Cognition, Technology & Work
https://doi.org/10.1007/s10111-018-0489-8

ORIGINAL ARTICLE

Cognitive challenges of changeability: adjustment to system changes and transfer of knowledge in modular chemical plants

Romy Müller[1]

Received: 16 September 2017 / Accepted: 18 May 2018

Abstract

In the chemical industry, highly changeable modular plants allow for system reconfigurations on shortest timescales: a number of processing units can be combined to optimize the plant setup for current demands. As a consequence, human operators are frequently confronted with newly assembled systems that differ from previous ones in some ways while not differing in others. This partial overlap creates a number of challenges with regard to operator performance and learning. Both differentiation and generalization of knowledge are needed, which leads to a goal conflict: on the one hand, operators have to know the specifics of the current system, update their understanding of functional relations between system parameters, and use operation procedures that are tailored to the requirements of the current situation. On the other hand, they need to apply the knowledge they have acquired in previous plant setups to solve problems in a new one. While unwanted carryover must be avoided, appropriate transfer is essential. The present article provides an overview of the challenges and potentials of learning and transfer in changing environments as discussed in the cognitive science and situated cognition literatures. This overview is of prescriptive nature: it presents results and theories that should be considered when analyzing operator performance and designing interfaces or training in modular plants. To this end, the article considers how learning is adapted to the volatility of the environment, how mental representations are updated, how conceptual and procedural knowledge is transferred to new situations, and how learning is shaped by interactions with the environment.

Keywords Modular plants · Cyber–physical systems · Operator tasks · Stability–flexibility balance · Learning · Transfer

1 Introduction

Cyber–physical production systems (CPPS) interconnect physical objects such as machines and products with virtual objects via global information networks (GMA 7.20 2013). They are optimized for a production that is flexible and tailored to specific customer demands, but at the same time highly efficient. Modular plants are a specific type of CPPS, with their characteristic feature being their changeability (Nyhuis et al. 2008). This means that depending on current demands, a limited number of processing units or modules can be combined to achieve an almost unlimited number of end products (Urbas et al. 2012). Accordingly, when in a given production context a particular module does not do an optimal job anymore, for instance because it is not efficient at the high temperatures required for the current chemical reaction, it can be exchanged for another module. For human operators, a result is that their work shifts towards highly context-sensitive and dispositive tasks (Hirsch-Kreinsen 2014). While in traditional supervisory control (Sheridan 2011) operators merely had to monitor the process and keep it within predefined limits or set points despite disturbances (see Fig. 1, middle), now they are actively involved in changing the process itself.

In a previous article (Müller and Urbas 2017), we analyzed the cognitive challenges arising from the fact that operators need to actively exchange or adapt modules according to current production demands and process states (see Fig. 1, left). For instance, when observing a problem in the ongoing production process, operators need to decide whether to use another module or merely alter the current module's parameters. Being responsible for such changes involves goal conflicts and trade-offs, because exchanging and adapting have complementary costs and benefits. For

✉ Romy Müller
romy.mueller@tu-dresden.de

1 Chair of Engineering Psychology and Applied Cognitive Research, Technische Universität Dresden, Helmholtzstr. 10, 01069 Dresden, Germany

Published online: 24 May 2018

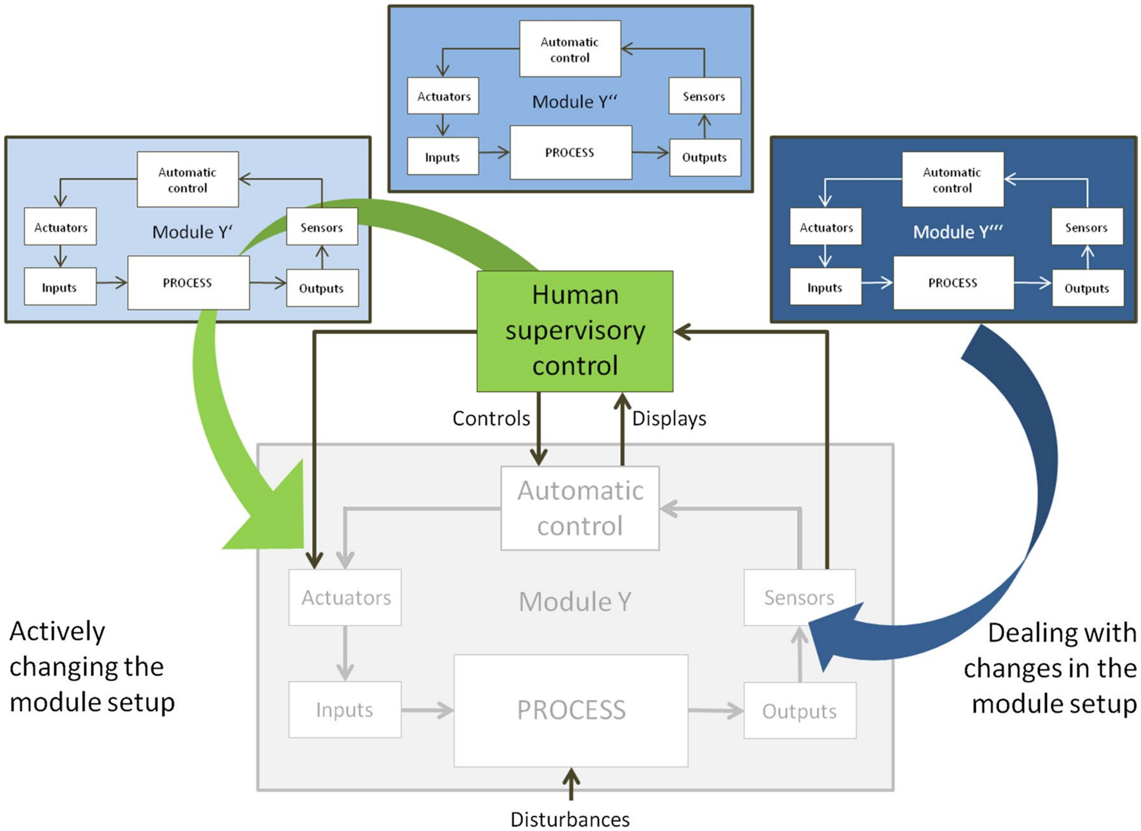

Fig. 1 Traditional supervisory control (middle) and how it changes in modular plants when operators can actively exchange modules (left) or are confronted with changes that have been made by others (right)

instance, while exchanging a module can be a good choice with regard to energy efficiency, it might put product quality at stake. In our previous article, we argued that in the presence of goal conflicts such decision-making in volatile environments requires flexible strategy selection on three interacting levels: intervention strategies, decision strategies, and cognitive meta-control strategies. While our previous article focused on the cognitive challenges of actively changing the module setup, the present one addresses the challenges of re-actively adjusting to changes in the module setup (see Fig. 1, right).

When faced with a new system, how flexible are operators in adjusting their conceptual and procedural knowledge? There has been ample scientific interest in situation awareness in dynamically changing environments, as it is needed for flying an airplane or moving a car through traffic (Ma and Kaber 2007), or for operating a plant with continuously changing process states (Lau et al. 2012). However, in modular plants the situation is characterized by more categorical changes: the system state does not simply vary over time but operators are confronted with different systems at different times. After a module exchange, the system may exhibit a different behavior and produce different outcomes (e.g., having shorter time constants and thus being more responsive to operator inputs). Similarly, the required decisions and classifications of situations may differ from those in the previous setup. When being confronted with such change, people need time to adjust, and the changes in their behavior and cognitive processing considerably lag behind the actual system changes. For instance, such lags are observed in the setting of decision criteria (i.e., being more careful vs. liberal), and people may need to experience about a dozen times that the old criteria have become inappropriate (Brown and Steyvers 2005).

Accordingly, module exchanges may lead to failures to adjust the interaction with a system to its current mode of operation (mode errors, Sarter and Woods 1992), failures to revise initial assessments when a situation changes dynamically (fixation errors, De Keyser and Woods 1990), and disruptions of skilled performance (Roth et al. 2015). The specific type of errors will depend on which features are similar and which are different after a module exchange. For instance, in a study of mixed-fleet flying (i.e., pilots switching between different versions of the same aircraft) changes could either concern the physical layout and/or the functionality of the system (Soo et al. 2016). Depending on the nature of the change, performance was affected in different ways: while different physical layouts got operators out of flow and thus led to disruptions of skilled performance, changes in functionality were more likely to go along with non-understanding and mode errors. Often pilots were not even aware of these errors and the autopilot carried out the actions as specified (but not as intended). Thus, although problems were most frequent when the physical layout differed while the functionality remained the same, they were most severe when the functionality changed. Importantly, all types of problems are not only to be expected when switching to a new system for the first time but also when switching back to a system that had been used in the past (Roth et al. 2015; Soo et al. 2016), and therefore are highly relevant in the context of changeable modular plants. Such problems can be ascribed to interference arising from the intermittent use of a new system as operators do not forget their most recent experiences.

To assess the potential impacts of module exchanges on operator performance, situation assessment, and learning in modular plants, the article presents insights from different literatures in cognitive science, the psychology of learning and instruction, and situated cognition, focusing on performance and learning in changing environments. To this end, different psychological concepts are introduced and explicitly linked to problems that might occur when operating a modular plant. The aim of this work is to provide a broad overview of results and theories that can inform the analysis of operator performance and the design of interfaces and training in modular plants. Accordingly, the article is intended to be prescriptive rather than descriptive: it is mainly concerned with the transfer of different literatures to a new area of application, instead of attempting to provide an exhaustive analysis of any particular literature.

The concepts to be discussed were selected based on the challenges expected in modular plants (e.g., Hirsch-Kreinsen 2014; Müller and Urbas 2017). When searching for articles, exemplar search terms were "cognitive flexibility", "transfer of knowledge", "function learning", and "variable practice". Articles were included that addressed performance and learning in changing contexts. That is, the literature search focused on articles dealing with differences between the learning situation and the situation in which knowledge needed to be applied, or gradual changes in the system state or contingencies over time that required adaptive performance. Moreover, articles were included that addressed the cognitive challenges of changing situations (in terms of both declarative and procedural knowledge required for problem solving), while changes that demanded an adaptation of manual or perceptual skills were not in the focus of the present work. When several articles on a particular topic were available, those were selected that provided the best match to the work requirements expected in modular plants. Articles were excluded when the mechanisms under investigation were only relevant for short-term changes (e.g., working memory demands). While the article mainly draws on findings from the cognitive science literature, Sect. 2.4 presents findings from alternative approaches essential to understanding learning and transfer in everyday performance. A metatheoretic discussion of the different approaches is provided in the discussion.

2 Cognitive challenges of dealing with change

Imagine the modular chemical plant BP-117. It produces specialty chemicals that are needed by only a few customers, who all have their own requirements in terms of product type, quality, and amount. To optimize the plant for the current production process, some modules are exchanged about once a week, others only once a year, and still others are never exchanged but may alter their processing behavior depending on the other modules in the setup. Last week, an urgent customer order demanded an exchange of reactor module Y for a more potent reactor module Y', which differs from Y in several ways and thereby poses a number of challenges for operators. First, strategy changes are needed: module Y' is much bigger, which makes it more efficient and allows for certain operation strategies, but also renders others impossible. For instance, it takes more time to fill and empty the reactor, so operators can no longer change the temperature of the medium by adjusting the ratio of hot and cold water inflows. Moreover, the exchange of Y for Y' also requires adjustments in other modules, and operating those modules like they were operated in combination with Y can lead to major safety risks. Second, changes in attention and cue utilization are required: with module Y' the production process is highly susceptible to temperature variations, so the module demands a careful monitoring of temperatures, which had not been necessary when using module Y. Third, conceptual change is necessary: while the reactor vessel of module Y has been heated with thermal oil that was pumped through its jacket, module Y' is heated with steam. This change in technology goes along with a different heating principle, which in turn causes differences in heat transfer rates. In order to make accurate predictions and control actions, operators need to update their understanding of the heat transfer process, but also learn how their parameter settings affect the temperature change in the reactor. However, besides these differences the two modules also have many features in common, and therefore operators need to transfer knowledge and experience that they have acquired when using module Y. This can be challenging for several reasons. First, the interface of module Y' looks different, and thus operators need to map the inputs they used to make when using module Y to the new interface, in spite of low surface similarity. Second, although module Y' uses a different heating principle and therefore requires different control actions to achieve a temperature change, operators still need to know that manipulations of temperature are an appropriate way of counteracting certain process deviations, and thus apply the same abstract principle despite differences in the specific strategy and procedure.

The following sections will discuss the cognitive requirements for mental representations and learning that are imposed by frequent system changes. It will be argued that two complementary mental activities are needed: a situation-dependent updating of mental representations (i.e., differentiation), and the transfer of previously acquired knowledge to new situations (i.e., generalization). In controlling the interplay between these activities, goal conflicts call for a balance between stability and plasticity of mental representations, as well as between optimization of attention and conceptual flexibility.

2.1 Mental representations in changing environments

2.1.1 Requirements for flexible representations

To solve problems in a highly changeable system, flexible mental representations of domain knowledge are needed (Krems 1995; Spiro et al. 1987): first, knowledge must be accessed from different perspectives and applied in different contexts. Operators must be able to categorize and interpret information in situation-specific ways, modifying their mental representations of the system according to current task demands. For instance, they may think of a module setup as a homogenization unit when considering whether a particular module can be exchanged, while they may think of the same setup as a reaction–separation–feedback scheme when checking for error propagation during fault diagnosis. Second, knowledge must be interconnected instead of ordered and compartmentalized. Modular plants rely on encapsulation of information and hiding the details within functional units. The resulting reduction of complexity, at least on a superficial level, invites compartmentalized reasoning and pigeonholing. However, on certain occasions it is crucial to understand how modules interact, especially when technical faults and process deviations result from the interplay of different modules. Such situations make it necessary to drill down into the internal complexity of modules, and knowledge structures on the level of principles and functional relations beyond the singular module are helpful. Third, knowledge representations cannot be holistic, hierarchical and pre-packaged but instead operators must be able to decompose and re-assemble them. Fragments of knowledge must be moved about and used in different ways, depending on the requirements of the specific situation. Given the diversity of possible situations and ways of setting up the plant, operators cannot possibly have a pre-packaged schema for every situation or module setup they may encounter. Fourth, knowledge should be stored in multiple cases and analogies rather than in a single or prototypical one. Abstract principles such as the principles from systems and control theory for the coordination and control of distributed technical systems are necessary but definitely not sufficient. Instead, aspects of different cases must be combined. In modular plants this is important, because many situations do not exactly match any previous one. Finally, problem solvers need to consider several alternative interpretations of a situation, and switch between them if necessary. For instance, a temperature of 200 °C may be completely normal when using reactor module Y, while it is critical and affords immediate intervention with reactor module Y'. Taken together, these requirements form a basis for being able to deal with the system changes encountered in modular plants.

2.1.2 Functions of flexible representations

When the plant setup is altered frequently, operators must deal with situations that may be somewhat similar to previous situations, but usually not identical. Therefore, they have to construct abstract schemas that go beyond the specifics of a particular situation. However, this does not mean that specific experiences are not important anymore. Quite the contrary, the construction of abstract schemas relies on concrete cases, and learning is fundamentally instance-based (Gonzalez et al. 2003; Spiro et al. 1987). So how can a construction of abstract schemas be achieved? In a nutshell, operators must learn to categorize novel situations (for an overview see Kruschke 2005), and the categories must be sufficiently flexible to deal with a variety of situations. One function of categorization is that it allows for differentiation: quickly learning new things while also retaining previously acquired knowledge, and being able to decide which is needed in what situations. For instance, operators may have learned about reactor modules of type Y, and then be confronted with a reactor module of type Y' that differs from Y in attributes such as coating, maximum volume, or type of agitator. In this situation, operators need to understand how module Y' needs to be operated differently. However, it would be bad if in order to deal with Y' they had to forget everything they have learned about Y modules, because in fact many things are transferrable. Thus, while needing to be aware of the differences, they also should be able to continue using the knowledge that remains applicable. Thus, a complementary requirement in changeable environments is generalization across different situations: when noticing that a situation belongs to a known category, people can go beyond the information that is available in the situation, because previously learned, associated information is retrieved and allows for an inference of unseen attributes (Kruschke 2005). For instance, if operators have learned that production outcomes can be affected by manipulations of temperature, they should be able to infer that production outcomes in module setup Y' can also be affected by manipulations of temperature, even when not having tried it out, yet.

2.1.3 Balancing stability and flexibility

Before detailing the cognitive requirements of differentiation and generalization in the following sections, a note of caution is due. While flexible representations are needed in modular plants, they also are quite costly, and mental efforts can be reduced by a higher degree of stability. It simply is much easier to use the information and mental operations you got used to. Thus, operators need to find an optimal balance between stability and flexibility (Goschke 2013). This conflict between stability and flexibility can take several forms (see Table 1). For instance, performance can be optimized by focusing only on the most relevant process parameters and ignoring less important ones. At the same time, this may mean that the impact of ignored parameters on the plant's processing behavior is not learned, and thus cannot be applied when working with a new module in which these parameters are essential. Accordingly, it is important to note that although flexibility is essential in operating modular chemical plants, there are good reasons for operators not to be as flexible and context-specific as they possibly could be.

2.2 Differentiation: updating of mental representations after system changes

Module setups may differ in the way they work and thus in the way they affect the production process. Therefore, operators need to update their conceptual knowledge and understanding of functional relations. The updating of knowledge is difficult especially when it requires fundamental changes to existing knowledge structures. Moreover, the rate at which operators learn and update their knowledge depends on specific features of a situation.

2.2.1 Updating conceptual knowledge

In modular plants, the processes change a lot, and thus what was true yesterday may be outdated or even wrong today. Accordingly, operators need to adapt their conceptual knowledge. The ease of doing so depends on the state of prior knowledge, with basically three conditions (Chi 2008). First, knowledge can be missing, so learning basically means adding knowledge. For instance, operators may not know that it is important to tightly monitor temperature in a module as it affects product quality by making thermal separation more effective. Second, knowledge can be incomplete, and while the person has some correct knowledge, it is insufficient for dealing with a new situation, so learning is a matter of filling the gaps. Operators may know that temperature is important for product quality, but they may have no idea what range is appropriate in module Y', or what can be done if the temperature is outside the required range. Third, knowledge can be incorrect when people have acquired concepts that are no longer applicable, and thus learning requires conceptual change. Operators may have learned that temperature is important because it affects product quality, and as product quality depends on the ratio of different product components, the appropriate temperature range is 210–230 °C. However, with the new module Y', temperature does not only affect product quality but also the degree to which the product is toxic, so the previous temperature range is inappropriate and temperature now needs to be 225–230 °C. The latter

Table 1 Trade-offs between stability and flexibility with regard to information processing, performance, and learning in modular chemical plants

Stability	Flexibility
Focusing only on diagnostic information and ignoring information that is irrelevant in the current task	Considering different features of a situation or object to be categorized
Avoiding interference from currently perceived or memorized information	Taking other influences and perspectives into account
Acquiring information from the same source	Considering a wide variety of information sources
Using general purpose strategies for information search	Using specialized information search strategies depending on the current context
Evaluating information consistently, using the same strategies and criteria	Changing evaluation strategies and criteria between situations
Ignoring new experiences and sticking to once acquired mental representations	Learning from new experiences and updating mental representations
Merely adding bits of information to one's mental representation	Fundamentally changing one's conceptual models
Focusing on the concrete details of each situation	Generalizing and acquiring abstract knowledge
Using knowledge only in the specific acquisition context	Transferring knowledge to other contexts

condition of misconceived knowledge is particularly challenging as it is highly resistant to change (Law and Ogborn 1994; Vosniadou and Mason 2012).

There are three different ways in which prior knowledge can be incorrect in the current situation (Chi 2008). The first one is false beliefs. A particular idea may conflict with correct information, for instance when operators believe that all vessels have a jacket. The second type of conflicting prior knowledge is flawed mental models, which is an incorrect collection of beliefs. Operators may have a conception of the heating and cooling system in which a vessel's temperature can be regulated most effectively by pumping water through the jacket. This mental model is usually correct for cooling. However, it is incorrect for heating above 100 °C, because the much more effective latent heat of condensation of vapor should be utilized. The third and most difficult type is category mistakes, where concepts are assigned to a wrong ontological category (e.g., whales are fish). Correction by re-locating the concept works well if the correct category is known and readily understood, as in everyday categories like “mammals”. However, correction is more challenging for the abstract categories that are needed for understanding complex systems like chemical plants. People typically try to assimilate abstract concepts into substance-based conceptions and thus reason about them in terms of how material objects behave (Reiner et al. 2000), they find it particularly difficult to understand causal relations and functions (Hmelo-Silver et al. 2007), and they do not take complex systems concepts like emergence or decentralization into account (Jacobson 2000). Even for experienced operators it can be tricky to conceptualize heat not as an entity (i.e., hot molecules, can be contained) but as an emergent process (i.e., speed at which molecules move, transfer of energy). In modular plants, such difficulties are exacerbated when different categories can be used in different module setups. For instance, for a reactor module *Y* that is heated with thermal oil, the inaccurate model of heat as an entity still produces satisfactory predictions, at least qualitatively, and thus provides a cognitively cheap way of conceptualizing heat transfer (i.e., hot molecules move from the jacket into the reactor). Conversely, when operating a vapor-heated module *Y*′, predicting the effect of the latent heat of condensation is impossible with this model, and a model of heat as an emergent process is indispensable.

The difficulty of learning information that contradicts or updates prior knowledge also depends on the type of shift. Learning is more difficult when the relevance of attributes has changed (George and Kruschke 2012; Kruschke 2005). Imagine that with module *Y*, operators have learned that temperature should be between 100 and 150 °C, and pressure is irrelevant. After a change to module *Y*′, it will be easy to learn that temperatures between 200 and 210 °C are required and pressure is irrelevant just like before. This is called an intra-dimensional shift, where the change consists of a new value on the same attribute, while the relevance structure of attributes remains intact. In contrast, it is much harder to learn that in *Y*′ a pressure between 4 and 5 bar is required, while temperature can be ignored. In such extra-dimensional shifts, a new and previously irrelevant attribute needs to be considered. Moreover, conceptual change is not only required when prior concepts are wrong in a new situation but also when it becomes necessary to differentiate or combine concepts. For instance, initially most people do not differentiate between density and weight (Carey and Spelke 1994) or heat and temperature (Wiser 1986). In modular plants, the importance of such differentiations can change between module setups. When using module *Y*, it may have been unproblematic not to differentiate between heat and temperature, while running the process with module *Y’* makes this differentiation essential.

2.2.2 Updating the understanding of functional relations

Changes in the module setup may not only require operators to update their conceptual knowledge, but also their understanding of the functional relations within a system. This is the case when module exchanges cause changes in the relations among multiple interacting parameters, such as temperature, pressure, and flow rate. That is, certain parameters may exert an influence of different magnitude on other parameters, depending on the current module setup. For instance, with reactor module *Y*, flow rate may influence pressure by a factor of 0.8 and temperature may influence pressure by a factor of 0.4 (these factors are coefficients that describe the magnitude of the influence, with 0 meaning no influence). Conversely, in reactor module *Y*′ that has a larger reactor vessel, flow rate may influence pressure only by a factor of 0.5, while temperature influences it by a factor of 0.3. Additionally, the filling level of the vessel influences pressure by a factor of 0.7 in both modules. Thus, at a given level, a flow rate of A and a temperature of B will result in a pressure of C in module *Y* but in a pressure of D in module *Y*′.

Given such differences in the functional relations between module setups, operators need to be able to do two things. First, they need to make predictions about metric outcomes, and therefore understand how the state of certain parameters affects that of others (i.e., function learning). Second, they need to flexibly adapt these predictions to the current context. While this sounds rather difficult, research has shown that people are quite adept and precise at learning about changing parameter relations, and they can change their utilization of parameters according to these parameters' current influence (Speekenbrink and Shanks 2010): when participants had to predict changes in a criterion based on the several cues and then the influence of one cue changed after some time, they smoothly adapted their cue utilization to the actual magnitude of the influence. Moreover, they adapted successfully even when not being explicitly informed about the changes or their magnitudes. This provides an optimistic prospect for modular plants, suggesting that even when the impacts of module exchanges on functional relations are not known in advance, operators may be able to flexibly adjust their control actions to them.

2.2.3 The trade-off between stability and plasticity

Flexible updating of conceptual and functional knowledge involves a goal conflict that can be referred to as the stability–plasticity dilemma (Goschke 2013): when experiencing new situations in a system, knowledge must be updated so that it can modify behavior accordingly, and it is not adaptive to be resistant to learning even after having experienced a similar situation repeatedly. However, it would also be inappropriate to update one's beliefs about the state of the environment and discard all previously acquired knowledge each time a random fluctuation occurs. While slow learning supports the gradual development of stable representations and actions, fast learning is necessary for rapid adjustments to changing contingencies in the environment. Or in other words, there is a trade-off between using as much of the previously acquired information as possible, and disregarding information that is outdated (cf. O'Reilly 2013). Thus, the question is how much people should adjust their beliefs in response to new observations. The meta-control parameter responsible for the magnitude of such adjustments is learning rate (Goschke 2013), which defines the impact of new and unexpected observations on beliefs about the environment. For instance, after an exchange of module Y for Y', operators might observe a lower viscosity of the product. This might either mean that Y' really has caused a different process state (e.g., due to its different agitator type) or that the perceived differences are just random fluctuations that might also have occurred with module Y and without a change in process state (e.g., because educts vary in their characteristics). Thus, an important question is how much evidence operators need before they assume a real change.

Learning rate should be tailored to the characteristics of the environment: beliefs should be stable in noisy environments but updated more readily when the environment really is volatile. But what factors make learning become faster or slower? It is not enough to simply adapt learning rate by discounting older observations at a fixed rate, unless the relevance of observations merely decays as a function of time. This is clearly not the case in modular plants where changes are more categorical than gradual, being bound to discrete events such as module exchanges. In such environments, people must be able to infer change from the information they observe. Estimating the probability of change makes it necessary to balance two considerations, namely how likely it is that the current observations are from the same distribution as previous ones, and how likely it is that there was a change (O'Reilly 2013). In the example above, a change in the processing behavior after switching to module Y' will more readily be inferred when it is very unlikely to observe such low viscosity values given the old process state, and when operators expect that module exchanges are likely to affect the process (e.g., because the chemical is very sensitive to changes in process parameters that could be caused by different agitator types). Computational modeling has identified three distinct influences on learning rate (McGuire et al. 2014): stronger belief updating occurs in response to surprising observations, when being less certain about the current belief, and after having experienced rewards. For modular plants this might imply that learning about a new module's functioning is enhanced when a module exchange results in strong and unexpected deviations of process parameters from previously observed ones, when operators were not really sure how the previous parameters came about anyhow, and when they have just experienced a positive outcome such as a gain in productivity following a module exchange. However, note that there is a difference between research on the adjustment of learning rates and the changes occurring in modular plants: operators usually know when changes have been made to the module setup, but might not know whether and how much these changes affect the production process. Thus, the challenge is not to detect change points per se but to infer the presence and magnitude of corresponding changes in plant function.

2.3 Generalization: transfer of conceptual and procedural knowledge

The previous sections were concerned with the differentiation between module setups. However, the other side of the coin is transfer. In modular plants, operators should not mix things up, but it is equally important that they can apply the knowledge they have gained in past situations. Although module setups may differ in their specifics, many principles of operation are comparable, and thus mental representations of the problem and solution (i.e., schemas) must exist on a more generalized level. In psychology, there is abundant research on the transfer of learning (for an overview see Day and Goldstone 2012), mostly emphasizing that transfer is quite limited.

2.3.1 Types of similarity as a determinant of transfer

There are three types of similarity between problems: surface similarity, structural similarity, and procedural similarity (Chen 2002). Surface similarity means that two problems share the same elements, structural similarity means that the problems share the same causal relations between the elements or the same solution principle, and procedural similarity means that two problems require the same way of transforming a general solution principle into concrete operations. For instance, imagine that operators need to stop a pump from cavitating, which can be done by increasing the pressure in the medium above its vapor pressure threshold. When using module *Y*, operators used to do this by slowing down the production: decreasing the flow rate of the pump, thereby decreasing the medium's velocity, and thus also increasing the pressure as it is proportional to velocity (see Fig. 2, left). However, now they are working with a new module *Y′* which has a much bigger reactor preceding the pump. This allows for removing cavitation without slowing down the production: operators can increase pressure by raising the level of the medium in the reactor (see Fig. 2, middle). Surface similarity is low, because different elements are involved in the solution in module *Y′*: a reactor, its size, and its level. However, the problems are structurally similar, because the causal relations and solution principle overlap: in both cases, the pressure in the medium is raised above its vapor pressure threshold by changing the magnitude of a process parameter. Instead, a structurally dissimilar solution would be to add less solvent to the medium in order to lower its vapor pressure threshold, while leaving pressure as it is (see Fig. 2, right). Obviously, the procedural similarity between the solutions in module *Y* and *Y′* is low as the concrete operations involved in changing the pump's flow rate and raising the level in a reactor are different.

Transfer is challenging and while usually people do a good job at near transfer, many interventions have failed for far transfer. An important factor in the learning context that determines transfer is the diversity of learning experiences, and also features of the person can have an influence on transfer, such the flexibility of mental representations (see below), or domain knowledge (Jonassen 2000). However, the greatest challenge is to notice that a new case is structurally similar and thus allows for an application of the same solution principle. Structural similarities are unlikely to produce remindings of their own, while surface similarities usually do (Gentner et al. 1993). However, even when people do notice the similarity, it still is difficult for them to apply what they have learned in a different context. In many cases, even hints or explicit instructions to use the original problem for solving the new one do not help (Chen 2002; Chen and Mo 2004; Gick and Holyoak 1983). Accordingly, a major determinant of transfer is surface similarity (Holyoak and Koh 1987). In modular plants, this can lead to unwanted transfer when modules have high surface similarity although they are functionally different and therefore require structurally and procedurally different interventions. Unfortunately, such misleading similarities are quite common as a result of

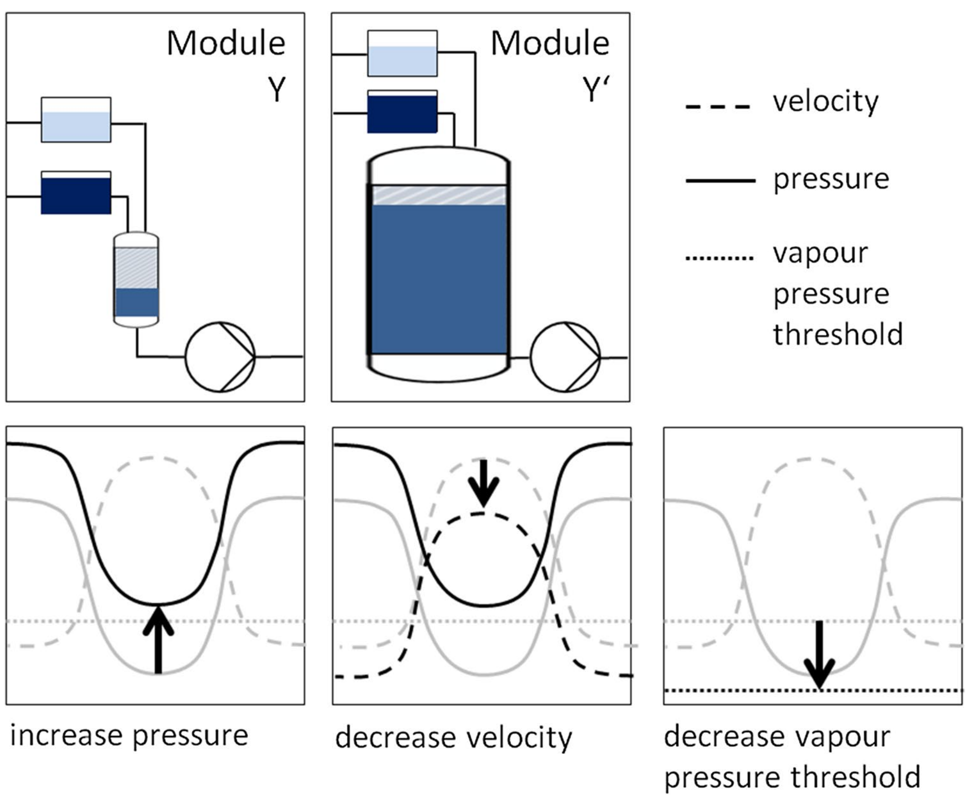

Fig. 2 Removing cavitation in a pump by either reducing the flow rate of the pump (left), increasing the level in the reactor (middle), or changing the ratio of different inflows (right). *v* Velocity, *p* pressure, p_v vapor pressure threshold

engineering processes that are optimized for lowering the costs of producing module variants instead of supporting operator cognition.

2.3.2 Procedural transfer

In changing work environments, not only theoretical and conceptual knowledge needs to be applied to new problem solving contexts but also the practical skills in performing complex tasks. Thus, the question arises under what conditions operators can generalize solution procedures to new module setups. The transfer of procedures depends on the induction of a generalized schema (Chen and Mo 2004). This means that people must go beyond the specific procedures they have encountered, and instead represent the problem in terms of the underlying rules or abstract solution principles. For instance, imagine two specific sequences for the production of two chemicals: (1) first adding chemical A, then adding solvent, then removing waste product, and (2) first removing waste product, then adding chemical B, then adding water. On a very general level, the common schema is that both chemicals are produced by adding and subtracting components. Generalization can occur on one or more dimensions, such as the sequence of component operations to perform (e.g., first adding A, then adding B, then removing C) or the type of problem to solve (e.g., distilling, refining). However, generalization is highly dimension-specific: successful generalization on one dimension does not imply that people are able to also generalize on other dimensions. Merely because operators have found out that a chemical's purity can be affected by adding and subtracting components (generalized from first adding A, then adding B, then removing C), this does not mean that they can apply this knowledge to the problem of optimizing viscosity. Successful transfer can be achieved when problems are similar on a very concrete level, namely the detailed procedure, while it is not enough to only share a general strategy or solution principle (Chen 2002). Imagine that operators work with the new module *Y′* and need to monitor the proper control of the processes in a reactor by applying what they have learned while working with module *Y* (see Fig. 3). If with *Y* they also had to do this by supervising the control of mass balance (principle) and even if they had to enact this principle by checking whether inflows and outflows are the same (strategy), this does not guarantee that they can solve a problem in module *Y′*, unless the specific way of checking the inflows and outflows is similar as well, for instance by analyzing a trend chart of three different flow indicators (procedure).

2.3.3 The trade-off between optimization and flexibility

With regard to transfer, there is a caveat attached to the benefits of category learning and abstraction: when learning to classify situations, a focus on diagnostic features

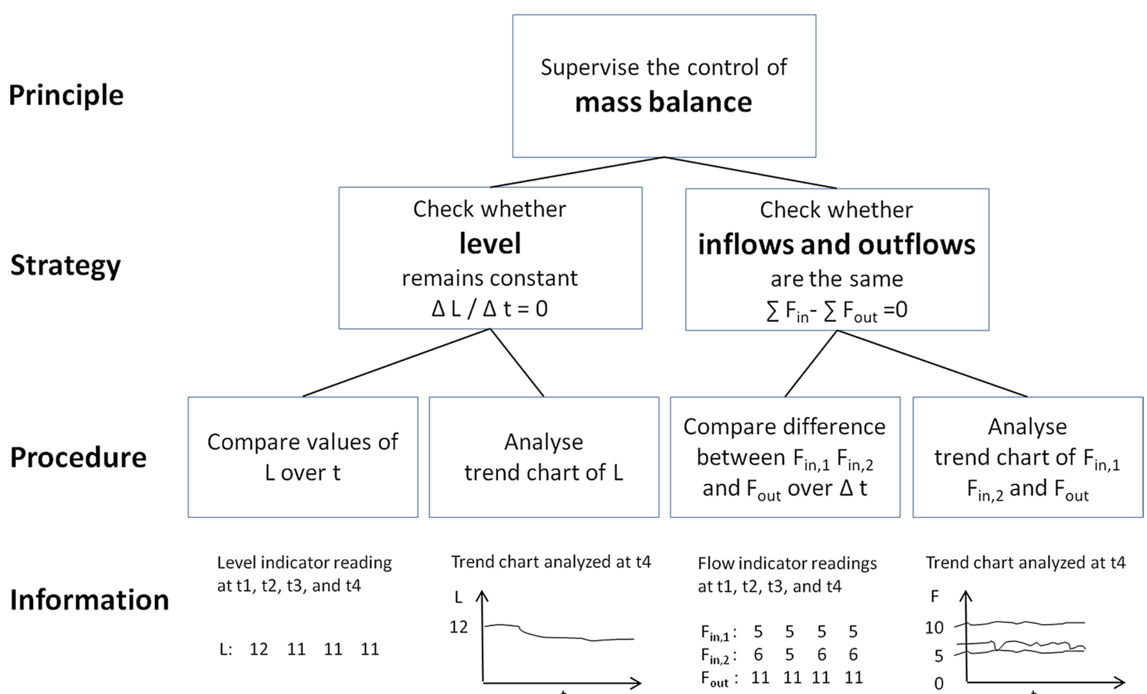

Fig. 3 Different ways of supervising the control of mass balance, differing in the similarity of strategies, procedures, and the information that needs to be used. *L* level, *t* time, *F* flow

reduces conceptual flexibility (Hoffman and Rehder 2010). During categorization, people learn to optimize their attention allocation, and with increasing experience they preferably attend to relevant attributes. For instance, in filter module *Y* operators may have learned to selectively attend to differential pressure (before vs. after the filter) as this it indicates the degree of filter clogging and thus is the most important attribute for scheduling cartridge cleaning. However, usually optimization is task-dependent, and improvements in one context can cause decrements in another. Learning to ignore information that is irrelevant for the current categorization task is problematic when it is just this information that matters in other contexts. In the example above, imagine that module *Y* was exchanged for module *Y′* which has a much narrower thermal operation range. With this new module, the learned strategy of focusing only on differential pressure is suboptimal or even dangerous, because at the limits of the thermal operation range both difference pressure and temperature need to be monitored closely to not damage the module. This leads to an inherent trade-off between the optimization of attention vs. flexibility. Over time, people learn to only attend to diagnostic features and ignore non-diagnostic ones, but in consequence they perform worse in transfer situations when the ignored features suddenly matter.

Good news for modular plants is that people can take the context into account for selectively attending to attributes, and this context-specific attention allocation can transfer to new situations (George and Kruschke 2012). If in module *Y*, pressure always was relevant for deciding whether a situation is critical and in module setup *Y′* temperature is relevant, operators presumably can tune their attention and selectively attend to pressure in module *Y*, to temperature in module *Y′*, switch between them if needed, and use this knowledge when dealing with new situations in module *Y* or *Y′*. Such context-dependent attentional shifts also protect learned contingencies from being overwritten when a new situation is encountered (Kruschke 2005).

2.4 Beyond mental representations: transfer as a consequence of interactions with the environment

While the cognitive science literature discussed so far tends to conceptualize transfer as a carryover of knowledge from one situation to another, the situated cognition approach puts more emphasis on the specific contexts in which learning takes place (Lave 1988; Roth and Jornet 2013). According to this approach, transfer results from the activities of people in their physical and social environments, during which both the person and the environment mutually transform each other.

2.4.1 Acting in the physical and social environment

Problem solving is shaped by people's activities in particular environments, and there is no such thing as decontextualized learning (Lave09). This is because people's activities largely determine what cognitive operations they use, and depending on the setting they approach structurally identical problems quite differently (Roth and Jornet 2013). For instance, studies on arithmetic performance in grocery shopping (Lave 1988) have revealed that the use of math in the supermarket differs from its use in math tests. Not only do people commit fewer errors when using math in grocery shopping, but they also match their strategies to the problems at hand. For instance, they flexibly switch between strategies for determining the best buy depending on the difficulty of computing the ratios of price and quantity, depending on whether package size is convenient for storing, and depending on other concerns about managing food (Lave 1988). Adaptive strategy selection is also observed in industrial settings, for instance in dairy workers' practices for calculating and organizing deliveries (Scribner 1986), and is expected to be important in modular plants. The current module setup, the customer's order, and the product will determine together how operators use single parameters (e.g., pressure, temperature, concentration) or higher level information (e.g., transportation of mass and energy) to calculate and to determine appropriate process control strategies. How do situations structure learning and transfer? One suggestion is that people draw connections between situations when perceiving the same affordances across them (Greeno et al. 1993). That is, transfer means adopting previous interactional roles in new situations, and it occurs when new situations allow for structurally comparable individual–environment configurations (Jornet et al. 2016). Accordingly, an adoption of similar interactional roles across module setups can be facilitated when the interfaces of different modules create similar affordances.

The physical environment has profound effects on people's cognitive activities. In fact, some of the findings on the supposed defects in reasoning and the absence of transfer (see Sects. 2.2 and 2.3) can be accounted for by the conditions created in the studies. For instance, research on children's conceptual knowledge shows that their apparent reliance on flawed mental models when reasoning about the earth (Vosniadou and Brewer 1992) is drastically reduced when a globe is present (Schoultz et al. 2001). This suggests that when cognitive activity can be grounded in the physical world, people reason more accurately. In traditional process plants, it is quite common for operators to off-load cognitive demands to the environment. They use the physical world as an external memory, for instance by leaving the doors of strip-chart recorders open as a prospective memory cue for monitoring particular parameters

(Mumaw et al. 2000). Moreover, direct perception of the plant environment is a valuable information source for operators to understand system states (Vicente and Burns 1996). In modular plans, a new challenge is that physical perception can be misleading, because different modules can achieve a similar function in different ways which also differ in their sensory effects. For instance, in module *Y* with one type of pump, certain problems can be inferred from the noise emitted by the pump, while in module *Y′* with another pump they cannot. Accordingly, operators' physical experience will be different and sensory information can only be interpreted when knowing about the current module setup.

The physical environment does not only influence explicit reasoning about abnormal situations but also the highly routinized performance of experts. Cognitive performance is organized on multiple levels, as exemplified in Rasmussen's skills–rules–knowledge framework (Rasmussen 1983). Much of the cognitive science literature on transfer is concerned with the rules and knowledge levels (i.e., explicit mental representations), while the situated cognition literature puts more emphasis on the skills level (cf. Roth et al. 2015). Skilled action is a steady flow of activity in response to the current situation, and appropriate actions are triggered by the perception of certain environmental cues (e.g., instrument readings). Interesting inferences for changeable modular plants can be derived from situated cognition studies of mixed-fleet flying, where pilots switch between different versions of the same aircraft (Roth et al. 2015). Even small differences in the physical system (e.g., changes in instrument location) can disrupt pilots' flows and thereby negatively affect performance. Switching back to a previous version of an aircraft after having flown a new version for several months can prompt pilots to accidentally leave out some operations, while erroneously inserting others. Such problems are largely due to habitual strings of action triggered by the environment, rather than memory for facts (Soo et al. 2016). Interactions between habits and environments go both ways. On the one hand, when in different versions of an aircraft operational sequences are triggered in the same way but differ somewhere along the way, disruptions of flows are particularly severe (Roth et al. 2015). On the other hand, flows can lead to inattentional blindness for some aspects of the environment, while making pilots automatically attend to others. In modular plants, both ways are important as there can be shifts in procedures between module setups as well as changes in the relevance of parameters which need to be attended in one setup but not in another. An interesting question for future research will be what findings from mixed-fleet flying can be transferred to modular plants, because the latter are operated on much larger timescales, and thus the consequences of delays and interruptions of habitual flows might be less severe.

Learning also depends on interactions with the social environment. In the most basic form, social interactions can foster transfer simply because multiple participants pursue different but related tasks (Engle 2006). Thus, people draw connections between situations as a consequence of observing others working on related tasks that are part of a common enterprise. Social framing can additionally encourage transfer by helping people to see their activities as embedded in a larger context (Engle 2006). For instance, such framing can be achieved in terms of time (i.e., framing situations as temporally connected) or in terms of participation (i.e., framing activities as contributing to a larger community). But social interactions also affect transfer more directly. First, social interactions determine which features of a situation people notice, which in turn determines how they interpret situations and draw connections between them (Lobato et al. 2012). For instance, in modular plants the interpretation of trend charts might be shaped by 'focusing interactions' among operators. When interpreting trend charts, some people focus on relations between quantities (e.g., mass over time), while others focus on certain process events (e.g., sudden decreases in level) which are displayed in small segments of these charts (Kindsmüller 2006). Depending on whether an experienced operator draws a novice's attention to either relations or to trend segments, the novice is likely to develop different strategies of interpreting trends. Second, groups engage in more meta-cognitive activities than individuals while spending less time interacting with the details of the task environment (McNeese 2000). Such focus on meta-cognitive activities can support the transfer of more complex elements. Similarly, social interactions can support generalization (Ellis 2011; Jurow 2004) by means of social practices such as building on another person's idea or encouraging justification and clarification. In modular plants, social activities that support generalization can arise from the interaction between control room operators and field operators. These operators bring different perspectives into a joint task (i.e., functional vs. physical view on the plant), which need to be combined and interpreted in relation to each other to derive a shared understanding of the situation.

2.4.2 Transfer as an individual process of constructing and discovering

Conceptualizations of transfer should go beyond the study of performance improvements as a consequence of one particular, predefined learning situation (Lave 2009; Roth and Jornet 2013). Instead, when solving new problems people incorporate personal experiences from different parts of their lives (Jurow 2004). The relations they draw between past and present situations are not just the most obvious, anticipated ones but prior knowledge contributes to learning in subtle ways (Carraher and Schliemann 2002). Not only specific knowledge, but also new patterns of thinking and acting are used in subsequent situations. For instance, transfer can mean that people generalize their use of explanation schemes (e.g., multi-causal explanations) to new problems (Engle 2006). To understand how people build on prior experience, transfer can be analyzed from an actor-oriented perspective (Lobato 2003). This perspective assumes that individuals draw their own connections between problems, depending on which features of a situation are salient to them. Therefore, studying transfer means to find out what connections they draw, why they draw them, and how or when these connections are productive. For instance, in a modular plant one operator may perceive module *Y* as similar to module *Y′* because the heat transfer process is similar, while another operator may perceive these two modules as similar because both use a coil reactor. Such operator-specific perception of similarities will depend on operators' individual experiences and may or may not lead to different outcomes, depending on what aspects are relevant in solving a particular problem.

When studying transfer as a change in understanding that results from people's activities, it is important to note that such change is a temporally extended process (Jornet et al. 2016). Usually, there is not a fixed learning situation and a subsequent transfer situation in which the acquired knowledge can readily be applied. Instead, the problem itself is continuously transformed during the process. People put considerable effort into trying to understand new situations. They actively produce similarity relations between situations, instead of simply perceiving or encoding them (Lobato and Siebert 2002). As a consequence of their activity in transfer situations, they also reorganize their prior knowledge to fit it to the new cases (Carraher and Schliemann 2002). Consider the example from Sect. 2.2 where two modules use different heating principles (i.e., thermal oil vs. vapor) and the latter made it essential to understand heat as an emergent process instead of an entity. The experience of temperature changes in the new, vapor-heated module *Y′* may change the understanding operators have constructed before, also transforming their previous interpretations of processes in the old module *Y* so that they fit into the updated model.

Transfer prepares people for future learning (Bransford and Schwartz 1999). In many situations, they find themselves discovering rather than intentionally carrying over knowledge, and are unable to anticipate the results of the change process while it is still going on (Jornet et al. 2016). They may see only after the fact that their ideas or actions share features with previously learned concepts. Evidence stems from studies where students discovered how a common scientific principle was underlying two situations (Jornet et al. 2016): in interacting with the problem environment, the initial discovery of analogies inspired inquiry and further exploration, which led to a gradual structuring process characterized by uncertainty, surprise, and sudden realizations. In the previous example on interpretations of the heating process, operators may not immediately see how temperature changes in the two modules can be explained by a common principle. However, upon closer observation, they may first get the vague impression that something is similar, then explore and manipulate temperature via their control actions, interpret the results, and gradually develop an understanding that finally allows them to see how the same principle can explain both situations.

2.4.3 The trade-off between generalization and situation-specific learning

There is an apparent paradox in the situated cognition approach: if it ties learning to specific contexts, local circumstances, and particular practices, how can it account for generalization? This paradox is resolved by the concept of situated generalization (Carraher and Schliemann 2002; Goldstone and Wilensky 2008; Jurow 2004; Nemirovsky 2002). Situated generalization is contrasted with formal generalization, which implies removing all misleading superficial features and abstracting away from the specific situation (Goldstone and Wilensky 2008; Nemirovsky 2002). Formal generalization has obvious benefits as in principle it allows for transfer to an infinite number of situations. However, the resulting abstractions (e.g., mathematic formulas) come with the risk of not supporting an intuitive understanding of situations when they cannot be tied to specific cases. Moreover, features that are thought to be superficial often turn out to be critical for understanding (Lobato and Siebert 2002). In modular plants, an example for formal generalization is to represent changes in the chemical balance as an interaction of concentration, temperature, and pressure. Conversely, situated generalization results from local, context-specific activities such as identifying commonality across cases and deriving broader results from particular cases (Ellis 2011; Jurow 2004). In consequence, generalizing can be achieved without ever representing the problem in an abstract, situation-free form (Nemirovsky 2002). In modular plants, an example for situated generalization is when people recall the causes underlying a deterioration of the chemical balance in a reactor module. They may remember cases from their past operation of module *Y* where there were gradual increases in the variability of a level indicator, cases in module *Y′* where they could observe unusual increases in temperature, and cases in module *Y″* where the problem was preceded by a whistling noise in a valve. Even when they are able to generalize that the problem is predicted by gradual destabilizations of the process, they will not forget the individual cases and their varying symptoms but think of them when being confronted with a similar problem again.

Situated generalization and transfer can be supported by grounding principles in specific experience, for instance by simulations that present general principles in concrete, physical contexts (Goldstone and Wilensky 2008). Having interacted with one simulation allows people to see events in other situations in new ways, even when they do not consciously notice the connections. Concrete, physical experience provides strong cues for reminding and thus effective ways of ensuring that the conceptual meaning of principles can be grasped and used.

2.5 Potentials for learning in highly changeable situations

While the changeability of modular plants poses a number of cognitive challenges for operators, the very same feature of these systems also provides rich potentials for learning. Variability in practice contexts facilitates learning across a wide range of domains such as sports, music, and computer programming (for an overview see Stokes et al. 2008). Most importantly for current purposes, it can enhance learning and transfer in the operation of new technologies (Jamieson and Rogers 2000), foster complex predictive judgments that depend on a prioritization of different cues (Helsdingen et al. 2011), and enhance strategy adaptation in complex dynamic problem solving (Cañas et al. 2005). Variability even fosters the adaptation of strategies to changes in the environmental conditions when the particular changes have never been encountered during training (Cañas et al. 2005). This suggests that variability can indeed increase cognitive flexibility, instead of just making people familiar with a particular change. As a result, they can adapt to different requirements by reorganizing their skills as needed. This should be beneficial especially in situations that change a lot, suggesting that modular plants will not only be optimal learning environments but also benefit from the flexibility that operators acquire when dealing with them.

Several mechanisms are hypothesized to underlie these beneficial effects of variability. For instance, it makes people more flexible in recombining the elements of a skill, teaches them to use more exhaustive search strategies, provides them with a richer set of retrieval cues, sensitizes them to changes in conditions, and helps them to activate or construct appropriate alternative schemas (Stokes et al. 2008). The varied contexts and thus learning experiences that operators are exposed to are likely to foster both differentiation and generalization. On the one hand, they should help operators to understand that situations can differ considerably and no single solution will be appropriate for all or even most of them. This provides them with a highly diverse base of possible cases that can be accessed and combined. On the other hand, varied learning experiences should stimulate operators to extract the essentials from a set of different situations, abstracting away from irrelevant features of the specific context. Research on problem solving demonstrates that such diversity diminishes fixed schemas (set effects). For instance, providing two problems in a learning phase instead of only one largely increases transfer of the solution principle to a new problem (Gick and Holyoak 1983). This benefit is even higher when the learning problems are semantically diverse, meaning that the problem descriptions differ in their surface features. The same is true for procedural diversity, where problems differ in their solution details while following a common, generalized procedure. Although exposure to more variable problems slows initial learning, it reduces set effects and fosters broader and more flexible schemas (Chen and Mo 2004). This principle of greater variety leading to better transfer holds for variability on different dimensions of the procedures, such as their specific sequence of solution steps or the type of outcome to achieve. However, diversity only enhances learning within dimensions, not across them. For instance, only because operators have learned that different modules require different parameter settings, this does not guarantee that they can cope with these modules having different time constants and thus requiring different waiting times.

Despite the benefits of variable practice, the phase of learning in which it occurs is important: variability may hamper skill acquisition when being introduced too early. In the context of motor skill acquisition, when variability is introduced before a learner has mastered a basic task, learning and transfer will suffer (Lai et al. 2000). It is likely that similar performance problems will emerge when operators of modular plants are confronted with frequent module changes before they have had a chance to acquire the basic skills of running a process. On the other hand, when early training is too easy, people may acquire less precise strategies, which impairs transfer to new stimuli and tasks (Doane et al. 1996). Operators who are not exposed to the complexities of modular plants early on, including the difficulties implied in discriminating between the similarities and differences between different modules, may have a hard time acquiring the flexible and context-dependent skills that are needed for operating these systems. Thus, again we are confronted with a trade-off that has been eloquently phrased by Stokes et al. (2008, p. 642): "Initial success in doing few things, or initial failure doing many, will lead to low variability in a domain".

3 Discussion

In modular chemical plants, operators frequently are confronted with changes in the module setup. This poses a risk of performance decrements and errors, which are most dangerous when actions and strategies that used to be successful in a previous module setup now lead to different outcomes. The operation of changeable modular plants calls for flexible mental representations, which enable both differentiation and generalization of conceptual and procedural knowledge. Differentiation works via the updating of knowledge about concepts and functional relations between system parameters, and is an inevitable prerequisite for adaptive control. However, the impact of new observations on mental representations should be matched to the volatility of the environment. In contrast, generalization is needed to make sure that knowledge acquired in a previous context can be mapped to the current one. Transfer can occur for conceptual knowledge as well as procedures, but in any case it is highly specific: successful generalization of knowledge on a particular dimension does not mean that generalization will be successful on other dimensions as well. People's activities in their physical and social environments play an important role in determining what is transferred between situations. Depending on which aspects of a situation are relevant within a given activity and depending on which ones are noticed, people actively create and discover similarity relations between situations. Finally, transfer can be enhanced by providing variable learning contexts. Therefore, changeable modular plants promise to be an ideal environment to foster ongoing operator qualification.

3.1 Cognitive and situated approaches to transfer in modular plants

Learning and transfer have been addressed by scientific approaches that differ with regard to their conceptualizations of the phenomena, the scientific methods they use, and the conclusions they draw. The cognitive science approach (see Sects. 2.2 and 2.3) focuses on mental representations that are studied in controlled lab experiments, and often finds that transfer is quite limited (Chen 2002; Chen and Mo 2004; Gentner et al. 1993; Gick and Holyoak 1983). In contrast, the situated cognition approach (see Sect. 2.4) emphasizes the interactions between people and their environments, and therefore learning is studied via in-depth observations of people's activity in natural situations. When transfer is conceptualized as situated and actor-specific, indications of transfer become apparent that would go undetected in traditional accounts (Lobato and Siebert 2002). Both perspectives make valuable contributions to our understanding of transfer in modular plants.

On the one hand, the cognitive science approach has lots to offer. First, knowledge-based processing and mental representations are highly relevant in operating a modular plant. Studying the exact cognitive mechanisms implicated in specific control tasks can inform our understanding of cognitive performance in modular plants as well as the design of interfaces. Second, despite the obvious benefits of conceptualizing transfer as actor-specific (Lobato 2003, 2006) and acknowledging that it can unfold in unexpected ways (Jornet et al. 2016), the safe operation of modular plants poses some strict requirements. Especially in abnormal situations, operators need to correctly understand the basic chemical processes and the interaction of modules. It would be insufficient for them to use whatever strategies they see fit, apply whatever knowledge they happen to construct, and draw the connections that appear most salient from their individual perspectives. To study the cognitive challenges of modular plants and ultimately support cognitive performance in these complex systems, it will also be necessary to ask what concepts must be known and learned, how operators master these pre-specified learning goals, and how they can apply particular concepts and procedures to new modules. Third, the cognitive approach is often criticized for the lack of generalizability that results from its use of simplified and idealized tasks. However, it is not without danger to treat rich, situation-specific details as necessarily beneficial, and there is evidence that idealizations can successfully support transfer, for instance in the context of simulations (Goldstone and Wilensky 2008). Modular plants can benefit from cognitive science studies that provide inspiration for an appropriate use of abstractions to support operator training and interface design. Finally, by striving for a high degree of experimental control and internal validity, the cognitive approach tries to attain reliable results that can be ascribed to the particular mechanisms under investigation. This can be beneficial when applying scientific results in safety-critical domains such as modular plants, because this makes it essential to know about the conditions under which the results can be found, their dependence on particular manipulations, and their statistical reliability.

On the other hand, we can learn from the situated cognition approach, because it emphasizes that learning depends on the specific conditions, and that our own conceptualizations as researchers will affect whether we do or do not find indications of transfer. Thus, when a particular kind of transfer is not observed, the problem is not necessarily with the people but might lie in the framework. Tasks in rich and complex environments such as modular plants are very different from the small-scale lab tasks with clear goals and correct solutions that are often used in cognitive science experiments. Accordingly, findings from these experiments may not generalize well to real world tasks (Lave 1988). Instead, our understanding of learning in modular plants can benefit from grounding the studies in theories of activity (Jornet et al. 2016; Lave 2009). This calls for extending the scope of analysis from the individual to the interaction between individuals and their environments, or to the process of how this interaction dynamically changes over time (Roth and Jornet 2013). For instance, instead of only asking whether operators will carry over knowledge from the operation of module Y to the operation of module Y', we should ask how the module's physical setup and the operations performed with these modules will shape operators' understanding, how operators work together with others, and how they actively construct knowledge over time. This shift in focus is promising, because with the introduction of modular plants the role the environment is changing: traditionally, chemical plants mainly were causal systems (Rasmussen et al. 1994), which means that operators' activities were largely determined by physical constraints (e.g., laws of thermodynamics). Accordingly, operators had to understand the chemical processes as well as rules and procedures to operate the system safely and efficiently. In modular plants, this dependence on physical constraints is complemented by an increasing impact of intentional constraints (e.g., costs, demand). The result is that in many situations there will be no single correct solution but good performance will depend on the coordination of different environmental constraints. In the situated cognition approach, learning can be understood as an individual's trajectory through a landscape of practices (Wenger 2010): each person develops his or her own unique trajectory by interacting with the physical and social environment, which largely depends on experiences, values and priorities. In modular plants, these learning trajectories are expected to become much more differentiated than today.

Therefore, we consider it promising to combine the benefits of both approaches, instead of selecting one or the other. Combining the benefits does not mean merging the paradigms and methods, for instance by making lab tasks as naturalistic as possible, or making situations for observing interactions between people and their environments more abstract. This would create a danger of eliminating exactly those features that make a particular approach powerful. Instead, by recognizing that different approaches investigate different but complementary aspects of learning, inspiration can be drawn from both in building and testing theories about transfer in modular plants.

3.2 Limits of available research

The article has discussed what we can learn from studies of learning and transfer in changing environments, but we also need to ask what we cannot infer from the available research. What questions that are essential for understanding the specifics of modular plants remain unanswered? And conversely, how can modular plants inspire future research and support the construction of theories about cognition?

One important factor is the kinds of prior experience that shape learning. Real-life learning situations span much larger time frames than most studies on learning and transfer (Lobato et al. 2012), and therefore influences of prior knowledge will come to bear that go beyond those addressed by an experimental manipulation (Carraher and Schliemann 2002). In modular plants, operators will have received vocational training and many of them will have years of experience in traditional plants. Vocational training does not support all the competencies operators need for coping with real-life situations, and falls short of preparing them to deal with abnormal situations and the complexities of coordinating multiple actors (Kluge et al. 2014). Learning in traditional plants is of limited use because it largely relies on procedures. Still, these prior experiences will influence how operators deal with problems in modular plants. Therefore, in order to understand how they use knowledge, we have to understand the specific ways in which the knowledge they gain in modular plants interacts with knowledge from other settings. A related issue is that in real-life situations in general and modular plants in particular, operators are not expected to use what they have learned as such but to use it as a preparation for future learning in the specific situations they encounter (Bransford and Schwartz 1999). Such future learning also involves the use of additional learning materials. In modular plants, operators can use the vast data base provided by the interconnected cyber–physical production system (CPPS). This database does not only inform them about the current plant state but also provides information on other constraints (e.g., current energy prices) and a case base of similar previous settings. Therefore, we need to understand how operators can use the right resources at the right time, and how training can support them in doing so.

A currently unaddressed challenge for learning is that modular pants are operated on a higher level in the abstraction–decomposition space (Rasmussen 1986). While operators' interaction with the system in traditional plants is based on low-level information about physics and specific process parameters (e.g., rotational speed of a mixer), in modular plants it is based on higher level information about function (e.g., resulting mass and energy transport). This is because modules are autonomous processing units that can take care of themselves while encapsulating the details. Currently, we do not know how this will affect the transfer between situations that are similar in function but differ in their low-level implementation. Research from the ecological interface design tradition suggests that functional information can support flexibility (Hajdukiewicz and Vicente 2002). However, in these studies operators were able to use the functional information to take care of the physics, while also having the low-level information available at all times. It is important to know how an encapsulation of low-level information will affect operation and learning in normal and especially in abnormal situations, and we need to understand whether, when, and how operators should be able to drill down into the internal workings of a module.

Finally, an issue that is central to modular plants but so far has received little attention in the transfer literature is the question of switching back and forth between physical setups. Typically, transfer studies focus on switching to new situations instead of switching back to old ones. How will the interaction with a previously known module be affected by intermittent interaction with new modules when later returning to the initial module? Studies on mixed-fleet flying suggest that interference will be an issue (Roth et al. 2015; Soo et al. 2016). However, these studies have focused on situations where the fixed procedures had to be enacted in different setups, while little is known about the impacts of switching back and forth between setups on the ability to deal with situations that are not fully specified but require an active structuring by the operator.

3.3 Goals and individual differences

An issue that is beyond the scope of the present article but important to consider when analyzing and designing modular plants is that the cognitive challenges of changeability will be modulated by the goals that operators pursue. Individual goals are important determinants of transfer (Lave 1988; Lobato 2006) and learning can be modeled as a dynamic flow among different types of value (Wenger et al. 2011). For instance, operators may perceive value in just participating in certain activities, gaining new insights that are potentially useful, actually being able to apply a learned concept, or realizing improvements in plant performance. Whether and how they will engage in a learning experience will depend on whether and how they perceive value in the things to be learned as transfer is expected only when people choose to use the acquired knowledge (Engle 2006).

In modular plants, personal values and goals will also interact with the goals imposed by the production environment. Learning requires exploration, and this is not always compatible with the production goals to be pursued in a chemical plant: operators need to produce certain amounts of a product while meeting high quality and safety standards. While specific, difficult goals can enhance performance (Locke and Latham 2002), they also have costs, especially when it is important to understand the underlying structure of situations (Earley et al. 1989) or to explore complex tasks (Kanfer and Ackerman 1989). Similarly, goal specificity biases learning towards isolated solution paths instead of testing hypotheses and understanding the problem space (Vollmeyer et al. 1996). Therefore, specific goals lead to good performance as long as the goal state stays the same but are less suitable when transfer is required. In contrast, learning goals have more positive impacts on transfer than outcome goals as they lead people to seek challenge, be more persistent in the absence of success, and use failure as a cue to increase their effort or analyze and vary their strategies (Dweck 1986). Especially in complex tasks, performance will benefit from learning goals (Winters and Latham 1996), and this can directly affect economic outcomes (VandeWalle et al. 1999). In line with the importance of learning goals, field studies examining control room activities confirm that exploration is an important contributor to the safe performance of control room teams (Smith et al. 2009). Therefore, a challenge for workplace design and training in modular chemical plants is to encourage exploration. On the one hand, this presupposes flexible routines that allow operators to adapt their actions and decisions to the requirements of the current situation (Grote et al. 2009). On the other hand, exploration can be fostered during ongoing operator qualification, for instance by using simulations in training programs (Kluge et al. 2014; Oppelt 2016). However, individual differences between operators should also be taken into account, because differences in general cognitive ability, conscientiousness, and cognitive style will determine how much operators can benefit from traditional drill-and-practice training or exploration-based training (Kluge et al. 2011).

3.4 Non-cognitive challenges and potentials of changeability

The present article has focused on the cognitive challenges of changeability. However, changeability has broader implications for job characteristics: operator jobs in modular plants are characterized by highly variable tasks, a wide variety of required skills, increased decision latitude, and higher uncertainty. In several models from work and organizational psychology, these job characteristics predict work-related outcomes such as performance, motivation, and well-being. These influences can be positive or negative (Bakker and Demerouti 2007). On the one hand, the high levels of job strain, complexity, and unpredictability that are expected in modular plants can lead to negative consequences such as burnout. For instance, in a meta-analysis that summarizes the findings from over 250 studies, job complexity and task variety were found to be strongly related to perceived overload (Humphrey et al. 2007). On the other hand, provided that people possess certain resources, high job demands can be conducive to performance, as exemplified by the following theories and empirical results: task variety, which means that people are able to perform a wide range of different tasks in their job, is positively related to satisfaction (Humphrey et al. 2007). Similarly, skill variety and thus being required to use different skills in performing one's job is considered as a modulator of motivation, satisfaction, performance, absenteeism, and turnover (Hackman and Oldham 1975), and is negatively related to burnout (Humphrey et al. 2007). Moreover, high decision latitude and high control can function as a buffer for high work strain, neutralizing potential negative effects of the latter (Karasek 1979). Finally, goal setting theory suggests that performance can benefit when people have room to decide how they will pursue goals

(Locke and Latham 2002). Thus, the changeability of modular plants offers rich potentials for creating diverse and challenging jobs, enabling operators to continuously apply and broaden their skills. However, for these potentials to really turn out as resources instead of stressors, careful workplace design is required.

4 Conclusion

Modular chemical plants confront operators with frequent system changes. In contrast to traditional plants, it will no longer be possible to solve problems by relying on extensive experience with one and the same situation. Accordingly, routines and knowledge gained from experience must be complemented with flexible strategies of acquiring and applying knowledge, which calls for both differentiation and generalization. However, at the same time these challenges provide unique potentials in terms of learning and job satisfaction. To make use of these potentials, an interdisciplinary cooperation between engineers, computer scientists, psychologists, anthropologists, and other disciplines will be necessary. A focus of such cooperation should be the translation of findings on human cognition and learning to suitable interventions for operator training and assistance that make use of the technical capabilities of CPPS.

Acknowledgements Parts of this work were supported by a grant of the German Research Foundation (PA 1232/6-1). I am especially thankful to Leon Urbas for providing lots of inspiration over the last years, for many valuable discussions about modular plants and the associated operator requirements, and for support in constructing some of the modular plant examples used in this article. Moreover, I want to thank two anonymous reviewers for their valuable feedback on an earlier version of the manuscript.

References

Bakker AB, Demerouti E (2007) The job demands-resources model: state of the art. J Manag Psychol 22:309–328. https://doi.org/10.1108/02683940710733115

Bransford JD, Schwartz DL (1999) Rethinking transfer: a simple proposal with multiple implications. In: Iran-Nejad A, Pearson PD (eds) Review of research in education, vol 24. American Educational Research Association, Washington, DC, pp 61–100

Brown S, Steyvers M (2005) The dynamics of experimentally induced criterion shifts. J Exp Psychol Learn Mem Cogn 31:587–599. https://doi.org/10.1037/0278-7393.31.4.587

Cañas JJ, Antolí A, Fajardo I, Salmerón L (2005) Cognitive inflexibility and the development and use of strategies for solving complex dynamic problems: effects of different types of training. Theor Issues Ergon Sci 6:95–108. https://doi.org/10.1080/14639220512331311599

Carey S, Spelke ES (1994) Domain-specific knowledge and conceptual change. In: Hirschfeld L, Gelman S (eds) Mapping the mind: domain specificity in cognition and culture. Cambridge University Press, Cambridge, pp 169–200

Carraher D, Schliemann AD (2002) The transfer dilemma. J Learn Sci 11:1–24. https://doi.org/10.1207/S15327809JLS1101_1

Chen Z (2002) Analogical problem solving: a hierarchical analysis of procedural similarity. J Exp Psychol Learn Mem Cogn 28:81–98. https://doi.org/10.1037//0278-7393.28.1.81

Chen Z, Mo L (2004) Schema induction in problem solving: a multidimensional analysis. J Exp Psychol Learn Mem Cogn 30:583–600. https://doi.org/10.1037/0278-7393.30.3.583

Chi MTH (2008) Three types of conceptual change: belief revision, mental model transformation, and categorical shift. In: Vosniadou S (ed) International handbook of research on conceptual change. Erlbaum, Hillsdale, pp 61–82

Day SB, Goldstone RL (2012) The import of knowledge export: connecting findings and theories of transfer of learning. Educ Psychol 47:153–176. https://doi.org/10.1080/00461520.2012.696438

De Keyser V, Woods DD (1990) Fixation errors: failures to revise situation assessment in dynamic and risky systems. In: Colombo AG, De Bustamante AS (eds) Systems reliability assessment. Springer, Dordrecht, pp 231–251. https://doi.org/10.1007/978-94-009-0649-5_11

Doane SM, Alderton DL, Sohn YW, Pellegrino JW (1996) Acquisition and transfer of skilled performance: are visual discrimination skills stimulus specific? J Exp Psychol Hum Percept Perform 22:1218–1248. https://doi.org/10.1037/0096-1523.22.5.1218

Dweck CS (1986) Motivational processes affecting learning. Am Psychol 41:1040–1048. https://doi.org/10.1037/0003-066X.41.10.1040

Earley PC, Connolly T, Ekegren G (1989) Goals, strategy development, and task performance: some limits on the efficacy of goal setting. J Appl Psychol 74:24–33. https://doi.org/10.1037/0021-9010.74.1.24

Ellis AB (2011) Generalizing-promoting actions: how classroom collaborations can support students' mathematical generalizations. J Res Math Educ 42:308–345. https://doi.org/10.5951/jresematheduc.42.4.0308

Engle RA (2006) Framing interactions to foster generative learning: a situative explanation of transfer in a community of learners classroom. J Learn Sci 15:451–498. https://doi.org/10.1207/s15327809jls1504_2

Gentner D, Rattermann MJ, Forbus KD (1993) The roles of similarity in transfer: separating retrievability from inferential soundness. Cogn Psychol 25:524–575. https://doi.org/10.1006/cogp.1993.1013

George DN, Kruschke JK (2012) Contextual modulation of attention in human category learning. Learn Behav 40:530–541. https://doi.org/10.3758/s13420-012-0072-8

Gick ML, Holyoak KJ (1983) Schema induction and analogical transfer. Cogn Psychol 15:1–38

GMA 7.20 (2013) Cyber-physical systems: chancen und Nutzen aus Sicht der Automation. GMA

Goldstone RL, Wilensky U (2008) Promoting transfer by grounding complex systems principles. J Learn Sci 17:465–516. https://doi.org/10.1080/10508400802394898

Gonzalez C, Lerch JF, Lebiere C (2003) Instance-based learning in dynamic decision making. Cogn Sci 27

Goschke T (2013) Volition in action: Intentions, control dilemmas and the dynamic regulation of intentional control. In: Prinz W, Beisert A, Herwig A (eds) Action science. Foundations of an emerging discipline. MIT Press, Cambridge

Greeno JG, Moore JL, Smith DR (1993) Transfer of situated learning. In: Detterman DK, Sternberg RJ (eds) Transfer on trial: intelligence, cognition, and instruction. Ablex Publishing, Westport, pp 99–167

Grote G, Weichbrodt JC, Günter H, Zala-Mezö E, Künzle B (2009) Coordination in high-risk organizations: the need for flexible

routines. Cogn Technol Work 11:17–27. https://doi.org/10.1007/s10111-008-0119-y
Hackman JR, Oldham GR (1975) Development of the job diagnostic survey. J Appl Psychol 60:159–170. https://doi.org/10.1037/h0076546
Hajdukiewicz JR, Vicente KJ (2002) Designing for adaptation to novelty and change: functional information, emergent feature graphics, and higher-level control. Hum Factors 44:592–610. https://doi.org/10.1518/0018720024496980
Helsdingen AS, Van Gog T, Van Merriënboer JJ (2011) The effects of practice schedule on learning a complex judgment task. Learn Instr 21:126–136. https://doi.org/10.1016/j.learninstruc.2009.12.001
Hirsch-Kreinsen H (2014) Wandel von Produktionsarbeit—Industrie 4.0. WSI Mitteilungen 6:421–429
Hmelo-Silver CE, Marathe S, Liu L (2007) Fish swim, rocks sit, and lungs breathe: expert-novice understanding of complex systems. J Learn Sci 16:307–331. https://doi.org/10.1080/10508400701413401
Hoffman AB, Rehder B (2010) The costs of supervised classification: the effect of learning task on conceptual flexibility. J Exp Psychol Gen 139:319–340. https://doi.org/10.1037/a0019042
Holyoak KJ, Koh K (1987) Surface and structural similarity in analogical transfer. Mem Cogn 15:332–340. https://doi.org/10.3758/BF03197035
Humphrey SE, Nahrgang JD, Morgeson FP (2007) Integrating motivational, social, and contextual work design features: a meta-analytic summary and theoretical extension of the work design literature. J Appl Psychol 92:1332–1356. https://doi.org/10.1037/0021-9010.92.5.1332
Jacobson MJ (2000) Problem solving about complex systems: differences between experts and novices. In: Fishman B, O'Connor-Divelbiss S (eds) Proceedings of the fourth international conference of the learning sciences, Mahwah, NJ, Erlbaum, pp 14–21
Jamieson BA, Rogers WA (2000) Age-related effects of blocked and random practice schedules on learning a new technology. J Gerontol Ser B Psychol Sci Soc Sci 55:P343–P353. https://doi.org/10.1093/geronb/55.6.P343
Jonassen DH (2000) Toward a design theory of problem solving. Educ Technol Res Dev 48:63–85. https://doi.org/10.1007/BF02300500
Jornet A, Roth W-M, Krange I (2016) A transactional approach to transfer episodes. J Learn Sci 25:285–330. https://doi.org/10.1080/10508406.2016.1147449
Jurow AS (2004) Generalizing in interaction: middle school mathematics students making mathematical generalizations in a population-modeling project. Mind Cult Act 11:279–300. https://doi.org/10.1207/s15327884mca1104_4
Kanfer R, Ackerman PL (1989) Motivation and cognitive abilities: an integrative/aptitude-treatment interaction approach to skill acquisition. J Appl Psychol 74:657–690. https://doi.org/10.1037/0021-9010.74.4.657
Karasek RA (1979) Job demands, job decision latitude, and mental strain: implications for job redesign. Adm Sci Q 24:285–308. https://doi.org/10.2307/2392498
Kindsmüller MC (2006) Trend-Literacy—zur Interpretation von Kurvendarstellungen in der Prozessführung. Shaker Verlag, Aachen
Kluge A, Ritzmann S, Burkolter D, Sauer J (2011) The interaction of drill and practice and error training with individual differences. Cogn Technol Work 13:103–120. https://doi.org/10.1007/s10111-010-0158-z
Kluge A, Nazir S, Manca D (2014) Advanced applications in process control and training needs of field and control room operators. IIE Trans Occup Ergon Hum Factors 2:121–136. https://doi.org/10.1080/21577323.2014.920437
Krems JF (1995) Cognitive flexibility and complex problem solving. In: Frensch PA, Funke J (eds) Complex problem solving: the European perspective (Chap. 8). Lawrence Erlbaum Associates, Hillsdale
Kruschke JK (2005) Category learning. In: Lamberts K, Goldstone RL (eds) The handbook of cognition. Sage, London, pp 183–201
Lai Q, Shea CH, Wulf G, Wright DL (2000) Optimizing generalized motor program and parameter learning. Res Q Exerc Sport 71:10–24. https://doi.org/10.1080/02701367.2000.10608876
Lau N, Jamieson GA, Skraaning G Jr (2012) Situation awareness in process control: a fresh look. In: Paper presented at the 8th American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation & Control and Human-Machine Interface Technologies (NPIC & HMIT), San Diego, CA, USA
Lave J (1988) Cognition in practice: mind, mathematics and culture in everyday life. Cambridge University Press, Cambridge
Lave J (2009) The practice of learning. In: Illeris K (ed) Contemporary theories of learning: learning theorists… in their own words. Routledge, New York, pp 200–208
Law N, Ogborn J (1994) Students as expert system developers: a means of eliciting and understanding commonsense reasoning. J Res Comput Educ 26:497–513. https://doi.org/10.1080/08886504.1994.10782106
Lobato J (2003) How design experiments can inform a rethinking of transfer and vice versa. Educ Res 32:17–20. https://doi.org/10.3102/0013189X032001017
Lobato J (2006) Alternative perspectives on the transfer of learning: history, issues, and challenges for future research. J Learn Sci 15:431–449. https://doi.org/10.1207/s15327809jls1504_1
Lobato J, Siebert D (2002) Quantitative reasoning in a reconceived view of transfer. J Math Behav 21:87–116. https://doi.org/10.1016/S0732-3123(02)00105-0
Lobato J, Rhodehamel B, Hohensee C (2012) "Noticing" as an alternative transfer of learning process. J Learn Sci 21:433–482. https://doi.org/10.1080/10508406.2012.682189
Locke EA, Latham GP (2002) Building a practically useful theory of goal setting and task motivation: a 35-year odyssey. Am Psychol 57:705–717. https://doi.org/10.1037/0003-066X.57.9.705
Ma R, Kaber DB (2007) Situation awareness and driving performance in a simulated navigation task. Ergonomics 50:1351–1364. https://doi.org/10.1080/00140130701318913
McGuire JT, Nassar MR, Gold JI, Kable JW (2014) Functionally dissociable influences on learning rate in a dynamic environment. Neuron 84:870–881. https://doi.org/10.1016/j.neuron.2014.10.013
McNeese MD (2000) Socio-cognitive factors in the acquisition and transfer of knowledge. Cogn Technol Work 2:164–177. https://doi.org/10.1007/PL00011499
Müller R, Urbas L (2017) Cognitive challenges of changeability: multilevel flexibility for operating a modular chemical plant. Chem Ing Tech. https://doi.org/10.1002/cite.201700029
Mumaw RJ, Roth EM, Vicente KJ, Burns CM (2000) There is more to monitoring a nuclear power plant than meets the eye. Hum Factors 42:36–55. https://doi.org/10.1518/001872000779656651
Nemirovsky R (2002) On guessing the essential thing. In: Gravemeijer K, Lehrer R, van Oers B, Verschaffel L (eds) Symbolizing, modeling and tool use in mathematics education. Springer, Dordrecht, pp 233–256
Nyhuis P et al (2008) Wandlungsfähige Produktionssysteme—Fit sein für die Produktion von morgen. Zeitschrift für wirtschaftlichen Fabrikbetrieb 103:333–337
O'Reilly JX (2013) Making predictions in a changing world—inference, uncertainty, and learning. Front Neurosci 7:1–10. https://doi.org/10.3389/fnins.2013.00105
Oppelt M (2016) Towards an integrated use of simulation within the life-cycle of a process plant. Shaker Verlag GmbH, Aachen
Rasmussen J (1983) Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models.

IEEE Trans Syst Man Cybern SMC 13:257–266. https://doi.org/10.1109/TSMC.1983.6313160
Rasmussen J (1986) Information processing and human machine interaction: an approach to cognitive engineering. North-Holland, New York
Rasmussen J, Pejtersen AM, Goodstein LP (1994) Cognitive systems engineering. Wiley, New York
Reiner M, Slotta JD, Chi MTH, Resnick LB (2000) Naive physics reasoning: a commitment to substance-based conceptions. Cogn Instr 18:1–34. https://doi.org/10.1207/S1532690XCI1801_01
Roth W-M, Jornet A (2013) Situated cognition. Wiley Interdiscip Rev Cogn Sci 4:463–478. https://doi.org/10.1002/wcs.1242
Roth W-M, Mavin TJ, Munro I (2015) How a cockpit forgets speeds (and speed-related events): toward a kinetic description of joint cognitive systems. Cogn Technol Work 17:279–299. https://doi.org/10.1007/s10111-014-0292-0
Sarter NB, Woods DD (1992) Mode error in supervisory control of automated systems. Proc Hum Factors Ergon Soc Annu Meet 36:26–29. https://doi.org/10.1177/154193129203600108
Schoultz J, Säljö R, Wyndhamn J (2001) Heavenly talk: discourse, artifacts, and children's understanding of elementary astronomy. Hum Dev 44:103–118. https://doi.org/10.1159/000057050
Scribner S (1986) Thinking in action: some characteristics of practical thought. In: Sternberg RJ, Wagner RK (eds) Practical intelligence: nature and origins of competence in the everyday world. Cambridge University Press, Cambridge, pp 13–30
Sheridan TB (2011) Adaptive automation, level of automation, allocation authority, supervisory control, and adaptive control: distinctions and modes of adaptation. IEEE Trans Syst Man Cybern Part A Syst Hum 41:662–667 https://doi.org/10.1109/TSMCA.2010.2093888
Smith P, Blandford A, Back J (2009) Questioning, exploring, narrating and playing in the control room to maintain system safety. Cogn Technol Work 11:279–291. https://doi.org/10.1007/s10111-008-0116-1
Soo K, Mavin TJ, Roth W-M (2016) Mixed-fleet flying in commercial aviation: a joint cognitive systems perspective. Cogn Technol Work 18:449–463. https://doi.org/10.1007/s10111-016-0381-3
Speekenbrink M, Shanks DR (2010) Learning in a changing environment. J Exp Psychol Gen 139:266–298. https://doi.org/10.1037/a0018620
Spiro RJ, Vispoel WP, Schmitz JG, Samarapungavan A, Boerger AE (1987) Knowledge acquisition for application: cognitive flexibility and transfer in complex content domains. In: Britton BK, Glynn SM (eds) Executive control processes in reading. Erlbaum, Hillsdale, pp 177–199
Stokes PD, Lai B, Holtz D, Rigsbee E, Cherrick D (2008) Effects of practice on variability, effects of variability on transfer. J Exp Psychol Hum Percept Perform 34:640–659. https://doi.org/10.1037/0096-1523.34.3.640
Urbas L, Doherr F, Krause A, Obst M (2012) Modularisierung und Prozessführung. Chem Ing Tech 84:615–623. https://doi.org/10.1002/cite.201200034
VandeWalle D, Brown SP, Cron WL, Slocum JWJ (1999) The influence of goal orientation and self-regulation tactics on sales performance: a longitudinal field test. J Appl Psychol 84:249–259. https://doi.org/10.1037/0021-9010.84.2.249
Vicente KJ, Burns CM (1996) Evidence for direct perception from cognition in the wild. Ecol Psychol 8:269–280. https://doi.org/10.1207/s15326969eco0803_5
Vollmeyer R, Burns BD, Holyoak KJ (1996) The impact of goal specificity on strategy use and the acquisition of problem structure. Cogn Sci 20:75–100. https://doi.org/10.1207/s15516709cog2001_3
Vosniadou S, Brewer WF (1992) Mental models of the earth: a study of conceptual change in childhood. Cogn Psychol 24:535–585. https://doi.org/10.1016/0010-0285(92)90018-W
Vosniadou S, Mason L (2012) Conceptual change induced by instruction: a complex interplay of multiple factors. In: Harris KR, Graham S, Urdan T, Graham S, Royer JM, Zeidner M (eds) APA educational psychology handbook, vol 2: individual differences and cultural and contextual factors. American Psychological Association, Washington, DC, pp 221–246
Wenger E (2010) Communities of practice and social learning systems: the career of a concept. In: Blackmore C (ed) Social learning systems and communities of practice. Springer, London, pp 179–198
Wenger E, Trayner B, de Laat M (2011) Promoting and assessing value creation in communities and networks: a conceptual framework. Ruud de Moor Centrum, Open Universiteit, Heerlen
Winters D, Latham GP (1996) The effect of learning versus outcome goals on a simple versus a complex task. Group Organ Manag 21:236–250. https://doi.org/10.1177/1059601196212007
Wiser M (1986) The differentiation of heat and temperature: an evaluation of the effect of microcomputer teaching on students' misconceptions. Technical Report 87-5. Educational Technology Center, Cambridge, MA