# **3.5** Cognition and experience of employees in digital work environments.

Michael Leyer<sup>2122</sup> and Jürgen Strohhecker<sup>23</sup>

**Abstract:** Digital work environments are changing the learning experiences for employees. We provide an explanation on how the mechanisms of cognition and experience are connected and affected. First-order learning is reduced by machines which negative effects for second-order learning of employees. The analysis is a first step towards balancing digital support and experiences.

Keywords: Cognition, Digitisation, Decision Making, Decision Support, Experience, Learning

## 1. Introduction

Controlling dynamic systems is an important part of many jobs in organisations. In increasingly digitalised work environments, more and more control tasks are supported by algorithms, automated things or machines using algorithms [Xi12]. Digital work environments are typically characterised by human-machine-interactions with human decision making and task execution supported by machine pre-processing of information. Higher order control, that is, decision making related to strategic and innovative aspects, however, is still mostly executed by human managers. Hence, work procedures for employees are expected to change [FS16]. However, it is not understood quite well, how employees will react [BZG10] and how their possibilities to build experience are affected.

One important perspective is how employees are able to improve processes or to come up with innovations. With pre-processing of data taken over by machines, employees will conduct first order control less comprehensively. They are in danger of missing opportunities to accumulate knowledge about the dynamic system and how to control and improve it. Building a sufficient knowledge base is important as digitally supported task execution is focussed on operational efficiency, but not on adaption to changing

<sup>&</sup>lt;sup>21</sup> University of Rostock, Institute for Business Administration, Ulmenstrasse 69, 18057 Rostock, michael.leyer@uni-rostock.de

 $<sup>^{22}</sup>$  Queensland University of Technology, School of Management, 2 George St, Brisbane QLD 4000

<sup>&</sup>lt;sup>23</sup> Frankfurt School of Finance & Management, Management Department, Adickesallee 32-34, 60322 Frankfurt, j.strohhecker@fs.de

environments (i.e., innovation). Such second order control typically has to be conducted by humans. However, it is hampered by an fragmentary experience and knowledge base of employees whose first-order control loop is weakened in digital work environments. Hence, the research question of this article is, whether weaknesses in innovation and improvement can theoretically be traced back to deficits in first-order learning in digital work environments. In order to answer the research question, we adopt the wellestablished dynamic decision making theory IBLT (instance-based learning theory) to develop a theoretical model experience building via first and second order control. We apply this model to digital work environments to show that important learning steps are weakened by partially automating first order control. We discuss the consequences for second order control. Therefore, the model is intended to help understanding the role of experience in digital work environments to ensure both productivity and innovation.

## 2. Digital work environments

Digital work environments are characterised by software taking over at least preprocessing tasks so that employees can make better and/or faster decisions and task execution is improved, thus creating digital work systems [LRS19]. Such systems are characterised by a fixed operational design within defined parameters. Improving procedures or innovations in the overall processes such digital systems are embedded in, are typically up to human employees [OK03]. This has been e.g. recognised by Toyota who realised that their productivity was decreasing as automated environments didn't develop in line with changes [Bo18]. These environments are optimised environments as part of overall value chains that are not optimal anymore in case of changes.

## 3. Instance-based learning theory

Adequately executing corrective action in dynamic systems over a certain time period requires individuals to follow a decision-making and learning process that involves a series of single decisions and observations of the related outcomes (e.g. [DS94]). IBLT [GLL03] builds on the dynamic control concept and describes this process as a continuous, closed learning loop whose main steps include recognition, judgment, choice, execution, and feedback. Within recognition, a decision maker tries to characterise the situation initially and to find prior experience in terms of instances consisting of a similar situation, the decision made, and the perceived utility (SDU). In addition, and especially when no similar SDUs are recognised, the situation has to be analysed in more detail regarding cause-and-effect relations, goals, environmental cues, instructions, heuristics, etc. In the judgment phase, a decision maker can either use relevant SDUs and/or has to estimate, based on the recognised and assumed characteristics of the decision situation, which decision is most suitable. This includes forming hypotheses, prognosing, and

planning [DS94] and often follows heuristic rules. For the choice that follows, IBLT proposes an "intermediate strategy between the optimising and satisficing strategies of choice" [GLL03]. Based on the ranking of options, the current best one is executed. As a result, the system state is changed and – typically with a delay – perceived and processed by the decision maker. IBLT suggests that an individual's experience base consists largely of a collection of SDUs that are stored in memory. Processing feedback information involves updating of SDU instances – specifically, changing their utility values [GLL03]. In the case of better (poorer) outcomes than originally projected, utility is upgraded (downgraded).

#### 4. Double-loop learning: Adaptation and Innovation

Experience can be gathered by employees in digital workplaces according to two sources [Ar76]. First-order learning occurs when employees or machines make their decisions to change a system, observe the outcome in the system and learn how their actions are influencing the system towards their intended state (Figure 1). Such learning however never questions the underlying experience (consisting of SDUs, a mental model of the dynamic system and heuristics or methods). Second-order learning changes the experience base due to the instance based learning process. This type of learning is essential to rethink the basic assumptions and to adapt to changes of the environment. In the context of work environments such second-order learning refers to improvements and innovation. The instance-based learning process described in section 3 combines both learning loops as the instances created from both sides are used to make decisions in the workplace.



Fig. 1: Interaction instance-based learning process and double-loop learning

#### 5. Experience and mental models

According to instance-based learning theory, experience is built while decision making by employees in the workplace. We suggest extending IBLT's concept of experience base beyond the collection of SDUs in three regards. First, we propose to add an element that captures the structure of the dynamic system (S) to the triplet of situation, decision and utility (SDU). This seems important, as even in dynamic systems of rather low complexity the current situation needs to be described by both system states and relations between these states. Second, we suggest to extend IBLT's perspective beyond instances and also include a component that we call mental model of a dynamic system (MMDS). Following a classic definition, a MMDS describes subjectively perceived "representation of causal factors and how they relate to each other" [SG14, p. 567]. An individual can develop a mental model by subjectively observing an environment to understand the relations between elements in a system [GW11]. Third, we suggest to explicitly add heuristics (or methods) to the experience base. Heuristics represent rules (of thumb) that are typically used in the judgement and choice stage, for instance, select the first SSDU that delivers a utility above a threshold and execute it. They can also represent more complex decision-making strategies such as the order-up-to rule known in operations management. Hence, experience encompasses a collection of SSDUs, a MMDS, and a set of heuristics/methods.



Fig. 2: Adapted IBLT (SSDU: Mental representation of system structure, situation, decision, and utility, MMDS: Mental model of (the structure of) a dynamic system)

In digital work environments, as described, machines typically take over the recognition of the environment and the judgement in form of gathering data by sensors and providing analyses. Employees have the role of choosing options for decision making in operational tasks as well as improvement and innovation in such an environment. Feedback is also gathered by the sensors of machines. Hence, both machines and employees build a memory of SSDUs. However, the memory of employees is missing experiences from the recognition, judgement and feedback phase done by machines. This has a negative influence on building adequate mental models among employees. Such mental models mainly include the relationships of machines and employees in terms of the workflow of orders. They allow employees to understand how everything is connected in the workplace to fulfil customer needs, i.e. how to best create customer outputs efficiently. These then incomplete and inaccurate mental models lead to employees not being able to conduct improvement and innovation activities sufficiently. This is nevertheless important as digital machines can have self-learning algorithms, but are limited to improving an operational work task. The overall connection of these tasks in processes and their change is up to humans which need experiences from the whole processing cycle to come up with ideas.

# 6. Implications, Limitations and Outlook

The model is a first attempt to understand the importance of experience of employees with operational work tasks in digital work environments. It enhances IBLT by integrating single- and double-loop learning and by describing the interaction between machines and humans. The model provides an explanatory foundation why mental models of employees are inaccurate when certain steps of executing and analysing operational tasks are automated and employees have no transparency how the underlying algorithms work.

Hence, employees will more likely lack an understanding of the work processes to be able to improve processes and come up with innovations. Organisations should thus be careful in increasing the degree of automation too much. Digital machines should support employees in executing operational tasks while allowing for more control by employees. Employees need to be empowered by this rather than become slaves of the machines.

Limitations of our model are that it is purely theoretical without providing empirical evidence. Future work should focus on analysing designs of digital workplaces that support employees (degree of automation, understanding of algorithms) but still allow for a sufficient gathering of experiences. In order to do this, a formal representation of our concept (e.g. as a system dynamics model) is helpful. Based on such a representation, experiments can be designed to empirically test the theory in exemplary work environments. Experimental conditions can vary the extent of computers taking over tasks as described and the performance of subjects in managing production environments can be compared to determine the impact of experience on performance.

## References

- [Xi12] Xia, F., Yang, L.T., Wang, L., Vinel, A.: Internet of things. International Journal of Communication Systems 25, 1101-1102 (2012).
- [BZG10] Bitner, M.J., Zeithaml, V.A., Gremler, D.D.: Technology's impact on the gaps model of

service quality. In: Maglio, P.P., Kieliszewski, C.A., Spohrer, J.C. (eds.) Handbook of Service Science, pp. 197-218. Springer, New York (2010).

- [Bo18] Bork, H.: Humanizing the auto industry. Think: Act Magazine 26, 52-58 (2018).
- [FS16] Ferretti, M., Schiavone, F.: Internet of things and business processes redesign in seaports. The case of Hamburg. Business Process Management Journal 22, 271-284 (2016).
- [LRS19] Leyer, M., Richter, A., Steinhüser, M.: Empowering shop floor workers with ICT. The role of participative designs. International Journal of Operations and Production Management (forthcoming).
- [OK03] Oliva, R., Kallenberg, R.: Managing the transition from products to services. International Journal of Service Industry Management 14, 160-172 (2003).
- [DS94] Dörner, D., Schaub, H.: Errors in Planning and Decision-making and the Nature of Human Information Processing. Applied Psychology 43, 433-453 (1994).
- [GLL03] Gonzalez, C., Lerch, J.F., Lebiere, C.: Instance-based learning in dynamic decision making. Cognitive Science 27, 591-635 (2003).
- [Ar76] Argyris, C.: Single-loop and double-loop models in research on decision making. Administrative Science Quarterly 21, 363-375 (1976).
- [SG14] Schaffernicht, M.F.G., Groesser, S.N.: The SEXTANT software. A tool for automating the comparative analysis of mental models of dynamic systems. European Journal of Operational Research 238, 566-578 (2014).
- [GW11] Gary, M.S., Wood, R.E.: Mental models, decision rules and performance heterogeneity. Strategic Management Journal 32, 569-594 (2011).