a reductionist treatment, though there is no escape from the necessity of treating the constituting phenomena individually.

Emergent phenomena are circumstance-dependent and volatile appearances and behaving of things with gradual coming forth and weaker causalities (Deacon 2007). They are results of multitude of positive interactions among prevailing factors. Emergence typically goes together with the formation of ‘new’ attribute, behavior, and relation patterns as a result of the increase in the number of elements between which simple relations exist (Patel and Schnepf 1992). Humans have created many familiar examples of emergent phenomenon, but nature offers even more. In experimental studies, we can cope with permanent phenomena easier, than with emergent ones. Bonabeau et al. (1995) provided many practical examples of emergent phenomena in various contexts. As discussed by Darley (1994), in the case of an emergent phenomenon, even perfect knowledge and understanding may not give predictive information. Therefore, he proposed to use predictive simulations in these cases. At the same time, he warned us that for prediction of an emergent phenomenon, the amount of computation necessary to directly simulate it can never improve upon our knowledge of the rules of its interactions.

In a simplified interpretation, scientific knowledge is a fabric of tested facts, rules, laws, and theories of all forms (Shapere 1984). It emerges from very personal and fallible human research activities. Its seeds are human beliefs. In general, a theory is a construct of empirical facts and/or rational concepts and their mutual relations, with a large amount of evidence and testing behind it and conveys propositions about them and their implications. A fact is a statement accepted as being tested true because it can be verified by many observers and several research means. Regardless of the person taking the observations, a fact: (i) merely tells us what is, (ii) is observable and measurable, (iii) is always seen in the same way, and (iv) always produces the same results. Concepts are seen as: (i) mental representations (reflections) existing in the human brain, (ii) abilities peculiar to cognitive agents, and (iii) abstract objects of thought, language, or referents. A research concept is an abstraction or generalization from experience, or the result of a transformation of existing ideas.

12.3 Kinds of Theories as Milestones of Knowing

Parsons (1954) defined theory as a body of logically interdependent generalized concepts of empirical reference. Concepts can be treated in theories both explicitly and implicitly. Important is that a derived theory may blend the implications of multiple hypotheses made based on existing theories. For it explains and correlates many different facts, a theory has a broader relevance than a hypothesis. The statements of a theory: (i) explain all of the concepts and facts in a given context, (ii) logically relate the concepts and facts based on their semantics (meaning), (iii) make the applicability of the theory clear, (iv) indicate what is left over of the theory, and (v) imply new hypotheses that can extend the theory to cover a broader field.

Starting out from the perspective of a progressive scientific inquiry, comprehension of a particular phenomenon goes through a sequence of stages, which together is often referred to as 'the ladder of inquiry' (Fig. 12.5). If the phenomenon to be studied is completely unknown, then the scientific inquiry process may advance through five stages, namely: (i) unearthing, (ii) characterization, (iii) understanding, (iv) forecasting, and (v) manipulation of the phenomenon. This scenario of progression determines the kind of theory that is sought for in the

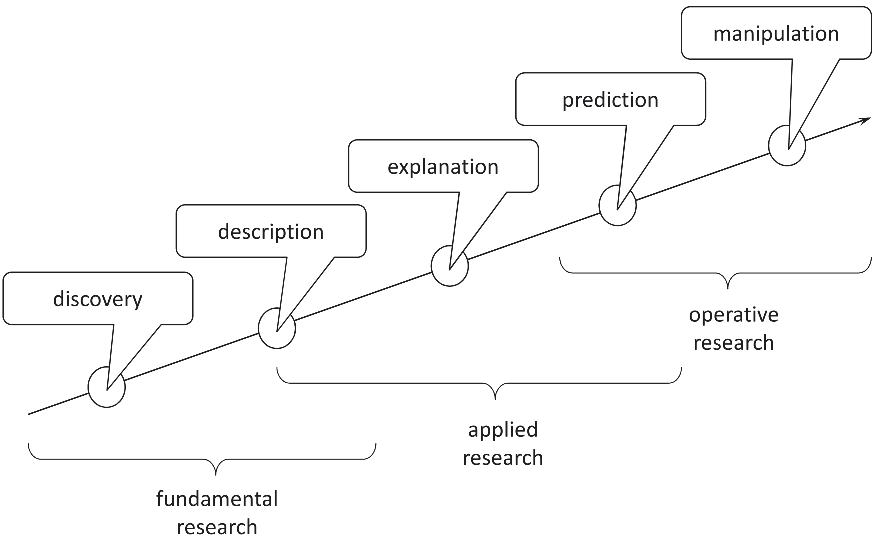

Fig. 12.5 The ladder of inquiry

subsequent stages of inquiry. Associated with the above stages, (i) explorative, (ii) descriptive, (iii) explanatory, (iv) predictive, and (v) regulative theories can be differentiated. As shown in Fig. 12.5, there is a relationship between the kind of theories and the fundamental, applied, and operative categories of scientific research, but clear-cut demarcation lines cannot be drawn between them based purely on the theories pursued.

As a consequence of the inherent uncertainty and ambiguity of discovery-oriented research, an explorative theory captures information that merely evidences the existence of a phenomenon and provides only an initial familiarity with it (Aliseda 2004). Descriptive research targets a careful and accurate observation and investigation, followed by a concrete rendering of the findings. Based on this, a descriptive theory is supposed to provide a complete and accurate account of all characteristics of a phenomenon. Explanatory research investigates the reasons why the investigated phenomenon behaves as it does and what happens with it in different circumstances and various contexts. An explanatory theory explains the influential factors, reasons, correlations, and causalities of behaving. Predictive research investigates probable outcomes of various interplays of the studied phenomenon with other phenomena. A predictive theory forecasts the effects of interplays in various contexts. Finally, manipulative research aims at developing theories concerning the control of the studied phenomenon and combining it with others toward practical advantages. Thus, a regulative theory conveys and operationalizes knowledge to support exploitation of the considered phenomenon in specific practical contexts.

In the rest of the chapter, theory building is regarded as a way of making sense of a disturbing situation (lack of knowledge). If the phenomenon chosen for the study is already known (observed or conceived), then the process of inquiry reduces to four stages and entails four of the theories mentioned above: (i) a descriptive theory that depicts what does exist in the studied phenomenon, (ii) an explanatory theory that clarifies why the phenomenon works as observed or assumed, (iii) a predictive theory that describes how the phenomenon influences other phenomena, and (iv) a regulative theory that facilitates the exploitation (of the implications) of a phenomenon in solving practical problems.

Theories can be substantive or formal. Substantive theories are developed for specific areas of inquiry and are transferable as a working theory only between similar contexts. Formal theories are validated and generalized across a range of inquiry areas and are transferable to different contexts. In the context of EDR, theories will be regarded as generalized accounts on manifestations of phenomena (how and why they occur). Design science needs a composition of formal and substantive theories. Agreeing with the position of Sjøberg et al. (2008), we argue that design theories should not only be correct, but also useful, because the objectives of designing cannot be achieved by theories of purely academic relevance and impact.

12.4 Philosophical Stances and Approaches of Scientific Theorizing

The related literature has identified and intensely analyzed the various approaches to theorizing, including all empiricist and rationalist models of thinking about scientific descriptions, explanations, and predictions. Historically, the first epistemological/methodological debates started with scrutinizing the role of empirical evidence and the logical inconsistences of creating inductive relationship between empirical data and a new theory. Inductive reasoning assumes a leap from singular observational statements to general theoretical statements, but struggles with the issues of incomprehensiveness or predictability. Therefore, the ideas of theoretically free empirical observation and naïve inductivism have been strongly criticized. Advocates of deductive reasoning (explanations) tried to show that unfamiliar phenomena can be reduced to some already-known phenomena in a rational (logical) manner.

As clarified by Salmon (1989), the move toward hypothetico-deductive model (HDM) of theorizing was driven by the idea that a given logical scheme can be employed to provide evidential support for a hypothesis to be tested. Due to its close relation to empirical research, HDM has been found restrictive in theory building in the eyes of post-empiricists. Thus, logical positivists tried to give a logical and linguistic formulation to their scientific theories. The quest for scientific explanation models continued in the early 1950s with the proposal of deductive-nomological model (DNM) (Brody 1972). As the study of physical and logical laws, nomology associates theorizing with revealing and structuring basic rules and laws by reasoning (Hempel 1955). Based on DNM, it is possible to logically deduce statements, which describe a phenomenon based on laws and on the consideration of background conditions. The idea behind the deductive-nomological theorizing is that the facts and logical relationships considered by the premises of the statements of a theory explain why the stated conclusions are obtained. DNM has been refined by introducing the deductive-statistical and the inductive-statistical models (Railton 1978).

It should be noted that the abovementioned models/methods are typical mechanisms of quantitative paradigm of reasoning. In the beginning of the 1980s, the issue of scientific explanation has been placed on new foundation that gave more space to various other ontological and epistemological stances (e.g., realism, pragmatism, interpretivism, and instrumentalism) (Kuipers 2013). The current situation is characterized not only by a peaceful coexistence, but also by non-decidability. Contemporary views on theory building give due attention to social influences on the development of scientific knowledge and there have been several convincing arguments made concerning socially constructed character of scientific knowledge (Mulkay 1979). For instance, one of the major claims of the interpretivist paradigm is the need for divergence from quantitative scientific explanation models. Interpretivist researchers prefer theory building based on qualitative methods rather than by means of hypothesis testing (Bendassolli 2013). They pursue achieving sufficient understanding of a particular phenomenon in a socially contextualized manner. For this reason, some alternative theory building methods have been proposed by them such as grounded theory methodology, which is driven by an analytic spiral of qualitative data interpretation and control. According to instrumentalists, a theory must be a diverse set of practical tools from which one can select those most helpful in solving any given (empirical) problem. Zhu (2010) argued that a pragmatist approach removes away the certainty and comfort that were promised by a master paradigm or a small set of mandatory paradigms; at the same time, it moves our theorizing closer to practice and changes it to theorizing about practices. A pragmatist strategy shifts the orientation of research from theory to practice and leads to operative experimental research (Knorr-Cetina 1981).

12.5 Systematic Building of Theories in Experimental Design Research

Discussed above, theory building is a long-debated issue for science philosophers and epistemologists dealing with the origins and creation of scientific knowledge. This chapter sets forth the argument that a basic unit of scientific inquiry is a research cycle and that every research project can be decomposed to a finite set of mutually dependent research cycles. In a general case, a research cycle may include multiple experiments or a chain of experiments. The very nature of a research cycle is defined by its epistemological and methodological completeness, while its practical manifestations are influenced by its objective, the context of study, and its methodological framing. Epistemological and methodological

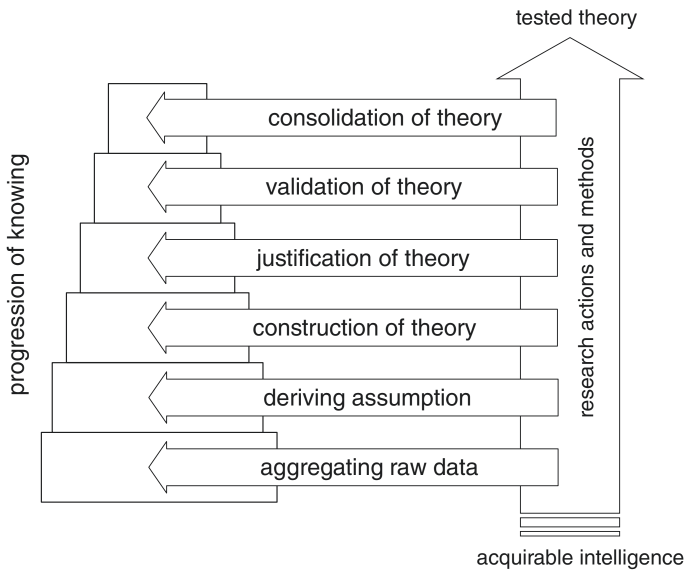

Fig. 12.6 Progression from data to theory in an experimental research cycle

completeness means that: (i) the generated knowledge fulfills the criteria of scientific knowledge, i.e., consists of properly tested correct beliefs, and (ii) theory building and theory testing research actions play equal roles in the conduct of research. Consequently, a common research cycle consists of two interrelated parts that are for: (i) attaining appropriate intelligence for theory building, and (ii) applying critical thinking for theory testing, respectively. We refer to the former as the exploratory part, and to the latter as confirmative part of a research cycle. The motion from data to theory is graphically depicted in Fig. 12.6.

The exploratory part typically includes three activities: (i) aggregation of scientific knowledge existing in the domain of interest, (ii) generalization of the findings and making assumptions for proper research challenges, questions, hypotheses, strategies, methods, instruments, and designs related to the studied phenomena, and execution of one or more experimental studies, and (iii) evaluation of data and findings, and deriving the targeted kind of theory based on them. The three major activities included in the confirmative part are: (i) explicit or implicit justification of the logical properness of the body and propositions of the derived theory, (ii) internal and external validation of the derived theory, and (iii) internal and external consolidation of the derived theory. This conceptualization is not in contradiction with the twenty-step process of experimental research discussed in Sect. 12.1, but makes a distinction between those research actions, which should be conducted within the framework of research cycles, and those which should be completed on research project level (e.g., deciding on the studied constituents of the research phenomenon and making decision on the overall research design).

Aggregation of related scientific knowledge is governed by the specific objective of the research cycle. Typically, a reasoning model concerning the related knowledge domain is constructed, which considers both primary sources (e.g., forerunning observations, experiments, and interrogations) and secondary sources (e.g., literature, Internet, and documents). Both qualitative and quantitative knowledge are sought for in a complementary manner. In the case of experimental research, data aggregation is done by using experimental method(s), but other methods of scientific knowledge aggregation such as literature review, expert interrogation, keywords-based Web search, and information mining are not at all excluded. However, design research has a peculiar feature with regard to knowledge aggregation, namely not only standard research methods are used for knowledge extraction and synthesis. Knowledge is also produced by many different intellectual activities such as critique of design practice, design discourse, design study, experiential experiments, narrative design reviews, to name but a few (Horváth 2004). As a result, formal (tested) knowledge is combined with informal (subjective and tacit) chunks of knowledge (Friedman 2003). This entails a chance that non-tested data, information, and knowledge weaken the basis that is used for further reasoning, e.g., hypothesis forming. There is no other (objective) criterion of when knowledge aggregation is completed than the assumed sufficiency of information for making informed assumptions in the next step. As discussed by Horváth (2013), additional goals are: (i) ordering the obtained knowledge according to the reasoning model, (ii) formulation of a critique of the current understanding and existing approaches, (iii) identification of knowledge gaps and limits of current knowing, (iv) identification of research opportunities for progression, and (iv) revisiting the research strategy and refining the planned research actions.

The next step is making research assumptions based on the specific findings of knowledge aggregation and creating a robust basis for theorizing. Generic assumptions are made by reasoning techniques such as inductive reasoning, taxonomic categorizations, and conceptual abstractions. In this chapter, hypothesis-driven systematic theory building is advocated; therefore, emphasis is put on the role of working hypotheses that enable the execution of one or more experimental studies. They have a kind of bridge function leading to theories. A hypothesis defines the orientation and scope of research activities, but more importantly, it should offer itself to testing and form a testable basis of a theory. A well-formulated hypothesis also says what will be measured and compared, and what it will establish. Appropriateness, testability, and strength of theorizing of the working hypotheses are true concerns. Hypotheses are usually based on previous observations or derived from existing theories that cannot explain the studied phenomenon satisfactorily due to their limits. The implications of the claim of the hypothesis are investigated by experimental work and the generated empirical data contribute to the body of a new theory.

The third step in the exploratory part of a research cycle is making various empirical and/or rational research actions to compile and structure the contents for a theory, which is able to fill in the knowledge gap and to describe, explain, predict, or manipulate the studied phenomena in the considered design context.

A presumption of theory building is that all generalizing assumptions made in the preceding step are defendable and the claims of the working hypotheses are testable. The theories are composed of generalizations which are not tied and relevant only to particular cases. Thus, they support understanding, but they can also be used for enhancement in multiple contexts, among other things, for building design prototypes that serve downstream confirmative stages as research means. As a vehicle of theory building, a combined empirical and rational hypothesis testing is advocated here. The objective is to arrive at a body of theory that is potentially open to disconfirmation by evidence (Rasmussen 2001). The actual strategy of theory building can be supported by: (i) adaptation of more generic theories (deductive theorizing), (ii) composition of implications of hypotheses (inductive theorizing), or (iii) finding the best explanation among several plausible or even competing explanations (abductive theorizing) (Peirce 1955). The chosen research strategy is supposed to be able to inform on how to get to a sufficiently comprehensible and dependable theory from research data through a process of theorizing, which can be validated. For instance, the abductive method of theorizing begins with an analysis of the antecedents and the consequences and then searches for reasons and explanations (Magnani 2004). That is, abduction is process-driven due to the need to distinguish between constructing possible explanations and selecting the best one (Kroll and Koskela 2015).

Suppe (1967) proposed to consider an instrumental view on scientific theories, according to which the most important function of a theory is to furnish material principles of inference that allows one set of facts from another, rather than to organize and assert statements that are true or false. When theories are regarded as principles of interference, rather than as major premises, we are no longer concerned with their truth or falsity directly, but with their usefulness in some practical contexts. This is important because theories of design science are supposed to be useful, but not necessarily absolutely true in all contexts. Nevertheless, design theories are supposed to be logically proper and functionally correct. These maintain the need for justification and validation of all candidate theories of design science.

Built theories can be documented in multiple forms, even in alternative forms in some cases. The most frequent presentation forms are: (i) qualitative narrative accounts, (ii) (set of) mathematical theorems, (iii) procedural mathematical models, (iv) computational models, (v) enumerative/evaluative visual diagrams, and (vi) multimedia representations. This order of listing has nothing to do with either the appropriateness or the power of a representation, which are primarily determined by the content of the theory and the targeted simplicity of delivery. Being a logical structure of verbal-conceptual statements, narrative accounts are used as frequently as mathematical or computational models. Usually, there are four basic objectives that the presentation of a theory should contribute to: (i) making obvious that the theory does fit and has overall relevance in the substantive area in which it will be used, (ii) supporting the understandability of the theory not only by professionals, but also by non-professionals, who are concerned with the substantive area, (iii) helping generalizability of the theory by capturing its essence in a context-independent manner, while providing indications of context-dependent applicability in the substantive area, and (iv) showing the potential of control of the captured phenomenon as it manifests itself in various changing situations. The above presentation also serves as means for communication of theories for different purposes.

Suppe (1977) argued that scientific theories cannot be defined in any simple or direct way in terms of other non-physical, abstract objects. According to him, a standard specification of a scientific theory consists of two parts: (a) an abstract logical calculus that includes: (i) the primitive symbols (theoretical words), (ii) the logical structure, (iii) the stated axioms and postulate, and (iv) the vocabulary of logic, and (b) a set of rules that assigns an empirical content to the logical calculus, including: (i) coordinating definitions and (ii) empirical interpretations. Both parts are needed for a complete definition of a theory. He also stated that without a systematic specification of the intended empirical interpretation of a theory, it is not possible to evaluate it in any sense as part of science. The model of a theory is highly abstract non-linguistic construct that facilitates its specification as a formal model using the language of mathematics or computation.

12.6 Testing of Theories

Experiments may vary largely in terms of their goal, scale, and conducts, but their commodity is that they are systematically done (involving repeatable procedures and tested methods), and that the findings and results are derived by rigorous logical analysis and empirical reflections. As an empirical and/or rational procedure, an experiment insightfully and carefully arbitrates between competing hypotheses or models of thinking. Despite these principles, there are many factors that may negatively influence the conduct and that may cause biases in the results of EDR. Ideally, none of the factors influencing an experiment are uncontrolled, but this is very seldom the case. For instance, randomized experiments are less frequently used to test the comparative effectiveness of different concepts and conceptual solutions than as it would be desirable in design research. Likewise, experimental tests of theorized human behaviors are typically made without relying on a random assignment of individuals to testing and control condition. Sometimes researchers are so busy at building their theory that they forget to look at observations that contradict the theory or feel too attached to it just because they "invented" it (hence commit what is often referred to as verification error). The abovementioned fact raises the need for and gives the floor to testing: (i) the experimental setup and its elements, (ii) the rationale and conduct of experimentation, (iii) the logical and practical properness of the findings and the derived theory, and (iv) the limitations, strong points, and implications of the derived theory.

The first step of theory testing is dedicated to a logical and conceptual justification of the theory. Justification determines if a design theory suffers from a fallacy. Theories may be discarded for not being logically consistent (if one contradicts

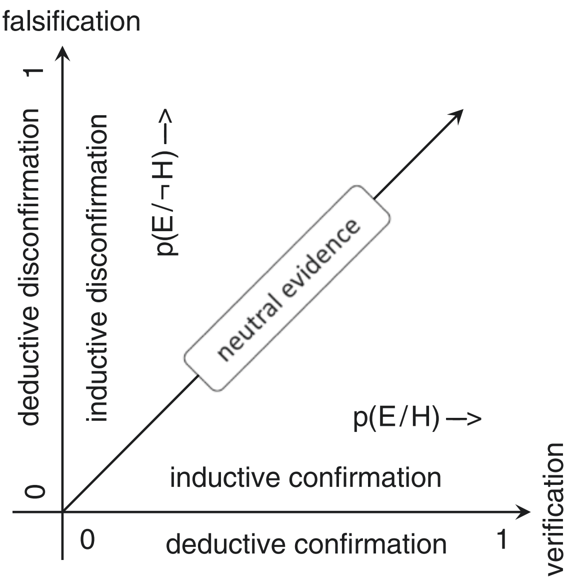

Fig. 12.7 Verification and falsification as strategies of confirmation of theories

itself) or for failing to correspond to the observable reality in some non-trivial way. There are various modes of inference as means of justification. In case of design research, justification of proposed theories much more often happens indirectly, than directly. Direct justification can be based on rational (e.g., mathematical) means or on empirical (e.g., observational or experimental) means. Both suffer from the induction problem that is associated with finding confirming or disproving cases. This has been investigated by many science philosophers in the context of both verification and falsification (Fig. 12.7).

In addition to testing the logical truth level and limits of the proposed theory, its conceptual integrity (consistence) and implications should also be taken into consideration. Advocates of verification argue that a statement of a scientific theory, which cannot be verified, is not necessarily incorrect or false, but principally meaningless because they are not demonstrable by empirical evidences. Testing the implications of theory paves the way to indirect justification that is in the practice governed by the strategy of ‘reasoning with consequences.’ The logical basis of this empirically oriented family of approaches is syllogism that claims that true conclusions can only be derived from true assumptions (that is, if the consequences can be justified, the theory that implied those consequences must be true). In practice, the reasoning with consequences approach involves operationalization of the theory by creating some sort of design prototypes (Zimmerman and Forlizzi 2008). Obviously, theories can rarely be tested as a totality, but from particular aspects only.

In the second step of theory testing, validation of the derived facts, laws and theories, and their implications takes place. Validity refers to the extent a study can be regarded as accurate and reliable, and its findings are relevant and useful in a given context or in general. Validity expresses the extent to which an actual research project or cycle satisfies the objectives that it was intended to achieve. In other words, validity refers to what degree the research reflects the given research problem, which introduces the aspect of time. Depending on the time of completion, validation can be: (i) prospective, (ii) concurrent, or (iii) retrospective validation. Based on the periodicity of application, it can be: (i) one-time validation, (ii) revalidation after change, and (iii) periodic revalidation.

According to its orientation, validation can be either internal or external. Internal validity is the extent to which the research design and the conduct of a study are likely to have prevented systematic bias, and therefore, the results may be considered reliable. Major aspects of testing internal validity in design research are: (i) investigator validity, (ii) concept validity, (iii) construct validity, (iv) method validity, (v) instrument validity, (vi) face validity, (vii) predictive validity, and (viii) environment validity. External validity concerns the extent to which the (internally valid) results of a study can be held to be true for other cases, for example, to different people, places, or times. In other words, it is about whether the propositions can be validly generalized. Hence, the measure of external validity expresses transferability or generalizability of the theory from one study to another considering different populations, settings, and arrangements. However, it is rather difficult, if not impossible, to capture the real meaning and manifestation of external validity with one single characteristic or feature in design research.

There are four major aspects of external validity: (i) population validity (if research participants are true representatives of the general population and how well the sample used can be extrapolated to a population as a whole along relevant dimensions), (ii) ecological validity (measuring the extent to which research results can be applied to real-life situations outside of research settings), (iii) utility validity (interpreting or measuring how much the new theory, model, or prototype is useful for the design practice in a broader sense), and (iv) similarity validity (consideration of the comparability of the conducted research project and other similar research projects). It is proposed that we can talk about general validity if, and only if, rigorousness, soundness, cogency, and convincingness are reflected by the research design and findings.

Finally, in the last step of theory testing, consolidation of the new knowledge (proposed theory, laws, and facts) is in focus. As a forerunning step, the investigation of external validity already addresses issues related to generalizability and reusability and provides information about the objectives and conduct of consolidation. It informs about how strongly the conducted research is dedicated to the given research problem, and what may be expected to occur in other research contexts. Consolidation can be seen from the perspective of the conducted research project (i.e., of the follow-up research cycles), and in more general disciplinary contexts.

Consolidation may involve both specialization and generalization of validated knowledge. Specialization is concerned with interpretation and adjustment of the facts and relationships of the theory to the same or refined contexts of the subsequent research cycle(s), where, combined with other aggregated knowledge, it is used as input. Generalization is concerned with putting parts or the whole of the constructed theory into a broader theoretical or epistemological context. Toward this end, the theory is typically decontextualized by means of critical thinking. Its context-dependent parts are peeled off and the limits of relevance or applicability of the context-independent part are defined. For instance, an example of generalization of explanatory knowledge is when the new theory about the experimentally found indicators of driving in haste is elaborated on to explain situations where humans should complete activities under time pressure and certain procedural constraints. Other form of generalization of a theory is integration (or blending) of its decontextualized part with some existing body of knowledge, with the intention of complementing the latter, while achieving high-level coherence and soundness. Obviously, generalization is difficult when the conducted experimental work has only a weak connection with or correspondence to real-world situations. This hazard is often out there in design research, for all or part of the investigated phenomena may be created as opposed to naturally occurring (Horváth and Duhovnik 2005).

12.7 Differences of Theory Building by Manifestations of EDR

In this section, we intend to cast light on the differences in the epistemological opportunities of theory building by using different experimentation methods. Due to space limitation, we could consider only three statistically supported theorizing approaches of experimental design research and the task of theory building in human context (Fig. 12.8). There are particular relationships among the various forms of experimental designs and the opportunities for theory building (or, from another aspect, for theories that can be derived based on these designs). For instance, pre-experimental research design usually has a loose structure and could be biased by uncontrolled factors, which have a strong influence on the opportunities of theory building.

In general, a quasi-experiment (or a pseudo-experiment) tries to prove causal relationships between two or more factors (variables) as in a true-experiment does. However, due to the differences in their manifestations it is done differently. It has been clarified earlier that a quasi-experiment deviates from a true-experiment in that it: (i) does not represent a full population (applies non-probabilistic sampling), (ii) lacks a random assignment of independent variables, (iii) not necessarily takes place in natural environment, and (iv) is often influenced by the presence of the investigator. These are important issues to be taken into consideration even if, evidently, a quasi-experiment can never be supposed to achieve a complete 'proof' of a hypothesis (it can only add support for the empirical and/or rational correctness of the assumptions). On the other hand, even a quasi-experiment may provide sufficient counterexamples that can disprove a hypothesis or an assumption about an existing theory. In design research, research experiments are often used to provide information about how physical processes work under particular conditions.

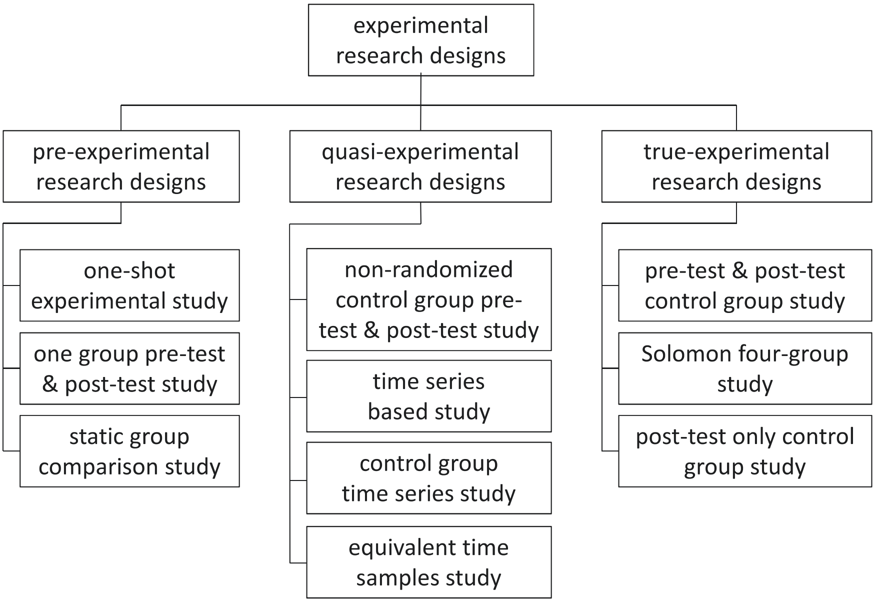

Fig. 12.8 The considered statistically supported theorizing approaches

A quasi-experiment may also aim to answer a 'what-if' question, without any specific expectation about what the experiment reveals.

There have been three statistically supported pre-experimental research designs (methods) identified in the literature. They have been named as: (i) one-shot experimental study (OSES), (ii) one group pretest and posttest study (OGPS), and (iii) static group comparison study (SGCS), respectively. OSES attempts to explain a consequent of a manifestation of a phenomenon by an antecedent, but suffers from limitation where there is a weak link between the antecedent and the consequent. ODPS investigates the relationship of a sampled group with the phenomenon, but it allows theorizing about the changes observed in the group, but only in the presence of the phenomenon. To eliminate the restriction of theorizing based on one group, SGCS intends to compare a group exposed to the phenomenon with a group not exposed to the effect of the same, but without investigating the pre-experimental equivalence of the groups.

Quasi-experimental design can be operationalized for theory building as: (i) non-randomized control group pretest and posttest study (NCPS), (ii) time series-based study (TSBS), (iii) control group time series study (CGTS), and (iv) equivalent time samples study (ETSS). NCPS investigates the essence, behavior, and effects of a phenomenon in situations in which random selection and assignment are not possible, accepting not equivalent test and control groups with a view to the pretest results. TSBS derives a theory about the phenomenon considering one group only, and after a series of initial observations repeat the experiment in different places under different conditions. To increase external validity, CGTS intends to strengthen the validity of the above experimental approach by involving a parallel set of observations with a control group not being influenced by the phenomenon. ETSS controls history in time designs with a variant of the above CGTS design, an on-again, off-again design in which the experimental variable is sometimes present and sometimes absent.

True-experimental design intends to achieve probabilistic significance in terms of theorizing about phenomenon and its effects, as well as greater control and context independence. There have been four research designs identified: (i) pretest and posttest control group study (PCGS), (ii) Solomon four-group study (SFGS), and (iii) posttest only control group study (POCS). PCGS derives a theory based on studying the effect of a phenomenon on a group, also considering its effect on a control group, with the objective to increase internal validity of theorizing. As an extension of PCGS, SFGS intends to reduce the effect of pretesting in theory building by putting the emphasis on the comparison of the variance of posttest results. POCS considers theory building, where pretesting is not possible and therefore, adapts the SFGS approach.

In addition to the above approaches, causal-comparative correlational studies (CCCS) and ex post facto studies (EPFS) are also often considered in EDR. CCCS seek for cause-and-effect relationships between two sets of data in a very deceptive procedure that requires much insight for its use. Causality cannot be inferred merely because a positive and close correlation ratio exists. EPFS search backward from consequent data for antecedent causes. As a matter of fact, this approach is experimentation in reverse. Logic and inference are the principal tools of this research design, but proof of the hypothesis through data substantiation is seldom possible. However, EPFS may investigate the effect of phenomenon across multiple (idiosyncratic) groups.

12.8 Conclusions

A treatise on scientific theorizing cannot be anything else, but incomplete. This is very much so when the issues of theory building and testing in experimental design research are addressed. Contrary to the obvious limitations, it is hoped that this chapter could overview the most important aspects and that it was able to provide sufficient insight into the most important issues. The main propositions are as follows:

- The knowledge exploration and exploitation processes of design are strongly influenced by techno-social constructivism, which lends itself to a 'designerly way' of knowing. As extension of Habermas (1993) categories of scientific knowledge, which are: (i) empirical analytical, (ii) hermeneutical historical, and (iii) socio-critical knowledge, design science contributes: (iv) techno-social constructive body of knowledge. Experimental research is one of the engines behind this effort.
- Experimental design research investigates recognized or conceived phenomena of the world around us and generates and tests theories that describe, explain,

forecast, and manipulate them. A phenomenon is experienced as given, but research may also study emergent phenomena, which are circumstance-dependent, gradual, and volatile in appearance, and behaves according to weaker causalities. Using predictive simulations seems to be a beneficial approach of dealing with emergent phenomena.

- Time has come to move beyond philosophical paradigms and stances of theorizing in experimental research. Contemporary views on theory building try to give due attention to objective realism and scientific rigor, as well as to social influences on the development of scientific theories and knowledge. Opposing mechanistic/nomothetic accounts, instrumentalist, and pragmatist approaches move experimental theorizing closer to practice. Important is to conceptualize and design experimental research in a socially properly contextualized manner.
- In the context of experimental design research, deductive theorizing is deemed to be a powerful approach to be considered. It provides a straightforward conceptual framing of the experimental work and initiates a novel reflection on the existing knowledge. However, it should also be considered that experimental research data are evidence of a phenomenon, not of the theory, which explains that phenomenon.
- In experimental design research, hypotheses are not only simple rational assumptions ('educated guesses'), but also patterns of concurrent reasoning. They can be explications for the factors influencing the studied phenomenon in experimentation-based theory building, but also links to practical evidences in experimental theory testing.
- Experimental design research can develop not only one kind of theory, but many, depending on the level of knowing the studied phenomenon, and the epistemological objectives the work. To systematize the procedure of theory building and testing, thinking in epistemologically and methodologically complete research cycles of experimental research is proposed. A research cycle consists of interlinked exploratory and confirmative parts. The former includes knowledge aggregation, assumptions on conducting data generation, and deriving a specific theory. The latter includes justification of logical properness, internal and external validation, and consolidation of the proposed theory.
- It is important for the researcher to make an attempt to maintain control over all factors that may affect the result of an experimental research. In doing this, the researcher should determine (or predict) at multiple stages of an experiment what may occur as not wishful concerning the study of a phenomenon.

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Chapter 13
Synthesizing Knowledge in Design Research

Kalle A. Piirainen

Abstract This chapter discusses knowledge synthesis in Design Research, bringing together the perspectives of experimental Design Research, or Research in Design Context that is treated extensively elsewhere in this book, with Design Inclusive Research as well as Practice-Based Design Research. Specific attention is paid to the question of how practice-based or problem-driven Design Research processes can be rigorous and yield contributions to knowledge. The main argument in this chapter is that a key to knowledge synthesis and scientific contribution is setting explicit design propositions that are instantiated within design artefacts and evaluated rigorously. This chapter starts with a discussion of knowledge creation and synthesis within Design Research. Following this, the chapter moves on to focus on setting a methodological framework for deriving design propositions. Lastly, this chapter elaborates on empirical aspects of evaluation of design artefacts and propositions and the associated knowledge claims.

Keywords Design Theory · Design Science Research · Design Propositions · Evaluation

13.1 Introduction

Design Research (DR) uses the scientific method to develop, test, and apply significant theoretical insights pertaining to design processes, designers, and design domains—the application areas under design (e.g. Cross 2001; van den Akker

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et al. 2006; Hevner 2007; Stolterman 2008). Historically, DR combines descriptive research of designers and design, as well as prescriptive methodological research on design processes, methods, and systems (e.g. Cross 1999, 2007; Bayazit 2004). As such, DR as a field holds a dual purpose to synthesize knowledge of different types; design researchers deal with, on one hand, experiential knowledge about design, useful tools, and methods for designers, as well as on the other hand significant theoretical contributions. It can be challenging, however, to synthesize the pragmatic goals of DR with the scholarly rigour of science in a way that both produces knowledge in the form of generalizable solutions to important classes of problems (practical insights) and yields rigorous contributions to academic knowledge and theory (scientific insights) (e.g. Cross 2004; Blessing and Chakrabarti 2009; McMahon 2012). A general challenge in DR is the focus on individual cases or situations and practical impact, often with weak or opaque theoretical grounding (Love 2002; Blessing and Chakrabarti 2009). This is especially true for problem-based DR focused on solutions, labelled Design Inclusive Research (DIR) and Practice-Based Design Research (PBDR). In these types of processes, the design process and artefact are as much in focus as theory development or testing (Horváth 2007, 2008).

In fact, Design Research and especially practice have a significant component of reflection in action (Schön 1983), which is not necessarily simple to codify to scientific knowledge. While this orientation supports achieving practical impact from research, generalization of the findings without knowledge or understanding of the underlying mechanisms is challenging, limiting both contribution to scientific knowledge and transfer of solutions. In other words, 'If we understand nothing of the causal mechanisms, then we can only achieve a given outcome by accident at first and by rote thereafter' (Briggs 2006). In recognition of this challenge, this chapter discusses knowledge synthesis bringing together the perspectives of experimental Design Research, or Research in Design Context that is treated extensively elsewhere in this book, and Design Inclusive Research as well as Practice-based Design Research.

The rest of this chapter is structured as follows: Sect. 13.2 lays out the philosophical grounds and discusses challenges for knowledge synthesis in (experimental) design research. Section 13.3 proposes a methodological framework to overcome these challenges specifically by developing and using design propositions as a nexus of knowledge synthesis. Section 13.4 focuses on expounding the connection between evaluation of design artefacts, propositions, and the associated knowledge claims. Finally, Sect. 13.5 presents the conclusion and discussions.

13.2 Challenges for Knowledge Creation in Design Research

This section lays out the philosophical framework and definitions for the discussion on knowledge synthesis. Building on that foundation, the discussion focuses on types and properties of knowledge and the challenges for knowledge synthesis in DR.

13.2.1 Philosophical Background and Assumptions

Horváth (2007) discusses three types of DR, called Research in Design Context (RIDC), Design Inclusive Research (DIR), and Practice-Based Design Research (PBDR). The distinguishing factor between these is the balance of focus between generation of knowledge about design and design of an artefact to satisfy specific needs. As presented in the context of this book, experimental design research often falls into the category of Research in Design Context, where the main focus is on generating knowledge about design processes, methods, and behaviours associated with design, as well as the products of design. In the other types of design research, DIR and PBDR, this interest in knowledge is paralleled with interest or ambition to create solutions to existing problems in the form of design artefacts.

Epistemologically speaking, out of the three types of DR, in particular, DIR and PBDR can be said to have adopted a pragmatic or instrumental approach to research, that is, placing precedence on utility and fitness to purpose of the design artefact and using that utility as a measure for evaluation of the artefact and claims to knowledge, most explicitly in Information Systems (Hevner et al. 2004; Gill and Hevner 2011; Piirainen and Gonzalez 2014). It follows that the ‘knowledge interest’ in this type of DR has been generally technical, that is, to understand and control the phenomenon of interest within the problem area (c.f. Habermas 1966; Donsbach 2008). In contrast, RIDC is not limited to technical interest, but framing can be motivated by a positive or critical knowledge interest. The epistemological orientation of DR is manifest in the framing of research questions, design, and evaluation (Niehaves 2007; Gonzalez and Sol 2012).

The ontological starting point for this chapter is a common-sense realist viewpoint after Moore (1959) that there is an external independent reality. Differing from earlier views of empiricists later known as (logical) positivists, Popper (e.g. 1978) argues that three ‘worlds’ exist: world one (W1) that is ‘real’ in the traditional sense, immutable, unchanging, and independent of the observer, a world of physical objects and events. The second world (W2) is the world of human observations, and emotions, in effect a kind of representation of the first world inside human psyche. The third world (W3) is a world of the artificial (Simon 1996). The third world contains the product of human mind, such as language, ontologies, and theories, as well as their instantiations as physical design artefacts.

In the context of this chapter, we refer to Design Research as systematic inquiry into the art, practice, processes, methods of, and behaviours associated with design or synthesis of artefacts and systems, and the behaviour and function of these artefacts (Cross 1999, 2007; Bayazit 2004). This denomination encapsulates also the terms Design Science and Design Studies unless specified otherwise. A potential source of disciplinary and etymological confusion in this chapter is that the field of Information Systems Research has developed a specific methodological framework called Design Science Research (DSR) independently from the traditions of Design Research, Design Studies, and Design Science (c.f. Winter 2008; Piirainen et al. 2010). Further, to relate this chapter to experimental Design Research, it represents a particular methodological orientation to DR. Later in this chapter, the relationship of DIR and PBDR to experimental approaches is discussed in detail.

Further, this chapter discusses knowledge creation and synthesis, which in this context are broader terms than theory building as described elsewhere in this book. The word knowledge is used in the sense of justified true beliefs and in particular in the context of this chapter about constructs, models, and methods related to design. Knowledge synthesis is used in a wide sense, encapsulating theory building as well as design where the conceptual functions are transformed into prescriptions of the structure of a design artefact, using knowledge from various sources to target the expected behaviours derived from the design problems (c.f. Gero 1990; Gero and Kannengiesser 2004).

13.2.2 Types of Design Research and Challenges of Knowledge Synthesis

Horváth (2007, 2008) proposes that RIDC process resembles what might be called a traditional research process. In RIDC, the main focus is on theory development and testing, while phenomenon and the corresponding unit and level of analysis may vary between design methods and theories to behaviours exhibited by designers during the process (see, e.g. Parts II and III in this book).

The case is more challenging in DIR and PBDR, as the actual design occupies more space in the research process and the researchers are more involved in the actual design work (Fallman 2008). This interplay makes it harder to separate design work and research, or to control for various factors. However, in the neighbouring Information Systems field, there is a discussion on generating and integrating knowledge in what might be called Practice-Based or Design-Integrated Research (PBDR and DIR).

The challenges of knowledge development and testing relate to the interaction between the three worlds as described by Popper (op. cit. Sect. 13.2.1) and to the ensuing problems of observing and measuring the phenomena of interest. The challenge of acquiring reliable information or knowledge of W1 is because of the limits of the human condition in observing the real world and translating our knowledge of either one of the worlds into representations that are able to convey the knowledge between the senders' and the receivers' inner worlds (W2) in the artificial world (W3) (e.g. Simon 1985, 1986; Wright and Ayton 1986). The interaction of people and the interplay between the three worlds cannot be bypassed, especially when research questions relate creativity, decision-making, and the use of methods or other aspects of human behaviour in design processes.

Generally, scientific knowledge is defined as a body or network of justified true beliefs, that is, in practical terms beliefs about causal relations between ideas and actions that are backed by evidence from the world (W1–3 depending on the unit of analysis) in some way. However, knowledge can be considered more broadly in terms of the object. Jensen et al. (2007) propose a distinction between four types of knowledge: (1) *know-what*—descriptive knowledge about phenomena and the state of the world, causality, or relationship between phenomena; (2) *know-why*—explanations behind observable phenomena; (3) *know-how*—procedural knowledge, skills, and routines for accomplishing given task; and (4) *know-who*—relational capital and knowledge about other people's knowledge and capabilities (c.f. Table 13.1).

Know-what and *know-why* are types of knowledge that are considered scientific theories, explaining phenomena with causal relations between constructs. *Know-how* and *know-who* are applied, representing capabilities to apply the different types of knowledge and achieve given ends with various means. *Know-how* specifically encapsulates experiential knowledge related to existing artefacts and theories, and their application to problems. In RIDC, the focus is more explicitly on the first two types insofar as the research aims to developed and evaluate theory, while DIR and PBDR may have a broader focus on *know-how* beside theory development. With regard to the worlds of ontology discussed, the types of knowledge may span all three, especially in the case of *know-what* and *know-why*. However, by inclination, *know-how* is more often associated with the artificial (W3), whereas *know-who* is associated with perceptions of other peoples' knowledge (W2).

Contextualizing the types of knowledge to design more specifically, the relevant knowledge domains include first knowledge about the environment and domain of design, which includes general contextual understanding and specific design problems and constraints (*know-what*, *know-how*). Second, there is extant 'solution' knowledge and existing artefacts (*know-how*), and theories applicable to the design problem and process or methodological knowledge, which allows executing the design process (*know-why* and *know-what*). Third, there is design knowledge, knowledge embodied in the product of design and insights borne through the design and evaluation (*know-how*). Even though there is wealth of literature on design methods, it seems that knowledge about the method is hard to

Table 13.1 Characterization of knowledge types (adapted from Jensen et al. 2007)

Type	Characteristics	
Know-what	General and explicit knowledge Codified in the body of scientific knowledge, e.g. publications 'How things work and why do they work like that' (W1–3)	Contextual understanding, phenomena, constructs, variables
Know-why		Relations between constructs and variables, existing theories
Know-how	Procedural knowledge, formal processes, skills, and routines Designed, learnt by doing, and/or observing 'How to do things effectively; how to do X with Y' (W2–3)	Contextual understanding, constraints 'Solution' knowledge, knowledge embedded in existing design artefacts Procedures, experiential practical knowledge
Know-who	Relational capital and knowledge Learnt through interaction and collaboration 'Who knows what and with whom can you work with' (W2)	Contextual understanding Perceptions of other peoples' knowledge, skills, and capabilities

articulate, or is quite tacit and not easily transferable as design problems appear unique. Schön's (1983) classical exposition on reflection in action illustrates how consideration of the problem, solution, and process blend together in professional practice, and it takes special effort to articulate the underlying rationale of a design process or solution after the skill of design is internalized (typical for *know-how*).

A key challenge in DR is synthesizing knowledge between the existing bodies of knowledge and emerging research findings. In DIR and especially PBDR where the interest is more practical, the challenge is to make an explicit connection to existing knowledge (*know-what* and *know-why*). The practical focus tends manifest itself as interest in some outcome variables pertaining to the design context or artefact, or industry context, often named, e.g. key performance indicators (KPIs).

One facet of the solution to this challenge is explicating logic between the phenomena, propositions, and observable variables, as named in existing research (*know-what*, *know-why*) and relevant to the research or design problem (*know-what*, *know-how*). In DR with a practical focus, the (outcome) variables that on one hand characterize the problem space and on the other hand are associated with perceived success of the design are a key attachment point for DIR and PBDR. The variables can link practical problem-solving to previous knowledge (*know-what*, *know-why*) and enable building theoretical design propositions. Further, the exploration of the problem space may lead to identification of relevant design constraints (*know-how*), which give further variables and outline some key constructs to work with (*know-what*) (c.f. Robinson in Chap. 3 of this book on measurement and research designs for treatment of constructs and variables).

The other side of this issue is operationalization of existing theoretical knowledge (*know-what*, *know-why*). If a designer or design researcher aims to leverage existing knowledge in the form of theory (*know-what*, *know-why*) in the design, the theoretical propositions need to conceptualized as constructs and operationalized in terms of measurable variables that can be pattern-matched to the problem space and the associated variables. This is the key to connecting existing knowledge on the solution space to the problem space as conceptualized by the relevant variables. It follows that the relevant discipline and body of theory to draw from are guided by these variables.

The caveat in this pattern matching approach to searching applicable knowledge is that, although it is said that a problem correctly stated contains its own solution (Simon 1996), design problems are underdetermined, in the sense that the setting of constraints and variables can be done in different terms with different indications for theory. Also within the underdetermined problem, there is not necessary one 'right' or even optimal solution. The solution or design artefact might be behavioural, technical, or a mix of socio-technical elements from different bodies of literature or disciplines. While this is an opportunity for multidisciplinary approaches, and as such a strength, it poses a challenge for defining the constructs and corresponding units and levels of analysis rigorously.

To summarize the discussion on challenges of knowledge synthesis, they include but are not limited to the following:

- Identifying the unit and level of analysis.
- Identifying phenomena and constructs.
- Operationalization of constructs in measurable variables.
- Matching the theoretical constructs and variables to the problem space.

In practice, the challenges revolve around the pivot of identifying the level and unit of analysis, and phenomena that can be matched with the existing body of knowledge. This enables leveraging the existing knowledge to the design problem and consolidating the emerging findings with existing knowledge and by extension accumulation of knowledge by corroboration, falsification, or modification of previous claims. The crux of the approach to answering these challenges is developing an explicit research framework and design propositions, which we will elaborate in the next sections.

13.3 Knowledge Synthesis and Experimental Evaluation of Claims

Building on the previous discussion, this section focuses on the methodological aspects of overcoming the challenges in knowledge synthesis. The section first discusses formulating explicit design propositions as a bridge between the existing and emerging knowledge, and the design artefact. Second, it discusses the methodological framework for knowledge synthesis and evaluation of the design propositions, enabling transparent validation of knowledge claims.

13.3.1 Setting Design Propositions

Breaking from the convention in DR, the following discussion on design propositions uses the term *Design Theory* (DT) in a sense specific to the Design Science Research literature, to explore how knowledge synthesis can be codified in Design Inclusive Research (Gregor and Jones 2007). That is to say, DTs in this chapter are not prescriptive systems, rules, or methodologies to use in design processes, as in, e.g., general design theory (Reich 1995), axiomatic design (Suh 1998), and mid-century modernism (Cross 1999), or theories of design to explain design as practice or activity (Friedman 2003). Rather, DT as discussed here is a framework for describing the knowledge contribution in its context and setting explicit design propositions to be evaluated. As such, DTs or design propositions are products of design together with the design artefacts; they bridge between *know-what*, *know-why,* and *know-how* and act as a platform for knowledge synthesis in Design Research.

In this conception, the role of explicit design propositions is to bring transparency and consistency to design and evaluation by bridging the design requirements and principles of form, with the design propositions. Additionally, the propositions codify the reasoning and rationale behind the artefact and interface it explicitly to existing knowledge, both practical and theoretical. As such, they act as a link between practical problem-solving and contributions to knowledge (Walls et al. 1992; Gregor and Jones 2007). Finally, the propositions enable transparent rigorous evaluation of the artefact and validation of the associated underlying and/or embedded theoretical claims and by extension contribute validity and cohesiveness of knowledge (Piirainen and Briggs 2011; Gonzalez and Sol 2012).

Often DIR and PBDR are ostensibly focused on creating knowledge of *know-how* type, often in the form of design artefacts that may include methods (embodying process knowledge) and classes of artefacts including constructs, models, instantiations of the previous, as well as tangible objects (embodying product knowledge) (adapting March and Smith 1995) to fill a certain (kind of) problem space (Markus et al. 2002). These artefacts are built on either intuition, practice-based, or experiential knowledge (*know-how*), principles derived from existing theory by matching constructs and relations to the problems space (*know-what*, *know-why*), or both (c.f. Table 13.1).

For the purposes of this chapter, the operational definition of a theory is that it establishes a causal link between constructs, predicting their interdependent behaviour. In scheme of knowledge (Table 13.1), validated theories are explicit and represent the type *know-what* and *know-how*. This does not, however, exclude integrating or synthesizing other forms of knowledge in the design propositions. On the contrary, the design propositions are modelled after theories, to enable synthesis between existing knowledge of different types and emerging research findings. The following list of questions outlines what constitutes a complete theoretical contribution (Dubin 1969; Bacharach 1989; Whetten 1989):

- *What* constructs and factors are relevant to explanation of the phenomenon of interest?
- *How* are the constructs related; what are the relationships?
- *Why* are the constructs are expected to behave as posited by the theory; what are the underlying dynamics of the interaction that manifest in the expected behaviour?
- *Who, where,* and *when?*—What are the boundaries of the expected interaction; what is expected to happen between the constructs, where, and when? What is not supposed to happen? These questions set the geographic, social, and temporal limits or scope of a theory and its corresponding applicability.

Table 13.2 presents a framework for setting explicit design propositions in a way that enables knowledge synthesis. As discussed in Sect. 13.2.1, the pivot of knowledge synthesis is formulation of explicit propositions that can be evaluated empirically, and either falsified of corroborated in the research process. Building on Gregor and Jones (2007) and Piirainen and Briggs (2011), this formulation of propositions essentially conform to the basic criteria of a theory, as it requires

Table 13.2 A framework for setting design propositions

Components	Guiding question	
Purpose and scope	Which class of requirements, goals, or problems does the artefact apply to? (Borders of problem space, level and unit of analysis, phenomena, borders of applicability)	*Core components*
Constructs	What constructs are needed to address the problem and describe the behaviour of the design artefact?	
Justification knowledge	Which theories explain the interaction of the constructs to help solve the problem? (Positioning to existing body of knowledge)	
Principles of form and function	Which (class of) artefacts meet the requirements; what are the key functions, characteristics, attributes? (Borders of solution space)	
Artefact mutability	How is the artefact expected to interact with its surroundings and evolve when instantiated? (Propositions about the design artefact behaviour in context)	
Testable *design propositions*	What are the expected behaviours of the design artefact and expected interactions with the socio-technical context? What is and is not supposed to happen? (Propositions about theoretical and other knowledge claims to be tested)	
Principles of implementation	How to build an artefact based on the justification knowledge and principles of form and function?	*Auxiliary components*
Expository instantiation	Is an artefact consistent with the principles of form and function, does it instantiate the propositions? (Verification and assessment of mutability)	

specifying constructs, their relations, explanations, and testable design propositions. The propositions and consideration of mutability in particular are *ex ante* prediction from theory, to be tested during the evaluation of the artefact. These propositions enable corroborating or refuting the embedded theoretical propositions and improving the theory, which enables in turn contributing back to the knowledge base.

13.3.2 Experimental Evaluation of Design Propositions

The Design Science Research (DSR) framework was born in the field of Information Systems (Research). Hevner et al. (2004) laid out a set of guidelines or criteria for what is essentially for DIR or PBDR. The key difference between design practice and Design Research is that DR by definition contributes to knowledge by solving classes of problems with artefacts that are evaluated through an instantiation in the given problem context, and contributes to existing scientific knowledge base through this process. It has been said that evaluation of the

Table 13.3 Guidelines for Design Research (adapted from Hevner et al. 2004; Venable 2015)

Guideline	Description
Identifiable contribution	Present an identifiable and viable design artefact One or more clearly defined new concept, model, new way for building an artefact, or a method One or more exemplary or expository instantiation (-s) of the artefact Identify the novelty, significance, and generalizability of the contribution explicitly
Relevance	Address an important and relevant business problem (or a class of problems) Develop the artefact by an iterative search for available means to attain the ends under the constraints of the problem and environment Address both academic rigour and relevance for professional audience
Rigour	Evaluate the utility, quality, and efficacy of the design artefact Apply rigorous, state-of-the-art, methodology to construction and evaluation of the design artefact

design artefacts, design propositions, and the underlying claims to knowledge puts the 'Research' in Design Research in the sense of DIR and PBDR. Otherwise '[w]ithout evaluation, we only have unsubstantiated … hypothesis that some … artifact will be useful for solving some problem' (Venable et al. 2012). Table 13.3 presents the core guidelines for DIR as conceived in the DSR literature to set a framework for the methodological approach.

The connection between relevance and rigour, the context of design, the (business) environment, and the scientific knowledge base built by the previous research is illustrated in the three related cycles of activity described in Fig. 13.1. These cycles are the *relevance cycle* (1), which links the environment with design,

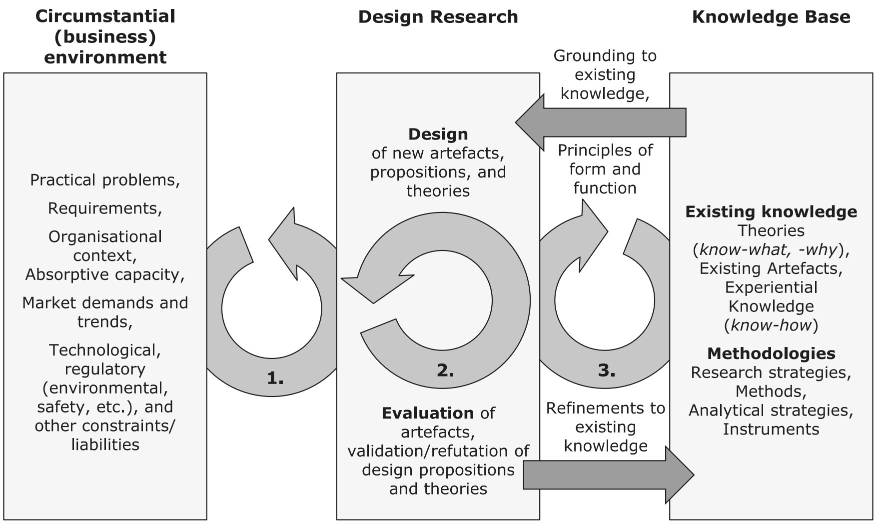

Fig. 13.1 The DSR framework and the three *cycles* (adapted from Hevner 2007; Cash and Piirainen 2015)

setting the problem space, and informing design with the associated requirements and constraints, and later in the process instantiating the artefact and disseminating the results. The central *design cycle* (2) comprises the internal design process of DSR, where the problem space and solution space interface and an artefact is synthesized and evaluated until it satisfies the criteria set for the design. Finally, the *rigour cycle* (3) links DSR and the scientific knowledge base, informing the solution space and contributing back to knowledge based on the evaluation. As such, the framework integrates the perspectives of 'design practice', 'design exploration', and 'design studies' (Fallman 2008).

Within this framework, the design propositions framed in Table 13.2 describe the principles of form and function, i.e. the theoretical principles and other embedded knowledge, embodied by the design artefacts. As such, they are the products of the design cycle (2). The propositions are tested through the evaluation of the artefact (Walls et al. 1992; Markus et al. 2002; Gregor and Jones 2007), which in turn validates the underlying or embedded knowledge claims (Piirainen and Briggs 2011).

During the DR process, the relevance cycle (1) feeds design problems, requirements, and constraint to the process and carries the output of design to the environment. A secondary relevance cycle (1) is found while the design is tested, demonstrated, and refined in the design cycle. The design cycle (2) interfaces both with the rigour cycle (3) and relevance cycle (1), as the rigour cycle feeds the design with theory and the evaluation with methodology, and with the relevance cycle as the artefact is piloted and evaluated. The rigour cycle (3) then feeds the principles of form and function to the design and feeds the findings of evaluation of the artefact back to the knowledge base.

The relationship between the cycles can vary depending on the design problem and solution and the methodological design of a DR project. In RIDC-type projects, the rigour cycle (3) has the most importance, and the design (2) and relevance (1) cycles may even be viewed from the outside as objects of study. Moving to DIR and PBDR, the relative weight of the relevance (1) and design (2) cycles grows, and the research project envelops more of the design cycle (2).

Relating to the relevance cycle (1), a large theme in the discussion about reflective practice and failure of Design Theory in the sense of rule-based design seems to amount to problem setting, i.e. uncovering the 'right' problem and the 'right' constraints (Schön 1983). In other words, a problem formulated correctly contains the kernel of its own solution (c.f. Simon 1996). This 'correct' problem framing however requires understanding the domain of the design and the application area (*know-why*, *know-how*), which is the subject of the relevance cycle (1).

Regarding the synthesis of different sources of knowledge in the design cycle (2) in reference to the discussion on the four types of knowledge (Table 13.1), the purpose of academic research is in the end to produce explicit knowledge of the *know-what* and *know-why* type. As discussed, design embodies the use of *know-how*, as well as *know-what* and *know-why*; thus, the design cycle in DIR and PBDR acts as a process of knowledge synthesis. Additionally, the *know-how* of individual professionals interacts with the design process and the artefact in the interpretation of the design artefact when it is instantiated and used in the chosen context through the relevance cycle (1). Insofar as the design process and evaluation include a feedback loop(-s) between the design and rigour cycles or descriptive elements of the instantiation and its use, the *know-how* element of the persons interacting with the design in the experimental context will be incorporated into the design and through the rigour cycle to the body of knowledge of the *know-why* variety.

For example, exploratory findings from the machinery industry indicate that one of the key prerequisites for creating value through designing products and services is understanding the users' process and application (e.g. Piirainen and Viljamaa 2011), which means finding the 'right' problem framing and constraints that relate to the daily activities of the client and end-user. This also entails that the knowledge needed spans not only domain-specific technical knowledge (*know-what*, *know-why*), but knowledge of the routines associated with the problem and knowledge about behaviour of people (*know-how*, *know-who*).

What is notable regarding the rigour cycle (3), the framework is not axiomatic, in the sense that it would have a fixed normative methodology. The DSR literature proposes rather a 'meta-methodology' or a prescriptive methodological framework, which enables use of different research strategies, methods, and field designs, as well as epistemologies within it. Thus, used apart from established research methodologies, it is an 'empty container', which allows integrating different onto-epistemological and methodological approaches. The next section expands on the key issues of combining practical and theoretical contributions in design.

13.4 Evaluation of Design Artefacts and Knowledge Claims

This section focuses on methodological choices for evaluating design propositions within the framework presented in Sect. 13.3. As discussed, the explicit setting of design propositions and their evaluation is what sets Design *Research* apart from design as practice or artifice. In the same vein, the often said purpose of evaluation is to examine whether the artefact proves to solve the design problem, following the pragmatic or instrumentalist logic that the underlying theoretical claim is true, if the artefact is useful (c.f. James 1995; Gill and Hevner 2011). In a more common sense, wording evaluation ensures that the artefact fulfils its requirements and that the associated knowledge claims are sound. Venable et al. (2012) expand on that and propose that there are five purposes for evaluating the design artefacts:

1. Establishing the utility and efficacy (or lack thereof) of the design artefact for its stated purpose.
2. Evaluating the formalized knowledge about the artefact's utility for achieving its purpose, i.e. validating the design proposition and other theoretical claims attached to the artefact.

3. Evaluating a design artefact in comparison with other artefacts designed for similar purpose, i.e. establishing performance of the artefact in relation to competition.
4. Establishing side effects or undesirable consequences of the artefact.
5. Identifying weaknesses and areas of improvement for a design artefact under development.

It is notable that four out of the listed five purposes are related either entirely or mostly with the practical utility of the artefact. In the interest of promoting research rigour in the knowledge synthesis, the following discussion focuses on the aspects related to evaluating design propositions and other attached theoretical claims.

Regarding the theoretical contribution and validating the underlying claims to knowledge (*know-what*, *know-why*, *know-how*) as codified by the design propositions, either by corroboration or refutation, the artefact and its instantiation(-s) are the interface between the world and the knowledge base. In previously used terms, design artefacts belong to the artificial (W3) and their evaluation in an empirical context will yield information about the instantiation in the 'real' world (W1), as well the interplay between the artefact (W3), the context (W1), and the surrounding people (W2). Hevner et al. (2004) propose that evaluation can use multiple empirical methodologies for either 'artificial' experimental evaluation in controlled environment or 'naturalistic evaluation' (Venable 2006), as well as analytical methods, including logical proof that the artefact solves the problem, as illustrated in Table 13.4. In relation to the theme of experimental Design Research as outlined especially in the first part of this book, only the category of 'experimental' methods strictly falls directly under this heading.

A less recognized task in evaluation is to verify whether the artefact actually instantiates the propositions and can be said to operationalize the theoretical claims. Any claims to knowledge are hollow if we cannot claim to know why exactly we get the observed results and what is the attribution, or at least contribution, of the design artefact to those results (Briggs 2006; Piirainen and Gonzalez 2014). This duality of evaluation and validation is referred to as 'verification and validation' in simulation modelling (e.g. Kleijnen 1995; Sargent 2005; Balci 2009; Sargent 2013). Translating this duality of purpose to evaluation of design artefacts, verification within the artefact evaluation corresponds to ascertaining that the instantiation of the design artefact is in fact built after the design and adheres to the intended design principles of form and function sufficiently, and further that it operationalizes the theoretical claims that are under scrutiny (analytical evaluation). Validation corresponds to determining whether the behaviour of the artefact is as projected by the design propositions and sufficient in terms of solving the original problem (testing, experimental, and field).

Another related, and also lesser discussed, dimension in evaluation is illustrated by McGrath's (1981) 'three-horned dilemma'. The dilemma is that in choosing a field design and methods, a researcher has to compromise between representativeness in a population, describing behaviour accurately, and taking the context

Table 13.4 Examples of evaluation methods for design artefacts and their underlying knowledge claims, in illustrative descending order of representing the empirical context accurately (adapted from Hevner et al. 2004; Siau and Rossi 2011; Gonzalez and Sol 2012; Venable et al. 2012)

Class	Evaluation approaches
Observational: field study of instantiations	Single or multiple case study, or other field study, of an instantiation of the artefact in the intended 'real' environment
	Action research to simultaneously design, implement, and evaluate the artefact
Experimental: controlled or experiments	Controlled experiments with users to test certain qualities of the artefact, its behaviour in context, and examination of design propositions
Computational/simulation	Simulation experiments of the artefact behaviour with various inputs, with real or generated data
Testing: functional or structural	Structural (white box) testing of the instantiation to test particular properties and functionalities
	Functional (black box) testing of the overall input–output functionality to identify defects in behaviour
Dynamic analytical: structural reasoning and performance analysis	Dynamic analysis of the performance and the stability/reliability of the artefact
	Optimization of the behaviour of the artefact and demonstration of the operational bounds
	Architecture analysis of the fit of the artefact to the surrounding operation environment and architecture
Static analytical: Descriptive, reasoning, plausibility of the artefact in use cases	Static analysis of the artefact structure
	Scenarios to demonstrate the behaviour and utility of the intended artefact in use
	Informed argument for the plausibility of the designed artefact and the design principles based on the knowledge base, i.e. previous experience and research

into account, often by choosing to optimize one (or two) dimensions and 'sitting uncomfortably' on (one or) two of the horns. In the design context, the less controlled the setting is and the wider the adoption, the less controlled the artefact use and the more mutable the artefact and its uses become, making it harder to establish attribution of the artefact to any observed changes in the system. On the other hand, the more controlled the evaluation, the more the artefact is abstracted from the 'natural' context, and thus the less 'realistic' the observations become. Thus, there tends to be a compromise between rigorously evaluating the design propositions and doing the evaluation in a realistic environment. Lastly, representativeness in population is in experimental evaluation mostly a question of sampling and resources, and in a naturalistic setting, it becomes a question of adoption and popularity of the artefact.

Essentially, this means that in terms of research design, triangulation between multiple methods enables better compromises in rigour and validity if complementary methods are chosen. A further aspect of complementarity is that choosing different methods enables answering questions regarding not only functionality of the artefact in its given setting, but also examining aspects of its interplay with the

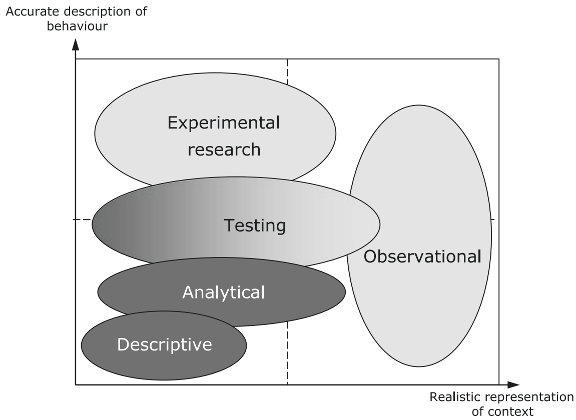

Fig. 13.2 Illustration of trade-offs in artefact evaluation designs [c.f. Table 13.4, *bubble size* for the purpose of illustration, not to scale; *light grey* colour indicates empirical design, *dark grey* analytical (non-empirical)]

users and other phenomena in the borders of the real (W1), artificial (W3), and social (W2) (for an extended discussion, c.f. the other chapters in this book and e.g. Morgan and Smircich 1980; Cunliffe 2010). Figure 13.2 illustrates the compromise between accuracy of behaviour and realistic context in the different evaluation designs presented above. In this scheme, the representativeness in population is a question of sampling and volume of field work and by extension the resources reserved for the evaluation.

In recognition of these compromises, it is recommended that an artefact should be tried in controlled conditions, either through testing or experiments, before moving to instantiation in a real or naturalistic environment (Hevner 2007; Iivari 2007). Further, it has been discussed that while by nature experimental designs are rigorous and, when properly designed, offer highly valid and generalizable results on specific hypotheses within the sampled population, cases can be more illustrative of complex cause–effect relations, especially over time (Kitchenham et al. 1995).

In terms of knowledge synthesis, the observational evaluation in naturalistic settings also enables capturing the emergent properties of the artefact over time and any externalities, contributing to *know-what* as well as *know-how*. Further, by nature, experiments tend to be scaled down or abstracted representation of phenomena and simplified in order to exert better control over the phenomenon under study. In the light of the three-horned dilemma, it is advisable to implement methodological triangulation and develop a progression of evaluation (including verification and validation) during the process of design.

As discussed above in Sect. 13.3.2, the design process is often not linear, and there is often uncertainty about the framing of the actual problem and constraints of the design, which may require some searching. Draft designs may act as convenient boundary objects for defining the design constraints, which is another reason to triangulate and start with non-empirical evaluation first, until the stakeholders are in sufficient agreement over the artefact before going into costly empirical evaluation. Some authors also have recommended specific research settings where a design is instantiated in an organization with the intention for making it a permanent solution that there is an additional descriptive in-depth case study on the mutability of the artefact and its use and function and associated issues included in the field design (Lukka 2003; Piirainen and Gonzalez 2014). The intention is to uncover further insight into the principles of form and function of the artefact in their emergent form, which further contributes knowledge, *know-what*, *know-why*, and *know-how*.

The nature of a DIR or PBDR research process (as described in Sect. 13.3.2) and evaluation or validation of design propositions also poses a degree of limitations to applicability and generalizability of knowledge (*know-what*, *know-why*, *know-how*) acquired through design. That is to say that design artefacts are only ever 100 % applicable to problems that are well defined and constrained, as well as stable, to start with. Further, the problem needs to conform to the same explicit and implicit constraints as the original design problem. If some of the constraints or requirements change entirely or in priority within a class of problems, the design may have to change; that is, the design artefact is mutable.

Another limitation is that when dealing with social processes and behaviour, the knowledge about behaviour around the artefact is not definite, but probabilistic. Thus, the prescriptions derived from design are ‘satisficing’ (Simon 1996); they meet or exceed a set of performance specification with a given confidence. For example, experimental results may point that a design artefact will raise productivity of a particular task x percent with 95 % confidence (or $p = 0.05$), given that college-educated people from a particular country within a certain age bracket use the artefact as originally prescribed (as limited by the experimental conditions, choice of population, and sample). When going outside this population and prescribed use script, the more uncertain and suggestive the results become. The less controlled the use of the artefact in its environment is, the more likely there are different interpretations and constructions of the artefact and its uses (e.g. Williams and Edge 1996); that is, if the artefact is found functional and useful for one problem or use, it is likely applied to a different context, in a different setting, or in a different way, or to an altogether new problem not originally considered during design, which add a degree of mutability. It follows that while DR has implications for practice, the knowledge is tentative and probabilistic, especially as the artefact moves outside the evaluation conditions.

13.5 Discussions and Conclusion

Within the framework of experimental design research, the bulk of this book is focused on methods for research settings that can be called Research in Design Context. Similarly, design as a practice, design methods and processes, and design knowledge have been discussed in the field of DR extensively. The focus on this chapter has been bringing these two discussions together in proposing methodological guidelines for conducting rigorous and relevant DR. Within this focus, particular stress has been on how to support knowledge synthesis and to extract a theoretical contribution from DIR and PBDR. The key messages of this chapter is that all types of DR, including DIR and PBDR, can be rigorous and can contribute to the knowledge base, when the design activity is coupled with setting explicit design propositions that are embodied in the design, followed by rigorous evaluation of the design artefact and the underlying claims to knowledge.

As for other lessons, it is the author's contention that the most usual apprehension towards structured process in Design Research in the more practice-based end of the spectrum is the perception that adding structure and methodological rigour to a 'designerly', DIR or PBDR, research project will constrain design unduly and halt creativity. However, these guidelines do not in any way constrain excellent design practice, nor are they meant to saddle creativity. The methodological guidelines described here do not constrain the design cycle or prescribe hard rules that disable use of *know-how*, including existing best practices and mastery of design. The purpose is however to support making deliberate choices about the research design to enable lifting excellent contributions to knowledge from excellent design practice.

There is a danger though that due to too much focus on the research execution, the actual design might be left to lesser attention. There are two types of errors that manifest this risk: One is locking the problem space too early on, which leads to arriving to an excellent solution to the wrong problem. Another is locking the solution space and focusing on a particular solution, possibly for a lack of effectuation (Drechsler and Hevner 2015), too early on. Both may lead to a solution that is sub-optimal for the stakeholders, while it may not detract from the value of the research as such.

These risks are related to working with explicit design propositions, if design propositions are taken as a checklist item that needs to be ticked off the to-do list as early on as possible, which may drive the design to a premature lock state. The purpose of the propositions is, on the contrary, to be an explicit codification of the principles of form and function of the design, and they need to live with the artefact. Otherwise, there is an additional risk that the evaluation will in fact not produce useful data for validation of knowledge claims.

A closely related risk is locking the evaluation field design, protocols, and instruments too early, before it is actually known what is being evaluated. Again, evaluation design should not be chosen in rote terms from a list, but judiciously following the type of the artefact and propositions, the corresponding level and unit of analysis, research questions, and the researchers chosen onto-epistemological approach.

With these remarks and reflections, the closing proposal is that these guidelines are not intended to replace or surpass the art of design in design research, but to create a framework that enables synthesis of knowledge by combining design excellence and creativity with the rigour necessary to derive excellent scientific contributions, *know-what* and *know-why*, as well as *know-how* from DR.

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Chapter 14
Scientific Models from Empirical Design Research

John S. Gero and Jeff W.T. Kan

Abstract For many, designing is an unknowable mystery. Science is founded on the axiom that things are knowable. Can designing be "known" through science? Science takes the approach that there are observables called phenomena that can be represented separately from the phenomena themselves and that these phenomena exhibit regularities. Further, science assumes that these phenomena can in some sense be measured. Hypotheses are conjectures about the regularities of these phenomena that can be tested against the data acquired through measurement. Tested hypotheses form the basis of the construction of models that can be used both to describe the regularities and to make predictions about the phenomena underlying those regularities. It has been argued that since the result of designing is a unique design, i.e., when you carry out the same design task again you produce a different design, where is the regularity that is required for science to apply to designing? The regularity in designing is not necessarily in the resultant design but in the process that produces that design—designerly behaviour. Using science to study designerly behaviour results in scientific models describing designerly behaviour based on empirical evidence rather than on personal experience. The remainder of this chapter will introduce a method for the capture of empirical data on designing. This is followed by the description of an ontology of designing that maps onto the phenomena of designing that are capturable. The rest of the chapter describes some of the scientific models that can be produced from this empirically grounded data.

Keywords Models · Empirical · Design cognition

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14.1 Empirical Research in Designing

Science allows for such questions as: What are the differences between designerly behaviour and problem solving? How does the task affect designerly behaviour? How does education affect designerly behaviour? How does the domain background of the designer affect designerly behaviour? and How does education affect designerly behaviour?

Studying designers requires that there be phenomena to be studied. Since designing is an activity of the mind its study can be carried out using concepts from cognitive science and brain science. In this chapter, we focus on cognitive studies of designing called *design cognition*. Cognitive science is the scientific study of the mind and its processes. It infers the activities and processes of the mind through the observable behaviours of individuals. Similarly design cognition is the scientific study of the minds of the designers through their observable behaviours—designerly behaviour.

Studies of design cognition have fallen into five methodological categories: questionnaires and interviews (Cross and Cross 1998); input–output experiments (where the designer is treated as a black box which produces the behaviours in the outputs for changes in inputs) (Purcell et al. 1993); anthropological studies (Lopez-Mesa and Thompson 2006), protocol studies (Ericcson and Simon 1993; van Someren et al. 1994), and more recently cognitive neuroscience (Alexiou et al. 2010). While each of these methods has produced interesting results, the most useful method continues to be protocol studies and it has become the basis of the current cognitive study of designers (Atman et al. 2008; Badke-Schaub et al. 2007; Christensen and Schunn 2007; Gericke et al. 2007; Gero and McNeill 1998; Kavakli and Gero 2002; McDonnell and Lloyd 2009; McNeill et al. 1998; Suwa et al. 1998; Suwa et al. 2000; Williams et al. 2013; Yu et al. 2015). Protocol analysis is a rigorous methodology for eliciting verbal reports of thought sequences as a valid source of data on thinking. It is a well-developed, validated method for the acquisition of data on thinking. It has been used extensively in design research to assist in the development of the understanding of the cognitive behaviour of designers. Protocol analysis involves capturing the utterances and gestures of designers while they are designing and converting them into a sequence of segments of coded design issues, where each segment contains one and only one coded design issue. The sequence of segments with their codes form a symbol string in a limited alphabet, which can then be analysed for a large variety of structures that form the basis of the development of models based on empirical data.

14.2 An Ontology of Designing

What are the phenomena of designing? This question raises many issues that are not pursued here. One way to develop the phenomena is to observe designers in action but this assumes that the observer knows what to observe. Another approach is to develop an ontology of designing that guides the observations. An ontology of designing can commence with the following axiom: the foundations of designing are independent of the designer, their situation and what is being designed. This leads to the claim that: all designing can be represented in a uniform way. In this chapter, designing is modelled as transforming design requirements from outside the designer into design descriptions. The function–behaviour–structure ontology (Gero 1990; Gero and Kannengiesser 2014) models this transformation of requirements (R) into design descriptions (D) in terms of three classes of variables: function, behaviour and structure. The function (F) of a designed object is defined as its teleology; the behaviour of that object is either expected (Be) or derived (Bs) from the structure (S), which is the components of an object and their relationships. Requirements can be expressed in terms of function, behaviour or structure. Description can be function, behaviour or structure. Thus, no new ontological variables are needed to express requirements and description. These six variables become the ontological issues of designing, called *design issues*. Figure 14.1 shows the relationship among those transformation processes and the design issues. The eight ontological designing processes are a consequence of the transformations between design issues and are as follows: formulation (1), synthesis (2), analysis (3), evaluation (4), documentation (5) and three types of reformulations (6–8).

14.2.1 FBS Coding

The empirical protocol data in this chapter was produced using a coding scheme that mapped onto the six design issues of requirement (R), function (F), expected behaviour (Be), behaviour derived from structure (Bs), structure (S) and description (D). The protocols are segmented strictly according to these six issues. In protocols, utterances that are not about designing are not coded as design issues; these may include jokes, social communication and management issues. These fundamental FBS classes denote the state of affairs of designing of each coded segment. They capture the essence of design activities, which will then be modelled, using statistical and mathematical methods.

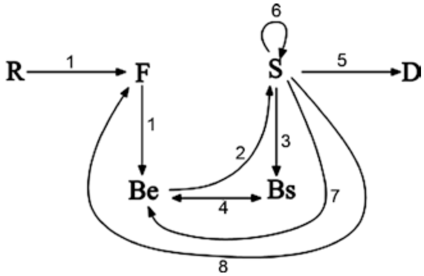


Fig. 14.1 The FBS ontology of designing (after Gero 1990; Gero and Kannengiesser 2004). *1* Formulation. *2* Synthesis. *3* Analysis. *4* Evaluation. *5* Documentation. *6* Reformulation I. *7* Reformulation II. *8* Reformulation III

14.3 Models for Design Issues

The protocols, after transcription, segmentation and coding, result in a chronologically ordered list of the six design issues identified by their codes (R, F, Be, S, Bs and D). This represents the distribution of cognitive effort across the design session captured by the protocol video. Descriptive statistics of design issues can quantify the distribution of cognitive effort while designing, producing a simple statistical model that characterizes one regularity of designing. This can be produced for a single design session as a case study or can be aggregated across many design sessions by different designers commencing with the same set of requirements, to produce a statistically robust model.

14.3.1 Statistical Model of Design Issues

Knowing the distribution of design issues can characterize a design session and make comparisons possible among different conditions and domains; for example, Williams et al. (2011) explore the effect of education on design cognition by recording protocols of students designing before and after taking a design course. Participants (28 students, 16 in semester 1 and 12 in semester 2) were asked to attend two out-of-class experiments. They were paired up and given 45 min to generate a design solution that meets the requirements. The distributions of design issues before and after the introductory design course are illustrated in Fig. 14.2. It is observed that students spent the majority of their cognitive effort on the design

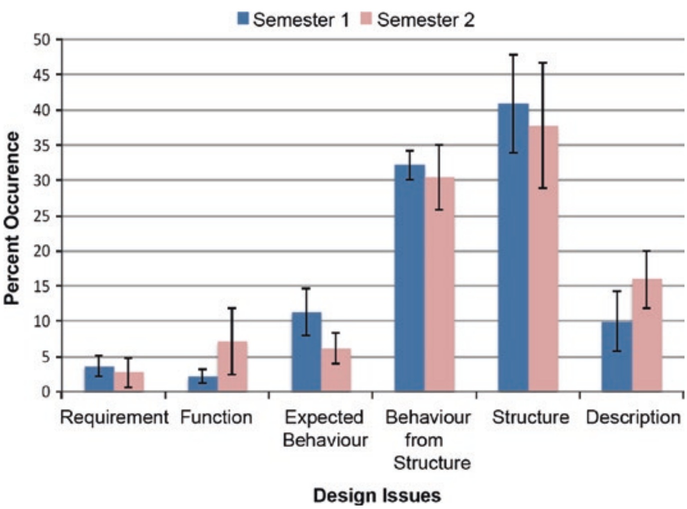


Fig. 14.2 Per cent occurrences of design issues before (semester 1) and after (semester 2) taking a design course

Table 14.1 Statistical significance testing of design issues before (semester 1) and after taking the design course (semester 2)

Design issue	$t(z)$ statistics	p-value
Requirement	−0.925	0.137
Function	2.904	0.003**
Expected behaviour	−3.495	0.004**
Behaviour from structure	−0.879	0.409
Structure	−0.717	0.490
Description	2.685	0.021*

*$p < 0.05$
**$p < 0.01$

issue of structure (37–40 %), followed by behaviour from structure (30–32 %). These two design issues accounted for two-thirds of their cognitive effort. Much less cognitive effort was spent on the design issues of description (9–15 %), expected behaviour (6–11 %), function (2–7 %) and requirement (2–3 %). The variations between before and after taking the design course have been identified for each design issue. The percentages of their cognitive effort related to function and description have increased approximately 5 and 6 %, respectively, whereas the percentages for all the other design issues decreased.

Are these differences statistically significant? Standard statistical significance techniques are used to test this. The results in Table 14.1 indicate that there are statistically significant differences for the percentages of cognitive effort on the three design issues of function, expected behaviour and description between the two semesters. This implies that students expended more cognitive effort on function, expected behaviour, and description after taking the design course and that these differences were not random results. These increases could be due to the major learning goals of the course: exploring the intention space and increasing effective oral and written communication of design. With the conjecture that issues of function will spawn issues of expected behaviour, the percentage of cognitive effort on expected behaviour significantly decreased from semester 1 to semester 2 is unexpected. It is possible that this cognitive change could be caused by the specific pedagogy of the design course.

Quantifying design activities with descriptive statistical models of design issues shows where cognitive effort is focused during designing, making it possible to compare designing across a wide range of scenarios. In this instance, two such descriptive statistical models are compared to examine the effects of an educational intervention.

14.3.2 Problem–Solution (P–S) Index Model

Herbert Simon's seminal work on artificial intelligence (Simon 1969) had a strong and continuing influence on design research; the paradigm of designing as problem solving dominated design research for many years. Jiang et al. (2014) mapped

Table 14.2 Mapping FBS design issues onto problem and solution spaces

Problem/solution space	Design issue
Problem space = Problem-focused design issues	Requirement (R), function (F), expected and behaviour (Be)
Solution space = Solution-focused design issues	Behaviour derived from structure (Bs) and structure (S)

the FBS design issues onto problem and solution spaces, Table 14.2, and produced a meta-cognitive model of designing as the problem–solution (P–S) index defined as the ratio of the sum of occurrences of the design issues concerned with the problem space to the sum occurrences of the design issues concerned with the solution space, Eq. (14.1).

$$\text{P}-\text{S index} = \frac{\sum(\text{Problem-related issues})}{\sum(\text{Solution-related issues})} = \frac{\sum(\text{R, F, Be})}{\sum(\text{Bs, S})} \tag{14.1}$$

The P–S index value quantifies the relative focusing on problem to solution. When the P–S index equals one, it indicates that equal cognitive effort was spent on both the problem and solution spaces. A design session with a P–S index larger than 1 can be characterized as having a problem-focused designing style, and a session with a P–S index value less than 1 can be characterized as having a solution-focused design style.

In a study on the effect of designers' educational domain and the effect of class of requirements on design cognition, Jiang et al. (2014) examined the design style of twelve industrial design students and twelve mechanical engineering students. Two participants, either from the same discipline or different ones, were paired to work collaboratively in two conceptual design tasks: design a coffee maker (CM) for the existing market and design a next-generation personal entertainment system (PES) for the year 2025.

Industrial design teams' PES sessions had higher P–S index values than the other sessions, demonstrating a strong tendency of focusing on problem-related issues, Fig. 14.3. The P–S index value of the industrial design CM sessions is around the threshold of problem–solution division. The results suggest that industrial design student teams have a design style that is more focused on the design problem than mechanical engineering student teams in both design tasks.

The P–S index can be considered as the meta-level structure over the cognitive processes behind design problem and solution spaces; in other words, how problem or solution focus is organized in the design cognitive process. This, in a narrow sense, models the style of meta-cognition of designing.

14.3.3 Cumulative Occurrence Model of Design Issues

Another simple model of designing based on the segmented and coded protocol is the cumulative occurrence model of design issues, defined as the cumulative occurrence (c) of design issue (x) at segment (n) in Eq. (14.2).

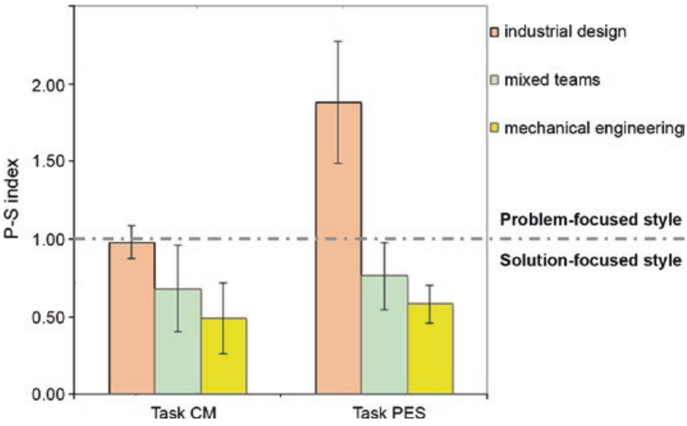


Fig. 14.3 Aggregated P–S index values and design style

$$c = \sum_{i=1}^{n} x_i \tag{14.2}$$

where (x_i) equals 1 if segment (i) is coded as (x) and 0 if segment (i) is not coded as (x).

Equation (14.2) can be expressed in a graphic form; the following five measures can be derived for each of the six classes of design issues and used to characterize designing:

- First occurrence at start: Whether a design issue first occurs near the start of designing?
- Continuity: Whether a design issue occurs throughout designing?
- Shape of the graph: Is the cumulative occurrence graph linear or nonlinear? This measures whether the cognitive effort for that design issue is expended uniformly across the design session.
- Slope: Of the linear cumulative linear graph, it measures the rate at which the cognitive effort represented by those design issues is expended.
- R^2 (coefficient of determination): A measure for the linearity of the graph.

Gero et al. (2014) used a cumulative model of design issues in a case study to investigate the commonalities across designing using data from thirteen existing design studies. These studies were highly heterogeneous including students and professional, novices and experts, architects, software designers, Web designers, and mechanical engineers, individuals and teams ranging in size from two to nine members. Figures 14.4 and 14.5 show the un-normalized cumulative design issues of function and structure of the protocols from 13 different studies. Since the protocols have different time span and segments so the graphs have different lengths. However, the five measures are independent of the heterogeneity of the data. Their

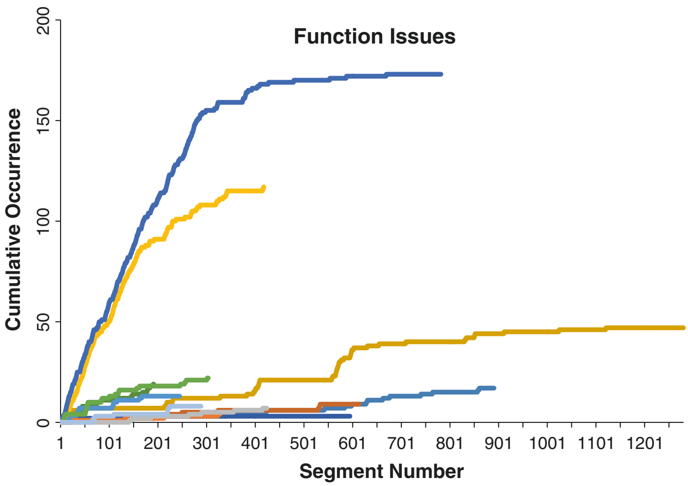


Fig. 14.4 Cumulative occurrence of function issues of the 13 design protocols

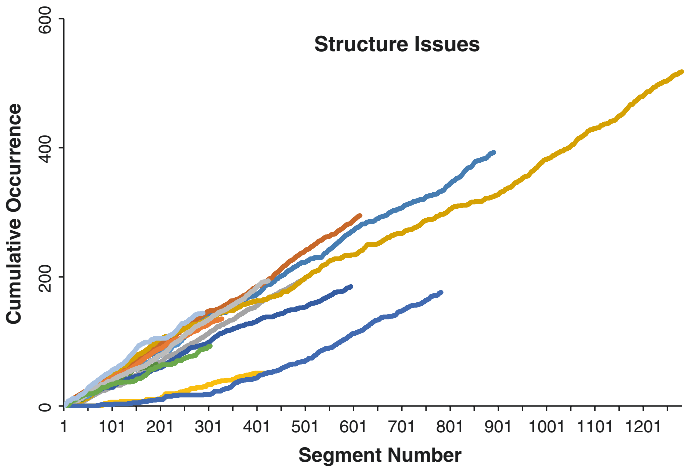


Fig. 14.5 Cumulative occurrence of structure issues of the 13 design protocols

empirical results (not presented here) indicate that there are commonalities across designing. For example, function issues occur from the start of a design session but are discontinuous, Fig. 14.4. The cumulative occurrence model shows that structure issues, Fig. 14.5, occur from the start of the design process (for 11 of the 13 studies) indicating that designers tend to commit to specific solutions early on with high continuity, linearity and at a rate of expenditure of cognitive effort that are very similar.

Further, the results in Fig. 14.5 indicate that the cumulative effort expended on structure issues is linear across almost all the design sessions, an observation that has been confirmed by further studies (Gero et al. 2014).

Results from using these three models based on FBS design issues provide support for the premise that designing can be studied as a distinct human activity that transcends disciplinary boundaries and specific design situations. Each provides an opportunity to investigate human designing in a way that can provide further insights of designerly behaviour.

14.4 Models for Designing Processes

Asimow (1962) described the design process using two orthogonal structures; a vertical structure involving a sequence of phases (from abstract to detail) and a horizontal structure containing decision-making that is common to all phases. His model of designing can be characterized by a series of cycles through analysis of the problem, synthesis of a solution and evaluation of the solution. His terminology is not the same as named FBS processes. Much design research codes protocols using coding schemes based on Asimow's three generic processes; however, the FBS processes can be directly derived from the FBS ontology and the relationship between coded segments, instead of coding them separately. In this section, two models of deriving these FBS design processes are depicted.

14.4.1 Markov Models

Markov chains, also referred to as Markov analysis and Markov models, produce a statistical model of the sequence of events; they describe the probability of one event leading to another (Kemeny and Snell 1960). More formally, a Markov chain is a discrete-time stochastic process with a number of states such that the next state solely depends on the present state. Here, syntactic design processes are defined as the transformation of cognitively related design issues by assuming that each design issue is directly related to its immediately preceding issue. This produces a syntactic linkograph. In Fig. 14.6, the first four segments (50–53) formed three syntactic design processes: formulation (Fe to Be), synthesis (Be to S) and analysis (S to Bs). Here, the design process of documentation (S to D) does not meet this definition.

Derivable from the Markov model or directly from the data, the mean first passage time is the average number of segments traversed before reaching a particular design issue from the current issue. Kan and Gero (2011) demonstrated, with a case study, that Markov models of syntactic design processes can be used to compare design activities across domains. They compared the mean first passage time and the Markov models (through the transition probabilities) of a mechanical

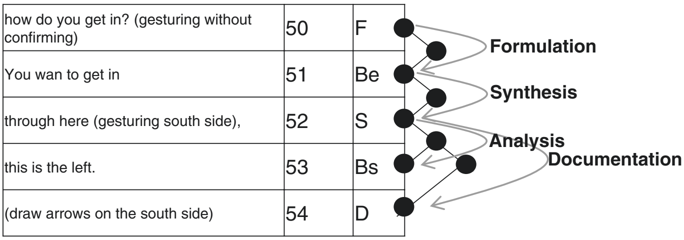


Fig. 14.6 Example of sequence of design issues, linkograph and design processes

Table 14.3 Five shortest mean first passage time of the three sessions

Architectural design	Software design	Mechanical design
Be > S (synthesis)	F > Be (formulation)	Bs > S
D > S (reformulation I)	R > S	S > S (reformulation I)
S > S (reformulation I)	Bs > Be (evaluation)	D > S (reformulation I)
F > Be (formulation)	D > S (reformulation I)	Bs > Bs
Bs > S	Be > S (synthesis)	S > Bs (analysis)

design, a software design, and an architectural design session. The transition probability is the probability of one design issue leading to another design issues. Table 14.3 contains the five shortest first passage time, indicating differences in design cognition of processes across domains.

Gero et al. (2013) employed a Markov model to produce design processes as part of their study of design cognition while using two different creativity techniques. Twenty-two senior mechanical engineering students were formed into teams of two. Each team was given the same two design tasks, respectively, using an unstructured concept generation technique (brainstorming) and a structured technique (TRIZ). They found that students using brainstorming sessions have higher percentages of analysis, documentation, and reformulation I syntactic design processes. When using TRIZ, students have higher syntactic design processes of formulation and evaluation, Fig. 14.7.

14.4.2 Models from Linkographs

Semantic design processes are the design processes that are derived by considering the semantic linkage of design issues, as opposed to their syntactic linkages. After constructing the linkograph, if there are *n* links there will be *n* processes. A standard statistical model can be used to model the distribution of these design processes. Figure 14.6 shows four semantic design processes derived from the linkograph, in which the first three overlap with the syntactic design processes (simple sequence of issues).

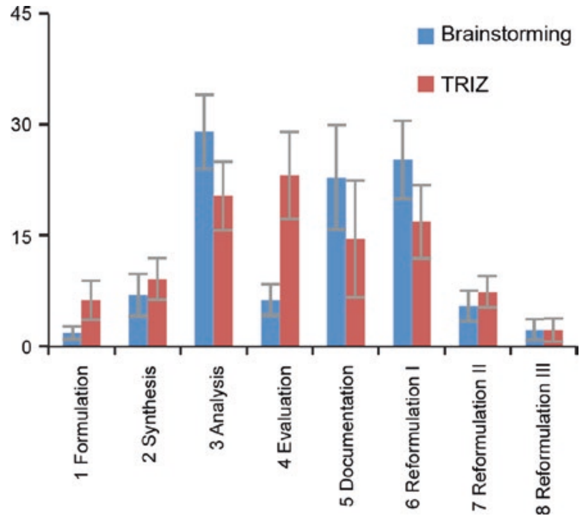


Fig. 14.7 Frequency distribution syntactic design processes (%)

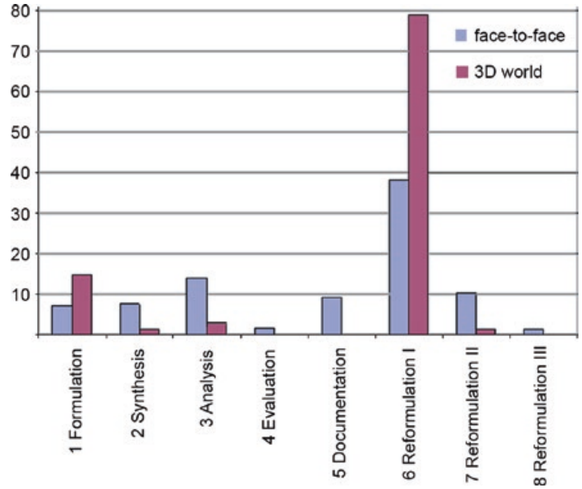


Fig. 14.8 The semantic design processes (%) of the face-to-face and the 3D-world sessions

Kan (2008), in a case study, compared a pair of designers collaborating face to face with the same designers using a 3D-world, an Internet-based virtual collaboration environment. The semantic design processes of the two sessions are shown in Fig. 14.8. All three types of reformulations were present in the face-to-face session, but only a type one reformulation was found when designing in the 3D-world. Both sessions have a relatively high type one reformulation. The face-to-face session has higher analysis, synthesis and evaluation processes. In the 3D-world session, the predominant process was the reformulation of structure, the remaking of forms.

The same statistical models used to describe overall design sessions can be used to investigate individual behaviour in teams. Statistic models of syntactic and semantic design processes show the distributions of team designing processes and individuals' designing cognitive processes. These provide the basis for further quantitative comparisons based on empirical design data.

When modelling designerly behaviour it is possible to analyse the semantic linkograph of a team-based design session and construct a model of the design processes of individuals who make up the team. Kan and Gero (2011) present such results for a 7-person team in industry. Two of the team members' models are presented graphically in Fig. 14.9, which presents the design process interactions of team members "Allan" and "Tommy". The results presented include their behaviour in the first, middle, and last thirds of the design session (shown, respectively, in blue, red and white) to provide information on any time-based change in behaviour. The horizontal axes show the design issue interactions with themselves and the other members of the team. The results for the two design processes of analysis and reformulation I are presented.

These results indicating that self is the primary source of design processes are surprising as many believe that brainstorming and group processes are the major sources for interactions.

With the same data, Gero et al. (2015) differentiated the structure of "communication while designing" and "design communication"; the former was modelled

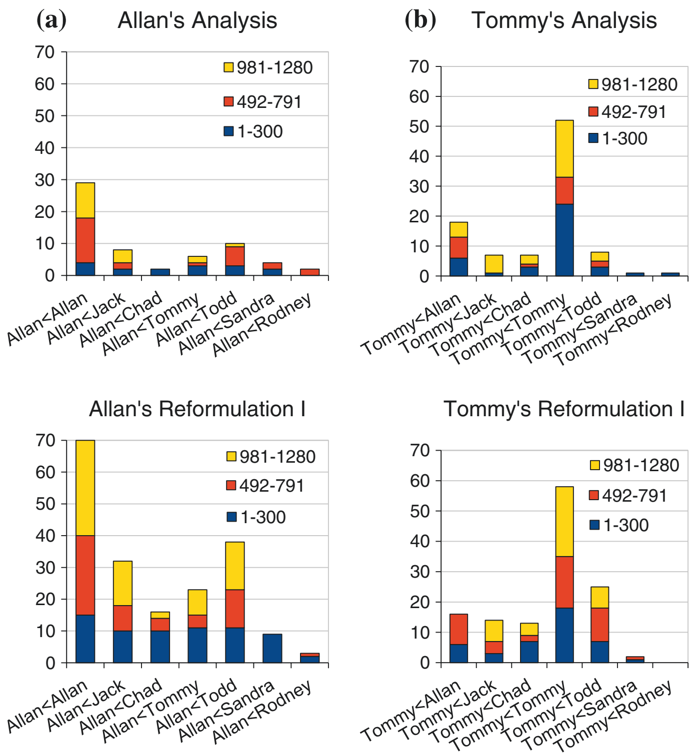


Fig. 14.9 Comparing the team design processes of **a** Allan and **b** Tommy

as conversational turn-taking among participants regardless of the content of utterances, the latter was concerned with the design issues in synthesis, analysis and evaluation. The syntactic structure of the two communications is then modelled as a sequence (first-order Markov model) of turn-taking and design issues, respectively. The resulting two structures, in the form of graphical models, are presented in Fig. 14.10, with the size of circle corresponding to the proportion of the transition probabilities.

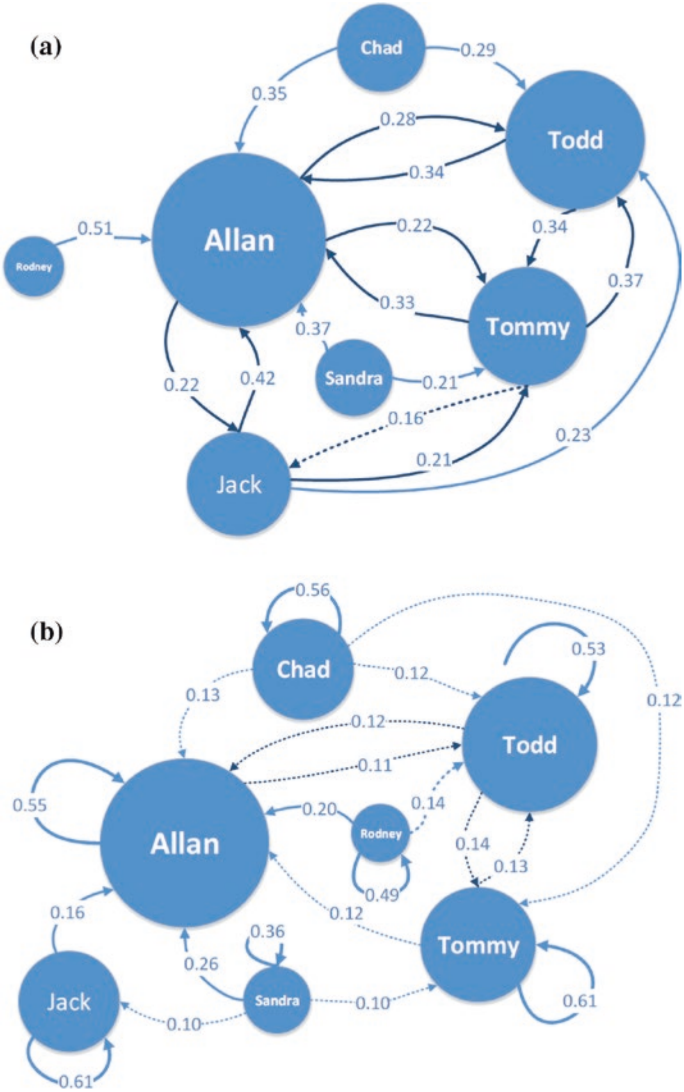


Fig. 14.10 The team structure of **a** "communication while designing" and **b** "design communication"

The team structure of “design communication” produces a richer graph than that for “communication while designing”; they concluded that some members’ contributions can only be revealed by modelling “design communication”.

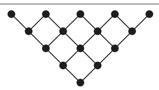
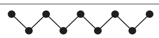
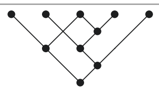
These studies illustrate that using semantic and syntactic models of FBS-derived design processes go beyond the surface of communication and reveal hidden relationships of team designing and individuals’ contributions.

14.5 Entropy Model

Kan and Gero (2005) proposed an approach to describing designerly behaviour based on using Shannon’s information theory (Shannon 1948) to build entropy models of linkographs. They suggested that a rich idea-generation process is one where: (1) the structure of ideas is reasonably integrated and articulated, and (2) there is a variety of moves. They argued that an empty-linked linkograph can be considered as a non-converging process with no coherent ideas and a fully linked linkograph represents a fully integrated process with no diversification (Kan and Gero 2009). Table 14.4 shows the entropy measurement of four hypothetical cases. Kan and Gero (2005) provide the details of the calculation of linkograph entropies of this model while Gero et al. (2011) describes a software tool to calculate the entropy. This model computes entropy based on the probabilities of the connectivity of each segment (either fore- or back-linked) together with the probabilities of distance among links. Entropy becomes a measure of the potential of the design space being generated as the designer(s) design.

Kan et al. (2007) compared 12 design sessions under two different conditions, normal versus blindfolded during designing, their design artefacts had been double-blind reviewed by three judges according to criteria including creativity, flexibility and practicality. Kan and Gero (2005) reported that the score differences

Table 14.4 Hypothetical linkographs, their interpretations and their entropies

	Linkographs	Interpretations	Entropy
Case 1		Five moves are totally unrelated; indicating that no converging ideas, hence very low opportunity for idea development	0.00
Case 2		All moves are interconnected; this shows that this is a total integrated process with no diversification, hinting that a premature crystallization or fixation of one idea may have occurred, therefore also very low opportunity for novel idea	0.00
Case 3		Moves are related only to the last one. This indicates the process is progressing but not developing indicating some opportunities for ideal development	5.46
Case 4		Moves are interrelated but also not totally connected indicating that there are lots of opportunities for good ideas with development	8.57

between the two conditions were insignificant and the score is not correlated to the overall entropy value of the linkograph. However, when they compared the highest and lowest ranked three sessions with entropy variations across their sessions, they found all three high-scoring sessions have concave-shaped or negative curvature in the quadratic fit curves, Fig. 14.11a, and all the low-scoring sessions have convex-shaped or positive curvature curves, Fig. 14.11b. The increase in entropy at the end of a session meant better connection of segments/moves at the end, which might indicate a consolidation of ideas. More experiments are needed to verify if there is a correlation between. However, what this does indicate is that models derived from empirical data have the potential to reveal regularities that are not available by looking at the source data alone.

The entropy model potentially provides a means to measure idea development opportunities. It provides another way to abstract information from a linkograph. The entropy variation during a design session is shown in Fig. 14.12. The linkograph was semi-automatically generated by connecting the noun synonyms in each

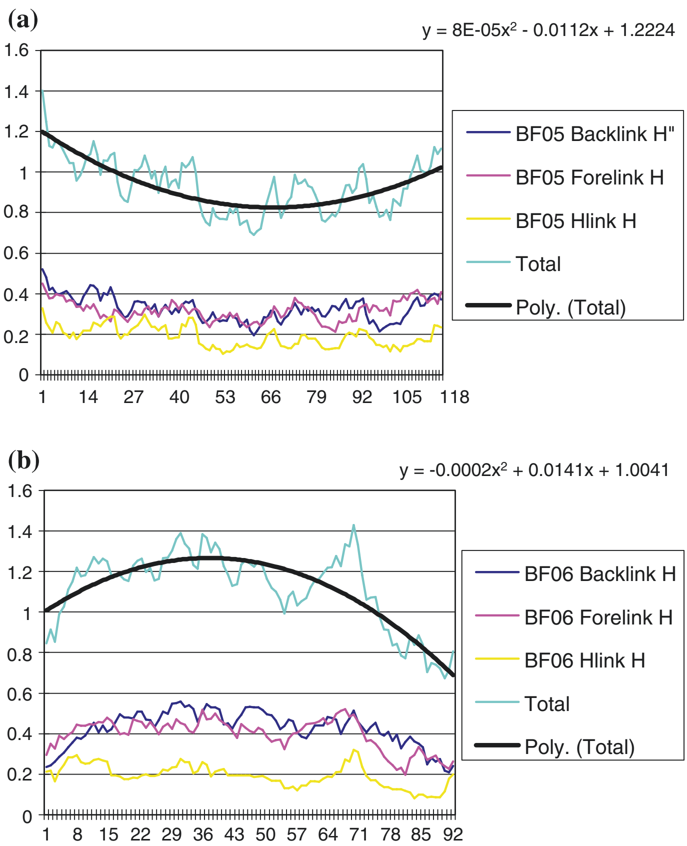


Fig. 14.11 Comparing entropy variation, the top graph (**a**) represents a high-scoring session and the bottom graph (**b**) represents a low-scoring session

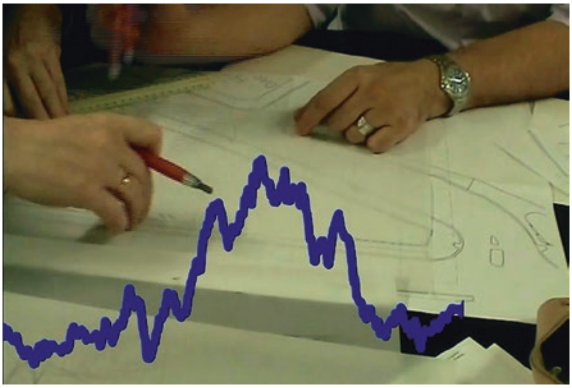


Fig. 14.12 Entropy variation overlaid on the video of a design session; time runs from *left* to *right*

segment of the protocol in Wordnet (Fellbaum 1998; Kan and Gero 2009). With the advance of voice recognition technology and computational power, it becomes possible to report entropy in near real time. This could potentially provide feedback to designers on their design productivity and idea-generation opportunities.

14.6 Conclusions

Designing is not a unitary activity and it is unlikely that a single coding scheme will be capable of capturing all its cognitive nuances. However, as in all science, the claim is made that there is a regularity in designing that transcends any individual and it is that regularity that is being studied. An ontology is one means to provide a framework for that regularity. Depending on the focus that is being taken a number of potential ontologies could be constructed, however, very few general ontologies have been produced for designing.

The scientific quantitative models in this chapter are founded on one highly referenced ontology of designing and are based on data from empirical studies. They all have as their goal the elucidation of the regularities that are part of designerly behaviour. They demonstrate that designing need not be an "unknowable mystery" and that designing can be investigated using the method of science. This does not make designing a science, just as using the same programming language for two different tasks does not make those tasks the same.

With common tools, it becomes possible to disassociate the analysis from the researcher, from the task and from the environment of the task through the development of models of designerly behaviour. These models can be utilized to test hypotheses and theories to gain a better understanding of designing, provide tools for design educators to assess the effectiveness of educational interventions and inform design practice in managing designing and design teams.

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