DEVELOPMENT AND EVALUATION OF A FRAMEWORK TO SUPPORT EXPERIMENTAL RESEARCH ON DATA ANALYTICS

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List of Abbreviations

DSR	Design Science Research
IDE	Integrated Development Environment
IEEE	Institute of Electrical and Electronics Engineers
IS	Information Systems
IT	Informationstechnologie
UI	User Interface
JVM	Java Virtual Machine

Abstract

Over the past few years, data analytics has become increasingly important for companies across all industries. With the massive amount of data that is now available, companies can use data analytics to gain valuable insights into consumer behavior, market trends, and internal operations, among other things. As a result, data analytics has become a critical tool for companies looking to gain a competitive edge in today's rapidly evolving business environment. However, while data analytics has become an essential tool for businesses, there has been relatively little research done in the area of behavioral research. Specifically, there is a lack of research on the decision-making process involved in data analytics, and how individuals and organizations use data analytics to inform their decisions. One of the major challenges in conducting research in this area is the high cost of developing custom applications for each study. The development of such applications can be time-consuming, expensive, and often requires specialized expertise. To address this challenge, this master thesis develops a generic application that streamlines the process of conducting studies in the field of data analytics. This application enables researchers to design, conduct, and analyze studies more efficiently and cost-effectively, allowing them to explore the field in greater depth. This will be accomplished by using the design science research approach. Firstly, the problem of a lack of behavioral research in data analytics is identified. Then, the objectives for a solution are defined through a literature review and the use of requirement engineering to gather requirements for the application. Next, the application is design, implemented prototypically and its functionality demonstrated. Finally, solution is evaluated through the usages of the requirements.

1 Introduction

1.1 Background and Motivation

The introduction and widespread usage of computers has proven to be disruptive for all industries. Entire industrial sectors have been reshaped, whole professions made obsolete and new career opportunities have been created. This shift towards the adaption of Informationstechnologie (IT) has been necessary for businesses to stay competitive in the fast changing economic environment of the twenty-first century. Nowadays, the digitalization of organizations is viewed as a prerequisite for a successful business, rather than being an endeavored state and computers are indispensable for all industries. This digital revolution enabled the emergence of the widespread creation and collection of data. The amount of data generated globally is rising yearly (Seagate, 2018) and the pressure to use these data volumes effectively in order to gain a business advantage rises.

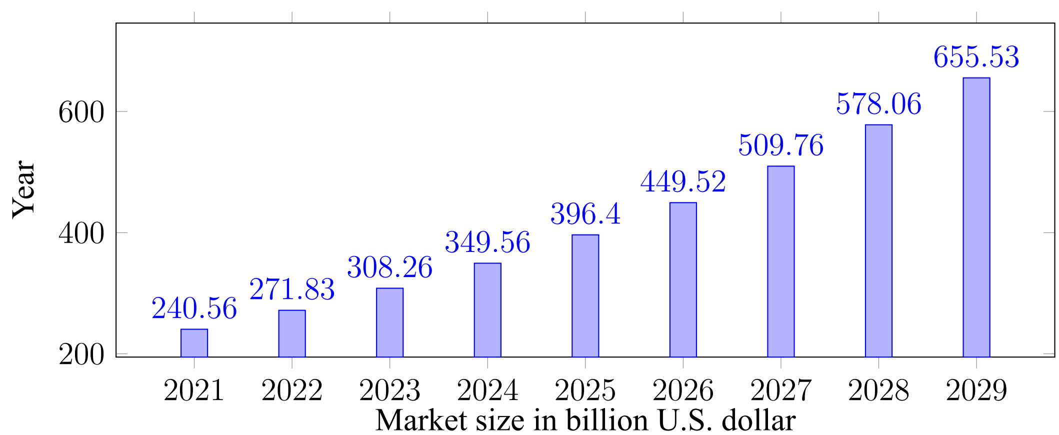


Figure 1: Size of the big data analytics market worldwide from 2021 to 2029 (Statista, 2022)

This new trend, often coined "big data" after the fact that never before seen amounts of data are generated and are available for processing, enables completely new business areas. This is reinforced, among other things, by the fact that many companies already view their data as a primary business asset (Redman, 2008). Simultaneously, the emergence of big data promises to completely reshape the decision-making process of traditional businesses through the adoption of data analytics. Although sales in the area of big data have risen significantly over the past years (BIS Research, 2018, Bitkom, 2018) and businesses already view big data as an important information technology trend (Bitkom, 2017) a lot of organizations struggle to effectivly utilize their data. Some 84% of industry-leading companies in the United States and around the world were already investing in big data analytics in 2019, according to their own statements, which only underlines the importance of data analytics for decision-making in the economy. (Statista, 2019). This is also reinforced by the market for big data analytics worlwide expected to more then double in size in the next 6 years (figure 1).

1.2 Applied & Theoretical Research Problem

In their article, Amankwah-Amoah and Adomako study the influence of big data usage on business failure. They come to the conclusion that the mere possession of big data as an asset has no positive effects on an organization (Amankwah-Amoah and Adomako, 2019) and that in order to prevent business failure, big data must be used effectively (Amankwah-Amoah and Adomako, 2019). Conducting research to resolve the underlying factors hindering the efficient utilization of data analytics in this particular context holds therefore crucial significance. However, although decision-making in data analytics has recently attracted scholars' attention (L. Chen et al., 2022) there is still a lack of research on non-technical aspects holding back the utilization of data analytics. Section 3 of this thesis uses the information-value-chain to look at the state of research in data analytics. Specifically, a literature review on boundaries and conflicts in the field of Data Analytics is conducted. The results of this literature review show that there is a lack of research on non-technical aspects of the information-value-chain. These literature gaps mainly consist of areas like decision-making and behavioral research. These results have been confirmed by studies in the past focussing on related fields (Trieu, 2017), which might indicate a persistant issues. This only becomes more apparent as new technologies, which overlap with data analytics like machine learning and artificial intelligence get more widespread. These "black-box"[1] technologies are already alternatives to human decision-making (Krakowski et al., 2023b). Moreover other studies confirm that aspects like company culture, business models and the overall commitment and strategy of organiza-

[1] Technologies whose exact internal sequence can hardly or not at all be explained, which therefore are acting like a "black-box"

tions have a big impact on the effectiveness of data analyitics (Holsapple et al., 2014). This lack of research on non technical regards could become a huge issue in the future, specifically for the decision-making process as firms' top priorities focus more and more on big data analytics for strategic decision making (Ghasemaghaei, 2019).

Furthermore, it is indicated in section 3 that the current state of research specifically lacks a variety of experiments conducted to confirm the validity of frameworks and hypothesis. The experiment being a particularly important tool for investigating causal relationships in research (Gniewosz, 2011). In addition other means of collecting information like inquest questionnaires, which are probably the most frequently used form of obtaining information (Mummendey and Grau, 2014) in quantitative research are not always the most suitable method. The behavior of people, for example, which comprises the literature gap found, can be better assessed by means of observational studies or experiments (Gniewosz, 2011). While prior research has conducted behavioral research of data analytics with surveys and case studies, little or no attention has been paid to the verification of research results and hypothesis through experiments. This general lack of experimental research in certain areas connects the applied business problem of better utilizing data analytics in organizations to the theoretical problem of lack of experimental research generally found in data analytics (refering to the results of the literature search in section 3). Improving the experimental research process in the field of data analytics could thereby significantly improve the future state of knowledge on said topic, whilste also allowing organizations to succeed in the fast paste economical environment of the digital-age.

1.3 Objective and Expected Contribution

The objective of this thesis is to improve the experimental research process in the field of behavioral research in data analytics. This is done through the following three objectives: (1) the review of prior research on data analytics and their methodological procedure (2) the development of an artefact which improves the research process in the field of behavioral research in data analytics (3) the validation of the artefact through the exemplary realization of a study in said field utilizing said artefact. In order to accomplishe the creation of this artefact the Design Science Research (DSR) methodology is used. This methodology contains six steps, *Identification of the Problem*, *Definition of Objectives for a solution*, *Design and Dev of artefacts*, *Demonstration of the Artifact*, *Evaluation of the solution* and *Communication* (Peffers et al., 2006, Dresch et al., 2015). The *identification of the problem* is conducted in section 3 through a literature search. To be more specific the current state of research in the field of boundaries and conflicts that limit the utilization of data analytics is investigates. As stated before this results in the identification of a gap in literature in the field of behavioral research in data analytics. After identifying the problem, the next step of the DSR Methodology is the *definition of objectives for a solution*. This is accomplished by specifying requirements for the final artifact using the current state of literature in data analytics and the *requirement engineering* approach. For this purpose, a second literature search is utilized to identify literature in the field of data analytics that uses experiments or whose research object would in principle have permitted the use of experiments. These insights are then used to conceptualize, analyze and validate requirements for the final artefact (Sommerville, 2011, Alain Abran, James W. Moore, 2004). As the name of the next step suggests the artefact is designed and implemented in the *design and dev of artefacts* phase using the requirements specified in the last step. Subsequently, the resulting artefact is then demonstrated in the *Demonstration of the Artifact* step. The *Evaluation of the solution* phase then implements a real experimental study in data analytics as an example to evaluate the artefact and its benefits for the experimental research process. This examplary implementation is then also used to validate the afformentioned requirements. The last step of the DSR framework, which focusses on communicating the results to its stakeholders, is ensured by this thesis itself.

The practical contribution of this thesis to research is twofold. On the one hand an artefact is created which accelerates research in the field of data analytics, through the improvement of the research process. On the other hand meta-knowledge about the research process itself is created, which not only improves the conduct of research through said artefact, but can also be used in off-topic areas beyond the use cases of this thesis.

In summation, the goal of this thesis is to develop an artifact that improves the experimental research process in behavioral research in data analytics. For this purpose, the DSR method is used to create an artifact. The requirements for this artifact are established using past experimental and non-experimental studies in data analytics and the requirement engineering approach. The artifact is then validated by implementing a real study as an example, thereby demonstrating the improvements to the experimental behavioral research process in data analytics.

2 Theoretical foundations

This section represents the theoretical fundamentals of this elaboration by defining the term “data analytic”, the concept of the “information value chain”, the DSR methodology, the *requirement engineering* approach and the experimental research process in general.

2.1 Data Analytics

The term “data analytics” originated in the early 2000s and describes an interdisciplinary field that combines areas such as statistics, machine learning, pattern recognition, system theory, operations research and artificial intelligence (Runkler, 2020). It can be generally defined “[...] as the application of computer systems to the analysis of large data sets for the support of decisions.” (Runkler, 2020). This definition showcases the broadness of the topic, as most computer systems process some amount of data and thus theoretically allow for some kind of decision making. Due to this broad definition, data analytics can cover slightly different subject areas depending on the context it is discussed in. In this elaboration, data analytics refers to the processing of large amounts of data, also referred to as “big data”, through mathematical procedures or machine learning methods with the goal of creating new knowledge. Subsequently, processes that merely prepare or show data are not considered data analytics, but only processes that process data in such a way that new knowledge can be derived from it. This distinction is made to differentiate data analytics from traditional data processing areas like business intelligence. The goal of data analytics, as is discussed in this thesis, is to retrieve some kind of previously unknown knowledge from a set of data. This process can be generally described using the “information value chain” model. In their research, Abbasi et al. analyze this model in the context of big data in an effort to create an inclusive research agenda for big data in information system research (Abbasi et al., 2016).

2.2 Information Value Chain

The information value chain (figure 2) is a set of phases that define the transformation of raw data to information and eventually into knowledge. “Data” describes raw facts without any structuring. Once organized, the processed data represents “information”. This

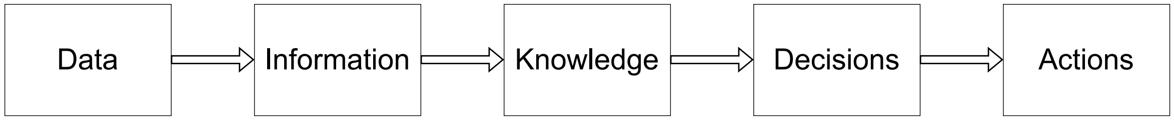


Figure 2: Information Value Chain

"information" is then used to find patterns and draw conclusions. At this time, the information becomes knowledge (Fayyad et al., 1996a), Fayyad et al., 1996b. This knowledge is then used to make "decisions" and take corresponding "actions" (Sharma et al., 2014). Each phase of the information value chain also includes a different set of technologies and methodologies. For example, the "data" phase contains technologies and actions regarding the basic storage of data like database systems or data warehouses (Abbasi et al., 2016). The conventional version of this information value chain represents an approach that generally explains the processing of data. The main steps of this information value chain are also applicable for big data (Abbasi et al., 2016). This general structure of processing data is also supported by literature from the data analytics field (Runkler, 2020). In addition, the information value chain contains the further phases "decisions" and "actions", which deal with the influence of the processed data. These phases reflect the impact of data analytics, since data analytics is primarily a technology for the decision-making process (Runkler, 2020). For this reason, the information value chain is a suitable model to structure different phases in the processing of data in the context of data analytics.

2.3 Design Science Research Methodology

In fundamental terms, design science is a research approach that aims to develop and validate science-based design knowledge and guide research to problem solving (Hevner et al., 2004, Dresch et al., 2015). The goal of DSR is to gain prescriptive knowledge about the composition of various artifacts, including software, methods, models, and concepts. This particular design knowledge facilitates a systematic and scientific approach to the design of future projects. The design process and its practical implementation generate design-oriented knowledge, enriching the existing knowledge in DSR (Hevner et al., 2004). Thus the result of design-science, especially in Information Systems (IS), is the creation of an effective IT artefact which deals with a certain problem (Hevner et al., 2004), making the DSR a suitable approach for this thesis. Nevertheless, the exact activities of the design science model may differ from author to author to some extent (Fulcher and Hills, 1996). This thesis aligns itself with the phases and steps outlined by Peffers et al. in their 2006 article "The design science research process: A model for producing and presenting information systems research". In their article Peffers et al. analyze literature that implements design science in order to create a generally accepted process for research in IS (Peffers et al., 2006). As a result of their work, they describe the design science research approach using the following six steps: (Peffers et al., 2006)

1. ***Identification of the Problem***: In this phase, the problem fundamentally solved by the resulting artifact is described. At the same time the value of resulting solution is justified.

2. ***Definition of Objectives for a solution***: This phase focuses on the specific goal of the solution and how its solving can be measured. The objectives for the solution can usually be divided into qualitative and quantitative characteristics.

3. ***Design and Dev of artefacts***: This step covers the specific functional design and scope of the artifact and how it is to be achieved. The phase covers both the conceptual design and the specific practical implementation of the solution.

4. ***Demonstration of the Artifact***: The focus of this phase is to demonstrate that the artifact implemented in the previous step can actually solve the initial problem. For this purpose, various methods such as experiments, case studies or other test setups can be used.

5. ***Evaluation of the solution***: This step evaluates the artifact and measures how well it contributes to a solution to the problem, therefore this phase tests whether the developed artefact is a valid solution to the research problem. If the artifact does not meet the corresponding requirements, the process is iterated back to step number three. If the artifact meets all requirements and contributes significantly to the solution of the problem, the last step is conducted.

6. ***Communication***: The last step ensures that the developed artefact and its value is communicated to the scientific community. The goal of this phase can be achieved through a number of different ways. The choice for the right way of communicating the results thereby relies on the specific topic and problem at hand.

2.4 Functional and non functional Requirements

As a means to create any artefact, the determination of requirements are important(Seacord et al., 2003). Requirements can be classified according to ISO/IEC 25000, respectively the quality model from ISO/IEC 25010, as quality criteria for software and systems.(ISO/IEC 25010, 2011). The Institute of Electrical and Electronics Engineers (IEEE) defines requirements as:

> ***"(1) A condition or capability needed by a user to solve a problem or achieve an objective. (2) A condition or capability that must be met or possessed by a system or system component to satisfy a contract, standard, specification, or other formally imposed documents. (3) A documented representation of a condition or capability as in (1) or (2). See also: design requirement; functional requirement; implementation requirement; interface requirement; performance requirement; physical equirement."*** IEEE, 1990

According to these definitions, requirements can be generally defined as properties that need to be met in order to achieve an objective. For this reason, the requirements for the artefact are derived from properties and characteristics of past studies in the field of data analytics. In addition, general requirements for experimental research are also taken into account. These requirements are further divided into functional and non-functional requirements. A functional requirement describes a function that a system or system component must be able to perform (IEEE, 1990). An example of a functional requirement would be the calculation of a pricetag in euros and in dollars. Non-functional characteristics describe on the other hand the behavior of a system (Seacord et al., 2003) and go thereby beyond the functional characteristics. Thus functional requirements describe what a system must be able to do and non-functional requirements describe how this should be done. Non-functional requirements also often describe the quality of the individual functions and can influence several other requirements (Balzert, 2011). An example of non-functional properties would be that the conversion from euros to dollars must be performed in “a few seconds”.

2.5 Requirement Engineering

In order to define an objective for a possible solution to the research question requirements for the created artefact must be engineered. In order to accomplishe that the *requirement engineering* approach for analysis and evaluation of requirements is utilized (Alain Abran, James W. Moore, 2004, Sommerville, 2011). This approach has been shown to clearly contribute to software project successes in the past (Hofmann and Lehner, 2001) and is therefore a suitable approach to define the objectives for a solution. The exact individual phases and steps of the *requirement engineering* approach can vary from source to source and use case to use case. In general, however, all steps fall into one of three main categories, the *Requirements Elicitation*, *Requirements Specification* and *Requirements Validation* (Alain Abran, James W. Moore, 2004, Sommerville, 2011, Fernandes et al., 2009). In the first step, possible requirements and use cases are collected via a variety of sources like analyses, surveys, literature or interviews (Sommerville, 2011). This thesis utilizes a literature review in order to discover requirements. In the next step, the requirements are then specified and categorized. An important distinction being the difference between functional and non-functional requirements. In the *Requirements Validation* step, the elicited requirements are then tested for their validity. This phase emphasis the reviewing of the requirements in order to find out whether these requirements are actually representive of the desired artefact (Sommerville, 2011). This is accomplished througt Validity, Consistency, Completeness, Realism, and Verifiability checks in conjunction with protoyping and testing the requirements (Sommerville, 2011).

2.6 Experiments and their research methodology

In the context of quantitative empirical research, the starting point for experiments is a preliminary theoretical work that results in the formulation of hypotheses. These hypotheses are often found in the form that certain conditions or sets of conditions are put forward as influencing factors for a phenomenon and causal assumptions are made (Gniewosz, 2011). Experimental research and field research are often based on these causal assumptions. However, the procedure for testing these assumptions is different. In field research, phenomena (dependent variable) are supposed to be predicted by measuring influencing factors (independent variable). Independent variables or influencing factors could therefore be for example "good teaching" whereas the resulting phenomena or dependent variable would be "good grades" for the students. This posterior approach raises problems in deriving causal conclusions in many correlational studies, because effects of third variables can never be completely excluded. To address this problem, in experimental designs, the expression of the independent variable is not measured but generated by experimental manipulations. This means that the expression of the independent variable is triggered by a specific experimental design. The influence of independent variables on the dependent variable, which can be clearly demonstrated without confounding factors, is referred to as internal validity. Laboratory experiments, which ideally eliminate all external factors, therefore usually have a very high internal validity. However, due to the fact that laboratory experiments can only represent a small part of the total population in an artificially created environment, they usually have a very low external validity. This circumstance is usually exactly the opposite for field research or field experiments. During a field experiment, not all external factors can be eliminated, which is why only a low internal validity can be guaranteed. Nevertheless, field experiments usually better represent the overall population, which is why they have a higher external validity. Another key feature of experiments is the elimination of confounding variables. Confounding variables are influencing variables that can also affect the dependent variable and thus affect the relationship between the independent and dependent variable. This influence must be neutralized or controlled for the planned experiment in order to identify the effects of the independent variable (Gniewosz, 2011). There are two types of confounding variables, those that depend on the individual participants of the experiment and those that arise from the experimental design itself (Gniewosz, 2011). In order to neutralized these confounding variables a number of different approaches exist, which are listed in table 1.

If these confounding variables are fully removed an experiment can be conducted where the test subjects assignment to the experimental conditions is completely determined.

Confounding variable	Description
Parallelization of confounding variables of the test subjects	The confounding variables of all test subjects are measured beforehand. the participants are then divided among the experimental conditions in such a way that the mean values of the confounding variable are approximately equal in all experimental conditions.
Randomization of confounding variables of the subjects	If it is not known which confounding variables might be relevant, the test subjects can be randomly assigned to experimental conditions, which from a probabilistic point of view, results in an equal distribution over the experimental conditions.
Removing confounding variables of the experimental situation	If it is known which experimental conditions triggers the confounding variables, these conditions should be eliminated in the experimental situation
Keeping constant confounding variables of the experimental situation	All confounding variables for all test subjects should have the same form
Random variation of confounding variables of the experimental situation	If the confounding variables cannot be removed or kept constant they can be randomly assigned over the whole experimental process. The confounding variable would vary randomly between the experimental conditions and thus not be able to mask the effect of the manipulated independent variable.
Control group	Another option to rule out confounding variables is the usage of a control groups
Control of expectation effects	Not telling participants and personnel performing the experiment the final goal of the experiment can counteract expectations, which could otherwise influence the outcome as confounding variables

Table 1: Counter measures for confounding variables in experimental research (Gniewosz, 2011)

If these confounding variables are not fully removed the effects of other influences cannot be completely ruled out. Experiments under these conditions are refered to as quasi-experiments. Furthermore, there are other characteristics by which experiments are categorized. For instance Single Factorial and Multifactorial Designs describe experiments that test a single or multiple dependent variables respectively. If the independent variable is subject ot the experiment on the other hand, the experiment categories as an univariate or multivariate a design. On top of that the distinction between "between subject" and "within subject" designs are made. "Within subject" designs describe experiments where the test subjects are tested multiple times with different experimental setups, whereas "between subject" experiments test different subjects with different experimental setups (Gniewosz, 2011).

3 Identification of the Problem

This part of the thesis defines the problem to be solved by the DSR approach. For this purpose, a literature search is first conducted to find potential gaps in the field of data analytics and methods used in this field. Subsequently, applications and tools are examined, which had been intended to support the research process.

In order to identify constrains on the research on data analytics a literature search is conducted. The main objective of it is to analyze the existing literature to find research gaps, particularities and interrelationships between literature. This is supposed to give insights into the current state of research and to find out which part of the research process on data analyitcs still has room for improvements. The literature search itself is conducted in the field of boundaries and conflicts that might hinder the usage of data analytics. As already presented, data analytics has become an extremely important topic for companies. Therefore, the identification and resolution of obstacles that limit the use of data analytics is fundamentally important for companies. For this reason and to expand the scope of the literature search, in addition to reviewing relevant literature on data analytics, an exploration of literature dealing with boundaries in data analytics is pursued. Consequently, relevant literature was identified and reviewed. Afterwards, the identified literature was categorized and analyzed. Initially, it was assumed that the topic of data analytics lies both in the field of information systems and business (Abbasi et al., 2016, Levina and Vaast, 2005). For this reason, the literature search was mainly conducted in literature databases that focussed on these topics. Table 2 shows the databases that were used.

Online database	Subject Focus
ABI/INFORM Collection	Business and management
Business Source Premier	Accounting, business, economics, management
EconBiz	Business and economics
ProQuest One Business	Business
AIS Electronic Library	Informatics
MIS Quarterly Website	Business informatics
Web of Science	Multiple databases that provide access to different academic topics
Google Scholar	Web search engine for scholarly literature across an array of disciplines

Table 2: Databases Used in the Literature Search

The literature search was conducted using a keyword search. The used keywords consist of phrases like “Data Analytics”, “Data” and “Boundary”. A full list of keywords that were used is included in the appendix.

In order to ensure the quality of the identified literature initially, only publications from certain journals were considered. These journals consist of the *Senior Scholars’ Basket of Journals* and the *UT Dallas Top 100 Business School Research Rankings*. The former includes journals in the area of information systems and the later includes journals in the area of business administration. A full list of included journals is listed in the appendix. Furthermore, only peer-reviewed articles were taken into account. This was done to ensure the quality of the found publications and to additionally exclude book reviews, editorials and opinion statements. Moreover, other ’non-scholarly’ texts or publications that did not meet scientific requirements were also not considered in the search. Secondly, the abstracts of the particular articles were inspected to narrow the search further. Consequently, literature that did not meet the topic of boundaries in data analytics was excluded from the search. The literature found in the search was then used for a backward and forward search. During a backward search, all cited sources of an article are examined and during a forward search all the literature that cites the original article is examined (Webster and Watson, 2002). The backward search was conducted using Google Scholar. In addition to this, articles from other journals were, in a second step, reviewed and included as well if they met the scientific requirements, were officially published and relevant to the topic. This process yielded 35 research publications. The results were then assigned to different phases of the aforementioned information value chain, their content best represents. This was done to find literature gaps in the general process of data processing. Additionally, the identified literature was categorized by their research methodology in order to find patterns and similarities in the literature. As stated before, the information value chain consists of the phases “data”, “information”, “knowledge”, “decisions” and “actions”. The found literature was assigned to these phases, in order to structure and analyze the findings. By mapping the literature found, parts of the data processing process that are over- or under-represented may become visible. From this, conclusions can be drawn about the current state of research. Furthermore, the categories “overspanning” and “other” were introduced to represent literature that either fits multiple phases of the information value chain or none. Using this method leads to the results shown in the "First Search" column of table 3.

Information Value Chain	First Search	Additional Search
Data	4	
Information	3	
Knowledge	21	
Decisions	4	0
Actions	0	0
Overspanning	0	3
Other	3	
Total	35	3

Table 3: Results Assigned to the Information Value Chain

Table 3 shows an overabundance of literature that got assigned to the "knowledge" phase of the information value chain. The significantly fewer entries for the other phases indicate less research on these sub-parts of the information value chain. However, it cannot be concluded that this underrepresentation is due to the fact that these phases are less relevant in the context of data analytics. For this, more literature would have to exist confirming that these areas are less important for data analyitics or less prone to boundaries. The underrepresentation of the phases "data" and "information" could also be explained by the fact that these phases are more technology driven and therefore less researched in a bigger organizational data analytics context. In fact, the corresponding literature, which was assigned to these phases mainly consists of publications researching the technical possibilitties and application of data. Their main research object does not directly consist of any broader topics for companies or the application of Data Anayltics. The focus of this literature is largely to overcome technical hurdles or to show how individual technical functions can be implemented. This circumstance is particularly worrying in the context of data analytics, since Amankwah-Amoah and Adomako (Amankwah-Amoah and Adomako, 2019) has already established that the mere existence of data does not yet have any added value for the organization. Research in these very technical areas, such as how data is generated in the first place, is therefore fundamentally important, but without further research it does not contribute significantly to the effective use of data analytics. Nonetheless, in total, seven individual publications could be found that fit into these two phases. In addition, these two phases ("data" and "information”) are mostly considered together in the further elaboration, since the literature which was assigned to these phases lies thematically very closely together.

Only four publications were assigned to the “decisions” phase and none to the “actions” phase. These results in particular call into question if the topic of behavioral research in data analytics has been extensively researched. The reason for this is the fact that data analytics is primarily a decision support method (Runkler, 2020). Therefore, an overabundance of literature delineating the decision-making process of data analytics should likely exist. This is compounded by the fact that no literature could be found that addressed overspanning issues, as no overarching theories could exist for an insufficiently studied topic. In order to ensure that the ratio of the literature found is based on the research state and not on the keyword search being biased in any way, a second literature search was conducted focussed on finding more literature that could be assigned to the “decisions” or “actions” phase. This was only done for these phases as these two are most relevant in the context of data analytics and because, in total, the least literature could be assigned to them (viewing “data” and “information” together). This second keyword search was conducted with the goal of finding more literature that could be assigned to the phases “decisions” and “actions”. Therefore, a new set of keywords including “decision”, “decision making” and “action” were added to the existing set of keywords. The full list of keywords is included in the appendix. Furthermore, the abstracts were examined with an emphasis on the aforementioned goal. The results of this second keyword search are represented in the “Additional Search” column of table 3. A total number of three additional publications were identified using this second search. These three publications were all assigned to the “overspanning” category. Consequently, no additional literature that could be assigned to the phases “decisions” or “actions” could be identified. This further indicates the fact that the topic of boundaries in data analytics is not researched extensively.

A total number of 38 publications were identified in these two searches and analyzed further.

In order to further analyze the literature and to potentially draw further conclusions, the found literature was also categorized regarding the research method that was used. This categorization is presented in table 4.

Research approach	Method	Number
Qualitative (22)	Case Study	13
	Interviews	4
	Experiments	2
	Observation	3
Quantitative (16)	Survey	12
	Data Analysis	6

Table 4: Research Approach Used in the Literature

The distribution presented in table 4 show significant discrepencies in the number of research methods used. Methods such as case studys and surveys are used more frequently than average in contrast to other methods. The least frequently used methodology is the experiment. This fact further indicates an insufficient exploration of the field of behavioral research in data analytics, as experiments are the most suitable method for researching the behavior of people (Gniewosz, 2011). In this context experiments are a particularly important tool for investigating causal relationships in research (Gniewosz, 2011).

As already indicated in section 2.2, much of the literature found could be assigned to the "knowledge" phase of the information value chain. In addition, literature can be identified which was assigned to the information value chain phases "data" and "information". This literature mostly consists of technical publications, whose main goal is to research areas of application and advantages of data analytics. These publications, are for the most part, only concert with very specific technical issues. These two research areas, which do not quite fit the context of data analytics, reinforce the assumption that this field is not researched extensively. Other indications that have already been mentioned are the lack of literature that overspans the topic as a whole and the lack of literature that can be assigned to the "decisions" and "actions" phases of the information value chain. This circumstance is supported by the fact that hardly any experiments could be found as a used method in the current literature, even though experiments should be an integral part of behavioral research in the field of data analytics (Gniewosz, 2011). This has not only created a blind spot in the current state of knowledge, but also a permanent limitation for new research, which lacks existing knowledge as a foundation for new science. In summary, the literature search indicates a gap in the literature on behavioral research on data analytics as well as a lack of experimental research in this area. Although current knowledge suggests that both behavioral and experimental research should be an integral part of data analysis research, the literature review of this section was able to show that both areas are extremely underrepresented in literature and research. This circumstance is further underlined by the fact that resources already exist to support experimental research in the field of behavioral science (for Social Sciences, 2023), but none of the articles analyzed utilized them.

In this section, the artifact is designed and developed based on the previously created requirements. At this point, the specific form of the artifact should also be discussed. Basically, no software component has to be developed based on the Design Science Research approach. A theoretical concept or a methodology can also arise from the Design Science Research approach. However, the conceptualized artifact should correspond to a form that addresses the original problem. As has already been shown, the original problem is the lack of experimental research in the field of data analytics. Section 4 shows that there is a need for support for the experimental setup in existing applications as well as in already conducted studies. The literature search in section 3 as well as the literature search in section 4 does not point to conceptual problems with the methodology in these studies. Supporting the execution of experiments therefore seems to be best implemented by an IT artifact instead of a methological concept or other possibilities for an artifact. For this reason, requirements for the direct experimental setup are recorded and these are then used to implement the artifact as a software component, with the goal of improving the performance of experiments.

4 Definition of Objectives for a solution

As described earlier, goals for solving the problem are described by requirements, which are established using the “requirement engineering” approach. Beginning with the *Requirements Elicitation* phase, applications and frameworks are reviewed, which enable the conducting of experiments. Subsequently, a literature review is conducted to establish further requirements for the field of data analytics based on previous research. Information gathered in this step are then used in the *Requirements Specification* step in order to specify requirements for the final artefact. These requirements are then validated in the *Requirements Validation* phase.

4.1 Requirements Elicitation

This phase gathers information in order to discorver possible requirements for the final artefact. These requirements are discovered by analyzing applications and frameworks that were created to support experimental research in related fields and through a literature review of studies that have utilized experiments in the field of behavioral research in data analyitics.

4.1.1 Existing Resources for Online Experiments

In this section, just three different resources for conducting online experiments are presented and then analyzed. A small example experiment was implemented with each of the applications in order to find out the advantages and disadvantages of the respective resource. The goal of this section is to draw conclusions and define requirements from the applications that allow to design an artifact for the field of data analytics. The applications analyzed are resources recommended for experiments by the Columbia Experimental Laboratory for Social Sciences. The selection of resources analyzed in the course of this thesis is limited to applications that allow the implementation of interactive experiments. Resources or applications that are only suitable for conducting surveys or passive experiments were neglected.

z-Tree Zurich Toolbox for Readymade Economic Experiments: z-Tree is a software componant which development started in 1998 by the University of Zurich. The software component was developed as a toolbox for conducting economic experiments. The technical set-up of z-Tree usually consists of a client/server architecture, where the experiment conducter runs a server and the test subjects participate via a client. In general, the program is written in C++ and requires a Windows operating system, making it compatable with around 28.59% of devices (statcounter, 2023). Simultaneously, however, this architecture ties the experiment setup exclusevly to desktop computers. An installation on devices that run other operating system necessarily requires a virtual machine or similar measures. Furthermore, the possibilities to use graphical interfaces in experiments are extremely limited. The same is true for computer interfaces that have been developed after the 1990s. Thus, the experiments implemented with z-Tree are mostly limited to mouse and keyboard inputs, while also limiting the amount of meta data which can be collected. Although technically all interfaces, data sources or other programs could be integrated, a software component of this age represents a significantly greater challenge for most extensions than applications designed under new standards and technologies. This is especially critical for the data analytics field, which is driven by extremely recent developments. Adapting z-Tree to newer experiments can thus involve a very high programming effort. (of Zurich, 2023, Fischbacher, 2006, D. Chen et al., 2016). Z-Tree is also a proprietary software which can be licensed for free, but it is not an open source software (Fischbacher, 2006). In conclusion, Z-Tree thus represents an outdated and extremely limiting software component, which is not suitable for experimental research in the area of behavioral research or data analytics.

oTree An open-source platform for laboratory, online, and field experiments:

oTree is a publicly accessible and web-driven software solution developed for the purpose of facilitating the implementation of dynamic experiments across diverse domains, including laboratory settings, online platforms, field studies, or any synergistic combinations thereof. One of the motivators for its development was to replace the outdated z-Tree of the University of Zurich. The newer oTree removed many of the restrictions of z-Tree, such as limited user interfaces, a Windows constraint, limited extensibility, and more. Another goal of oTree was to simplify the execution of field experiments in contrast to z-Tree. OTree is open source and based on the Python programming language. By default oTree supports simple interactive experiments, more complex experiments have to be implemented by Python, requiring programming expertise. Experiments implemented in oTree work exclusively via a client/server architecture, where the experiment performer has to set up a server and the experiment participants then participate in the experiment via any device using a browser. This has great advantages especially for field experiments where participants can be recruited via a customized web-link.Nevertheless, oTree requires a lot of technical programming expertise to setup and additional hardware in form of a server. Depending on the complexity of the experiment, the work that oTree saves the developer is therefore rather limited. At the same time, simple experiments still require a certain amount of technical know-how, making oTree unsuitable for quick experiments. These circumstances could lead to little use of oTree, especially in the area of data analytics (D. Chen et al., 2016). In conclusion, oTree is in principle a solid solution for performing experiments. In conclusion, oTree is in principle a solid solution for conducting experiments, but due to its high level of technical expertise and other limitations, it seems to be rather unsuitable as a basis for conducting experiments in the field of data analytics. Nevertheless, as requirements for the artifact which is designed in the course of this work, especially the properties which oTree wanted to improve over its predecessor zTree should be included. These are mainly related to the use of complex and up to date user interfaces, the deployment on non windows platforms, the open-source approach and the possibility to add own program code for the experiments.

LIONESS Lab a free web-based platform for conducting interactive experiments online: LIONESS Lab constitutes a cost-free, web-based platform designed for the facilitation of interactive online experiments. It is developed by the Centre for Decision Research and Experimental Economics (University of Nottingham, UK) and the Chair of Economic Theory (University of Passau, Germany). Thus, Lioness Lab is not only a proprietary software solution but also requires special access for its use and emphasizes the conducting of field experiments. This is free of charge, but it depends entirely on the Universities in question to obtain it. At the same time, the publishers of LIONESS LAB repeatedly emphasize that their solution hardly requires any programming knowledge to perform experiments (Giamattei et al., 2020). A circumstance that can complicate the use of complex custome coding for complex experiments. In addition, this paradigm removes much of the complexity of the software from the coding level to the customizing level. A problematic circumstance since this limits the extensibility and basically does not reduce the perceived complexity (Chou and Chang, 2008b). Other unique features of Max include the ability to reduce waiting time, spontaneously form groups, handle participant dropouts, and a so called "robotic" feature that mimics user input for testing purposes. Also, because of the way experiments can be conducted using the software, the focus of effort tends to be more on field experiments as well (Giamattei et al., 2020). In summary, LIONESS Lab is a platform that stands out due to a variety of functions, but unfortunately is not open source. At the same time, the extensibility of the platform is very questionable, which makes it a good choice for suitable experiments, but unfortunately unusable for more complex experiments. Requirements resulting from this application are mainly a focus on openness of the platform, the creation of different groups regarding the test subjects and the possibility to use unrestricted coding if needed.

In summary, the analysis of the three applications showed important insights into alternative attempts of an application or platform to perform experiments in related scientific fields. The resulting findings are included in the requirements for the final artefact. These include openness of the platform, the creation of different participant groups, advanced user interface capabilities, the possibilitie to run custom code and and the delivery of the artifact with a minimum of standard functionality for creating experiments. These requirements, including requirements from other sources and description, are included in Table X in subsection 4.2. Nevertheless, a closer look at the applications could also show reasons as to why such applications are not suitable for experimental research in the field of behavioral research in data analytics. Which is supported by the lack of usage of these applications in the literature search of section 3 and 4.1.2.

4.1.2 Studies in Data Analytics - A Literature Review

In order to establish further requirements a second literature search is conducted, which focusses on articles and studies in the field of behavioral research in data analytics. The goal of this second literature review is to understand commonalities and challenges of studies and especially experiments conducted in the area of data analytics, in order to establish requirements for the creation of the artifact. Due to the assumption that data analytics lies both in the fields of information systems and business administration the same databases where used as for the literature review in section 3. Table 2 gives an overview of the databases used. By using the same databases as in section 3, it is also ensured that the requirements are elicited based on the same general selection of literature as the original problem was identified with. The approach to the literature search, established in section 3, was also used for this literature review, ensuring a thorough examination of relevant research while avoiding unnecessary altering the process of finding literature. Therefore, to maintain the integrity of the identified literature and to avoid repetition, a process was followed as described in the previous literature review (section 3). Specifically, publications from journals were selectively considered, including those listed in the *Senior Scholars' Basket of Journals* for Information Systems and the *UT Dallas Top 100 Business School Research Rankings* for Business Administration. The full list of these journals can be found in appendix 8.3 and 8.3. As for the previous literature review, in order to ensure the quality of the publications, only peer-reviewed articles were considered, while book reviews, editorials, and opinion pieces were excluded. In addition, "non-scientific" texts or publications that did not meet scientific criteria were excluded from the search. The research was further refined by carefully reviewing article abstracts, which ensured that the selected literature remained relevant to the topic of experimental research in data analytics. The abstracts were reviewed not only for the use of experiments in the study, but also for research designs that could have allowed hypothesis testing by experiment. This was done to counteract the effect of selection bias. Selection bias generally describes the effects of making assumption based on a sample size, which does not represent the full population (Heckman, 2010). A simple example of Selection Bias would be to calculate the average Disposable Income of families based on the annual tax bill. This experimental design would reduce the total population to taxpaying families and thus lead to potentially grossly inaccurate results, since families living below the taxable threshold would not be included in the study. For the same principle, studies in which no experiment was performed are included in the literature review. The goal of this thesis is to improve the process of experimental research in the field of data analytics in general. Considering only studies that already perform experiments would not be representative of the full field and would therefore be prone to selection bias. It could be, for example, that certain circumstances, possibly the lack of an appropriate application, make it difficult to perform experiments. This fact would be completely lost if only studies that already perform experiments were considered. An adequate example of an article that falls into this category is Sebastian Krakowski, Johannes Luger and Sebastian Raisch's 2022 article "Artificial intelligence and the changing sources of competitive advantage", in which they research how atrificial intelligence change the compatitive advantage by being substitues to humans in managerial tasks and decision making. For this purpose, they are examining data from chess tournaments that have already been held. However, the same research question could have been answered by conducting experiments with chess players instead of using historical data from tournaments. Remarkably, the authors seem to come to a similair conclusion, stayting further research in this area should be conducted through experiments (Krakowski et al., 2023a). Furthermore, it should be noted that the focus of this literature review was not to outline the current state of research, but to identify as many appropriate articles as possible. For this reason, fewer search terms were used and articles from different subareas were generally admitted, as long as they are located in the larger context of data analytics or decision making. For this reason, a backwards and forwards search was also omitted. The search terms used for this literature review are "Data Analytics", "Decision Making" and "Big Data". With these terms, the search process should be kept as broad as possible. As already mentioned, these terms were used to search the databases from appendix 8.3 and 8.3 for matching articles. The search was furhter limited to articles written in the english language. The abstracts of all articles were then analyzed. The number of found articles for each database are displayed in Table 5. This table indicates how many articles per corresponding term are contained in the respective database, which were published in one of the relevant journals. In this way, the abstract of a total of 19,955 articles were considered. The other databases listed in the appendix (among others, AIS Electronic Library, ACM Digital Library, IEEE Xplore / Electronic Library, ProQuest) did not contain articles in the corresponding journals that could be found by using the search terms and are therefore not included in the table.

This process initially yielded 46 research publications, which were supplemented by articles from the previous literature review corresponding to the criteria. This resulted in a total number of 56 articles. The results were then classified according to the research method they utilize and whether a qualitative or quantitative approach was used. The results of this classification are presented in table 6. An important note at this point is that the number of

	Academic Journals in Business Source Premier			JSTOR			EconBiz		
	Search Phrase: Data Analyt-ics (36,028)	Search Phrase: Business Intelli-gence (12,694)	Search Phrase: big data (39,062)	Search Phrase: Data Analyt-ics (41,269)	Search Phrase: Business Intelli-gence (145,917)	Search Phrase: big data (316,288)	Search Phrase: Data Analyt-ics (2,753)	Search Phrase: Business Intelli-gence (6,775)	Search Phrase: big data (4,583)
The Accounting Review	0	0	0	182	187	685	1	0	1
Journal of Accounting and Economics	0	0	0	0	0	0	0	0	0
Journal of Accounting Research	0	0	0	67	45	373	1	3	8
Journal of Finance	0	0	0	103	91	870	4	25	15
Journal of Financial Economics	0	0	0	0	0	0	1	3	1
The Review of Financial Studies	0	0	0	107	70	441	0	0	2
Information Systems Research	61	41	0	79	243	187	2	51	28
Journal on Computing	43	18	0	0	0	0	0	0	0
MIS Quarterly	70	49	52	139	327	312	6	5	5
Journal of Consumer Research	0	0	0	34	128	366	0	0	0
Journal of Marketing	52	33	50	295	988	1508	7	4	14
Journal of Marketing Research	123	17	97	151	210	347	1	1	0
Marketing Science	50	31	54	119	99	256	1	1	4
Management Science	194	60	108	361	411	752	11	55	36
Operations Research	89	96	186	350	230	520	11	12	17
Journal of Operations Management	45	0	0	0	0	0	0	6	4
Manufacturing and Service Operations Management	0	0	0	0	0	0	0	0	1
Production and Operations Management	0	0	0	0	0	0	5	1	3
Academy of Management Journal	0	23	0	50	279	583	0	0	1
Academy of Management Review	0	26	0	36	244	241	0	0	0
Administrative Science Quarterly	0	0	0	25	157	374	0	0	1
Organization Science	0	21	0	48	280	435	0	1	0
Journal of International Business Studies	0	26	0	42	237	401	0	0	0
Strategic Management Journal	0	67	0	73	252	451	0	0	0
Decision Support Systems	242	151	166	0	0	0	0	0	0
European Journal of Information Systems	0	0	0	0	0	0	0	0	0
Information & Management	75	29	59	94	373	221	18	99	51
Information and Organization	0	0	0	0	0	0	0	0	0
Information Systems Journal	0	0	0	94	373	221	5	15	13
Journal of the AIS	0	0	0	0	0	0	0	0	0
Journal of Information Technology	56	24	50	0	0	0	3	8	1
Journal of Strategic Information Systems	0	0	0	0	0	0	0	0	0
Journal of MIS	0	0	0	0	0	0	0	0	0
Total	**874**	**571**	**720**	**2449**	**5224**	**9544**	**77**	**290**	**206**

Table 5: Number of articles identified in their respective database

articles using experiments does not contradict the gap identified in section 3, since in this literature review specifically filtered for research articles that use experiments. Thereafter, the exact experimental setup of the articles was analyzed in order to discover requirements for their individual experiments and therefore for the artefact which is subject of thesis.

Research Method	Total
Case Study	16
Interview	3
Experiment	10
Observation	3
Survey	17
Data Analysis	7
Quantitative	34
Qualitative	32

Table 6: Research Methods of second Literature review

The requirements derived from this are included in Table A. As already mentioned, not only requirements of performed experiments were included, but also requirements of setups that would have been suitable for an experiment. The column “Proper” indicates whether a requirement was actually mentioned directly in the article and the column “Extra” whether this requirement would have had to be used theorethically if the study had conducted an experiment. As already explained, this should ensure that not only requirements that fit to already performed experiments are discovered, in order to counteracted selection bias.

Requirement	Proper	Extra	Requirement	Proper	Extra
Reusable	11	0	Participant Data	24	23
Interoperability	1	0	Displaying Information	22	23
Meta Data Collecting	8	0	Different Groups	14	2
Post-Interview	2	0	Additional Logic	12	0
Time-Flexibility	9	0	Evaluation of Data	27	22
Multi-Source	1	0	Participant Input	21	25
Vizualize Final Data	2	0	Real-Time Exchange	3	0
Proactive System	2	0	Distant Communication	18	0
Pre-Loading Data	1	0	Selecting Data	2	0
Monitoring of Study	1	0	Simplicity	1	0
Debrefing Info	1	0			

Table 7: Requirements Uncatagorized

4.1.3 Further relevant reference resources

In addition to already developed applications and the relevant articles themselves, this section includes other sources that can be derived into requirements. These sources and requirements mainly refer to external influencing factors or specifications. Only requirements that have not yet been established by the previous methods are included. In their book on Empirical Educational Research, H. Reinders,H. Ditton and C. Gräsel describe, among other things, the structure and empirical theory in relation to experiments. An important part of conducting experiments, according to the authors, is to educate the subjects about the experiment and its benefits. Rather than explaining the design of the experiment, this involves explaining the actual benefits and goal of the experiment to the participants after it has been conducted (Gniewosz, 2011). As already mentioned in the theoretical part about the theory behind the execution of experiments, confounding variables have to be eliminated for the effective execution of experiments. Although some of these measures must be implemented on a case-by-case basis by the individual experimental setup itself, the artifact is intended to assist in this process when possible. Especially the measures "Parallelization of confounding variables of the test subjects", "Randomization of confounding variables of the subjects" and "Control group" represent measures which can be supported by an artifact. For this reason, the requirements "Random or targeted assignment of test subjects" are included in the list of requirements. The creation of control groups via different participant groups is already included as a requirement from several sources.

4.2 Requirements Specification

After the requirements have been discovered and roughly outlined in the previous section, they are concretely specified, organized and classified in this section. For this purpose, the requirements were specified concretely with explanation and categorized based on their task. At the same time, the requirements were classified into functional and non-functional requirements. Table 8 contains the functional and Table 9 the non-functional requirements. The requirements are composed of the requirements discovered in sections 4.1.1, 4.1.2 and 4.1.3 and are included together in the tables. Requirements derived from multiple sources and methods are also just listed once in the table.

Requirement	Description
Information	
F1.1 Displaying Information	Information must be able to be displayed.
F1.2 Debrefing Info	Debrifing Information must be able to be displayed.
Data Collecting	
F2.1 Participant Data	Basic data about the participants must be able to be collected.
F2.2 Meta-Data	Meta data must be collected.
F2.3 Post-Interview	It must be possible to collect data after the experiment.
Pre-Loading	
F3.1 Pre-Loading Data	Data must be able to be pre-loaded.
F3.2 Selecting Data	Data must be able to be pre-selected and deleted.
Experiment Setup	
F2.1 Additional Logic	Custom logic/program code can be executed within the artifact.
F2.2 Participant Input	The artefact enables user input.
F2.3 Proactive System	The artifact can pro-actively propmt a user action
Groups	
F4.1 Different Groups	The artifact must allow the division of participants into different groups
F4.2 Communication of Groups	The different groups must be able to interact with each other.
F4.3 Targeted Assignment	Groups of test subjects must be able to be created based on certain attributes like confounding variables
F4.4 Random Assignment	Groups of test subjects must be able to be created based on random assignment

Table 8: Functional Requirements Structured

Requirement	Description
Time-space non-reliance	
N1.1 Distand Communication	The artifact can be used regardless of the location of the participant.
N1.2 Time-Flexibility	The artifact can be used independently of a given period of time.
Data Postprocessing	
N3.1 Evaluation of Data	The data can be retrieved in a suitable way for further processing and evaluation.
N3.2 Vizualize Final Data	The data can be retrieved in a suitable way for further visualization.
Simplicity	
N4.1 Simplicity	The artefact is simple to use.
Reusable and Interoperable	
N5.1 Reusable	Experiments with the artefact are easy to re-do.
N5.2 Interoperability	The artefact is interoperable.
N5.3 Openness of Platform	The artefact is open to changes and enhancements.
Monitoring	
N6.1 Monitoring of Study	The study conducted with the artefact can be monitored.
Pre-Loading	
N7.1 Multi-Source	Data from multiple-sources must be pre-loaded.
Advanced User Interface	
N8.1 Advanced User Interface	The Artefact enables the usage of modern user interface components.

Table 9: Non-Functional Requirements Structured

4.3 Requirements Validation

In this section, the previously established requirements are validated. The criteria Validity, Consistency, Completeness, Realism, and Verifiability from the requirement engineering approach are used for this purpose. The validity criterion indicates whether the requirements imposed actually correspond to the intended functions. Since the requirements were drawn up by taking into account applications that have already been developed and studies that have already been carried out, it can be assumed that the requirements correspond more precisely to the functions that are actually required than if they had been drawn up by any stakeholders. In addition, the requirements were established using a clearly defined scientific process and by adding literature from the field which should also increase validity. Some of the requirements derived in subsection 4.1.1 are also conform with requirements from subsection 4.1.2 and 4.1.3, indicating that the requirement search covers the problem to be solved very well. For these reasons, it is assumed with a high probability that the validity of the requirements is guaranteed. Moreover, the established requirements in Table A and B do not contradict each other, which means that the consistency criterion is also met. The "completeness" criterion, which describes whether the overall scope of the functions is covered by the requirements, is difficult to confirm. The reason for this is the open nature of the artifact, which should enable the improved execution of arbitrary experiments. Thus, the functional scope of the artifact is theoretically endless. Nevertheless, this criterion can be confirmed considering requirement F2.1. Requirement F2.1 ensures that additional logic and program code can be implemented within the artefact, which means that theoretically an infinite number of further functions can be implemented by the person performing the experiment (as far as these requirements can be implemented by a Turing-Complete programming language). As a result, the "Completness" criterion is also considered to be fulfilled. The criterion "realism" can also be confirmed. No requirement indicates that it could not be implemented technically. However, this point will be discussed in more detail in the implementation of the artifact. At this point in time, this point is considered to be fulfilled. The last criterion to confirm the validity of the requirements is the "Verifiability", which describes whether the individual requirements are formulated in a way that they can be tested. An important point, since the artefact must be tested for all requirements following the DSR approach. In order to be able to formally confirm the criterion, a test-case is therefore designed which checks the artifact against the requirements. This approach is also supported by the scientific literature for the validation of requirements and is later used in the DSR approach to confirm the requirements (Sommerville, 2011).

ID	Test Description	Requirement
T1	A welcome and goodbye message is displayed	F1.1, F1.2
T2	Participants are prompted to input their age at the beginning and prompted to input how the liked the experiment at the end	F2.1, F2.3, F2.2, F2.3
T3	The information about how long the experiment took is collected	F2.2
T4	The sex and the weight of the participant is pre-loaded into the experiment from different files. The sex of the participant is deleted.	F3.2
T5	A chess game is added as custom logic	F2.1, F2.2, F2.3
T6	Two groups are created, one of the groups is particularly chosen the other one randomly selected	F4.1, F4.3, F4.4
T7	A chess turn is played by both parties not using the same device	F4.2, N1.1, N1.2
T8	The results of the experiment are retrieved and displayed in third party software	N3.1, N.3.2
T9	The experiment is redone a second time and another experimental setup is implemented	N5.1
T10	The experiment is conducted on different devices	N5.2
T11	During the experiment the current state of the chess board is exported to the conducter of the experiment	N6.1

The non-functional requirements simplicity, openness of platform and advanced user interface cannot be precisely tested by a test case due to their subjectivity. One way to counteract this would be to formulate the requirement more precisely and for example to replace “advanced user interface” with “a user interface that was developed in 2023” This would satisfy the verifiability criterion, but no longer the validity criterion, since this requirement is actually fairly subjective and the test might not capture the initial intention of the requirement. For this reason, the three requirements Simplicity, openess of platform and advanced user interface are valid requirements, but no test cases are included for them. Nevertheless, they are taken into account in the development of the artefact and finally evaluated as best as possible.

By successfully setting up these tests, the “Verifiability” criterion can thus also be confirmed. Thus, the established artifacts meet the criteria Validity, Consistency, Completeness, Realism, and Verifiability and are thus valid requirements for the artifact.

5 Design and Development of the Artefacts

The artifact, which is intended to improve experimental research in behavioral research in data analytics, is to be implemented as a software component or application. In this step, a suitable architecture is developed based on the established requirements. For this purpose, the application is first fundamentally conceptualized. This involves analyzing possible technologies and the corresponding processes. The architecture is then implemented in practice on the basis of this basic conceptualization.

5.1 Process Conceptualization

In order to effectively implement the requirements for the application, the processes described by the requirements and validated by the test cases are represented in the following swim lane diagrams. The goal of this is to illustrate the individual processes in a technology-independent manner. The reason for this is that the individual processes are initially presented in generalized form, irrespective of technological restrictions or limitations. The following Swim Lane diagrams represent the individual steps of the experiment. Swim lane diagrams depict processes by showing business activities in relation to each other and how they are associated with each other (Caudle, 2009).A large part of the final functionalities can be divided into two different categories. An example of this are the requirements (F2, F3 and N5.1), whereby the application should offer both the possibility to read in and save user data and data corresponding to the experiment setup itself. These requirements can be summarized in functions and data concerning the experiment and functions and data concerning the participants. The two lanes “Participant Repository” and “Experiment Repository” are representative for those two categories and data sources. The “User” lane shows the activities performed by the test subjects, the “Experimental Repository” lane shows all activities that can be associated with the experimental setup, and the “Patricipant Repository” lane shows all data and activities that are related to the test subjects.

Figure 3 shows the basic structure of an experiment with the conceptualized application. The whole experiment is divided into different experiment steps, which are executed one after the other until the experiment is completed. The application is started first and then

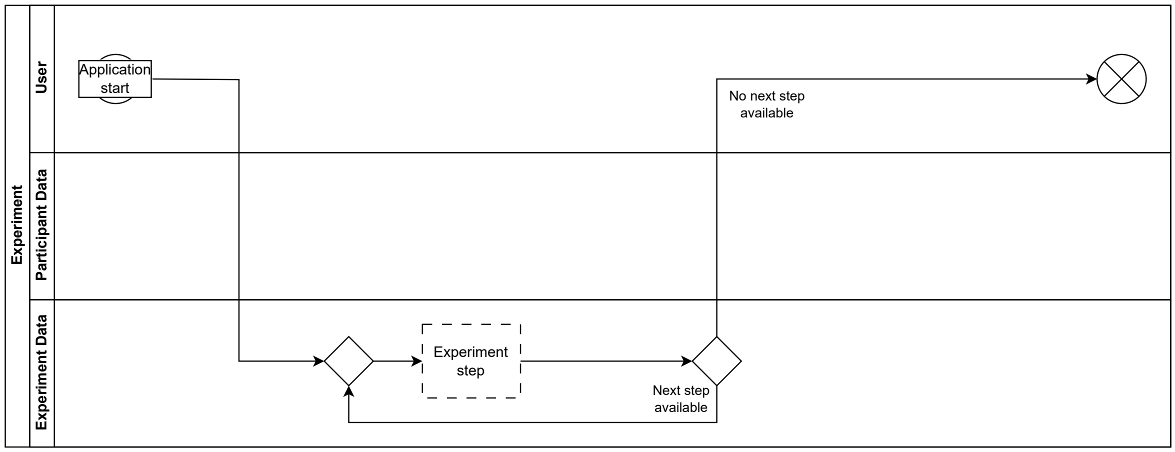


Figure 3: Experiment - Swim lane

the first step of the experiment is executed. This could be for example an information message for the participants. After that the next step is executed if another step is available. If no further step is available, the experiment ends. This simple abstraction of an experiment concentrates on the essentials and thus allows the most flexible and adaptable construction kit for an experiment. The individual steps of the experiment, which are executed one after the other, can be customized by the person performing the experiment as well as mapped by standard steps. The standard steps represent steps which have to be used in a multitude of experiments and thus partially represent requirements. In the following, some of these experiment steps which illustrate standard steps that are included in the application are illustrated with the help of swim lane diagrams. Figure 4, 6, 7 and 8 represent these standard steps. The dashed box “Experimental Step” of figur 3 can be replaced by any number of these. For this reason, the graphics mentioned also begin and end in the “Experimental Repository” lane.

Figure 4 represents the process step of reading data from one or more sources. The assumption is that this data must first be processed or standardized before it can be meaningfully assigned to the participants.

Figure 5 enables the mapping between the test subject and their ID which will be used for the rest of the experiment.

Figure 6 represents the process of assigning individual participants into groups. This can either be the case that participants are divided according to a predefined group, arbitrarily or according to certain criteria.

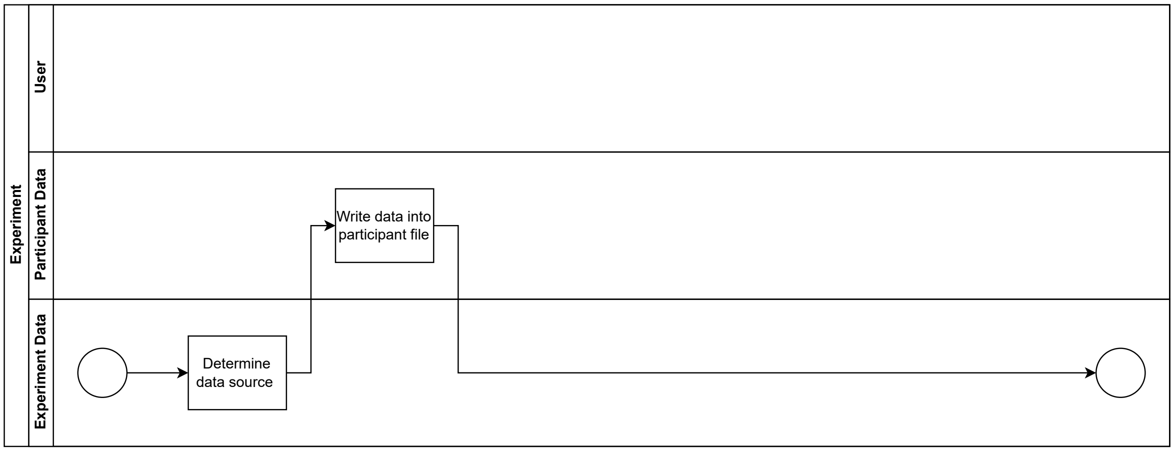


Figure 4: Data input step - Swim lane

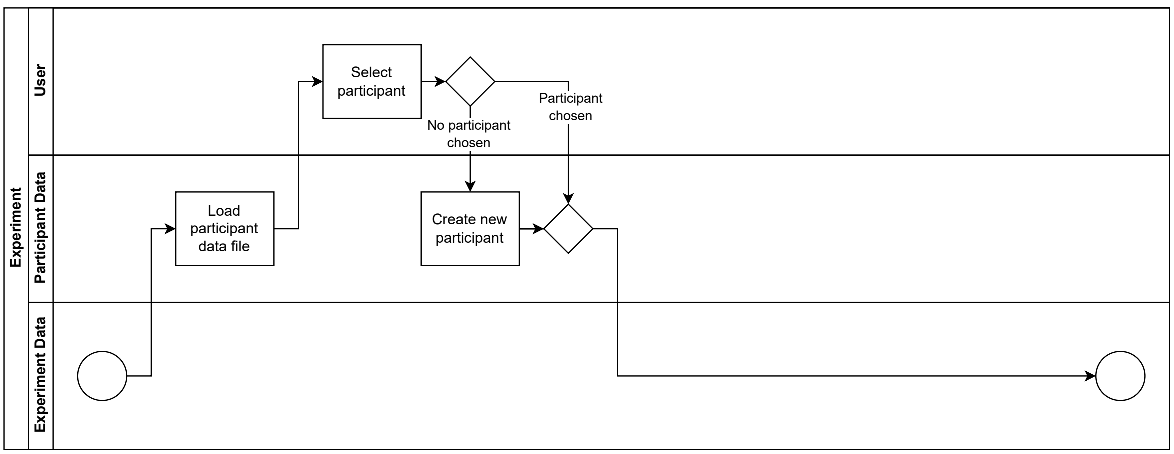


Figure 5: Choose test subject step - Swim lane

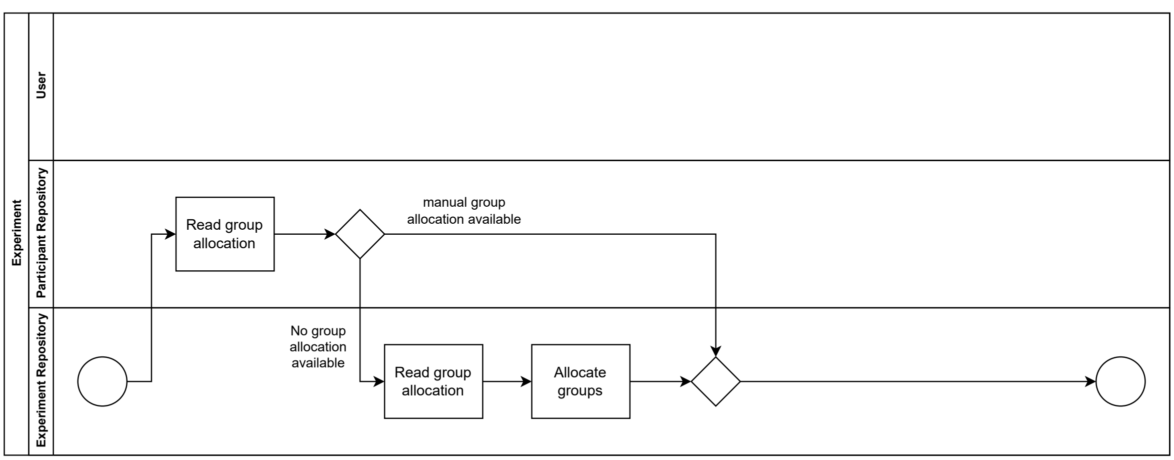


Figure 6: Group allocation step - Swim lane

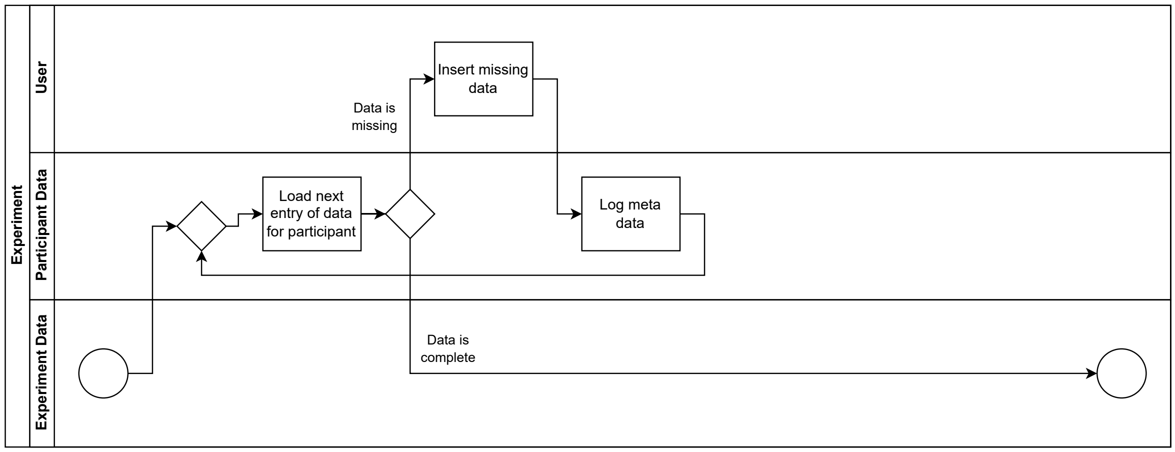


Figure 7: Questionair step - Swim lane

Figure 7 is used to complete mising information or data about the participants. For this purpose, test subjects are asked questions based on missing data entries. This process is conceptualized similarly to the general experiment setup, so that any number of questions or no questions are displayed for completion, depending on the number of missing data points about a test subject. An example would be a test subject for which the age is missing. An input field is automatically displayed for the participant to fill in the missing data about himself. If all data for a test subject is complete, nothing is displayed.

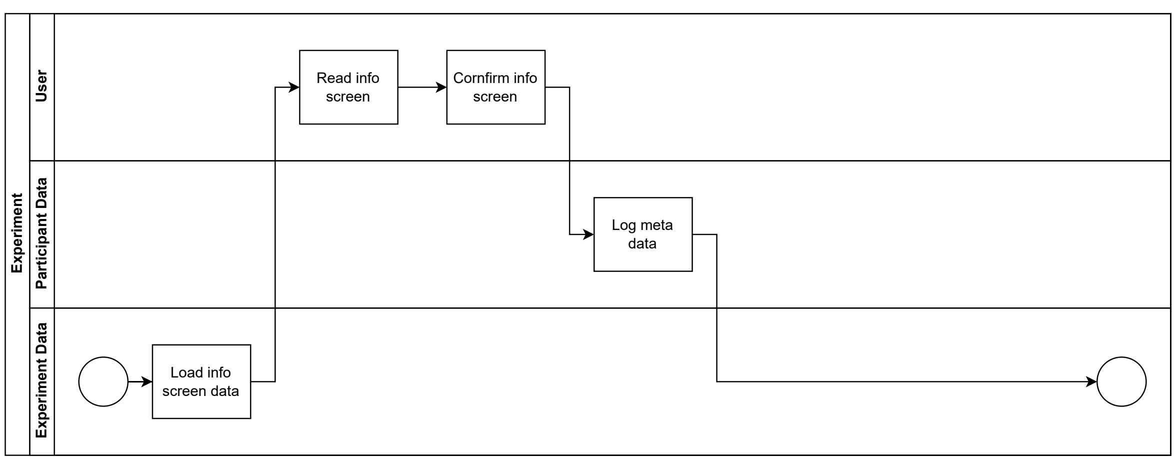


Figure 8: Info screen step - Swim lane

Figure 8 displays information to the test subjects and can be used both as a means of notification during an experiment and as a representation of information.

5.2 Technology Selection

In order to select appropriate technologies for the implementation of the application, the established requirements must be considered. It can be assumed that all functional requirements can be implemented by any modern programming language that is turing complete. The non-functional requirements N3.1 (Evaluation of Data), N3.2 (Vizualize Final Data), N7.1 (Multi-Source) are represented by the availability of various interfaces. Furthermore, the two non-functional requirements N1.2 (Time-Flexibility) and N6.1 (Monitoring of Study) are not relevant to the technology selection as these refer to the way the application is implemented and not its technological nature. This leaves requirements N1.1 (Distand Communication), N4.1 (Simplicity), N5.1 (Reusable), N5.2 (Interoperability), N5.3 (Openness of Platform), N8.1 (Advanced User Interface) and the afformentioned availability of interfaces as requirements for selecting a suitable technology. In the following chapters, various technologies and tools are presented that are intended to meet these requirements.

5.2.1 Android and Android Studio

Android is an open source operating system for mobile devices which was first announced by Google in 2013. To date, Android has achieved a market share of over 90% in the mobile sector and is the most used operating system over all, being used in almost every second device (statcounter, 2023, E. Richter, 2019). The standard development environment to develop Android is the Integrated Development Environment (IDE) Android Studio, which supports a wide range of developer tools and functionalities. As an open source project and, due to its high distribution on various devices Android suits the openness of platform and interoperability requirement (E. Richter, 2019). Applications for the Android operating system are called apps. These apps are programs designed for touch inputs, which are specifically designed for mobile devices. However, as a widely used open source operating system, Android also supports other input options, advanced network capabilities and a variety of interfaces and extensions (E. Richter, 2019). Thus it can be assumed that the interface and distand communication requirements can be fulfilled through the usage of Android. The two programming languages that can be used to develop these Android apps are Java and Kotlin.

These apps then can be tested either directly on an Android device or on a variety of virtual devices integrated in Android Studio, which further facilitates the development of said applications (E. Richter, 2019). As a mobile operating system, one of Android's main focuses is the user interface as an input function, in addition to network functionalities and a variety of interfaces. Android therefore has a wide range of design guidelines, interface functionalities and is updated at very regular intervals (Statista, 2023, E. Richter, 2019). Due to these regular updates, the widespread use of Android and the focus on User Interface (UI) intensive use cases, it can be assumed that an app developed in Android supports the latest user interface technologies and therefore fulfills the advanced user interface requirement.

5.2.2 Java

Java is a programming language originally developed by Microsystems. Since 2009 Java is part of the product portfolio of Oracle Corporation. Java is an object-oriented programming language, which makes it an universally applicable and robust programming language (Ullenboom, 2017). Unlike many other programming languages, one of the special features of Java is its platform independence. Most programming languages use a compiler or interpreter to translate program code into byte code, which varies depending on the hardware and can only be executed on the appropriate processors. Java avoids this limitation by first having a compiler translate the Java program code into byte code, which is then executed via an interpreter in a virtual environment which is called Java Virtual Machine (JVM). In this way, Java code can theoretically be executed on any system (Ullenboom, 2017). This makes Java not only a programming language but also a runtime system, which is made clear by the naming of the Java Platform by Oracle. The Java Platform supports beside Java itself also the execution of some other programming languages as for example Kotlin (kotlinlang.org, 2023). Due to this fact, Java is especially suitable for the implementation of the artefact based on the requirements N5.1 (Reusable) and N5.2 (Interoperability). Java also supports a variety of programming concepts through standard libraries. These include data structures, string processing, date/time processing, graphical interfaces, input/output, network operations, threads and more (Ullenboom, 2017), which ensures the N1.1 (Distand Communication) requirement and the availability of interfaces. The Java runtime environment also enables fast code execution and comes with various utilities such as a garbage collector and output name handlers. The syntax of Java is generally considered to be very easy to understand and beginner-friendly (Ullenboom, 2017), fulfilling the requirement N4.1 (Simplicity). In addition to technical aspects, Java is also Open-Source, extremely widespread, popular and a variety of literature for it is available (Ullenboom, 2017), which generally indicates an openness of platform (Requirement N5.3 Openness of Platform) and convenient to develope code (N4.1 (Simplicity)). Disadvantages of Java, which are also mentioned for the sake of completeness, mainly relate to very specific platform-dependent use cases. Since Java was developed as a general-purpose programming language and platform-independent, it is very difficult to access hardware or drivers directly. However, these use cases are irrelevant in the course of this work (Ullenboom, 2017).

5.3 System Architecture Development

Overall, it can be summarized that the non-functional requirements, which consider properties of the system, are completely fulfilled by using the Android operating system in combination with the Java programming language. In general, most of the requirements could already be met by both Android and Java alone, so the combination of the two provides a solid foundation for meeting the remaining requirements. However, as already noted in Section 4.2, the fulfillment of the non-functional requirements is by no means a binary state, but can be partly of a subjective nature, which is why no test cases could be set up for these requirements. Taking the above arguments into account, and especially the extremely wide distribution of the Android operating system, the technical combination of Android and Java for the implementation of the artifact is considered the best option. Furthermore, there is the possibility that at a later point in time another technology combination may be able to better reflect the requirements. At this point in time, however, the requirements can best be met by the combination of Android and Java. In addition, for the reasons mentioned, it can be assumed that this combination of technologies will remain the best way to implement the requirements in the long term. However, the fact that these technologies will no longer be up to date at a later point in time exists, but cannot be ruled out for any other technology too. On the contrary, Android and Java are a sensible and sustainable choice in the long term for the above-mentioned reasons according to the current state of research. For this reason, the artifact is implemented in the form of a mobile Android application.

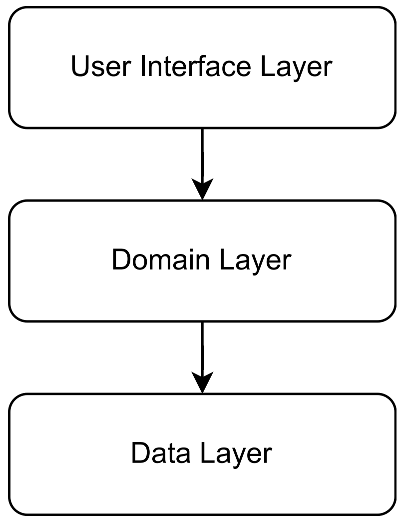


Figure 9: Android App Architecture (Google, 2023)

The recommended architecture for an Android app is shown in Figure 9 and consists of three layers, the UI layer, the domain layer, and the data layer. The UI layer displays application data and the app itself to the user. The UI layer is further divided into “UI elements” and “State Holders”. “UI elements” correspond to the displayed screen elements and the “State Holders” to temporary data of the current state of the UI. The domain layer is optional. It is used for abstraction and structuring of the data layer and is recommended above all if the application is to represent very complex business cases or the application must be designed to be very reusable (Google, 2023). Due to the requirements N5.1 (Reusable), a domain layer is therefore used in the conceptualized application. Classes in this layer are usually called use cases or interactions and always represent a single functionality. For example, the output of the time could be a functionality that must be used by several components. This functionality would then be represented by a *GetTime* class. The data layer contains the data and business logic of the application (Google, 2023). This layer defines to what extent data is processed, modified or stored. It is also divided into two parts, the repositories and the data sources (Google, 2023). The repositories are responsible for exposing the data to the rest of the application, to centralize changes to the data and to resolve conflicts between data sources. A repository can contain zero or multiple data sources. The repositories also contain the business logic and abstract the data sources from the rest of the application. Each data source is represented by one data source class which is the link between the system for data operations and the application. Sources for these data sources could be a file, a network or a local data base (Google, 2023). The communication between the individual layers is solved in Java via so-called call-back methods. Call-back methods are special methods to which program code is passed, which is executed at a certain time or event and which then notifies the higher-level program. In this way, the call-back function does not have to be modified each time, but said program code can be passed. An example would be a data retrieval, the code for this is passed using a call-back method, which is then executes when the event that the queue is processed is triggered, which then notifies the parent program of its execution and result (Zaccagnino, 2020). In the following, the concrete implementation of the architecture of the artifact is presented. The technical components are divided into the UI layer, the domain layer and the data layer.

5.3.1 Data Layer

The individual data sources are masked from the rest of the application by the so-called repositories. In principle, however, a large number of different data sources can be used. Among others, local files, database systems or network storage. The number of data sources can vary between none and any number. The individual data sources depend on the respective experiment, which is implemented with the help of the artifact that is developed in this thesis. For this reason, a simple local CSV file is used as a placeholder for different data sources. This is done for the sake of simplicity, in the final application this placeholder file can then be replaced by any other sources. The important part of the design work is the repositories and how they process the data. The actual data sources are negligible and strongly dependent on the use case. The data layer as a whole corresponds to the *Particpant Data* and *Epxeriment Data* lanes from the previously defined processes 3, 4, 5, 6, 7 and 8 as these contain the business logic for elements associated with the experiment itself and the test subjects respectively. For this reason and in order to clearly abstract the standard data sources of the artefact from potential data sources that get implemented within experiments two repositories called *ParticipantRepository* and *ExperimentRepository* are implemented.

The ParticipantRepository could also contain multiple data sources for information about the participants. This architecture is illustrated in Figure 10. As already mentioned, the conceptual design of the artifact is limited to a single data source for the experiment itself and the participants for the sake of simplicity. This is reflect by the colored elements of Figur 10, the gray parts are only exemplary placeholders for an extension of the data sources.

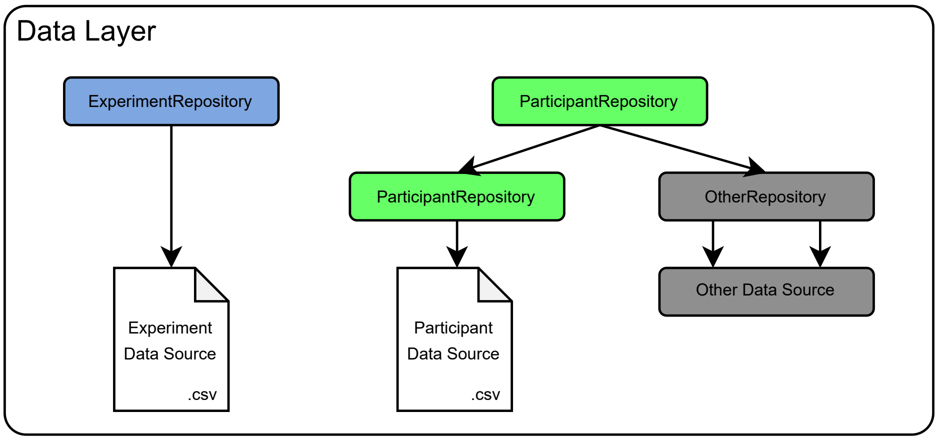


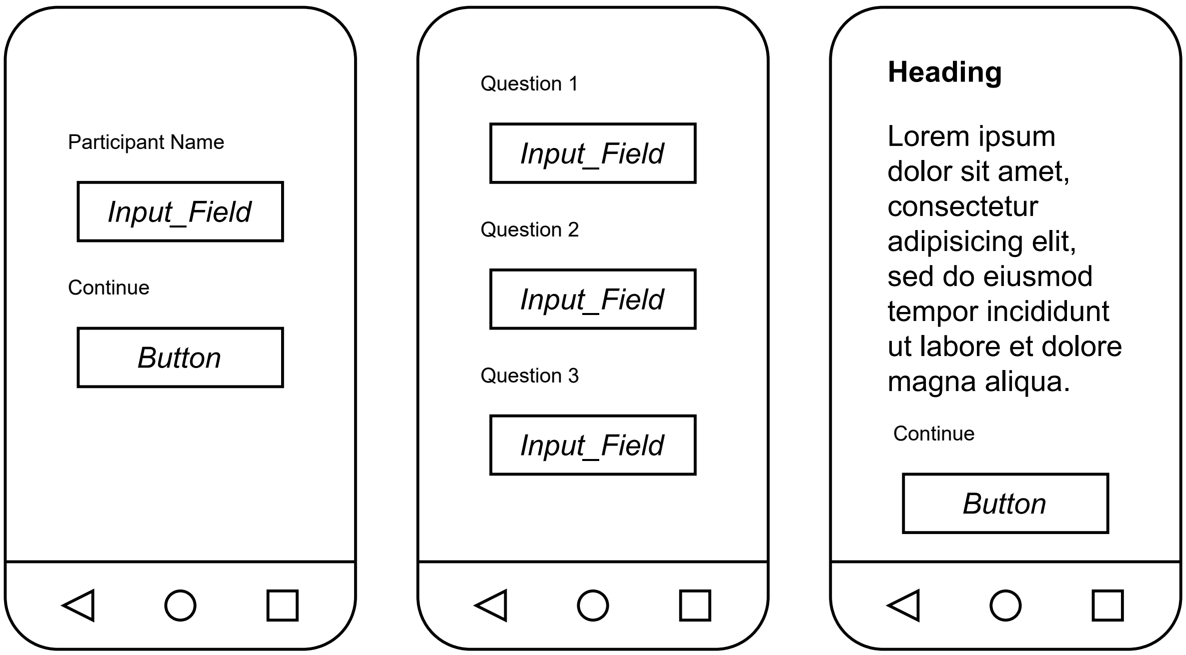
Figure 10: Data Layer of the Artefact

5.3.2 Domain Layer

The domain layer is an optional layer that encapsulates complex business logic or logic that needs to be reused frequently (Google, 2023). Since it is not known to what extent the individual elements will be used in an experiment and a special focus is placed on the reusability of the individual components, this optional layer is implemented in the artifact. Further advantages resulting from the use of a domain layer are the avoidance of duplicated code, the improved readability of the architecture, an improvement in the testability of the app and the avoidance of large classes by splitting the tasks. The domain layer classes are accessed in the same way by the UI as repositories of the data layer are accessed. An example of a domain layer class would be to request the addresses of the best authors of the year to send them an award. In this example there would be two data sources with repositories, one for authors and their addresses and another one containing the best selling books including authors. A domain layer class would hide access to these two repositories and the complex logic of determining the addresses of the best authors of the year from the rest of the application. To keep the classes of the domain layer simple it is adviced that each class should contain only a single functionality and should not contain mutable data (Google, 2023). These individual functions are also called use cases. Use cases (Domain Layer classes) can call each other and can be hierarchically dependent with each othre within the domain layer as needed. Since one use case is supposed to represent one function at a time, a domain layer class (or use case) is created for each function or action that appears in one of the process swim lane diagrams in the *Experiment Data* and *Participant Data* lane from section 5.1. Since these UseCases can be layered arbitrarily in the domain layer, UseCases are also created for all processes that do not contain user interaction, i.e., Swin Lane diagram 6.

5.3.3 User Interface Layer

The concept of graphical user interfaces is implemented in Android via so-called activities. While the entry in regular Java applications takes place via a *main()* method, an Android application initiates code via activities. The Android developer documentation describes an activity as "[...] entry point for an app's interaction with the user" (Google, 2023). The required UI elements of the app are generated in the activity. An activity corresponds to a screen. Apps can contain several different UI screens and thus several different activities. Activities can also call other activities and navigate to them as desired. An app is therefore a sequence of different activities that represent different screens. Usually, an activity serves as the entry point to the app. This activty, also called the main activty, is the first screen that is shown when the application is started. Although Activities together form a complete app, Activities are only very superficially connected to each other. Basically, each activity is a replaceable, self-contained component that can be called in any order. This reusability and separation makes Activities the perfect foundation to implement the individual "experiment steps" described in Section 5.1. Based on this fact and the fact that an Activity corresponds to a UI, a separate Activity is designed for each process step from Section 5.1. The three experiment steps, which include user inputs are the *choose test subject*, *questionair* and *info screen* step, depicted in figure 5, 7 and 8. Figure 11 depicts these three use cases as a UI prototype. Figure 11a represents the process step of choosing a test subject depicted in figure 5. Figure 11b represents the process step of letting the test subject answer questions depicted in figure 7. Figure 11c represents the process step of showing information to the test subject depicted in figure 8. The three UI sketches show the basic division of UI elements, to which the actual implementation of the activities is oriented. Furthermore, further custom steps from an experiment would also be implemented using Activities. In this way, the reusability and separation of the individual experiment steps is guaranteed.



(a) Choose test subject step (b) Questionair step (c) Info screen step

Figure 11: User Interface Prototype of Artefact

After the basic UI has been designed, the navigation between the individual steps must be conceptualized and implemented. Generally, the sequence of screen calls is stored in the manifest of the application (Google, 2023).

5.4 Consolidated System Architectural Summary

In general, it can be summarized that the processes that have been illustrated by swim lane diagrams have been technically implemented as follows:

- Diagram A depicts the process of an experiment in general. The event ”Experiment Step” is representative for all other Swim Lane process diagrams.

- The ”User” lane of the diagrams represents the interaction of the user. The individual events in this lane are therefore represented by UI activities.
- For each diagram that does not contain a user input and is therefore not represented by an activity, a UseCase is also created.
- The lane ”Experiment Data” and ”Participant Data” are representative for all events which are associated with data of the respective parts.
- The actual data resides in various data sources and is abstracted from the rest of the application by repositories. Although the two swim lanes are representative of the data layer, data source and repository are not illustrated into the swim lanes.
- The individual events of the ”Experiment Data” and ”Participant Data” lanes are each represented by a single use case and thus form the domain layer.

6 Demonstration of the Artifact

7 Evaluation of the solution

7.1 Prototype Testing

7.2 Requirements validation

7.3 (App Performance and Usability / User Feedback and Satisfaction)

8 Conclusion

8.1 Summary of the Study

8.2 Contributions and Implications

8.3 Future Work and Recommendations

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Literature search: Boundaries and conflicts in data analytics

List of Keywords (First Search)

- Data Analytics
- Data AND Boundary
- Organization AND Data Analytics
- Big Data
- boundary
- boundary theory
- boundary spanning
- boundary objects
- boundary spanner

List of Keywords (Second Search)

- Data Analytics
- Data AND Boundary
- Organization AND Data Analytics
- Big Data
- boundary
- boundary theory
- boundary spanning
- boundary objects
- boundary spanner
- Decision
- Decision Making
- Action

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- Journal of AIS
- Journal of Information Technology
- Journal of MIS
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- The Accounting Review
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- Journal of Consumer Research
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- Administrative Science Quarterly

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