Current Psychology (2023) 42:21805–21819
https://doi.org/10.1007/s12144-022-03293-7

Measurement and performance impact of team mental models on process performance

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Accepted: 30 May 2022 / Published online: 4 June 2022

Abstract

Efficient business process execution is an essential part of an organisation's success. It depends on good dynamic decision making of process actors that is guided by their mental models of business processes (MMBP). The study investigates the effect of MMBPs on process performance at two levels. At the level of individuals, the impact of MMBP accuracy on performance is analyzed, and at the level of a team, the effect of similarity of MMBPs of all team on performance is researched. At both levels, MMBPs are differentiated in a narrow part that focuses on the mental representations of process steps that precede or follow on the one conducted by the actor and a holistic model that captures the process as a whole. We use laboratory observations with 159 participants in 10 teams from a real effort loan processing role play. We obtain individual MMBP accuracy measures by using a process knowledge test and measure the process performance of teams with the outcome of the role play. Our study contributes in three ways to existing research. First, the measurement approach of individual MMBP accuracy and similarity is extended to the level of teams. Second, the study shows that the accuracy of both narrow and holistic MMBPs as well as similarity of holistic MMBPs positively impact team process performance. Third, by using an observable team process performance measures from a real-effort task, we increase the validity of our findings compared to other research relying on self-assessed performance measures.

Keywords Dynamic decision-making · Business process · Operational performance · Mental models · Team mental models · Instance-based learning

Introduction

Achieving excellent business process performance within the management of operations is a demanding, meanwhile crucially important challenge, for any organisation. Production research largely focuses on technical process analysis tools to increase performance, for instance, the identification and elimination of bottlenecks, balancing the work across resources, or creating demand-oriented staffing plans (Cachon & Terwiesch, 2008). In addition to such process optimisation, management research agrees that a correct and homogeneous process understanding – or, to adapt the terminology from dynamic decision-making research (Gary & Wood, 2011) – accurate and similar mental models of a business process (MMBP) among the actors engaged in this process is beneficial (Berner et al., 2016; Figl, 2018; Hammer & Stanton, 1999). It is argued that employees in such a team can better control and coordinate their workflow in processes running across several functions within and even beyond the organisational boundaries (Kettenbohrer et al., 2016; Segatto et al., 2013) if their team's MMBP accuracy and similarity is higher (Babić-Hodović et al., 2012; Olaisen & Revang, 2018). For example, if the team equally understands the process flow correctly, its members are able to identify bottlenecks and implement short term local measures, as for instance, using flexible work time, rerouting of orders or calling-in of stand-by personnel.

The concept of shared mental models has been employed in management as an important concept to understand the success of making decisions for managing and changing

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processes (Bortolotti et al., 2018; Braunscheidel et al., 2011; Gutiérrez Gutiérrez et al., 2009; Moosmayer et al., 2020). Empirical tests of the relation between MMBP accuracy/similarity and operational process performance at the level of teams are largely missing though (Edwards et al., 2006; Figl, 2018). One reason might be that a measurement concept of a team's MMBP accuracy and similarity is not readily available (Floren et al., 2018). While dynamic decision-making and system dynamics researchers have developed methods to capture decisions makers individual mental models of dynamic systems (MMDS) (Gary & Wood, 2011; Groesser & Schaffernicht, 2012) and to aggregate them at the team level (Edwards et al., 2006), there is no equivalent for the domain of MMBPs. Moreover, specific measurement approaches are missing that allow to distinguish between accuracy and similarity of team MMBPs. Thus, this article asks the following two research question: First, how can accuracy and similarity of team MMBPs be measured by determining and aggregating the correctness of individual MMBPs? Second, what is the impact of a team's MMBPs accuracy and similarity on its process performance?

Adressing our research questions, we follow the example of Walker et al. (2015) and adopt a behavioral theory. These authors used goal systems theory to investigate how mental representations affect individual motivations to conduct operational tasks. In our research, we adopt mental model theory as a behavioural theory (Holyoak & Cheng, 2011; Mohammed et al., 2010) that explains how mental models are built on a team level and how they affect operational performance. More specifically, we answer the two questions raised by building on mental model literature from dynamic decision-making and system dynamics research (Doyle & Ford, 1998; Gary & Wood, 2011; Groesser & Schaffernicht, 2012; Holyoak & Cheng, 2011; Johnson-Laird, 1983) as well as instance-based learning theory (IBLT, Gonzalez et al., 2003).

Using data from a laboratory observation of a fictive credit loan process with 159 participants in 10 teams, we measure MMBP accuracy at first at the level of an individual adapting the measurement concept from dynamic decision-making research. In a second step, we aggregate the individual accuracy measures of all team members directly involved in the business process at the level of teams. By using both the average and the standard deviation of MMBP accuracy, we obtain measures for a team's MMBP accuracy as well as similarity that we then use to investigate the impact of both of these variables on team process performance.

Our results contribute to the decision making literature in various ways: First, we provide a conceptualisation for shared mental models of processes in the domain of managerial decision making. For this, we transfer the theoretical ideas and measurements of individual mental models from dynamic decision-making research (Gary & Wood, 2007) to business processes and operational performance. This domain is more specific in capturing relationships between objects compared to more abstract and general measurements for example in strategic manufacturing (Moosmayer et al., 2020). Second, we provide a novel measurement approach that can be used to integrate individual actor's understanding of a real process or of a formal process model on the team level. The approach can be used for any business process, thus addressing the issue of contextualised mental model measures (Floren et al., 2018). The aggregation of individual accuracy measures at the level of teams allows us to determine the team MMBP accuracy and similarity. These measures are helpful in unveiling inconsistencies in the process knowledge of teams that could then be actively managed and resolved. Third, we introduce an extended version of IBLT as underlying theoretical concept of how mental process models are built. We are first in adapting the theory in this regard which advances our understanding of the MMBP building process and, at the same time, explains the impact of MMBP accuracy and similarity on process performance on an individual level. Fourth, we observe participants in a controlled setting of a serious business game that forces them to execute real tasks instead of just analysing a graphical process model (e.g., Mendling et al., 2012). By this, we show how observational data on process performance can be obtained that reflect an experimental setting one step closer to real life than in the typical laboratory.

Theoretical foundation

Mental models of processes

An individual MMDS describes a subjectively perceived "representation of causal factors and how they relate to each other" (Schaffernicht & Groesser, 2014, p. 567). It is one's subjective view on an observed system of relations and it can be used by a person being involved in such a system to take actions (Gary & Wood, 2011, 2016). Originated in psychological research (Holyoak & Cheng, 2011; Mohammed et al., 2010), it has also established a tradition within dynamic decision-making research (Doyle, 1997; Doyle & Ford, 1998, 1999; Forrester, 1992; Hall et al., 1994; Sterman, 2000). The terminology is not consistent in this literature. Alternative labels used for MMDSs include cognitive maps, industry recipes, implicit theories, dominant logic, schema, heuristics, analogies, knowledge structures, strategic frames, belief structures, routines or causal maps (Gary & Wood, 2016; Walsh, 1995). Independent from terminological differences, MMDS are commonly understood as representations of dynamic systems that consist of system variables and instantaneous or delayed causal relationship between them that can form reinforcing as well as balancing feedback loops (Forrester, 1961; Groesser & Schaffernicht, 2012).

MMDS do not only exist at the individual level, but also at higher organisational levels, as, for instance, at the team level. These MMDS shared among teams refer to “organised mental representations of the key elements within a team’s relevant environment that are shared across team members” (Mohammed et al., 2010, p. 867). They allow members of the team to share expectations, to anticipate actions and to coordinate their behaviours (Levesque et al., 2001; Lim & Klein, 2006; Moosmayer et al., 2020).

Transferring the theory and concept of MMDS to the business process management domain, we suggest that actors develop individual mental models of business processes (MMBP) they are involved in. Business processes are typically described as a number of activities that are related with each other towards a certain goal (Davenport & Short, 1990). Orders (or, alternatively, process instances, or entities, or tokens) for a business process are received from customers or other stakeholders, they are then typically worked on in different activities using different resources (e.g. machines, information systems, individuals having roles); at completion, they are either handed back to the customers or stakeholders or they are archived or disposed. Typically, there is a certain and order-type-specific logic how the activities are connected with each other, which can range from a linear process flow to a complex process flow with multiple start and end points (Collier & Meyer, 1998; Kim et al., 1996). In that sense, orders are processed by flowing through a more or less complex network of activities. Very often, more than one role is needed to perform these activities so that handovers occur not only at the start and the end of the process, but also internally.

The networks of activities that business processes form show similarities to causal systems: process activities are linked to each other in a very similar way as there are causal links between system variables. Hence, we propose that employees being involved in business processes as resources develop similar mental representations of these processes as they create MMDS; that is, they create a mental image of where they start and end, how the single activities are connected, how the orders flow through them, which resources are needed and when handovers take place (Leyer et al., 2020).

As feedback and time delays in dynamic systems increase their dynamic complexity, changing flows of orders through the network and/or changes in the network itself – depending on certain conditions of the environment or the orders characteristics (Leyer, 2011) – increase the dynamic complexity of a business process. This complexity is mainly driven by the size of the network of activities, the role an employee has in this network and the visibility of the network:

- Network of activities: The more activities (elements) and handovers (relations) a process has, the higher is its complexity and the more difficult it is to understand the interdependencies between the process activities (Škrinjar & Trkman, 2013; Zarei et al., 2014).
- Role of an employee: Employees being involved with several activities in a process create a higher level of process complexity compared to a situation where they performed only one activity. At the same time, these employees are supposed to have better insights in the process as a whole than employees working in one activity only.
- Visibility of the process: “Invisibility” of a process or parts of it increases its complexity. Such invisibility can be introduced by digitalisation, for instance by electronic workflow systems or email handovers. Compared to employees receiving and sending their work electronically, personal handovers are more salient and less abstract. Often, employees who can see the process in reality and have personal contact with other actors recognise critical situations earlier and handle handovers better.

In the domain of dynamic decision-making, instance-based learning theory (IBLT) is an established theory that describes how individuals make these decisions, learn from their consequences (feedback) and accumulate knowledge (Gonzalez et al., 2003). Memory instances play an important role in IBLT; they are seen as triplets of information: a description of the decision-making situation, the decision made and the outcome/utility experienced (SDU). In a situation that requires a decision, decision makers search their memory for instances of similar situations (recognition), evaluate (judgement) the outcome of possible actions using either heuristics (atypical situations) or previously accumulated SDU instances (typical situations), determine the best course of action (choice) and execute it. In that sense, IBLT proposes that dynamic decision maker’s accumulate knowledge by accumulating SDU instances. As (Gonzalez et al., 2003, p. 595) define the situation part of an SDU as “a set of environmental cues”, information on the causal structure of a dynamic system is included. Therefore, by accumulating SDUs, a decision maker develops his/her MMDS at the same time. MMDS are constructed from at least one, but mostly many SDUs capturing similar situations in dynamic systems. MMDS are neither perfect nor static. Complex relations as well as delays between cause and effect make it difficult for individuals to create accurate SDU instances (Gonzalez et al., 2003), and, thus, MMDS are often inaccurate as well. As SDUs can be updated and refined in the judgement and feedback stages, mental models change as well as new information on the situation or the outcome become available.

Adapting IBLT to the context of business processes, we propose that MMBPs emerge in a similar way as MMDS from instances being accumulated by process actors. We see instances still as triplets of information: a description of the situation (S) including both information on the process (seen as a more or less complex network of activities) as well as the actor's position in this network and the characteristics of the order received, a series of activities (A) (or a single one) being performed by the actor as well as all handovers, and a result (R) being observed (SAR), for instance based on typically used process performance measures. Every time, an employee receives an order, she or he searches for similar SAR instances in the memory. In case this new situation is a typical one, that is, is similar to situations stored in previously accumulated SAR instances, the judgement of how to proceed is based on previous knowledge: all instances similar to the current situation are retrieved from memory, the flows of activities are evaluated, and the resulting performance is obtained. In the other case of a rather atypical situation, judgements are based on a broader range of heuristics (including instructions) and/or on reasoning. Following on the judgement stage, the actor chooses the best course of action that she then executes. Feedback while or after execution is used to update SAR instances. This feedback includes on the one hand immediate and directly observable elements as, for example, the sequence of activities performed by herself or physical handovers between her and other actors (for example, receiving a file with papers). On the other hand, it contains information on less well observable process elements, as, for instance, activities conducted by other actors or handovers in which she is not directly involved. As a consequence of these different types of feedback, the MMBPs of actors – created from a set of one to many similar SAR instances – consist of often very accurate representations of sections of the process that are directly work related and a typically less accurate representation of the complete process. We refer to the immediate work-related part of an individual's MMBP as his or her narrow model – NMMBP – and to the comprehensive MMBP as the holistic model – HMMBP.

Using the theoretical concept outlined above, we are able to define the accuracy of the MMBP of an individual as its conformance with the explicit, formalised process model. Accuracy of a team's MMBPs is then determined by aggregating the team members' individual MMBPs to the mean or the median. Moreover, similarity of MMBPs of team members is defined as the level of congruency between the individual MMBPs, measured by calculating the standard deviation, mean absolute deviation or interrater reliability. In doing so, we follow the aggregation approach for team mental models as proposed by Edwards et al. (2006) in the context of a dynamic and complex aviation video game task (Space Fortress).

Impact of MMBP accuracy and similarity on team process performance

While empirical evidence on the relation of team MMBP accuracy and team process performance is lacking, we can identify evidence from related fields highlighting the general connection of cognition and knowledge on performance. From the perspective of general MMDS accuracy, various experimental research has identified a positive impact of the accuracy of individuals' MMDS on individual decision-making performance (Davis & Yi, 2004; Gary & Wood, 2016; Ritchie-Dunham, 2001; Ritchie-Dunham et al., 2007; Rowe & Cooke, 1995; Stout et al., 1997; Wyman & Randel, 1998). Aggregating such individual MMDS, accuracy and similarity of mental models among members of a team involved in a joint task has been found to positively impact team performance (Edwards et al., 2006; Lim & Klein, 2006; Mathieu et al., 2000, 2005). The context used in these studies refers to military situations (virtual or real) with participants performing various tasks related to combat operations together. Furthermore, a longitudinal study of Olaisen and Revang (2018) demonstrated that individual tacit knowledge could be transformed into shared collective explicit knowledge that would increase innovation performance via mental models, however, without a detailed analysis of such mental models. In addition, Bortolotti et al. (2018) refer to the positive effect of common team mental models, operationalised as goal clarity, on the success of transformations and learning regarding processes.

In the domain of business processes, a comprehensive review from Figl (2018) analyses the effect of using visual process models that are intended to help individuals building better MMBPS. The only two studies identified in the review that relate such aids to performance are very limited to one showing that some depictions (no swim lanes) of processes have a positive effect on individuals' problem-solving performance (Bera, 2012) while the other one shows that a syntax highlighting with colors has no effect on experts' performance (Reijers et al., 2011). Only one study by (Berner et al., 2016) provides evidence that enhanced process visibility has an impact on performance on an aggregated level using multiple case studies in the environment of IT service management (Berner et al., 2016). However, the measurement of process performance is limited, as it is based on team leaders' perceptions. In addition, MMBPs of individuals or teams are not elicited. Further studies linking the individual level to an aggregated performance level focus on self-reported general task knowledge. However, only the knowledge of general task procedures is captured in this measure. Specific task knowledge and especially the knowledge about the relationships between tasks is not included. Such studies report on a positive effect of task knowledge on firm level performance with regard to operations

(Babić-Hodović et al., 2012; Škrinjar et al., 2008), on firm level performance with regard to financials (Movahedi et al., 2016) as well as process performance on a team level with regard to quality (Leyer et al., 2017). These studies provide no evidence on the relation between individual MMBPs and team MMBPs accuracy as well as on team process performance. The results are however helpful in supporting our assumption for a relationship between individual MMBPs, their aggregation on a team level to team MMBPs and the process performance on a team level.

We address the identified gap in the literature by drawing on IBLT as our underlying theory as outlined in 2.1. An individual having an accurate MMBP can be assumed to have experienced many order executions in a process at its own or colleagues' workspaces resulting in a large collection of correct SAR instances. According to IBLT, this affects positively individual task execution. However, the procedure of building a memory of instances with situations, actions and results requires cognitive effort resulting in a certain cognitive load (Sweller et al., 2011). Performing one's tasks adds to cognitive load as well so that the ongoing process of building a mental process model is in competition with task execution. As a consequence, it is not clear beforehand, which effect dominates on the individual level.

Even when individual task execution is improved, it is not obvious that a positive effect can still be seen at the level of the overall process, which is at the level of the team. For a process to show a better performance, the performance at the bottleneck resource is critical. It is easy to conceive scenarios where process performance remains unchanged despite most individuals increase their performance, because the one bottleneck resource is not improving.

Having a correct understanding of how one's own work is connected with the work done by direct colleagues increases the understanding of potential side-effects: it is then more obvious that and how the own work affects the work of those colleagues that downstream. In contrast, if employees have inaccurate MMBPs, bottlenecks are more likely to occur as they do not consider the impact of their own work on other parts of the process adequately. Hence, if the mental models of the members of a team are of higher accuracy, the work is better coordinated, less problems emerge and team motivation increases (Ziemiański et al., 2021). Concluding, we expect a positive influence of team MMBP accuracy on process performance.

Coming back to the differentiation between narrow and holistic MMBPs (as outlined in Section 2.1), we can distinguish between direct work relations (narrow) and the overall process (holistic). First, a higher accuracy of the narrow MMBPs of the process actors leads to a better process performance, as the actors have a better understanding of their direct environment and consider their direct co-workers when executing their tasks (Movahedi et al., 2016). The higher this understanding among all participants, the higher is a joint positive effect on the joint process performance. Thus, we formulate hypothesis H1.1 as follows:

H1.1: *The higher the accuracy of a team's narrow MMBP the higher is the team's process performance.*

Second, a higher accuracy of the teams holistic MMBP is assumed to have a positive influence as well, as it allows actors to understand better how they are contributing to the overall process. Employees having an accurate MMBP, of which their work is part of, take the larger process into account when performing their daily activities (Leyer & Wollersheim, 2013). They are more considering the impact of their work activities on the preceding and subsequent process activities and thus also on the overall process outcome (McCormack, 2001). In consequence, actors take the overall process into account when executing their tasks, which prevents them from focusing solely on improving their individual performance, which might have caused negative effects on the overall performance. Hence, we formulate hypothesis H1.2 as follows:

H1.2: *The higher the accuracy of a team's holistic MMBP the higher is the team's process performance.*

Regarding the second dimension that we are interested in, MMBP similarity, it is important that mental models of process actors are coherent. First, if there are strong deviations of narrow mental models among participants, it is very likely that bottlenecks occur. This can be illustrated by the following example: An actor not knowing and considering the subsequent process step might still maximise his speed (by compromising on quality) although work is already piling up at his colleagues desk; a more forward looking actor would instead spent more time on ensuring high quality of his work, and, by this, reducing the amount of rework to be done later. If all individual process actors share an aligned understanding of their direct work relations, balancing of speed and quality is likely to occur locally within the regular process flow based on bilateral and multilateral observation and communication among the actors involved (Langan-Fox et al., 2004). This is likely to increase the overall process performance. Hence, we formulate hypothesis H2.1 as follows:

H2.1: *The higher the similarity of a team's narrow MMBP the higher is the team's process performance.*

Second, at the overall level of the process, mental model similarity of process actors also matters. For example, if one actor has a perfect understanding of the overall process, but the other actors ' mental models of the same process vary, the positive impact of one single actor with an ideal process understanding will vanish, or, at least, be damped. Controversial discussions about who has the correct mental model and whose model is wrong are likely (Moosmayer et al., 2020). Hence, we formulate hypothesis H2.2 as follows:

H2.2: *The higher the similarity of a team's holistic MMBP the higher is the team's process performance.*

Methodology

Design of the study

In line with the strong tradition of laboratory experiments in system dynamics research to investigate perceptions and cognitive schemata such as mental models (Capelo & Dias, 2009; Gary & Wood, 2016; Kunc & Morecroft, 2010; Mendling et al., 2012; Sterman, 1994), we apply a laboratory setting in the context of this study. This allows us to observe human behaviour in a controlled experimental environment while at the same time taking advantage of tools and techniques from systems thinking (Doyle, 1997). With our research design, we aim to achieve the nine objectives outlined by Doyle et al. (2008) for any rigorous study analysing mental models: Attaining a high degree of experimental control, separately measuring and improving, collecting data from individuals in isolation, collecting detailed data from the memory of each individual, measuring rather than perceiving change, obtaining quantitative measures of mental model characteristics, employing a naturalistic task and response format, avoiding bias, and obtaining sufficient statistical power.

For the purpose of this study, we adopt the role play developed by Börner et al. (2012) for our laboratory observation. This choice is based on the plays unique position as the only published role play that provides a realistic process environment with multiple process activities and roles as well as not introducing the overall process flow to role play participants beforehand. The play simulates a business process from the banking industry, where loan applications have to be managed.

Participants are randomly assigned to functional roles (being executed at functional stations). Information on their role and work instructions is provided on each role's table, also containing general information on the bank and its goal. The setting is function-oriented, i.e. each participant works at his/her station without any communication with colleagues; applications are received from the preceding role via inboxes and send to the next station via outboxes placed on the tables. Intentionally, the complete process flow is not made visible to avoid that participants simply memorise from this overview. Hence, participants neither receive explicit information on it (for instance by showing them a process flow diagram or the numbered arrows in Fig. 1), nor is the room layout oriented at the process flow (see Fig. 1). However, the role play is paper-based and takes place in a single seminar room following the design description of Börner et al. (2012). This allows all participants to observe all activities of all roles at all stations.

There are four branches (north, east, west, south) that each hand in one loan applications every minute to the bank's back-office for processing. A courier is picking up the loan

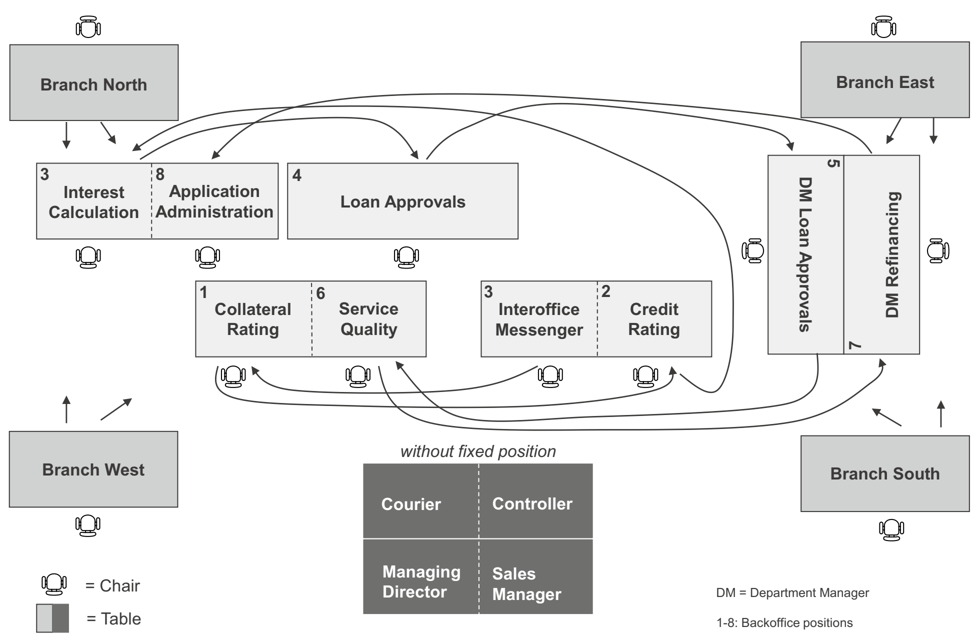


Fig. 1 Room layout and flow of the loan application process (Börner et al., 2012) (1…8 refer to the sequence of activities as described in appendix A-1)

applications and delivering them to the back office by placing them in the interoffice messenger's inbox. This messenger is responsible for transporting the loan applications between the different participants (functions) by collecting one from an outbox and delivering it to the inbox of the succeeding station. The process has a linear flow meaning that there is only one way through the process for each loan application (as indicated by the numbers in Fig. 1). After the last role finished its work on a loan application, he/she places in his/her outbox which the courier is tasked to constantly observe. The courier then transports loan applications to the respective branch that handed it out, thus, finishing the process.

In addition, there are also observant roles such as the managing director, the sales manager and controller who do not contribute to process performance as they are supporting roles not directly working on the loan applications.

Measures

Our measurement approach of the accuracy of individual MMBPs follows the concept described by Gary et al. (2012) and subsequent applications (e.g., Leyer et al., 2021; Martignoni et al., 2016) for determining MMDS accuracy. There, participants have to assess the cause-and-effect relationship between two variables. They can either indicate the direction of the effect (same or opposite), state that there is none relationship at all or that they do not know. This approach can be transferred to processes as they also represent a network of connected activities with possible directions between these activities (Leyer et al., 2021). Since the chosen role play focusses on individuals assigned to roles in the process, we choose roles as perspective for describing the connections in the process (Schmidt et al., 2009). Hence, we present statements on relationships between activities performed by roles. In the role play each role is assigned to one set of activities only and each participant takes exactly one role. Therefore, relations between roles (and thus between activities) are rather easy to observe. The post-stage-one questionnaire includes all in all 35 statements of the type: "The activity of role X follows close upon the activity of role Y". Participants can choose between three answers: (1) "Correct" (2) "Wrong"; (3) "I do not know". 17 out of 35 statements are true as the process has as many connections and 18 are false, following the individual measurement of process connections from an activity perspective (Leyer et al., 2021). Participants are informed that there are true and false statements, but they do not know how many. By this, we discourage random guessing. Figure 2 provides an overview on the bivariate pairs in the experimental.

The accuracy of an individual actor's holistic MMBP is calculated as the sum of all correct answers (resulting in values between 0 and 35) divided by the maximal number of correct answers (35) with 1 meaning that a 100% accuracy is achieved. While the questionnaire is anonymous, we ask for the role of each participant in each play; by this, we are able to link the questionnaire data with the participants' role taken in the play (focusing on the operational roles one to eight only). This allows us to also calculate a participant's narrow MMBP as the percentage of correctly answered statements on relations in which the participant is involved. By calculating the mean value of both the narrow and holistic MMBP accuracy of all participants within each of the 10 teams respectively, we determine the MMBP accuracy at the team level (Fig. 3). To determine the similarity of the individual MMBPs of the team members, we considered the standard deviation of the individual process actors within each group. Another option to assess similarity are interrater concepts such as Krippendorff or intraclass correlation coefficient on the level of the 35 statements (Krippendorff, 2013; Shrout & Fleiss, 1979). Such an aggregation analyses the similarity of ratings per statement and reflects whether participants have similar agreements regarding specific parts of the process. To increase validity of our results and the chosen aggregation, we perform the respective analysis as a further robustness test for the holistic MMBP.

Process performance of a team (TPP), the dependent variable of the study, is measured objectively using data gathered from stage 1 of the role play. It is the number of

Fig. 2 Bivariate pairs in the experimental loan process

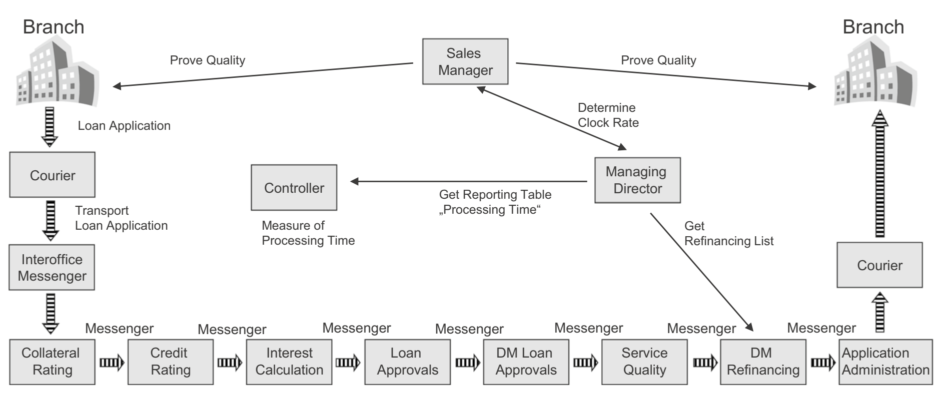
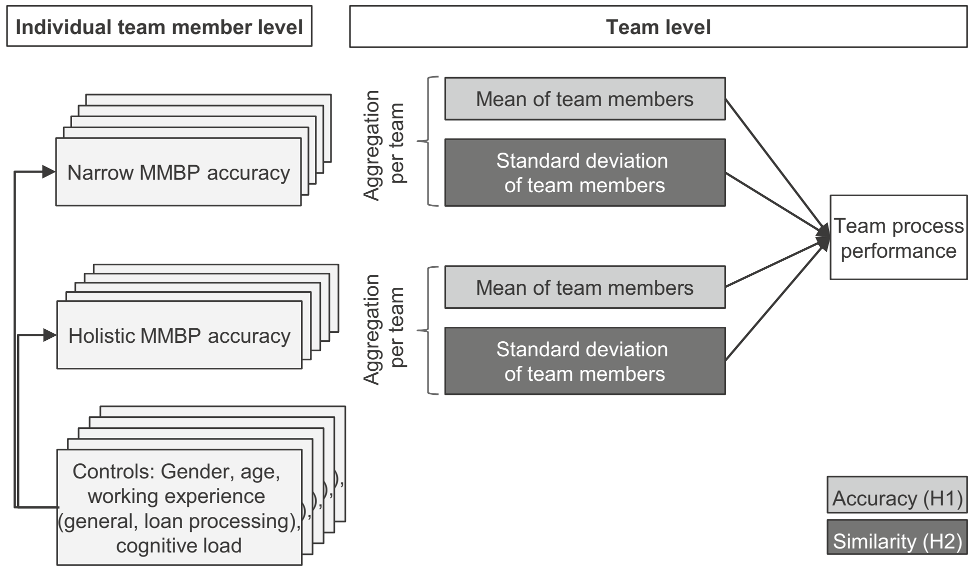


Fig. 3 Research model



mistakes (incorrectly calculated rating, late returns of loan applications, and wrong assignment of branch specific information) divided by the number of fully processed orders multiplied by the factor three (representing the number of possible mistakes per loan application) (Börner et al., 2012). The resulting value is then subtracted from one to achieve a positive value (the less mistakes the better the performance) and multiplied with 10^6 (Tjahjono et al., 2010).

Additionally, with the post-stage-one questionnaire, we collect descriptive data regarding gender, age, working experience in general and working experience related to loan processing. Furthermore, we ask participants to indicate their perceived cognitive load when performing their activities in the process on a scale from 1 (extremely easy) to 9 (extremely hard). Such measurement of cognitive load with a single self-rated scale is well-established in the literature (e.g. Chen et al., 2011).

Participants and procedure

To ensure highly motivated participants, the observational experiment is embedded in professional and academic trainings pursuing the primary goal of increasing the trainees' process-orientation. Therefore, participants are employees from mid-sized banks, employees from non-banks as well as students on graduate level of a university. The groups in the experiment are however homogenous regarding these three backgrounds. Employees are predominantly chosen as they are familiar with working in a business process environment and thus are experienced with a mental model building process. In addition, students are considered as novices in terms of experience with working in a business context. While the role play allows for 12 to 22 participants, the average group size during the observations was 16. Overall, the role play was conducted ten times with a total of 159 participants (every participant only participating once) of which 94 are bank employees, 30 are non-bank employees and 35 are students. Participants are 49.7% male, have an average age of 32.7 years (SD: 12.9) as well as 11.8 years of work experience (SD: 13.6) and 1.2 years of work experience in loan processing (SD: 3.6) with 135 participants not having any prior experience in loan processing.

Participants do not receive any information on the detailed schedule of the experiment. Specifically, it is not disclosed that their mental model of the business process in stage one of the play will be measured afterwards, to avoid any interference with their behaviour. After receiving the instructions for their individual roles, participants are given the chance to clarify any comprehension question with the invigilator (who is present throughout the role play). Before starting the first stage, a trial round with one sample loan application is conducted to make sure, that every participant understands his/her respective role. Participants of a play are instructed to see themselves as part of a team whose objective is to perform as good as possible. Stage one of the role play runs 20 min. Immediately after completion of stage one, each participant is asked to complete an anonymous questionnaire with which we obtain descriptive personal data as well as the raw data to measure MMBP accuracy. Conversations among participants are prohibited until completion of the questionnaire.

Statistical analysis

The statistical analysis of our model is done at the level of teams using the measures depicted in the research model (Fig. 3). To conduct our analysis, we choose an aggregation approach instead of a two-level approach as our dependent variable – team process performance – is only available at the aggregated level. The widely cited ecological fallacy (Robinson, 1950) is no concern in our analysis because this study's primary interest is focused on the relations between MMBP and process performance at the team level (Piantadosi et al., 1988). In addition, to ensure the validity of this aggregation, we also conduct robustness tests regarding similarity using the median accuracy of narrow and holistic MMBPs as well as Krippendorffs Alpha, Intraclass Correlation Coefficient and the average of the standard deviations of the similarity values. Since all variables on the aggregated level are metric and parametric, we apply Pearson correlations to test our hypotheses. In order to calculate the effect sizes, we use the measure of η^2 which can be best applied for the low number on the group level as it is a robust indicator (Cohen, 1988).

To shed some light on typical control variables' impact on performance, we conduct a descriptive analysis including bivariate Pearson correlations at the level of individual data.

Results

Descriptives on the individual level

Table 1 provides an overview on the descriptives on the individual level.

We observe a high variance between the individual narrow MMBP's accuracy. Figure 4 provides an overview on the narrow MMBP accuracy of the participants.

Coming to the holistic MMBP accuracy values (ranging from 0 to 1), we can observe a statistical significant correlation of age and mental model building (0.183, $p < 0.05$)), but not for working experience (0.149, ns)), gender (-0.109, ns) and cognitive load (0-0.060, ns).

The values regarding the holistic MMBP accuracy are equally spread (Fig. 5).

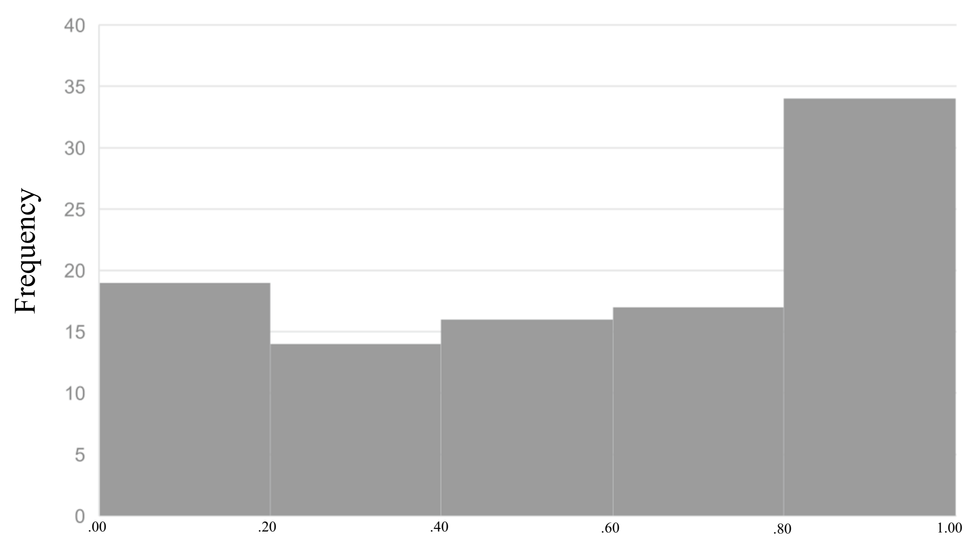
Regarding the holistic individual MMBP accuracy, we do not observe any statistical significant correlation with mental model building (Age: 0.129, ns; working experience: 0.040, ns; gender: 0.046, ns; cognitive load: -0.080, ns).

Table 1 Descriptive results at the individual level

		INMMBP	IHMMBP	Male	WE	Age	CL
N	Valid	100	100	99	99	98	99
	Missing	0	0	1	1	2	1
Mean		0.5670	0.3821	0.4545	12.5234	32.9898	2.3838
Median		0.5857	0.3429	0.0000	5.0000	27.0000	2.0000
Std. Deviation		0.34710	0.24508	0.50046	14.03409	13.29405	1.68249
Range		1.00	0.86	1.00	51.33	46.00	7.00
Minimum		0.00	0.00	0.00	0.00	16.00	1.00
Maximum		1.00	0.86	1.00	51.33	62.00	8.00

INMMBP accuracy of individual narrow mental model of the business process, *IHMMBP* accuracy of individual holistic mental model of the business process, *WE* work experience, *CL* cognitive load

Fig. 4 Histogram of narrow individual MMBP accuracy



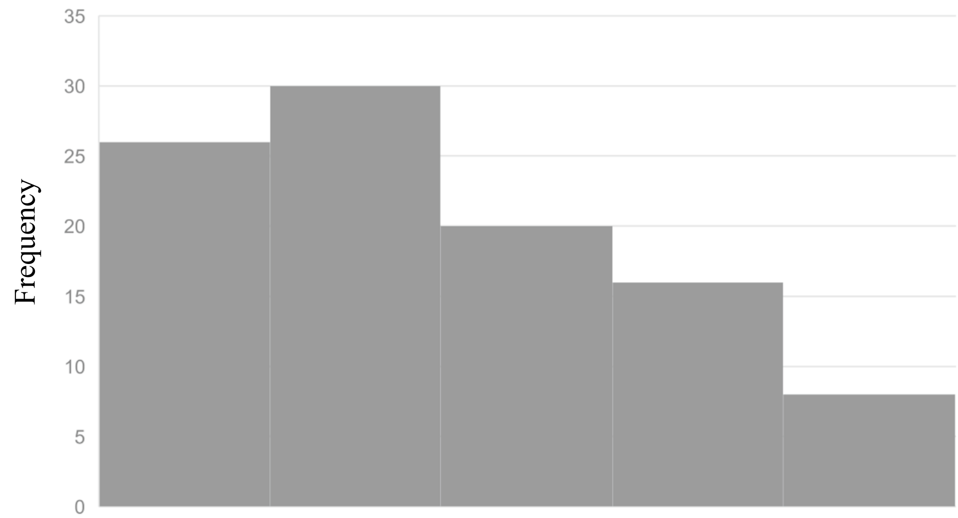


Fig. 5 Histogram of holistic individual MMBP accuracy

Table 2 Variables on the team level, $n = 10$

	M	SD
(1) Narrow MMBP accuracy on a team level	0.53	0.09
(2) Holistic MMBP accuracy on a team level	0.40	0.11
(3) Similarity of narrow MMBPs on a team level	0.33	0.05
(4) Similarity of holistic MMBPs on a team level	0.24	0.04
(5) Process performance	450,477	176,990.46

M Mean, *SD* Standard Deviation

Table 3 Results regarding hypotheses

	Process performance
H1.1: Narrow MMBP accuracy on a team level	0.682*
H1.2: Holistic MMBP accuracy on a team level	0.556*
H2.1: Similarity of narrow MMBPs on a team level	-0.042 ^{ns}
H2.2: Similarity of holistic MMBPs on a team level	-0.567*

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results regarding the hypotheses

As described in our research model, we aggregate the individual's MMBPs accuracy by determining the average at the team level. Table 2 provides an overview on the variables.

The correlation results regarding the hypotheses are summarised in Table 3.

For the ten groups in the dataset, correlation analyses results show that there is a significant correlation between process performance and the mean accuracy of narrow as well as holistic MMBP of participants. Regarding the effect size, the value of $\eta^2 = 0.46$ (95%-Confidence Interval: 0.04–1.00) for the narrow MMBP accuracy indicates a medium effect size. The value for holistic MMBP accuracy is $\eta^2 = 0.29$ (95%-Confidence Interval: 0.00–1.00) also indicating a medium effect size. Thus, we find empirical support for both H1.1 and H1.2 stating that higher levels of accuracy of a team's narrow and holistic MMBPs lead to a higher process performance. The robustness analysis shows that similar results are achieved with using the median values instead of the means (Narrow MMBP accuracy on a team level, 0.551*; holistic MMBP accuracy on a team level, 0.617*).

Regarding hypothesis 2.1, stating that the similarity of narrow MMBPs of process actors enhances process performance, the results indicate no relationship for the narrow MMBP. Hence, there is no impact of the narrow MMBP similarity on process performance and there is no empirical support for this hypothesis.

Contrary for hypothesis 2.2, stating that the similarity of holistic MMBPs of process actors enhances process performance, the standard deviation of individual MMBPs has a significant relationship with process performance. The effect size is $\eta^2 = 0.35$ (95%-Confidence Interval: 0.00–1.00) indicating a medium effect size. A higher standard deviation is thus having a negative impact on performance. Hence, hypothesis 2.2 is supported that a higher similarity of MMBPs of process actors increases process performance. The robustness analyses using Krippendorffs Alpha (0.66, $p < 0.05$) and Intraclass Correlation Coefficient (0.55, $p < 0.05$) as well as the average of the standard deviations of the statement judging (0.56, $p < 0.05$) are significant and are in the same direction of the baseline results.

Discussion and conclusion

Theoretical implications

This study makes three contributions to the literature of managerial decision making. First, a concept for measuring MMBPs' (narrow and holistic) accuracy is developed in this study and the performance implications of MMBPs accuracy on a team level and their similarity are analysed. The MMBP measurement concept builds on methods suggested in dynamic decision-making contexts (Gary & Wood, 2007, 2011) and for the measurement of individual MMBPs (Leyer et al., 2021). It allows a universal application to any real-life process in order to gain insights about the existence and the extent of accurate and similar MMBPs among process actors. It answers the call for cognitive models in the context of process comprehension (Figl, 2018; Recker et al., 2014) as well as developing measures for accuracy and similarity of shared mental models in general (Floren et al., 2018), however adding to our understanding of different levels and dimensions of usefulness of shared mental models (e.g. to strategic understanding of remanufacturing (Moosmayer et al., 2020) or enabling shared goal clarity (Bortolotti et al., 2018) in management. Moreover, a specific measurement concept for shared mental models of processes as a foundation of managerial decision making is added to the toolset.

Second, we introduce IBLT to the domain of business processes, which provides us with the foundation of developing a theory of mental model creation in the process context. The theory can also be used to explain how process performance is influenced by the accuracy of individual team members' MMBPs. We find evidence for a positive impact of the accuracy of both narrow and holistic MMBPs as well as similarity of holistic MMBPs on process performance. The non-significant result regarding the similarity of narrow MMBPs can be explained by the limited impact of deviances in parts of the process. Differences of employee's knowledge of the direct interfaces does not seem to lead to bottlenecks that reduce the overall performance, but rather that the overall perspective is important. Other employees throughout the whole process can cope with narrow deviance when having a better holistic understanding so that performance is higher for teams with a holistic MMBP similarity. This extends literature on the performance impact of mental models in the domain of dynamic decision-making (e.g. Gary & Wood, 2011; Gary et al., 2012; Kunc & Morecroft, 2010; Lim & Klein, 2006; Martignoni et al., 2016; Mathieu et al., 2000, 2005) by providing evidence from a process context. Our results indicate a tendency towards putting more emphasis on creating homogeneous knowledge among team members regarding their process thus being in line with the results from Edwards et al. (2006). It is not sufficient to focus on training a small number and hope that these employees allow for a high process performance. This holds true especially for teams where communication is limited (e.g. different locations like in internationally operating companies and switching assignment of team members like in aircrafts).

Third, our results contribute to strengthen the external validity of experimental results that typically use hypothetical process models instead of being based on field insights (Mendling et al., 2012). Our results demonstrate the effects of building MMBPs through experiencing a real life process that is intense at the one hand, but also consumes time required for task execution at the other hand. These results extend insights from Berner et al. (2016) which are limited to analysing process visibility to self-reported performance measures. Hence, we demonstrate the effect especially of holistic MMBPs on a team level on process performance and thus support the importance of capturing and better understanding mental models in the context of processes.

Practical implications

The importance of looking at business processes from a cross-functional perspective and of fostering an in-depth process understanding have been emphasised in both academic and practitioner-oriented literature for decades (Hammer, 1996; Zarei et al., 2014). Our findings further underline this importance from a decision making perspective by showing that better mental models of processes are correlated with a higher process performance. The results point at conducting trainings that lead to homogeneous mental models among process participants. Furthermore, this study is the first attempt that provides managers with a measurement concept that they can use to gain an understanding of their process actors' MMBPs. The technique applied to measure the MMBP within the context of this study can be transferred to any process context. For process owners, this information can reveal useful insights about the accuracy of the process actors' understanding of the process they are part of and the similarity of their perceptions. This can help to identify needs for training, documentation or intensified dialogue among the actors involved in the process.

Limitations and future research

This study provides a first attempt to define and measure team mental models of process. Its emphasis lies on capturing a static snapshot of mental models of process of participants after being exposed to an unfamiliar role for a short period of time and to analyse its performance implications.

This static observation leaves questions on adaption and learning mechanisms of instance-based learning and the role of cognitive load over time without answer. Future research should build on this to enhance theory on process mental model creation.

Another limitation is the limited number of groups in our statistical analysis. While the sample size seems statistically acceptable and unveils significant results, the statistical power of the analysis with ten groups (although containing 100 individuals) is limited. Future studies should increase the number of groups and, at the same time, use different process settings to improve the generalisability of the findings.

Furthermore, within the scope of this study, we limited our focus on two dimensions of process understanding: The overall process (holistic) and the direct relations to the actors of neighbouring activities (narrow). Avenues for future research include the inclusion of distance-related mental model measures that consider a continuous distance measure of all process actors. This could also comprise a stepwise building of a net structure starting from the individual's role to direct neighbours, to second-level neighbours, etc. Furthermore, such a measure could include relevance weightings of those activities that are more and less relevant for the individual's task purpose.

Moreover, we limited our analysis to a specific process with a certain level of complexity. While the level of complexity is adequate when compared to real business processes, future research should include different levels of complexity to enrich the understanding of how MMBPs on a team level and process performance are related.

Another limitation is that the study was conducted in a cultural environment that is Western European which could have an influence on the results especially via the dimension "individualism vs. collectivism" as defined by Hofstede et al. (2010). This could lead to different results regarding the similarity of team mental models. Hence, future research should repeat the study in other cultural backgrounds that are characterised by a higher degree of collectivism.

In addition, the laboratory character of the study allowed us to observe individual behaviour in a controlled setting where the only process-related information that was available was provided by the invigilator. Future research should address the impact of the availability and access to additional process information such as documented process knowledge on performance. In addition, a more in-depth observation of the laboratory setting (e.g., video documentation, analysis of personal documents such as notes) could provide additional insights. Participants should be trained with a process (compared to non-trained participants), followed by a measurement of their mental models and the subsequent observation of performance when executing the process. Contrary, real life data should be gathered from processes of companies in which employees work together in teams to verify the effect strength of team mental models of processes on process performance.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12144-022-03293-7.

Authors' contributions Not applicable.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data availability Data available on request due to privacy/ethical restrictions.

Code availability SmartPLS 3.3.3

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflicts of interest/Competing interests The authors have no relevant financial or non-financial interests to disclose.

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