BEYOND DATA: PEOPLE

LESSONS FROM A DATA-DRIVEN DECISION MAKING ADOPTION PROCESS

AUTHOR: JOLIEN ROES
STUDENTNUMBER: S2872609
STUDY: MASTER BUSINESS ADMINISTRATION

UNIVERSITY OF TWENTE.

BEYOND DATA: PEOPLE

LESSONS FROM A DATA-DRIVEN DECISION MAKING ADOPTION PROCESS

AUTHOR: JOLIEN ROES
STUDENTNUMBER: S2872609

FACULTY: BEHAVIOURAL MANAGEMENT AND SOCIAL SCIENCES
STUDY: MASTER BUSINESS ADMINISTRATION
SPECIALIZATION: DIGITAL BUSINESS & ANALYTICS

FIRST SUPERVISOR: FONS WIJNHOVEN
SECOND SUPERVISOR: MAARTEN RENKEMA

DATE: 26-07-2022

UNIVERSITY OF TWENTE.

Abstract

This research aims to describe the process of data-driven decision making (DDDM) adoption within the insurance industry. To understand this process, we analyze the adoption of data-driven decision making as an organizational learning process. This organizational learning process can be described as the creation of improvements (i.e., single loop learning) or innovations (i.e., double loop learning) and the creation of norms, rules, and conditions by which these knowledge creation processes may be done best (i.e., deutero loop learning). To describe the organizational learning challenges for this adoption process of a DDDM tool, an in-depth, qualitative case study is conducted. The main method is participant observation, including informal (semi-structured) interviews and conversations with organizational members to follow up and verify our observations. We identify the influence of each organizational learning process for the adoption of the DDDM tool. For each of this learning processes we describe double loop, triple loop, and institutional deutero loop learning processes that must be realized for an effective DDDM adoption. If transparency about the DDDM tool recommendations is not realized during the internalization process, triple loop learning is not possible. In the discussion, we identify the theoretical and practical implications, and we generate further research directions based on the limitations of this research.

Keywords

Data-driven decision making – Insurance – Adoption – Organizational learning – System dynamics

Acknowledge

I would like to thank my supervisors dr. A.B.J.M. Wijnhoven and dr. M. Renkema, who have guided me during this research on behalf of the University of Twente. I also want to mark my appreciations to X, who supervised my project at X, as well as the organization as a whole. Thank you for this great opportunity. Furthermore, I would like to thank all the respondents for their openness and honesty. The conversations were very instructive and interesting. Finally, my thanks go to my family and friends. Their support during this master year made me do it.

Table of contents

1 Introduction

1.1 Context

Data-driven decision making (DDDM) aims at making the decisions of organizations smarter in terms of performance, output, productivity, and effectiveness (Brynjolfsson et al., 2011; Müller et al., 2018; Surbakti et al., 2020). Yet, for DDDM to improve these outcomes of organizations, it must be accepted by and interact with its users (Murray et al., 2021; Taherdoost, 2018; van den Broek et al., 2021). Explaining user acceptance of new technologies and tools is often described as one of the most mature research areas in contemporary information systems (IS) literature (Taherdoost, 2018; Venkatesh, 2022), but the process theory of interactions between the user and DDDM interactions are being yet under-researched. There is an urgent need for a better understanding and sustainable management solutions in the topic of DDDM (Raisch & Krakowski, 2021). Therefore, this article takes an organizational learning perspective on DDDM, with a focus on developing knowledge to let the interactions between users be effective (Wijnhoven, 2021).

DDDM has an *indirect* effect on actual human decision making, as a consequence of the concept human in the loop. The concept of human in the loop helps to examine the tasks assigned to and performed by people in the human-machine configurations (Grønsund & Aanestad, 2020; Wijnhoven, 2021). These tasks and roles change by the introduction of the data-driven tool. The work of Grønsund and Aanestad (2020), in particular, contributes to understand of the nature of “augmentation work”, consisting of auditing and altering the data-driven tool. Augmentation work is also described by Murray et al. (2021) as one of the four forms human and non-humans interactions can take place. A direct effect of DDDM, where computers take over human decision making, is often infeasible in professional contexts because of the required decision accountability, the problem ambiguity, and the decisional uncertainty involved. The simpler cases that are highly repetitive and involve not much diversity of insights and sources, could be run by rule-based systems. But, many professional cases, require understanding of personal situations (Wijnhoven, 2021).

The use and acceptance of new technologies and tools is one of the most mature research areas in IS literature. For decades, scholars have applied this lens to understand how humans use technology tools to achieve goals across a wide variety of organizational contexts (Ahuja & Thatcher, 2005; Wang et al., 2013), consumer context (Goh et al., 2013; Kwon et al., 2016) and societal context (Venkatesh et al., 2003). Technology use literature has emphasis on human agency rather than data-driven tool agency. According to Baird & Maruping (2021) only recognizing human agency is insufficient. The new generation of agentic data-driven tools has the capacity to learn, adapt, act autonomously, and can be aware of the need to act without an active request of its users. This research extends this theory by describing the process of adoption of this new generation of agentic data-driven tools. In more detail, we describe the process of an adoption of DDDM within the insurance industry, since the academic discussion on DDDM in this industry is underrepresented (Eling & Lehmann, 2018). To describe this adoption process of DDDM systems in the insurance industry, we analyze the adoption of decision support systems (DSS) as an organizational learning process. This adoption process can be divided in four organizational learning processes, namely socialization, externalization, combination, and internalization. These organizational learning processes can be described as "the creation of improvements (i.e., single loop learning) or innovations (i.e., double loop learning) and the creation of norms, rules, and conditions by which these knowledge creation processes may be done best (so-called deutero loop learning or institutional learning)" (Wijnhoven, 2021, p. 3). DDDM within the insurance industry can contain of clustering techniques for risk classification, prediction of claim costs (Yeo et al., 2001) and customer segmentation (Wen et al., 2021). DSS is thus a collection of data driven systems for decision making. Literature on DDS in the insurance industry has reported challenges in realizing DDDM. Yeo et al. (2001) mentioned huge amounts of data are necessary for risk classification and prediction of claim costs. However, these data sets are not always available and if they are, there is not always the possibility to combine these data sets through missing unique identifiers (Patel & Lincoln, 2019; Pugnetti & Seitz, 2021; Wamba et al., 2015). End users are also concerned with the accuracy and the transparency of classifications and predictions (Boobier, 2016; Rau et al., 2021). Data policies, especially regarding privacy, are necessary and insurance companies need to adapt their processes and experts (Pugnetti & Seitz, 2021). Dealing with these DDDM adoption challenges require specific capabilities, like individual and personal skills and organizational skills, here fore we explore DDDM adoption as an organizational learning process.

1.2 Objective and Research question

This research aims at theory synthesis, which is described as "seeking to achieve conceptual integration across multiple theories or literature streams, through offering a new or enhanced view of a concept or phenomenon by linking previously unconnected or incompatible pieces in a novel way" (Jaakkola, 2020, p. 21), from a DDDM adoption case and by this, create an organizational learning theoretical foundation for DDDM development in organizations. The kind of theory that we realize here is a process theory, which "… provides explanations in terms of the sequence of *events* leading to an outcome (e.g., do A and then B to get C)" (Langley, 1999, p. 692). This brings us to the following research question: *"What is the role of the organizational learning processes in the process of data-driven decision making adoption?"*

1.3 Scientific and social relevance

This research aims to provide a process theory through which researchers and practitioners will be able to disentangle the complexity of interactions between the user and DDDM tools in processes of DDDM adoption and will be able to develop and implement these systems. It will contribute to the existing academic literature through contributing to the need for more reliable theories, a better understanding, and sustainable management solutions in the topic of DDDM in management. This will be realized, by extending the discussion of the current literature about technology use, organizational learning processes and the concept of human-in-the-loop. This extension is realized by describing the process of the development, implementation, and adoption of a DDDM tool. This case description is analyzed, and the influence of each organizational learning process is discussed. For each of these organizational learning processes the occurrence of double loop learning, triple loop learning, and deutero loop learning is identified. By amplifying these discussions, mainly the literature of Wijnhoven (2021) and Grønsund & Aanestad (2020) will be extended. Furthermore, the social relevance relates to providing businesses useful in-depth insights for practitioners about the process of adopting DDDM and the challenges related to this adoption as an organizational learning process. These practical insights derive from the analyzed case description and are described in a prescriptive way.

1.4 Research design

To realize the objective of this research, we present an in-depth, qualitative case study of an organization that introduced the adoption of DDDM for its analysis whether or not to conduct a re-inspection. The fieldwork is done April 2022 and June 2022 and the main method will be participant observation.

1.5 Outline of the paper

The next section further describes the theoretical background of DDDM, technology use and acceptance, the human-in-the-loop concept, and the organizational learning approach to DDDM adoption, after which we explain the case methodology. Section four represents our results of a DDDM adoption case and section five discusses the results. Section five entails the key findings, the theoretical and practical contributions, and reflects about further research and possible limitations of this study. Section six entails the conclusion.

2 Theory

This chapter discusses the theoretical background of DDDM, after which we discuss technology use and acceptance. Subsequent the organizational learning approach to DDDM adoption is described through the SECI model and the concepts of single loop, double loop, triple loop and deutero loop learning. Furthermore, we discuss the concept of 'human in the loop'. We end this chapter with the central model of this study.

2.1 Data-Driven Decision Making

Decision-making is "the process of choosing among alternative courses of action in order to attain goals and objectives" (Forman & Selly, 2001, p. 2). Decision-makers are constantly trying to make more well-informed decisions and they need to be able to understand and utilize data in order to base their decisions on data (Elgendy & Elragal, 2016). The process of making decisions based on data we call data-driven decision making (Thiess & Müller, 2018). DDDM is rooted in different technical disciplines, such as business intelligence (Chen et al., 2012), machine learning (Bishop & Nasrabadi, 2006) and decision support systems (Arnott & Pervan, 2008; Shim et al., 2002) and is the outcome of data science, data processing, and data engineering processes (Provost & Fawcett, 2013).

The economic benefits of DDDM have been discussed conclusively. Davenport et al. (2007) conducted a survey among 32 companies and found a positive relation between the adoption of DDDM and the annual growth rates. A survey research study among 179 companies by Brynjolfsson et al. (2011) supported the findings of Davenport et al. (2007) by showing how DDDM affects firm performance. Their research statistically verified that the more data-driven a company is, the more productive it is. In more detail, their research states an increase of the productivity by 5%-6% when a firm adopts DDDM instead of other investments and information technology usage. Research of Müller et al. (2018) showed that data-driven decision making on average increases the productivity of a firm with 4%, with some reaching an increase of even more than 7%. They conducted their research among more than 800 companies over a period of seven years. Similar results about the positive effect of DDDM on the productivity of companies is reported by the work of Wu et al. (2020). However, yet before DDDM can improve these outcomes of organizations, it must be accepted and used by its users (Murray et al., 2021; Taherdoost, 2018; van den Broek et al., 2021).

2.2 Technology Use and Acceptance

The information system field has extensively discussed IT adoption. Research has yielded numerous models, each with different sets of acceptance determinants. One approach is the "theory of innovation" which is grounded in the work of Rogers (2010). The theory of innovation describes the process innovation adoption as a five-stage process of awareness development, persuasion, decision to adopt, implementation and continuation of use. These stages include learning processes where the individual first collects information where the innovation is about, next decides about whether to adopt or not, and finally collects information for deciding on continuation of adoption and possible more extensive use. The innovation adoption process affects five categories of adopters, namely innovators, early adopters, early majority, late majority, and laggards. These categories are based on different levels of technology adoption in the social system, they differ on their willingness and ability to take varying levels of risk with innovation adoption decisions. Innovators are willing to take risk, have financial liquidity, the highest social status, and have the closest contact to scientific sources and other innovators. Laggards are the last to adopt an innovation. People in this category show little to no opinion leadership and have typically an aversion to change-agents. Laggards typically tend to be focused on traditions, lowest financial liquidity, lowest social status and oldest among adopters. In the social system, innovators and laggards are the smallest groups and the early majority and late majority the largest. Innovation adoption involves social pressures, norms and values, and personal risk and prestige. In DDDM adoption some professionals may want to be innovators or early adaptors for generating prestige where others will be laggards and risk averse (Wijnhoven, 2021). To be able to act such as an innovator or early adaptor, these professionals need to have resources and reputation (Hull & Lio, 2006).

Rogers' (2010) innovation diffusion model is a useful and popular view for understanding adoption. However, it is important to recognize the weaknesses of this model and add some nuances. This model assumes 100 percent adoption (Rogers, 2010), which often will not occur (Guttentag & Smith, 2020). Therefore, some authors added an additional category of adopters to the innovation diffusion model, namely non-adopters (Emani et al., 2018; Palm, 2020; Verdegem & de Marez, 2011). Moreover, the categories divisions from the innovation diffusion model are established very rigidly (Kardasz, 2013; Mahajan et al., 1990).

Technology acceptance models explain how and why individuals adopt new information technologies. Personal and environmental factors can influence an individual's decision to whether or not adopt new technologies and innovations. Venkatesh et al. (2003) has conducted a review which resulted in the identification of eight key competing theoretical models of technology acceptance: Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivation Model (MM), Theory of Planned Behavior (TPB), Combined TAM and TPC (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). Based upon the conceptual and empirical similarities across these models, they formulated a unified model: the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT holds seven constructs that appeared to be significant direct determinants of behavioral intention or usage behavior. Of these, the key constructs are (1) performance expectancy, (2) effort expectancy, (3) social influence, and (4) facilitating conditions. The remaining constructs (5) attitude towards using technology, (6) self-efficacy, and (7) anxiety are theorized not to be direct determinants of use intention. Although this theory is among the most cited theoretical lenses in research on technology acceptance and use, its primary focus is on the users' perceptions and it pays little attention to the capabilities and actions of the tool (Baird & Maruping, 2021). For example, the UTAUT theory is not suitable for situations where the tool can initiate their own actions. Furthermore, the theory overlooks the complicity of tools in goal achievement. According to Baird & Maruping (2021) technology acceptance should not be described and researched in terms of user perceptions and intentions to use, but the actual use of technologies. Baird & Maruping (2021) describe the UTAUT theory as an incomplete overview of how agentic IS tools can contribute to goal achievement. They highlight the need to envision new forms of relationships between people and agentic DDDM tools. Murray et al. (2021) contribute to this view of Baird & Maruping (2021) on technology use and acceptance by distinguishing four forms of conjoined agency between people and technologies. These four forms of conjoined agency, which can be defined as "constituting a shared capacity between humans and nonhumans to exercise intentionality" (Murray et al., 2021, p. 555), result from the shifting locus from people to a broader overview at which agentic technologies are included. Therefore, they have "categorized the four forms of conjoined agency based on which actor – human or technology – has the capacity to exercise intentionally over protocol development or action selection" (Murray et al., 2021, p. 555). The first form, conjoined agency with assisting technologies, exists when the technology in the human-machine interactions does not have the ability to develop protocols and neither has the ability to select actions. This form of human-DDDM tool interaction takes place when a DDDM configures as an evaluation software, an assisting technology. Based on multiple variables determined by the user, the DDDM tool can sort, analyze, and identify different outcomes. In this way, the DDDM tool is wielded by the users who apply procedures and rules (i.e., protocols), to rank the outcomes and determine which outcome will be selected (i.e., select an action). Conjoined agency with arresting technologies exists when “the technology in the human-nonhuman ensemble (a) does not have the ability to develop protocols, but (b) does have the ability to select actions” (Murray et al., 2021, p. 556). People can set the protocols for the DDDM tool at which the outcomes are based. The tool itself can define the best outcome and can make sure this outcome is executed. People are unable to stop these actions before they have taken place. The third form is conjoined agency with augmenting technologies, which “is a form of conjoined agency in which the technology in the human-nonhuman assemble (a) has the ability to develop protocols, but (b) does not have the ability to select actions” (Murray et al., 2021, p. 557). These technologies complement people in practice. An example of an augmenting technology is a structured machine learning algorithm. This technology has the ability to identify patterns and make recommendations. If the expectations from people diverge from the recommendation outcomes of the technology, people must determine whether or not to select the action. The last form is conjoined agency with automating technologies, which is “a form of conjoined agency wherein the technology in the human-nonhuman ensemble (a) has the ability to develop protocols and (b) has the ability to select actions” (Murray et al., 2021, p. 558). These technologies are given an objective and are expected to figure out how to achieve it by developing protocols and actions on its own. These technologies substitute people.

DDDM adoption has many organizational consequences and therefore the development of knowledge for user adoption is a critical organizational learning process. This process requires socialization, externalization, combination, and integration of relevant knowledge for adoption decisions (Wijnhoven, 2021).

2.2 Data-Driven Decision Making Adoption as Organizational Learning

Organizational learning can be described as “the creation of improvements (i.e., single loop learning) or innovations (i.e., double loop learning) and the creation of norms, rules, and conditions by which these knowledge creation processes may be done best (i.e., deutero loop learning or institutional learning)” (Wijnhoven, 2021, p. 3). Such learning processes are emergent knowledge creation processes. In this process we can make a distinction between two types of knowledge: tacit knowledge and explicit knowledge (Nonaka, 1994). Knowledge expressed in numbers and words only represents a tip of the iceberg. Explicit knowledge refers to “knowledge that is transmittable in informational, systematic language” (Nonaka, 1994, p. 16). Tacit knowledge, on the other hand, “has a personal quality, which makes it hard to formalize and communicate. Tacit knowledge is deeply rooted in action, commitment, and involvement in a specific context” (Nonaka, 1994, p. 16).

At a fundamental level, knowledge is created by individuals. An organization cannot create knowledge without individuals, it can only support individuals or provide a context for such individuals to create knowledge (Nonaka & Konno, 1998). Therefore, it is possible to distinguish several levels of social interaction at which the knowledge is created by an individual is transformed and legitimized, based on the assumption that knowledge is created through conversion between tacit and explicit knowledge (Nonaka & Lewin, 1994). This allows us to distinguish four different "modes" of knowledge conversion: (1) socialization: from tacit to tacit knowledge. This mode of knowledge creation enables us to convert tacit knowledge through interaction between individuals. Professionals may discuss outcomes and problems with colleagues for verification and to learn from each other. One important note here is that an individual can acquire tacit knowledge without language, but by imitation, observation, and practice. It is the process of creating tacit knowledge through shared experience (Nonaka, 1994; Wijnhoven, 2021); (2) externalization: from tacit to explicit knowledge. This mode of knowledge can be created in the process of realizing the organizational conditions for DDDM and may be materialized in inter-organizational data sharing standards, IT management policies or (privacy) laws. Metaphors play an important role here. As a method of perception, metaphor depends on imagination and intuitive learning through symbols, rather than on the analysis or synthesis of common attributes shared by associated things; (3) combination: from explicit to explicit knowledge. During this stage explicit knowledge held by individuals is combined. Individuals exchange and combine knowledge through such exchange mechanisms as the creation of data warehouses, analytic outcomes, and rule-based expert systems. This mode of knowledge creation involves the use of social processes; (4) internalization: from explicit to tacit knowledge. The advanced combined explicit knowledge can create recommendations to decision makers. These decision makers can internalize by integrating it with values, skills, personal experiences, which we call tacit knowledge. "Action" is deeply rooted to the internalization process. Through an iterative process of trial and error, concepts are articulated and developed until they emerge in a concrete form. This experimentation can trigger internalization through a process of learning by doing. Through action, participants share explicit knowledge, which is gradually translated, through interaction and a process of trial and error, intro different aspects of tacit knowledge. Externalization and internalization relate to patterns of conversion involving both explicit and tacit knowledge. These conversion modes capture the idea that explicit and tacit knowledge are complementary and can expand over time through a process of mutual interaction (Nonaka, 1994). Knowledge develops by a continuous emergent process of socialization, externalization, combination, and internalization.

Because DDDM adoption is the adoption of DDDM tools for (professional) decision making, DDDM adoption happens in and for an organizational context and is related to knowledge work(ers). Although knowledge is not a new concept, recognizing knowledge as an organizational asset is (Davenport & Bean, 2018). Knowledge workers are "experts who create, learn and analyze information and knowledge and then act upon it" (Smuts & Smith, 2021, p. 3). The application of DDDM suggests people are obsolete to some extent, knowledge workers are still required for a successful DDDM adoption and application (e.g., training of models, future engineering, learning human preferences) (Smuts & Smith, 2021). Since DDDM happens in and for organizational contexts the learning processes are organizational, and organizations can enable or constraint these processes in several ways (Datt Bhatt & Zaveri, 2002). Organizations may also learn to influence single loop and double loop (Wijnhoven, 2021). As defined by Argyris (1999, p. 68), single-loop learning occurs "whenever an error is detected and corrected without questioning or altering the underlying values of the system", and double-loop learning occurs "when mismatches are corrected by first examining and altering the governing variables and then the actions". These learnings may happen in the socialization process, in which participants may share existing (single loop learning) and new knowledge (double loop learning) (Wijnhoven, 2001).Triple loop learning is the learning from a DDDM system and integrating these insights in the stock of human knowledge (Seidel et al., 2019). Triple loop learning requires the development of capabilities, not only from the involved autonomous tool but from the users as well (Grønsund & Aanestad, 2020). Single loop learning in the triple loop learning model involves designers and tools interacting to generate design outcomes. It is the tool that primarily generates the design alternatives. Double loop learning can take two alternative forms in triple loop learning: human learning or machine learning. From a human perspective, the second loop involves the human designer evaluating the alternatives and modifying input parameters, tools settings, and evaluation criteria for a given design problem. From a machine perspective, the second loop involves the tool learning from designer feedback in the design process in order to modify itself and improve its model so it can generate better alternatives. Triple loop learning involves human designers learning about the mental models embedded in the tool and/or the tool learning about the human designers' mental models (Seidel et al., 2019). Argyris (1976) calls mental models "master programs". The master program of the designer of the autonomous tool may not be aligned with the master program of the autonomous tool for a variety of reasons (Lake et al., 2016). For example, designing the autonomous tool usually involves more than one person; the designer using the tool is probably not the same person as who programmed it. Multiple designers may have different perceptions about what a master program does.

Triple loop learning only happens after the DDDM-based recommendations are delivered to the decision maker in the internalization process (Seidel et al., 2019), which is one of the four modes of conversion required to create new organizational knowledge. Learning enabling and constraining processes are named deutero learning (Visser, 2007; Wijnhoven, 2001), which involves the development of dynamic capabilities, i.e., the continuous building up of resources for innovation (Kraaijenbrink et al., 2010; Wijnhoven, 2021). Some authors have equated deutero learning with triple loop learning, but we reserve the term deutero learning for learning to manage the organizational processes (Visser, 2007; Wijnhoven, 2001) and triple loop learning for the integration of human and machine learning processes (Seidel et al., 2019). For DDDM adoption, the learning process is both user-oriented single, double, and triple loop learning and an institutional deutero learning process involving the development of enablers, like motivation, resources and capabilities, and constraints for these individual learning process. The actual effects of DDDM on decisions are the outcomes of these individual and organizational learning processes which contain the interactions of human learning and machine learning. These processes are difficult to predict since DDDM has an indirect effect on actual human decisions as a consequence of keeping human in the loop.

2.3 Human in the loop

In contrast to replacing human work, DDDM adoption requires new roles and redistribution of extant expertise to augment and improve the accuracy of the tool, improve human feedback and responsibility for performance management, exception handling and improvement (Grønsund & Aanestad, 2020). This indicates a human in the loop pattern. The work of Grønsund & Aanestad (2020) suggests that a DDDM adoption requires a human in the loop pattern, whereby DDDM-based augmentation might keep the human in the loop (Bailey & Barley, 2020; Markus, 2017). Augmentation consist of the work of auditing as well as the work of altering the algorithm and the data acquisition architecture. To be able to audit the DDDM tool, a reference input for classification or prediction outcome is needed, as well as a reference input from a human classifier or trusted source. Based on these reference points we compare, identify, and represent the gap based on the discrepancy of the reference inputs. For altering the tool, the input is information related to the gap identified in the auditing work. Based on this gap, decisions and actions are taken. These decisions and actions can relate to altering and adjusting the tool (Grønsund & Aanestad, 2020).

Both augmentation roles are crucial parts of human in the loop configurations. They can improve the accuracy of the DDDM tool and transform data into value and are mutually dependent of each another and eventually form a feedback loop (Grønsund & Aanestad, 2020). The feedback loop suggests that the processes of automation and augmentation influence one another in a reciprocal manner (Raisch & Krakowski, 2021). Furthermore, algorithms have a recursive nature, which reflects a cyclical process in which algorithm management is shaped and influenced by the autonomy and value of workers. They are based on human training which determines the human behavior and learn from human action (Meijerink & Bondarouk, 2021). The learning in DDDM implementations is not only human or technical single or double loop learning, but also triple loop learning. This triple loop learning requires a development of capabilities of not only computer scientists involved, but also from the users (Wijnhoven, 2021). To define the end of such a learning process may be difficult as long as triple loop learning generates new insights and deutero learning variables can act as enablers or constraints.

As described earlier the process of automation and augmentation influence one another in a reciprocal manner. Whereas automation implies that machines take over the human task, augmentation means that humans are "in the loop" and they collaborate closely with machines to perform a task (Raisch & Krakowski, 2021). Earlier research prioritize augmentation, but we cannot neatly separate augmentation from automation (Raisch & Krakowski, 2021). Augmentation and automation are not only separable and conflicting, but also interdependent (Schad et al., 2016). They provide complementary functionalities that are both potentially useful in organizations. In particular, researchers emphasize augmentation's potential to improve service quality, foster innovation, and increase productivity. Moreover, the combination of complementary machine and human skills will increase the speed, quality, and extent of learning in organizations (Brynjolfsson & McAfee, 2014; Daugherty & Wilson, 2018; Davenport & Kirby, 2016). But over-emphasizing either automation or augmentation fuels reinforcing cycles that not only harm an organization's performance, but also have negative societal implications (Raisch & Krakowski, 2021). Focusing on automation only can lead to extensive job losses and result in the deskilling of people who relinquish tasks to machines, which could cause further risks of social inequality and rising unemployment (Brynjolfsson & McAfee, 2014). Conversely, a one-sided focus on augmentation is likely to cause a digital divide, with social tensions arising between those few who have the capabilities and resources of augmentation and those who do not (Brynjolfsson & McAfee, 2014). This paradox of augmentation-automation suggests that both perspectives are equally biased. Nor of them is good or evil per se. The complex interaction of augmentation, keeping human in the loop, and automation can have both negative and positive organizational and societal implications. However, augmentation is one approach to keep the humans in the loop. Another approach is the "agentic system" theory grounded in the work of Baird & Maruping (2021). When considering agency with respect to DDDM tools, we consider an agentic DDDM tool to be "rational software-based tools that have the ability to perceive and act, such as take on specific rights for task execution and responsibilities for preferred outcomes" (Baird & Maruping, 2021, p. 317). Such tools are assumed to be designed "to achieve the best outcome or, when there is uncertainty, the best expected outcome" (Russel & Norvig, 2016, p. 4). However, not all agentic information system (IS) tools are created equally. To address this variation, Baird & Maruping (2021) make a distinction between four types of agentic IS tools archetypes. This distinction between the four archetypes is based on a continuum from autonomy with very simple task on the lower end to full task completion with the responsibility for an outcome on the higher end. At the lower end of the continuum, agentic IS tools act as assistant-like agents with limited agentic abilities (Woolridge & Jennings, 1995). At the higher end, agentic IS tools act as more freely autonomous agents. These tools can make complex decisions and can be trusted to act on their own (Russel & Norvig, 2016). Because of these 'higher end tools', human agents can delegate more complex tasks and even outcome preferences to these increasingly autonomous tools. It is even possible for agentic IS tools to delegate tasks to human agents. This can be preferrable when people have situational preferences. The framework provided by Baird & Maruping (2021) proposes three delegation mechanisms: appraisal, distribution, and coordination. Appraisal occurs when an agent "assesses what is at stake with respect to the other agent and what can be done in response to it" (Fadel & Brown, 2010, p. 108). Appraisals play a central role in the decision whether or not to accept the advice, whether or not the tasks are delegated to the tool, and whether or not tools will be leveraged. Distribution is considered by the framework as the distribution of rights and responsibilities between agents. The last delegation mechanism, coordination, is described as "managing of dependencies between agents and tasks and alignment of actions to achieve goals" (Baird & Maruping, 2021, p. 329). These delegation mechanisms raise two questions: whether or not delegation is likely to occur, i.e., the willingness to delegate, and whether or not delegation will successfully yield goal attainment or progress, i.e., effective delegation. As stated before, this delegation can be both from human agent to DDDM tool agent and the other way around. However, for raising the most valuable outcome in terms of effectiveness, performance, efficiently, and productivity the human agents and agentic tools have to interact.

The work Grønsund & Aanestad (2020) and Baird & Maruping (2021) points out to the strategic importance of a human in the loop pattern for organizational reflexivity to ensure that the performance of the algorithm meets the organization's requirements and changes the environment. The human in the loop configuration can be seen as a strategic capability.

Thus, DDDM aims at making the decisions of organizations smarter. Yet, for DDDM to improve these outcomes of an organization, it must be accepted and interact by its users. The adoption of IT has many organizational consequences and therefore the development of knowledge for user adoption is a critical organizational learning process. This process requires socialization, externalization, combination, and integration of relevant knowledge for adoption decisions. The actual effect of DDDM on decisions are the outcomes of individual and organizational learning processes. These processes are difficult to predict since DDDM has an indirect effect on actual decisions as a consequence of keeping human in the loop. Figure 1 represents a system dynamic view of the theory of Nonaka (1994) and Wijnhoven (2021), which means that knowledge stocks are represented by the boxes in the model and these stocks receive growth from a learning process that creates an inflow and new knowledge (the wide arrows) and the deutero enabling or constraining variables represented by the oval. These inflows have a bigger impact if they reuse the knowledge or insights from previous stocks represented by the thin gray broken arrows. Note that we see learning as a continuously increasing knowledge needed for adoption, since there is no outflow from the stocks. In the socialization and combination process, people can create new insights which can be integrated in stocks of knowledge (double loop learning). This entire process we behold as an organizational learning process whereby deutero learning influences double and triple loop learning. This organizational learning process continuously has no clear beginning or end, as continuously improvement is possible.

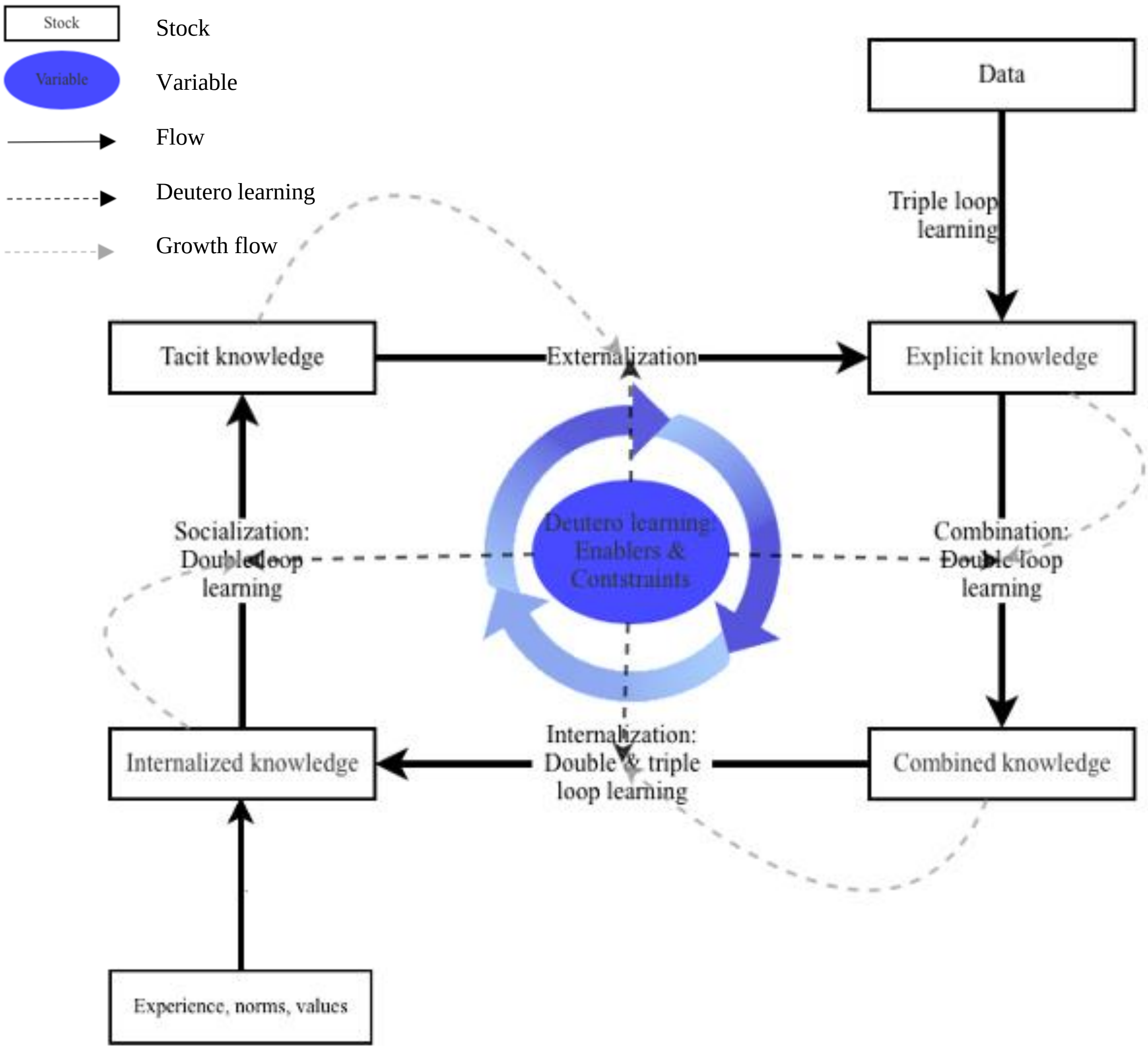

Fig.1 The organizational learning process in the context of DDDM adoption

3 Methodology

This chapter discusses the case study and context of this research, after which we present how the data is collected followed by a description how the data is analyzed including the coding scheme which is used for encoding the transcriptions.

3.1 Case Study and Context

This study wants to describe the organizational learning challenges for a concrete implementation and adoption process of a DDDM tool and seeks to achieve conceptual integration across multiple theories or literature streams, through offering a new or enhanced view of a concept or phenomenon by linking previously unconnected or incompatible pieces in a novel way (Jaakkola, 2020). To be able to analyze this process, a specific case study is conducted at X, an insurance company located in the Netherlands. This company strives to become a data driven insurer. One of the projects by which the company tries to achieve this goal, is the implementation of a DDDM tool within the Risk Engineering department. To describe the role of organizational learning challenges for a concrete implementation and adoption process of a DDDM tool, an in-depth, qualitative case study is conducted. The main method is participant observation, including informal (semi-structured) interviews and conversations with organizational members to follow up and verify our observations. Documentary sources are reviewed, and informal conversations are realized to be able to expose the initial phases of the DDDM trajectory.

3.2 Data Collection

The participant observation is done between April 2022 and June 2022. During this observation the process of the development, implementation, and adoption of the DDDM tool is explored and observed through documentary sources and interviews (Table 1). The collected data is used to describe and analyze the three different phases: pre-induction phase, introduction phase, and post-introduction phase. The boundaries of these phases are set by the development and execution of the DDDM tool. The actual start of the development of the DDDM-tool acts as the boundary between the pre-introduction and introduction phase. The boundary between the introduction and post-introduction phase is set by the completion of the pilot implementation. To uncover the 'pre-introduction of the DDDM tool' phase, documentary sources such as initial e-mails and PowerPoints are reviewed. Furthermore, three informal conversations and interviews with the manager of acceptance, the manager of risk experts, and the employee from product portfolio and management who is responsible for which re-inspections will be conducted. During these interviews we will ask them about the current way of working according to (re)inspections and the initial phases of the DDDM tool development, implementation, and adoption up to April 2022. In order to analyze the 'introduction of the DDDM tool' phase, five risk experts are interviewed. One of them was involved in the process of the development of the DDDM tool. During the interview we will ask him about his contribution, which was related to sharing his expertise and knowledge, in order to give the data scientists, the opportunity to validate the model. Furthermore, this interview is conducted to able to explore what the work of a risk expert entails and the influence of and opinion about the renewed re-inspection model. Moreover, two risk experts are interviewed who have been involved in the pilot, which was conducted to test the model. These interviews were conducted to find out their opinion about the renewed re-inspection model, the impact of it on their daily work and their view about the process of the pilot that took place. Lastly, two risk experts who are not involved during the pilot are interviewed for this phase. During these interviews we ask them about what their work entails and their opinion about the goal of X to become a data-driven insurer. These two interviews will give us the opportunity to make a fair assessment compared to the two risk experts who were involved during the pilot. The last phase, 'post-introduction of DDDM tool', entails the phase which has no clear end because the organizational learning processes will give the organization the opportunity to continuously improve. For this phase we will interview the manager of the risk experts for the second time. We will ask him about his opinion of the process of the pilot, the role of the risk experts compared to the renewed (re)inspection model and the goal for the post-introduction phase. Lastly, the data scientists who started this project and who developed and implemented the DDDM tool are interviewed. This interview will cover the pre-introduction, the introduction and the post-introduction phases of the development, implementation, and adoption of the DDDM tool.

During the fieldwork period, informal interviews and conversations with organizational members include one-to-one meetings and face-to-face conversations in the field as well via Teams. Documentary sources such as PowerPoints, e-mails, reports, websites, databases, and software are reviewed.

Respondent	Phase
Manager of acceptance	Pre-introduction phase
Employee responsible for re-inspections	Pre-introduction phase
Manager of risk experts	Pre- and post-introduction phase
Risk expert involved during development (one person)	Introduction phase
Risk expert not involved in pilot (two persons)	Introduction phase
Risk expert involved in pilot (two persons)	Introduction phase
Data scientists (two persons)	Pre-introduction, introduction, and post-introduction phase

Table 1. Overview of respondents

3.3 Data Analysis

To be able to analyze the data, we follow the data strategy approach of Jarzabkowski et al. (2016). This approach analyses qualitative process data and daily activities as they unfold. Therefore, we "study 'emerging patterns', where the actors themselves are trying to delineate and construct a direction or order within their activities. In such cases, there may be no clear beginning or end" (Jarzabkowski et al., 2016, p. 244).

The first phase of this approach includes using initial observations from conversations or meetings to confirm our case gives us the opportunity to investigate in DDDM adoption. For the second phase of our research, we set boundaries for our analysis by focusing ourselves on the development, implementation, and adoption of the renewed re-inspection model. The third phase of data analysis includes a more in-depth analysis of our empirical findings. During this phase we still engage in our field, and we collect data. We describe these three phases as a process theory, by explaining the sequence of events leading to an outcome. We engage to this kind of theory by linking the collected data in a previously unconnected novel way. The data collection phase concerns the registration of the process of development, implementation, and adoption of the DDDM tool. The data collected during the semi-structured interviews will be recorded and transcribed. For the analyzing process the transcribed interviews will be encoded. The coding is based on theory and is related to the theoretical framework as described in Chapter 2. The theory from Nonaka (1994) is used as foundation for the coding of organizational learning, Grønsund & Aanestad (2020) for human in the loop, and Murray et al. (2021) and Baird & Maruping (2021) for technology use and acceptance. Based on their theories, the dimensions and indicators are identified. Before the actual coding of the collected data, a pre-defined list of codes, containing of dimensions and indicators, is created as showed in Table 2. This deductive approach helps to focus the coding, ensures structure, and theoretical relevance from the start (Skjott Linneberg & Korsgaard, 2019).

To ensure the research reliability and validity, the transcribed and encoded interviews has been sent back to the specific interviewee so if needed, feedback and corrections could be applied (Whittemore et al., 2001). The concept validity within the semi-structured interviews is assessed by checking the concepts with the data scientists and manager of risk experts involved.

	Dimensions	Indicators
Organizational learning *The creation of improvements (i.e., single loop learning) or innovation (i.e., double loop learning) and norms, rules, and conditions by which these knowledge creation processes may be done (i.e., deutero loop learning or institutional learning)*	Socialization (Nonaka, 1994)	Knowledge sharing culture within X.
		Relevant employees from all different areas/departments are involved in projects within X.
		There are cooperate projects across different departments within X.
	Externalization (Nonaka,, 1994)	The benefits of the externalization process (from tacit to explicit) are feasible and clear within X.
		Data is available within X, and good standards are developed.
	Combination (Nonaka, 1994)	Repositories of information are well-developed within X.
		Data sharing between applications is easy within X.
	Internalization (Nonaka, 1994)	Within X there is analytical transparency.
		Within X there is room for learning by doing and a process of *trial* and error.
Human in the loop *The augmentation, accurate feedback and responsibility for performance management, exception handling and improvement.*	Altering (Grønsund & Aanestad, 2020)	Within X the tool is altered by employees.
	Auditing (Grønsund & Aanestad, 2020)	Within X the tool is audited by employees.
Technology acceptance and use *The actual use and interactions of technologies by constituting*	Human-machine interactions (Baird & Maruping, 2021; Murray et al., 2021)	Within X the technology in the human-machine interactions has not the

a shared capacity between humans and nonhumans to exercise intentionality.		ability to develop protocol or the ability to select actions
		Within X the technology in the human-machine interactions has not the ability to develop protocols, but does have the ability to select actions.
		Within X the technology in the human-machine interactions has the ability to develop protocols, but does not have the ability to select actions
		Within X the technology in the human-machine interactions has the ability to develop protocols and has the ability to select actions

Table 2. Coding frame

4 Results

This section presents the data using a chronological structure representing the shifting configurations of human-machine interactions, the technology acceptance and use, and the organizational learning phase. After which we analyze the circumstances that influence the different organizational learning processes.

4.1 Case description

First, we describe the nature of the extant work practices, after which we describe the introduction and the first pilot of the DDDM tool. Finally, we describe the post introduction.

4.1.1 Pre-introduction of the DDDM tool

Before the introduction of data driven decision making within the department of Risk Engineering, inspection guidelines were used by the departments of Acceptance and Project Portfolio Management (PPM). These inspection guidelines consist of two matrixes, one for join inspection and one for re-inspections. The process before the introduction of the DDDM tool was as follows: (1) a company wants to become a client; (2) the department Acceptance determines whether or not to accept this client. This department checks on risks, predicts the claim costs, and segments the client. If necessary, a join inspection is executed to collect additional information for assessing the application. If the client is accepted then; (3) based on the risks of the new client the department PPM, who is responsible for the return of the portfolio, determines how many times per year the client will be reinspected. These (re)inspections are planned by the planners and are executed by the department Risk Engineering. 35 specialists, with at least five years of relevant experience, work at the Risk Engineering department and they (re)inspect 4500 companies on an annual basis. Based on the portfolio of X they should (re)inspect 15000 companies per year. The goal is to improve the (re)inspections in terms of quality – (re)inspect those companies where they can make the most impact in terms of occurrence of damage. Currently, the decision whether to (re)inspect a company or not, is based on expert judgement. When feeling is the superior function for decision making “every conclusion, however logical, that might lead to a disturbance of feeling is rejected at the outset; all thinking is subordinate to feeling values” (Franco & Meadows, 2007, p. 1622). Through judgement we have the possibility to add the capacity for sympathetic awareness to decision making. However, decisions fully based on judgement are not suitable for situations where decision also should make the company smarter in terms of effectiveness, productivity, output and performance (Franco & Meadows, 2007).

Based on inspection guidelines “Acceptance” makes sure the join inspections are scheduled and PPM does for re-inspections. These guidelines are based on rules of thumb and policies, for instance burglary attraction, the sum insured, or quality score of the last inspection in case of re-inspections. If there is a greater risk of burglary or if the sum insured is higher than for instance 1 million, join and re-inspections should take place. If there is almost no risk of burglary and the insured sum is lower than for instance 1 million, join and re-inspections are not necessary according to the policy. However, this mark of 1 million could also have been 9 tons or 1.1 million. This number is not based on data. The primary function of an analyst is to provide Acceptance, PPM, and other stakeholders with up-to-date benchmark information about risks, fire hazard and new developments, like lithium batteries or solar panels. Their mode of work is illustrated in Figure 2, which visualize the sequence, as described above, for the process of planning and executing (re)inspections before the introduction of the DDDM tool.

The current research focuses on the policy used for re-inspections. Based on this policy, PPM determines whenever a re-inspection should take place. Both risk experts and PPM would typically specialize on certain segments based on the size of a company, resulting in the following classification: middle and small business, industry, and large business segment. The risk experts and PPM are assisted by their deep and long understanding of patterns, types of companies and possible risks. The risk experts draw on long term experiences of inspecting, re-inspecting, and verifying the assignments planned by PPM. If their judgement, before or after (re)inspection, is different from the policy or from PPM, this is considered and most of the time their expert judgement is taken over. Nevertheless, R9 (data scientist) says: “*The risk is you follow the damage; after two years you notice that there are a lot of damages in one segment or market. So, they plan more re-inspections for that specific segment. This results in the fact that you are actually always one step behind. Furthermore, it’s really one-dimensional. You are looking per sector, (..) If you zoom in, you will probably find out it is not the whole sector*

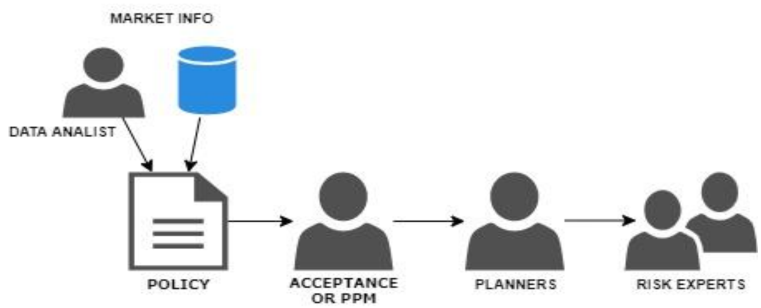

Fig.2 The process of planning and executing a (re)-inspection.

which is not doing that well. Maybe mainly the large companies are not doing that well, or not, because the large companies have arranged their business and small companies have not". This is why PPM suggested in 2018 the re-inspection model should be renewed and should be based on data. This suggestion can be seen as a deutero loop learning enabler, since it is the creation of conditions by which the knowledge creation processes may be done best. The organization recognizes the need for a renewed re-inspection model and supports this idea. Moreover, double loop learning takes by this suggestions place since new insights are generated about the current way of working.

4.1.2 Introduction of the DDDM tool

During the period 2018-2022, two internal data analysts developed themselves as data scientists. During these years, they developed the DDDM tool. However, the quantity of data available to build and test the model is minimal. R9 (data scientist) says: "*It is very difficult to build the model and predict the future damages, because in the end we have very little cases of actual damages each year."*. The quantity of data available can influence the externalization process at which tacit knowledge is transformed into explicit knowledge. R9 continues: *"We started with the idea of putting in as many features and as much knowledge as possible. But at the end, a much simpler model has emerged. (..) In the beginning, we were not really that good at Data Science either. Later we really started pruning."*. These features were obtained from information provided by their clients and the BAG, the Dutch organization for collecting data of all addresses and buildings in the Netherlands. Initially 150 features were used as input for the model, for example year of construction, surface area, purpose of use and location. In the end, only four features were used as input for the model, namely insured amount, average numbers of claims per year, average cost of claim per year, and activity of the customer. Based on logistic regression they build a model. Logistic regression estimates the probability of an event occurring and the dependent variable is bounded between 0 and 1. Through this model the data scientists were able to predict the top 100 of buildings risk experts should re-inspect. This top 100 was based on damage probability first and later on also cost of damage. With this method, it does not matter if a building is in place 600 or 3000, only the top 100 does.

Even before the pilot took place, the model was evaluated many times by learning by doing and a process trial and error. Here, deutero learning enablers since arise since there is room, in terms of time, for learning. This may result in an atmosphere in which an internalization process may occur: the combined explicit knowledge can be integrated with values, skills, and personal experiences from the data scientist. With all the data they had from 2018 they tried to predict 2019. The data scientist knew what the actual damage was in 2019, so they could optimize their model over and over again to get as much damage, in terms of possibility and cost, as possible in the top 100. In the end, they did three or four test years. This initial version of the configuration between people and the DDDM tool is in Figure 3. In this phase of the DDDM development the novel work tasks fell on a large degree to the data scientists. These tasks consisted of evaluating the top 100 produced by the tool and altering and pruning the features from the tool to improve the predictive performance of the tool. During this initial phase the human-in-the-loop evaluated the data scientists altering the DDDM tool. The sequence of this visualization is as follows: the data scientist alters the DDDM tool and the market information. The market information obtained from clients and the BAG serves as input for the DDDM tool. The output of the DDDM tool is the top 100 of re-inspections based on damage probability and cost of damage. This process took place many times since the data scientists tried to get as much damage in the top 100.

In the meantime, the data scientists have presented the model many times. R9 (data scientist) says: "*I have been working at this company for four years now. This means I have a whole collection of PowerPoints and files. I have also presented this story quite often.*". One question raised many times is "How successful is this model?". R9: "*When we were presenting this model, it was quite a hallelujah story. Our director, (..), saw this (..) and said, "we are re-inspecting 500 buildings, and we will save 1.8 million euros!". Well, it is not that simple. Because (..), you will never prevent all the damage.*" This mode of presenting the model led to high expectations. In addition, there can be a possibility of misinterpreting the results of the model, as the director did. This leads to reticence on the part of the data scientists further in the process when it comes to presenting the results of the DDDM model. Moreover, R9 says: *"The question we got many times: "okey, but how many damage can we prevent?"*. As confirmed by the data scientist, this question is asked many times. However, it is difficult to formulate an answer. Deutero learning constraints arise since the added value of the DDDM tool, and even

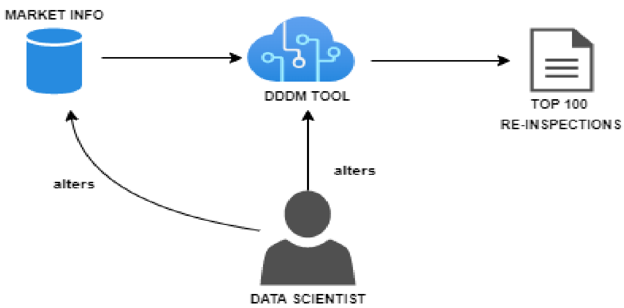

Fig.3 Configuration between DDDM tool and people during the initial phase

perhaps re-inspections in general, is questioned. This can create conditions by which the knowledge creation processes can be limited. However, to be able to give an answer to this question and validate the model, a risk expert and the manager of the risk experts got involved. Via the data scientist, the manager risk experts, and the risk expert where able to alter the model indirectly. Together they formulate questions and weightings and put these into Arena (the system risk experts use to register and process the (re)inspections). One of those questions was "how useful was this (re)inspection and why?". The risk experts were able to rank the usefulness on a scale from 1 to 5 and were able to explain themselves. In this case, a re-inspection with a rating of the number '1' was not a useful re-inspection and a re-inspection with a rating of the number '5' was a really useful re-inspection. However, the data scientists were not able to combine the answer to this question into the model, because there is no connection between the DDDM tool and the Arena system resulting from the fact of no matching unique identifier. R3 (manager risk experts) says: *"People are not fully aware of how it works. And that's a shame (..). We are looking for a solution like standard formats or something, so the margin of error is minimal."* Sequentially, the data scientists do not have the possibility to use own data about historical (re)inspections, stored in Arena, as input for the model. This has an effect on the combination process whereby explicit knowledge is combined through bringing different externalized parts together in one system. R9 (data scientist) says: *"The text field was a number and in 30% of the cases I could link it and in 70% of the cases I have no idea what the number was. (..) That has been the case for all inspections for 3 years now. That's too bad."*

After a while, the data scientists found out the ranking bullet from 1 to 5, used for giving an answer to the question "How useful is this reinspection?", was default on 5. This resulted in a usefulness of score 5 in two third of the re-inspections. Later on, the default answer was changed in "no opinion". If a risk expert changes this default answer from "no opinion" to a number from 1 to 5, it is known for sure that the completed answer is correct. Furthermore, the data scientists asked "Acceptance" to check the top 100 resulting from the model. One person checked whether he found the buildings should be re-inspected and wrote down his opinion per building. However, the data scientists did decide to go to all the buildings to check whether or not this person is right. Some input was considered. R9 (data scientist) says: *"For example, he told us there are a few residential houses in the top 100. Those are not separate houses, but it is a neighborhood, and they are insured together. It may well be that the damage chance and cost is high, but it is not useful."*

During the second version of the human-DDDM tool configuration, as in Figure 4, more people were involved and added to the human-in-the-loop. They serve as an extension of the previous visualization: they provided the data scientists with feedback how they could alter the DDDM tool to be able to get more useful (re)inspections and to be able to validate the tool. Together they assessed whether this feedback is useful and based on this, the feedback is applied or not.

The DDDM tool was introduced at the Risk Engineering department by a pilot. During this pilot ten risk experts were chosen to participate. On beforehand, the risk experts did know which re-inspection was based on the model and not the normal policy, however they did not know based on what features the building was chosen. It was a design choice from the creators of the DDDM tool to not share this information to make sure the risk experts did not develop a tunnel vision during the re-inspections trying to emphatically looking for the information provided by the model. R4 (risk expert) says: "*What would have been the reason the tool chooses this building? During a normal re-inspection we would like to know if there are some special reasons or special concerns. The same encounters for this situation.*" However, to ensure recommendations are adopted by risk experts, these recommendations have to rely on transparent procedures. The risk experts can internalize by integrating it with values, skills, and personal experiences. This process we call the internalization process. Transparency is reported to be beneficial for trust and acceptancy of the tool by the risk experts during this process and which enables triple loop learning. Furthermore, the risk experts were not informed well. R6 (risk expert) says: *"Well, the model is explained to us. However, this is done afterwards. If they did that before the pilot, that would have been better."* Involving all relevant users in the development stage of the DDDM tool can influence the socialization process, whereby tacit knowledge is shared between individuals. Socialization may result new insights, thus double loop learning.

During this pilot the risk experts should initially re-inspect the buildings who ended up in the top 100 of the renewed re-inspection model. However, because of a slow start of the pilot they were only able to re-inspect 72 buildings. The other clients have, for example, terminated

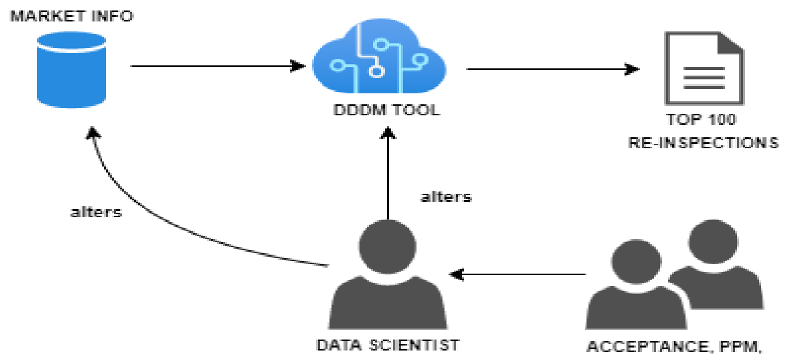

Fig.4 Human-DDDM tool reconfiguration involving domain experts

their contract by X. They only had no data of 5 cases, which results in data of 67 re-inspections. Because the ranking of the usefulness score during the pilot was default 5, they decided to eliminate every re-inspection which had a usefulness score of 5. R9 (data scientists) says: "*You do not know for sure if the risk experts thought the re-inspection should score a five out of five based on usefulness or the usefulness score was not filled in. Because it was in the two thirds of the cases, we treated it as "no judgement"."* This resulted in 30 re-inspections which could be analyzed.

4.1.3 Post-introduction of the DDDM tool

By May 2022 the pilot of the tool was evaluated. One major caveat that must be made is the fact that the analysis is based on 30 cases. Therefore, R9 (data scientist) says: *"it is difficult to draw conclusions based on these 30 cases"*. However, based on the quality-scores the data scientists build into Arena, the model scores 0.2 points better than the regular policy. Based on the usefulness score asked to the risk experts, the regular policy scores 0.7 points better. The data scientists decided to not share the results of the pilot broadly. R9 (data scientist) says: "*You can draw many different conclusions. That is why we have held the presentation evaluating the results of the pilot only with those who are involved in the project."* Transparency and providing all relevant stakeholders involved with information needed and available is important during the internalization process to be able to learn from the DDDM tool and integrate these new insights into stock of knowledge (i.e., triple loop learning). Transparency (about the results) is reported to be beneficial for trust and acceptancy of the tool by all people involved. A lack of transparency can have a negative effect on the internalization process at which decision makers can learn from the recommendations provided by the tool.

R9 (data scientist) says: *"We are happy that the model does not score far below the current policy. Because now the model actually scores as good as the current policy, and there are ways to improve the model."* As a result of the pilot, further development opportunities for the upcoming period have been drawn up by the people involved in this process. One of them is connecting the DDDM tool to Arena, after which the data from historical (re)inspections and the usefulness score given by the risk experts could be used as input for the model. Such a connection between Arena and the tool would make it possible to create the feedback loop from the risk experts to the model. However, there is a lack of data sharing protocols. R3 (manager risk experts): "*You need the feedback loop between the actual damage and our data. However, it is not possible at this point. And I foresee that it would not go very quickly either."* For the combination process, combinations of other data sources and systems need to be realized, whereas combinations may result into new insights (i.e., double loop learning). For this, well-developed standards, policies, and system architectures are needed. However, much of the time, the data scientists are trying to convince people and try to manage the opinions instead of improving the model. R9 (data scientist): "*I feel much more like a business change manager and stakeholder manager. I give a lot of presentations about data driven decision making. (..) So in practice we are very busy with peripheral matters. Not with the technical implementation, but the organization implementation.*". If the combination between the model and Arena could be made historical data from (re)inspections can be used. R9 (data scientist) says: *"We can include what is observed last time. (..) And we can combine this with other features."* Sequentially, risk experts can interact with the DDDM tool since their opinion has an influence on future re-inspections and this interaction may result in integrating new insights into stock of knowledge, thus triple loop learning. This results in a shifting human-machine interaction: from only the technology being able to develop protocols and select actions to people being able to select actions. A feedback loop between the DDDM tool and the risk experts arises: the risk expert audits the model by their input about the usefulness of (re)inspections and the model helps the risk expert to make smarter decisions. This results in a human-machine configuration as showed in Figure 5.

Further planned development possibilities are adding a usefulness-score based on historical (re)inspections to the model and providing the risk experts with feedback why the model has chosen this re-inspection. The usefulness-score will determine how useful a (re)inspection will be. In other words, what is the impact what could be made with this (re)inspection. This usefulness score can be equal to the cost of damage: when there is a higher

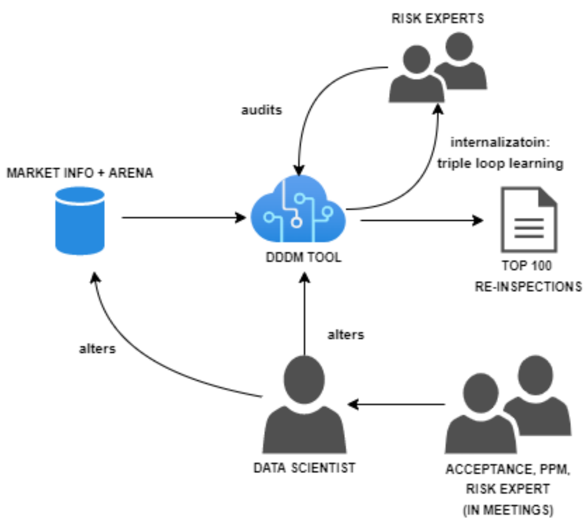

Fig. 5 Human-DDDM tool reconfiguration integrating the risk experts

cost of damage, the usefulness score will be higher. However, this will not be the case in all situations. At that point, a discussion will arise at which the DDDM tool should be able to balance between the cost of damage and the usefulness of a re-inspection. The model should be able to filter out the non-useful inspection, without reducing the cost of damage which is within the top 100. By providing the risk experts with feedback from the DDDM tool on what features this re-inspection is chosen, the risk experts can make the re-inspection more focused and triple loop learning can arise. However, a tunnel vision must be prevented, since the DDDM tool is basing the recommendations on available data. At this point, the available data is static, since it is based on information provided by their clients and data obtained from the BAG. If it is possible to link the model to the data stored in Arena, the data could be updated on a more regular basis. However, recent client investments are not always shared with the insurance company, such as solar panels, or deliberately withheld information is not included in the judgement of the DDDM tool.

Furthermore, increasing the quality of the data stored in Arena deserves additional attention in the coming years. R3 (manager risk experts) says: "*At least we need to know that the output from the model is right. That it is correct on a qualitative level, and we can combine it with different data sets. (..) We should not have to doubt the output. However, at this point, I do not always dare to bet money on that.*". People must be able to trust the model in terms of quality of the output, which can influence the degree of acceptance of the model. Furthermore, the quality of the data consists of uniformity and no missing data, which influences the externalization (from tacit to explicit knowledge) process. R3 says: "*We are pointing on the quality side of the risk, and we are making investments. We need to guarantee a certain uniformity in the assessment of risks by our risk experts. So, a certain lock, do we agree about the quality of this lock? Sometimes you can still find some different opinions about it. (..)Therefore we invest in knowledge. That is the fundament of the quality of our data.".* Therefore, R3 says: "*On a regular basis we are checking the quality of data: is the insured amount correct? Is the policy number correct? Are crucial field filled in or not?"*. To influence the externalization process in a positive way, data standards need to be developed and checked on a regular basis.

To make the risk experts aware of the fact that their output of the (re)inspections is not only important for "Acceptance" or PPM anymore, but acts as input for a DDDM tool, an awareness and cultural program is set up. R3 (manager risk experts): *"That is the data fan. And actually, every employee within X should become one."* A knowledge sharing culture, whereby tacit knowledge is shared through interaction between individual, socialization process, constitutes the foundation for becoming data driven and enables double loop learning. Therefore, R3 (manager risk experts) says: "*We are trying to reach this by an awareness program. (..) That is actually a program, a culture program. We want to become a data-driven insurer, a data-driven department. This is the foundation*". Looking ahead, the executive team aims to do more than just simply implement an DDDM tool in the everyday organizational work. They envisioned to embrace the overall goal of X, becoming a data driven insurance company. Core to achieving this is building a culture of learning and experimenting. The lessons learnt from the recent pilot will be implemented in the upcoming months and the next pilot will take place in the beginning of 2023. The need for technical-scientific maturity of the DDDM tool and its outcomes, before an actual implementation, points to deutero learning constraints. This can create conditions by which the knowledge creation processes can be limited.

4.2 Analysis of case description

Our case analysis covers the initial phases of the development and adoption of a DDDM tool within the insurance company X. The starting point for the initiative was the idea the selection of re-inspections should be based on data instead of judgement. After the suggestion of PPM to renew the current re-inspection policy, the data analysts developed themselves as data scientists during the years allowing novel tasks and roles to emerge. Figure 6 summarizes the circumstances which influence the socialization, externalization, combination, and internalization processes. For the socialization process, emphasis on knowledge sharing culture within X acts as a fundamental basis (Nonaka, 1994). During the socialization process relevant stakeholders of different departments develop consensus, involving the development of the DDDM project. This is a critical process for later DDDM adoption learning (Wijnhoven, 2021). The risk experts are involved in a minimum level during the initial phases of the project. Although, they are not the end users of the tool and in essence an executing party, their expertise is important for the quality of the tool and the creation of new knowledge (i.e., double loop learning). Involving them during the initial phase of the development of the DDDM tool, influences the trust in and acceptance of the DDDM tool (Nonaka, 1994; Wijnhoven, 2021). In the process of further externalization of the data, data standards and data quality are variables which influence the trust regarding the output of the DDDM tool. Lacking data standards and lacking data quality in terms of missing data and uniformity affect the acceptance of the tool by the users (Wijnhoven, 2021). Well-developed standards, policies and system architectures are needed for the combination process. Combinations of the DDDM tool with other data sources and systems may result into new insights (i.e., double loop learning) (Nonaka, 1994; Wijnhoven, 2021). At this point, it is not possible to combine the DDDM tool with Arena, the data source at which historical data about (re)inspection is stored, because of no unique identifier. As a result, it is not possible to integrate the usefulness score of (re)inspection given by the risk expert and it is not possible to integrate the expertise of the risk expert in the DDDM tool. So, the feedback loop between the risk expert and the DDDM tool cannot be realized, and the augmenting role of the risk expert is not included in the outcomes of the DDDM tool. As identified by Wijnhoven (2021) poor data sharing among different applications is seen as a challenge for organizational learning. The process of combination is much of the time slowed down as a result of the data scientist trying to convince people and try to manage the opinions instead of improving the model. For internalization, the presence of learning by doing and a process of trial and error within X has a positive effect on organizational learning (Nonaka, 1994). However, the people involved must become convinced that recommendations from the DDDM tool can be trusted (Nonaka, 1994; Wijnhoven, 2021). Transparency and providing all relevant stakeholders involved with information needed and available is important during the internalization process to be able to learn from the DDDM tool and integrate these new insights into stock of knowledge (i.e., triple loop learning) (Nonaka, 1994; Seidel et al., 2019; Wijnhoven, 2021). At this specific case, there is no transparency to the risk experts about the features on which the re-inspections are chosen. This makes learning from the DDDM tool for the risk experts impossible. Moreover, there is limited transparency about the results of the pilot, which has a negative effect on the acceptancy of the DDDM tool by the people with who the results of the pilot have not been shared. Furthermore, the caveat that the result of the pilot is only based on 30 cases, affects the trust people have according to the DDDM tool. Results based on such little data has a negative impact on the generalizability of results of the pilot. Poor generalizability of the results affects internalization. Since the results may differ when it is based on 30 other cases, there may be reluctance to internalize the recommendations of the DDDM tool which effects learning from the DDDM tool (i.e., triple loop learning) (Seidel et al., 2019; Wijnhoven, 2021).

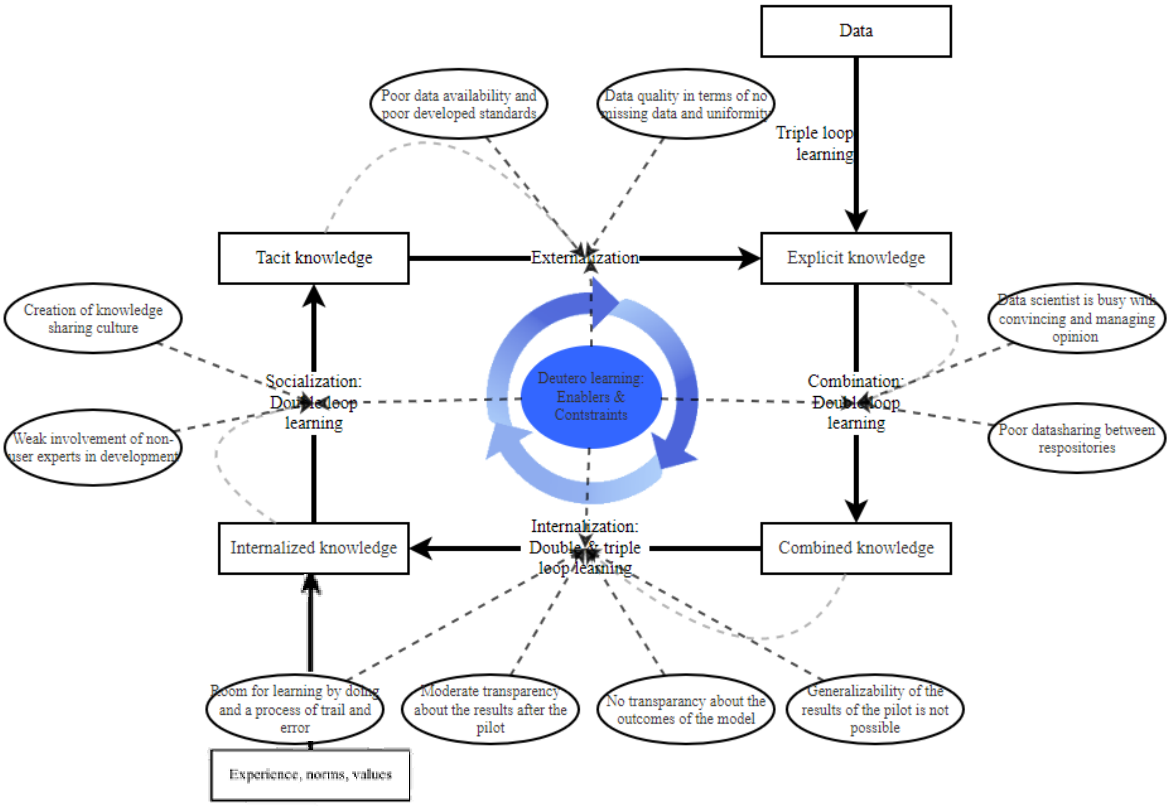

Fig. 6 Circumstances which influence organizational learning during the adoption of data driven decision making.

5 Discussion

This section formulates an answer to the research question, after which the theoretical and practical implications are given. The section concludes with an outline of the limitations and suggestions for further research.

5.1 Main findings

This research realized an understanding of a data-driven decision making adoption process in the boarder context of data-driven decision making adoption as an organizational learning process. This research bridges the gap of how to adopt the new generation of agentic data-driven tools which has the capacity to learn, adapt, act autonomously, and can be aware of the need to act without an active request of its users, by describing the adoption of DDDM as an organizational learning process, within the insurance company X. This brings us to the following research question: *"What is the role of the organizational learning processes in the process of data-driven decision making adoption?"* To be able to answer this research question we described the process for the development, implementation, and adoption of the DDDM tool using a chronological structure. After which we analyzed the case using the organizational learning processes according to the SECI sequence, which emphasizes the importance of tacit knowledge as the start and end of every organizational learning (Nonaka, 1994; Wijnhoven, 2021). The organizational learning processes are influenced by deutero learning processes. In our case, deutero learning constraints who have an impact on the organizational learning processes are the need for technical-scientific maturity of the DDDM tool and its outcomes before an actual implementation and the event that the added value of the DDDM tool, and even perhaps re-inspections in general, is questioned since it is almost not possible to calculate the added value of it. The adoption of the DDDM tool is influenced by the socialization process in which not all relevant stakeholders are involved during the development of the DDDM tool. Moreover, during the externalization process data standards and data quality are questioned. Lacking data standards and lacking data quality in terms of missing data and uniformity affects the acceptance of the tool by the end users and therefore the adoption of the DDDM tool. Additionally, it is not possible to combine the DDDM tool with Arena, because of no unique identifier. In this case, there is a shortage of "combination". The process of combination is slowed down as a result of the event the data scientists have to convince people and try to manage the opinions instead of improving the model. As a result, the feedback loop between the risk expert and the DDDM tool cannot be realized, and the augmenting role of the risk expert is not included in the outcomes of the DDDM tool. Finally, the adoption of the DDDM by the users is hampered by a lack of transparency in the internalization process, which makes learning from the recommendations from DDDM tool impossible (i.e., triple loop learning). In short, for all four organizational learning processes there are improvements to made. These improvements will have a positive effect on the adoption process of the DDDM tool.

5.2 Theoretical implications

This research described the process of an adoption of DDDM within the insurance industry. By describing and analyzing this process, this research fulfils the gap in literature as described in Chapter 1.

First, this research found the executing employees, who are not seen as the end users, are still important stakeholders for the adoption process of the DDDM tool. In this specific case the executing party, the risk experts, are specialists who are drawing on long term experiences of inspecting, re-inspecting and (if applying the regular policy) verifying the assignments planned by the department Product Portfolio and Management. In contrast to earlier research which stresses on the acceptance of only end users (Boobier, 2016; Rau et al., 2021), this research shows that, in the case of an industry with specialists involved, the importance of these specialists for the adoption process of the DDDM tool should not be underestimated. The tacit knowledge of these specialists plays an important role in the socialization process. Furthermore, their knowledge is valuable for the learning capacity of the DDDM tool. Providing the DDDM tool with feedback about the usefulness of the outcomes of the model, helps the DDDM tool to learn and improve itself. Despite the fact the specialists are not the end users, they should be actively included in the process of DDDM development, implementation, and adoption.

Secondly, different literature on DDDM as organizational learning processes indicated which factors influence the adoption process of the DDDM tool. Many findings of scholars were also confirmed in this research: the effect of trust (Boobier, 2016; Pugnetti & Seitz, 2021; Wijnhoven, 2021) and transparency (Boobier, 2016; Rau et al., 2021; Wijnhoven, 2021; Zarifis et al., 2019) on the adoption process of the DDDM-tool. This research shows that transparency is especially valuable during the internalization process. On beforehand, the risk experts did know which re-inspection was based on the model and not the regular policy, however they did not know based on what features the building was chosen. However, to ensure recommendations are adopted by risk experts, these recommendations have to rely on transparent procedures. Transparency is reported to be beneficial for trust and acceptancy of the tool by the risk experts. Since transparency is not provided in this case, developing new knowledge and learning form the recommendations of the DDDM tool is not possible (i.e., double, and triple loop learning). Furthermore, this research shows the development of data standards and quality standards is desirable for the trust in the outcomes of the DDDM tool. In this case, data standards and quality standards are underdeveloped which can raise questions about whether the model's output is always correct. Transparency and trust effect on the acceptance of the DDDM tool during the adoption process.

This study also adds to the research on human-machine configurations that has study several forms of interdependencies between people and machines (Grønsund & Aanestad, 2020; Raisch & Krakowski, 2021; Seidel et al., 2019). Our research describes the emerged human-machine configurations over time during the process. Over time, more people got involved in the human-machine configurations. These people alter or audit the DDDM. The human-machine interdependency emerged from a configuration whereby the machine was able to set protocols and select the outcomes, to a configuration whereby the machine is able to set protocols and people are able to determine the definitive outcomes. In this human-machine configuration, the DDDM tool complement people in practice. Furthermore, in line with the work of Seidel et al. (2019) our research recognizes the importance of mutual learning to correspondent the different types of rules and reasoning that people and machines apply. In our case, mutual learning between people and the DDDM tool is not possible because of the missing feedback loop between risk experts and the DDDM tool. However, before the DDDM tool can learn and improve itself based on the executed (re)inspections, this feedback loop as showed in Figure 5 must be realized.

Furthermore, this research is an extension of and addition to the of the research of Grønsund & Aanestad (2020) and Wijnhoven (2021). The study of Grønsund & Aanestad (2020) is conducted in the logistic industry and the introduction of the algorithm had the purpose of automating human work. They conclude the human in the loop pattern appears to have an augmentative rather than a controlling purpose. In contrast, the introduction of the DDDM tool in our case study has the purpose to support the work of specialist, namely the risk experts, instead of replacing them. We see, in the first place, the risk experts have a controlling role regarding to the recommendations of the DDDM tool. Subsequentially, their controlling role acts augmentative if their opinion differs from the recommendations of the DDDM tool. The work of Wijnhoven (2021) is conducted in medical industry and highlights the differences from non-medical cases, such has higher requirements for legal backing and patient risk live avoidance. Our research acts as an addition to the work of Wijnhoven (2021) since it is conducted in a different industry, however our case still deals with specialists. We found similarities of circumstances which influence the organizational learning processes. However, our research differences from the work of Wijnhoven (2021) since, in our case study, there is no transparency about the recommendations of the DDDM tool and we highlight the importance of involving non-end users during the adoption process.

Finally, this research was conducted in a knowledge intensive service-oriented department and organization. This type of organizations highly depends on the expertise and the tacit knowledge of their employees. Therefore, the socialization process in which all relevant stakeholders should be involved deserves even more attention. In this case, the risk experts are not involved during the development, implementation, and adoption process. However, their knowledge is valuable as input of the DDDM tool, and their knowledge is valuable for auditing the outcomes of the model. If especially the employees with highly valuable expertise and tacit knowledge, are not involved, the degree of acceptance of and trust by these types of employees in the model will be affected. This shows the emphasize of the adoption process of the DDDM tool can be slightly different based on organizational type, in this case knowledge intensive service oriented. Therefore, this research contributes to the literature on knowledge intensive service-oriented organizations.

5.3 Practical implications

These insights have practical implications for the design of DDDM tool implementation processes. In this case, different employees from different departments are involved. These employees do not have a neutral view on this process and possibly each of them acts in their own interests. For example, the design choice to not share the information on what features the building was chosen for re-inspection. This design choice was made to make sure the risk experts did not develop a tunnel vision during the re-inspection trying to emphatically look for the information provided by the DDDM tool. However, normally the risk experts do receive information if there are special reasons or special concerns. Therefore, there should be a neutral project manager involved who concerns all different opinions and makes sure the best decision possible is made. The project manager should assess the context, the different organizational learning stages and the challenges which should be overcome per learning process. The deutero learning constraints and enablers should be considered and must be deployed in such a way that the process is speeded up and moved into the desired direction (Wijnhoven, 2021). The project manager must be aware that learning in this case is not only double loop learning, but also triple loop learning, i.e., developing interactions between the DDDM-tool and people with mutual learning (Seidel et al., 2019). This triple loop learning does not only require a development of capabilities of data scientists involved, but also of (professional) (end) users (Grønsund & Aanestad, 2020). This organizational learning process has no clear end as triple loop learning will give the organization the opportunity to continuously improve. Besides enabling triple loop learning, the project manager may also develop new organizational norms (i.e., deutero learning) that enables triple loop learning.

Furthermore, this research shows the need for new job descriptions after the implementation of the DDDM tool. The risk experts should not be seen as just the executing party. They meet the need of human auditing and novel tasks are added to the daily work of risk experts. Additionally, updating the job descriptions of the risk expert, with a stress on the concept of keeping human in the loop, will affirm the risk experts that they are not replaced by data-driven decision making but their work is supported by data-driven decision making.

5.4 Limitations and further research

It must be acknowledged that this research has limitations. However, these limitations can give guidance for further research. First, the majority of the department Risk Engineering are highly educated and are man with an average age of 55, which make them a relatively homogenous sample or case study. To our knowledge, this is not typical for the insurance industry, so it would be interesting to see if the results hold up in other companies in this industry with more heterogeneous employees in age, gender, and education. Therefore, for further research, it would be interesting to perform similar research in an organization (within the same industry and the same adoption process) with larger variability among the respondents to verify these results. We expect that there are differences in the adoption of data-driven decision making when the respondents are more heterogeneous in terms of age, gender, and education.

Furthermore, there are possible drawbacks based on the design of this research. The process of the introduction of the DDDM tool is described in an objective manner through the conducted interviews, without influencing the respondents with the concepts that are central to this research. The concepts are used for analyzing the case description. Nevertheless, it is likely the researcher has still included the concepts in the subconscious mind during the interviews. This makes the case description less objective. Therefore, further research needs to be conducted to verify the results of this research on the data-driven decision making adoption. This can be realized through interviewing employees in a similar data-driven decision making adoption process by an interviewer who is not familiar with the central concepts of this research. We expect these interviews will not deviate and therefore verify the results from this research.

Lastly, the product design of a DDDM tool comes along with legislation and responsibilities. This research falls short on investigating in legislation and who is responsible for the outcomes of the DDDM-tool in terms. Further research needs to be conducted to analyze legislation and responsibilities regarding the outcomes of the DDDM-tool.

6 Conclusion

Conclusively, it can be stated that the circumstances per organizational learning process have an influence on the adoption of DDDM. It is essential for organizations to get insights in the process of adoption of data-driven decision making and how the organizational learning processes influence this adoption. This research found different circumstances per organizational learning process which an influence on the trust in and acceptancy of the DDDM tool. In addition, it was found that no transparency about the recommendations of the model and the result of the pilot makes the internalization phase, and therefore triple loop learning, impossible. Therefore, it can be stated this research extends the theory on organizational learning and DDDM by describing the process of adoption of new generation of agentic data-driven tools which has the capacity to learn, adapt, act autonomously, and can be aware of the need to act without an active request of its users. Further research can be beneficial to help organizations with the process of DDDM adoption as an organizational learning process.

Bibliography

X. (2022, July 17). *About Us*.

Ahuja, M. K., & Thatcher, J. B. (2005). Moving beyond Intentions and toward the Theory of Trying: Effects of Work Environment and Gender on Post-Adoption Information Technology Use. *Source: MIS Quarterly*, *29*(3), 427–459. https://doi.org/https://doi.org/10.2307/25148691

Argyris, C. (1976). Single-Loop and Double-Loop Models in Research on Decision Making. *Administrative Science Quarterly*, *21*(3), 363–375. https://doi.org/https://doi.org/10.2307/2391848

Argyris, C. (1999). *On Organizational Learning* (2nd edn.). Oxford: Blackwell.

Arnott, D., & Pervan, G. (2008). Eight key issues for the decision support systems discipline. *Decision Support Systems*, *44*(3), 657–672. https://doi.org/10.1016/j.dss.2007.09.003

Bailey, D. E., & Barley, S. R. (2020). Beyond design and use: How scholars should study intelligent technologies. *Information and Organization*, *30*(2). https://doi.org/10.1016/j.infoandorg.2019.100286

Baird, A., & Maruping, L. M. (2021). The next generation of research on is use: A theoretical framework of delegation to and from agentic is artifacts. *MIS Quarterly: Management Information Systems*, *45*(1), 315–341. https://doi.org/10.25300/MISQ/2021/15882

Bishop, C. M., & Nasrabadi, N. M. (2006). *Pattern Recognition and Machine Learning* (1st ed., Vol. 4). New York: Springer.

Boobier, T. (2016). *Analytics for Insurance: The Real Business of Big Data*. John Wiley & Sons.

Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). *Strenght in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance?* https://doi.org/http://dx.doi.org/10.2139/ssrn.1819486

Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of brilliant Technologies. In *WW Norton & Company*. WW Norton & Company.

Chen, H., Chiang, R. H. L., Storey, V. C., Lindner, C. H., & Robinson, J. M. (2012). Business Intelligence and Analytics: From Big Data to Big Impact Quarterly-Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, *36*(4), 1165–1188.

Datt Bhatt, G., & Zaveri, J. (2002). The enabling role of decision support systems in organizational learning. *Decision Support Systems*, *32*(3), 297–309. https://doi.org/https://doi.org/10.1016/S0167-9236(01)00120-8

Daugherty, P. R., & Wilson, H. J. (2018). Human + machine: Reimagining work in the age of AI. In *Harvard Business Review Press*. Harvard Business Press.

Davenport, T. H., & Bean, R. (2018). Big companies are embracing analytics, but most still don't have a data-driven culture. In *Harvard Business Review*.

Davenport, T. H., Harris, J. G., Jones, G. L., Lemon, K. N., Norton, D., & McCallister, M. B. (2007). The Dark Side of Customer Analytics How can these companies leverage the customer data responsibly? *Harvard Business Review*, *85*(5), 1–37. www.hbrreprints.org

Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines.* Harper Collins.

Elgendy, N., & Elragal, A. (2016). Big Data Analytics in Support of the Decision Making Process. *Procedia Computer Science*, *100*, 1071–1084. https://doi.org/10.1016/j.procs.2016.09.251

Eling, M., & Lehmann, M. (2018). The Impact of Digitalization on the Insurance Value Chain and the Insurability of Risks. *Geneva Papers on Risk and Insurance: Issues and Practice*, *43*(3), 359–396. https://doi.org/10.1057/s41288-017-0073-0

Emani, S., Peters, E., Desai, S., Karson, A. S., Lipsitz, S. R., LaRocca, R., Stone, J., Suric, V., Wald, J. S., Wheeler, A., Williams, D. H., & Bates, D. W. (2018). Perceptions of adopters versus non-adopters of a patient portal: An application of diffusion of innovation theory. *Journal of Innovation in Health Informatics*, *25*(3), 149–157. https://doi.org/10.14236/jhi.v25i3.991

Fadel, K. J., & Brown, S. A. (2010). Information Systems Appraisal and Coping: The Role of User Perceptions. *Communications of the Association for Information Systems*, *26*(6), 107–126. https://doi.org/10.17705/1CAIS.02606

Forman, E. H., & Selly, M. A. (2001). Introduction: Management Decision-Making Today. In *Decision by Objectives* (pp. 1–14). WORLD SCIENTIFIC. https://doi.org/10.1142/9789812810694_0001

Franco, L. A., & Meadows, M. (2007). Exploring new directions for research in problem structuring methods: On the role of cognitive style. *Journal of the Operational Research Society*, *58*(12), 1621–1629. https://doi.org/10.1057/palgrave.jors.2602346

Goh, K. Y., Heng, C. S., & Lin, Z. (2013). Social media brand community and consumer behavior: Quantifying the relative impact of user- and marketer-generated content. *Information Systems Research*, *24*(1), 88–107. https://doi.org/10.1287/isre.1120.0469

Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *Journal of Strategic Information Systems*, *29*(2), 1–16. https://doi.org/10.1016/j.jsis.2020.101614

Guttentag, D., & Smith, S. L. J. (2020). The diffusion of Airbnb: a comparative look at earlier adopters, later adopters, and non-adopters. *Current Issues in Tourism*, 1–20. https://doi.org/10.1080/13683500.2020.1782855

Hull, C. E., & Lio, B. H. (2006). Innovation in non-profit and for-profit organizations: Visionary, strategic, and financial considerations. *Journal of Change Management*, *6*(1), 53–65. https://doi.org/10.1080/14697010500523418

Jaakkola, E. (2020). Designing conceptual articles: four approaches. *AMS Review*, *10*(1–2), 18–26. https://doi.org/10.1007/s13162-020-00161-0

Jarzabkowski, P., Le, J., & Spee, P. (2016). *Taking a strong process approach to analyzing qualitative process data*. The SAGE handbook of process organization studies,.

Kardasz, S. M. (2013). What are the Best Approaches for Encouraging the Diffusion of a New Instructional Technology among Faculty Members in Higher Education? A Look at Eportfolio Use at Stony Brook University. *Journal of Educational Technology Systems*, *42*(1), 43–68. https://doi.org/10.2190/et.42.1.e

Kraaijenbrink, J., Spender, J. C., & Groen, A. J. (2010). The Resource-based view: A review and assessment of its critiques. *Journal of Management*, *36*(1), 349–372. https://doi.org/10.1177/0149206309350775

Kwon, H. E., So, H., Han, S. P., & Oh, W. (2016). Excessive dependence on mobile social apps: A rational addiction perspective. *Information Systems Research*, *27*(4), 919–939. https://doi.org/10.1287/isre.2016.0658

Lake, B. M., Ullman, T. D., Tenenbaum, J. B., & Gershman, S. J. (2016). Building Machines That Learn and Think Like People. *Behavioural and Brain Sciences*, *40*. https://doi.org/10.1017/S0140525X16001837

Langley, A. (1999). Strategies for Theorizing from Process Data. *Source: The Academy of Management Review*, *24*(4), 691–710. https://doi.org/https://doi.org/10.5465/amr.1999.2553248

Mahajan, V., Muller, E., & Srivastava, R. K. (1990). Determination of Adopter Categories by Using Innovation Diffusion Models. *Source: Journal of Marketing Research*, *27*(1), 37–50. https://doi.org/https://doi.org/10.1177/002224379002700104

Markus, M. L. (2017). Datification, Organizational Strategy, and IS Research: What's the Score? *Journal of Strategic Information Systems*, *26*(3), 233–241. https://doi.org/10.1016/j.jsis.2017.08.003

Meijerink, J., & Bondarouk, T. (2021). The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation. *Human Resource Management Review*. https://doi.org/10.1016/j.hrmr.2021.100876

Müller, O., Fay, M., & Brocke, vom J. (2018). The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics. *Journal of Magament Information*, *35*(2), 488–509. https://doi.org/https://doi.org/10.1080/07421222.2018.1451955

Murray, A., Rhymer, J., & Sirmon, D. G. (2021). Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, *46*(3), 552–571. https://doi.org/10.5465/amr.2019.0186

Nonaka, I., & Konno, N. (1998). The concept of "Ba": Building a foundation for knowledge creation. *California Management Review*, *40*(3), 40–54. https://doi.org/https://doi.org/10.2307/41165942

Nonaka, I., & Lewin, A. Y. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Source: Organization Science*, *5*(1), 14–37. https://doi.org/https://doi.org/10.1287/orsc.5.1.14

Palm, A. (2020). Early adopters and their motives: Differences between earlier and later adopters of residential solar photovoltaics. *Renewable and Sustainable Energy Reviews*, *133*. https://doi.org/10.1016/j.rser.2020.110142

Patel, K., & Lincoln, M. (2019). It's not magic: Weighing the risks of AI in financial services. In *Centre for the Study of Financial Innovation Working Paper*.

Provost, F., & Fawcett, T. (2013). Data Science and its Relationship to Big Data and Data-Driven Decision Making. *Big Data*, *1*(1), 51–59. https://doi.org/10.1089/big.2013.1508

Pugnetti, C., & Seitz, M. (2021). Data-Driven Services in Insurance: Potential Evolution and Impact in the Swiss Market. *Journal of Risk and Financial Management*, *14*(5), 227. https://doi.org/10.3390/jrfm14050227

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and management: The automation-augmentation paradox. *Academy of Management Review* , *46*(1), 192–210. https://doi.org/https://doi.org/10.5465/amr.2018.0072

Rau, R., Wardrop, R., & Zingales, L. (2021). *The Palgrave Handbook of Technological Finance*.

Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.

Russel, S. J., & Norvig, P. (2016). *Artificial Intelligence: A Modern Approach* . Pearson Education Limited.

Schad, J., Lewis, M. W., Raisch, S., Smith, W. K., & Lerner, A. (2016). Paradox research in management science: Looking back to move forward. *Academy of Management Annals, 10*(1), 5–64. https://doi.org/https://doi.org/10.5465/19416520.2016.1162422

Seidel, S., Berente, N., Lindberg, A., Lyytinen, K., & Nickerson, J. v. (2019). Autonomous tools and design: A triple-loop approach to human-machine learning. *Communications of the ACM*, *62*(1), 50–57. https://doi.org/10.1145/3210753

Shim, J. P., Warkentin, M., Courtney, J. F., Power, D. J., Sharda, R., & Carlsson, C. (2002). Past, present, and future of decision support technology $. *Decision Support Systems*, *33*(2), 111–126. https://doi.org/https://doi.org/10.1016/S0167-9236(01)00139-7

Skjott Linneberg, M., & Korsgaard, S. (2019). Coding qualitative data: a synthesis guiding the novice. In *Qualitative Research Journal* (Vol. 19, Issue 3, pp. 259–270). Emerald Group Holdings Ltd. https://doi.org/10.1108/QRJ-12-2018-0012

Smuts, H., & Smith, A. (2021). Collaboration of Human and Machine for Knowledge Work: An Organisational Transformation Framework for Data-driven Decision-making. *Emerald Publishing Limited.*, 25–59. https://doi.org/https://doi.org/10.1108/978-1-83909-812-320211002

Surbakti, F. P. S., Wang, W., Indulska, M., & Sadiq, S. (2020). Factors influencing effective use of big data: A research framework. *Information and Management*, *57*(1). https://doi.org/10.1016/j.im.2019.02.001

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, *22*, 960–967. https://doi.org/10.1016/j.promfg.2018.03.137

Thiess, T., & Müller, O. (2018). Towards Design Principles for Data-Driven Decision Making-An Action Design Research Project in the Maritime Industry. In *26th European Conference on Information Systems: Beyond Digitization - Facets of Socio-Technical Change*. https://aisel.aisnet.org/ecis2018_rp/144 van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the machine meets the expert: An ethnography of developing ai for hiring. *MIS Quarterly: Management Information Systems*, *45*(3), 1557–1580. https://doi.org/10.25300/MISQ/2021/16559

Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1), 641–652. https://doi.org/10.1007/s10479-020-03918-9

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *Quarterly*, *27*(3), 425–478. https://doi.org/https://doi.org/10.2307/30036540

Verdegem, P., & de Marez, L. (2011). Rethinking determinants of ICT acceptance: Towards an integrated and comprehensive overview. *Technovation*, *31*(8), 411–423. https://doi.org/10.1016/j.technovation.2011.02.004

Visser, M. (2007). Deutero-Learning in Organizations: A Review and a Reformulation. *Source: The Academy of Management Review*, *32*(2), 659–667. https://doi.org/https://doi.org/10.5465/amr.2007.24351883

Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How "big data" can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, *165*, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031

Wang, Y., Meister, D. B., Gray, P. H., & Manning, F. C. (2013). Social Influence and Knowledge Management Systems Use: Evidence from Panel Data. *MIS Quarterly*, *37*(1), 299–313. https://www.jstor.org/stable/43825947

Wen, C., Gao, K., & Xiao, Y. (2021). Data-Driven Market Segmentation in Insurance Industry and Other Related Sectors. *Journal of Finance and Accounting*, *9*(6), 268–272. https://doi.org/10.11648/j.jfa.20210906.17

Whittemore, R., Chase, S. K., & Mandle, C. L. (2001). Validity in qualitative research. *Qualitative Health Research*, *11*(4), 522–537. https://doi.org/10.1177/104973201129119299

Wijnhoven, F. (2001). Acquiring Organizational Learning Norms: A Contingency Approach for Understaning Deutero Learning. *Management Learning*, *32*(2), 181–200. https://doi.org/https://doi.org/10.1177/1350507601322002

Wijnhoven, F. (2021). Organizational Learning for Intelligence Amplification Adoptioin: Lessons from a Clinical Decision Support System Adoption Project. *Information System Frontiers*, 1–14. https://doi.org/https://doi.org/10.1007/s10796-021-10206-9

Woolridge, M., & Jennings, N. R. (1995). Intelligent agents: theory and practice. *The Knowledge Engineering Review*, *10*(2), 115–152. https://doi.org/https://doi.org/10.1017/S0269888900008122

Wu, L., Hitt, L., & Lou, B. (2020). Data analytics, innovation, and firm productivity. *Management Science*, *66*(5), 2017–2039. https://doi.org/10.1287/mnsc.2018.3281

Yeo, A. C., Smith, K. A., Willis, R. J., & Brooks, M. (2001). Clustering technique for risk classification and prediction of claim costs in the automobile insurance industry. *International Journal of Intelligent Systems in Accounting, Finance & Management*, *10*(1), 39–50. https://doi.org/10.1002/isaf.196

Zarifis, A., Holland, C. P., & Milne, A. (2019). Evaluating the impact of AI on insurance: The four emerging AI- and data-driven business models. *Emerald Open Research*, 1–19. https://doi.org/10.35241/emeraldopenres.13249.1