DESIGNING HUMAN-CENTERED HYBRID DECISION SUPPORT SYSTEMS

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Doctoral Dissertation

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ABSTRACT

Innovative decision support systems (DSSs) are revolutionizing key processes in organizations. These systems are used in managerial decision-making to solve increasingly complicated decision tasks, for example, using artificial intelligence. This research starts with the observation from practitioners' workshops that they have significant concerns about existing DSSs. Earlier research also shows that DSSs have often been designed with an over-emphasis on machine capabilities. This one-sided design approach is problematic since it ignores human capabilities in decision-making.

Consequently, organizations need more advanced DSSs that take account of two aspects: 1) they are designed with a human-centered intent; and 2) these DSSs should better utilize the complementary capabilities of humans and machines. In this study, such DSSs are called human-centered hybrid decision support systems (HC-HDSSs).

The purpose of this dissertation is to contribute design knowledge supporting the development of HC-HDSSs. To achieve results, the action design research method has been used to build, intervene in, and evaluate the designed HC-HDSSs in three iterations. Two main results are presented: 1) a prototype of HC-HDSSs, which serves as an example of HC-HDSSs; and 2) five design principles concerning how HC-HDSSs should be developed.

Keywords: Decision support system, Decision making, Decision-making, Hybrid system, Human–machine hybrid, Human-centered, Human-centered AI, Design science research, Action design research, Design principle, Multi-grounded theory

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ABBREVIATIONS

ADR	Action Design Research
AI	Artificial Intelligence
AR	Action Research
BIE	Building, intervention and evaluation
BPMN	Business Process Modeling Notation
DDI	Data-Driven Innovation
DP	Design Principle
DR	Design Research
DSR	Design Science Research
DSS	Decision Support System
FEDS	a Framework for Evaluation in Design Science
GTM	Grounded Theory Method
HCAI	Human-Centered AI
HCI	Human Computer Interaction
HC-HDSS	Human-Centered Hybrid Decision Support System
IS	Information Systems
ISDT	Information Systems Design Theory
IT	Information Technology
MGT	Multi-Grounded Theory
UML	Unified Modeling Language

CHAPTER 1

INTRODUCTION

This is a Design Science Research (DSR) dissertation that investigates how to design digital systems supporting humans in managerial decision-making[1]. These digital systems are labeled decision support systems (DSSs). The study is positioned in the Information Systems (IS) field. The purpose of this first chapter is to introduce the research background (in section 1.1) and research problem (in section 1.2), to present the research aim, research question, and scope of the study (in section 1.3), and to illustrate the structure of the remaining part of the dissertation (in section 1.4).

1 In this dissertation, "managerial decision-making" ("decision-making" for short) is defined as a process of identifying a problem or opportunity, framing the particular choice, comparing the alternatives, and selecting one (Simon, 1977, p. 40).
The term "decision-making" has no uniform definition because studies of decision-making are spread over a diverse set of disciplines. There are decision-making studies in economics (e.g., Kahneman, 2011), management science (e.g., Simon, 1977), cognitive psychology (e.g., Hastie & Dawes, 2010), informatics or information systems (e.g., Arnott & Pervan, 2005), and computer science (e.g., Power & Sharda, 2007), etc. In these different fields, decision-making is studied from different points of view to serve the aforementioned specific fields. This study is about managerial decision-making, and therefore applies the definition from management science.

1.1 BACKGROUND

We are witnessing revolutionary change as digital systems are becoming increasingly intelligent. This dramatically changes how organizations are managed.

Historically, digital systems have been widely used in organizations to support humans in making managerial decisions. These digital systems are often known as DSSs (Arnott & Pervan, 2005; Arnott & Pervan, 2014; Aronson et al., 2005, p. 15; Di Vaio et al., 2022; Meski et al., 2021). In the 1970s, DSSs were designed to support individual managers' decision-making (e.g., Mills et al., 1977); in the 1980s, individual support was extended to support groups of managers (e.g., Pinsonneault & Kraemer, 1989). In the 2000s, there were studies of the creation, transfer, and application of organizational knowledge to support managers' decision-making (e.g., Burstein & Carlsson, 2008).

Along with technological advances, such as data mining and machine learning, DSSs are becoming more advanced and intelligent[2] (Aronson et al., 2005, p. 15; Cognizant, 2017). In recent years, there has been a significant increase in studies of DSSs that apply artificial intelligence (AI) (e.g., Di Vaio et al., 2022; Meski et al., 2021). AI, which stands in contrast to human intelligence (De Cremer & Kasparov, 2021), is defined as "the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity" (Rai et al., 2019, p. iii).

Gradually, the boundary is blurring between DSSs applying AI and digital systems that can automatically make decisions (e.g., Romanov et al., 2023). Digital systems applying AI are designed to imitate human intelligence in order to make decisions like humans (i.e., increasing the systems' capability of making autonomous decisions). These digital systems make decisions based on prewritten algorithms or programs and learning ability (also known as machine learning) without the involvement of human decision-makers. Meanwhile, these systems are expanding into new fields where decisions were previously made by humans. For example,

2 Digital systems are developed by utilizing different types of technologies.

in March 2021, a proposal to the Minister for Civil Affairs in Sweden suggested applying automated decision-making in municipalities and regions (Höglander, 2021). The purpose was to take advantage of the efficiency that exists in digital working methods and tools.

Consequently, on one hand, digital systems are becoming increasingly intelligent. These systems are thought to be superior to humans in decision-making in some areas (Baxter & Sommerville, 2010; Borst, 2016; van den Broek et al., 2021; Zarsky, 2016). Developments of digital systems that support decision-making open up new fields for applications. On the other hand, advanced and intelligent digital systems that try to mimic humans also create a fear that these systems could replace humans when making decisions in the future. For instance, Jarrahi (2018, p. 577) stated that AI "has penetrated many organizational processes, resulting in a growing fear that smart machines will soon replace many humans in decision-making." The increased use of machine learning in society causes anxiety, as it results in less dependence on human judgment (Coglianese & Lehr, 2016).

Now is the time to rethink how we approach issues of humans and technologies, because technologies augment human capabilities but also can cause confusion and limit human ability (e.g., learning ability) (Bannon, 2011). Humans should explore "new forms of living with and through technologies that give primacy to human actors, their values, and their activities" (Bannon, 2011, p. 50).

1.2 PROBLEM FORMULATION

This study is grounded in both practice and research. It starts with a problem related to the use of DSSs in practice. This problem is then developed into a research problem based on earlier research. The identified research problem is a lack of design knowledge[3] of Human-Centered Hybrid Decision Support Systems (HC-HDSSs). The following sub-sections follow the problem formulation journey.

3 Design knowledge is knowledge of design; for more information, see section 4.1.1.

1.2.1 THE STARTING POINT OF THE STUDY

This study was conducted as a part of a larger research project called Data-Driven Innovation: algorithms, platforms and ecosystems (DDI)[4]. The project was initiated in 2016 and was hosted by the University of Borås. The project consists of both university researchers and practitioners. Practitioners came from the information technology (IT) departments of several Swedish organizations. The participating organizations use a variety of DSSs for several purposes, for instance, to save organizational costs, improve the efficiency of employees, and/or increase productivity.

A problem related to using DSSs was perceived in a series of DDI project meetings and workshops involving both practitioners and researchers. There were expressions from DSS users indicating that they sometimes had concerns about the digital systems' or machines' (suggested) decisions. For instance, one representative shared his thoughts and stated that "sometimes we don't trust [the decisions made by] machines." Many other participants agreed, preferring the decisions made by humans.

The perceived problem stimulated the author's interest in exploring further. Two additional meetings with representatives of two case organizations[5] were arranged. The purpose of both meetings was to collect more information that could help elaborate on the above-mentioned expressions. In one meeting, the representative gave more details about using DSSs in the organization and clarified that he/she and many other colleagues did not want to rely only on existing digital systems when making decisions. To some extent, they still relied more on human experts' experience and expertise (i.e., human capability). In the second meeting, one practitioner confirmed that humans have important knowledge for making decisions, and that it is problematic if one relies solely on existing digital systems for making managerial decisions.

4 The DDI project consists of three sub-projects. This study is part of sub-project two, which "seeks to advance requirements engineering for digital platforms supporting service innovation, through a qualitative and semi-automated approach that includes collecting and analyzing data from databases and human experts" (the quotation comes from the project application).

5 For more details of the two case organizations, see section 4.3.

The results of the above two meetings can be summarized as follows: DSSs users have concerns about the decisions supported by existing DSSs, and they expect human capabilities to be utilized in DSSs. In what follows, the relevant literature is reviewed to understand this problem from a more theoretical perspective.

1.2.2 THE IDENTIFIED DESIGN PROBLEM

Research outlines the capabilities of DSSs or the so-called machine (actors) examined in this study;[6, 7] for example, they can be efficient and effective (van den Broek et al., 2021) and be continuously upgradable in memory, algorithms, and computing ability (Sotala, 2012). However, there is an over-emphasis on the capabilities of DSSs or machines that ignores human capabilities (i.e., the "important knowledge" or "experience and expertise" mentioned above by practitioners). This one-sided design approach is problematic since it leads to a situation where practitioners think that existing DSSs are not good enough (Dellermann et al., 2019b; Demartini, 2015; Jensen et al., 2011; Reeves & Ueda, 2016).

Furthermore, about 30 years of research shows that DSSs do have weaknesses. This study identifies these weaknesses, and classifies them into three groups.[8] The first group of weaknesses concerns the fact that the outcome of DSSs relies on input data (quality and types) and data analy-

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6 This study treats DSSs as machine actors ("machines" for short) when discussing their capabilities or weaknesses in decision-making; in contrast, humans are regarded as human actors. This is aligned with several studies of human–machine hybrid systems (e.g., Demartini, 2015, Demartini et al. 2017), which will be introduced in section 1.2.2.1.

7 This study identifies the capabilities and weaknesses of machines from studies of digital systems related to decision-making. These studies include but are not limited to discussing DSSs. As mentioned in the background section, the boundary between DSSs applying AI and digital systems that can automatically make decisions is blurring. Studies of digital systems using AI to support humans in making decisions may not use the term DSSs. Therefore, searching for studies of digital systems related to decision-making provides a broader base.

8 The list of weaknesses presented in this study is not exhaustive. There may be other weaknesses of existing DSSs. As mentioned below, one focus of this study is human–machine hybrid systems. Therefore, the discussed weaknesses (and capabilities) are identified from studies of hybrid systems related to decision-making.

sis algorithms (i.e., the first weakness of machines in decision-making).[9] Digital systems provide insights or predictions to support human decision-making. However, the outcome provided by these digital systems is based on the algorithms used to analyze large volumes of data (Kulkarni et al., 2017; Lyytinen et al., 2017). The outcome also relies on what type of data can be collected and the quality of the collected data (Demartini, 2015).

The second group of weaknesses concerns the fact that DSSs cannot acquire tacit knowledge (human expertise and experience learned in context) (i.e., the second weakness of machines in decision-making). Studies show that important knowledge and competencies that affect decision-making are not represented in existing digital systems (e.g., Borst, 2016; Demartini, 2015, Demartini et al. 2017; Kahneman, 2011). Such knowledge and competence are not based on technical algorithms or mathematical calculations of large volumes of data. Instead, they exist in organizational structures, personal memories, and cognitive thought patterns (Göranzon, 2009). This knowledge is often based on professional experiences, personal reflections, branch-specific events, contextual factors, relationships with other involved actors, and organizational culture (Göranzon, 2009). This knowledge can be regarded as tacit knowledge.[10]

The third group of weaknesses concerns the fact that existing DSSs introduce unwanted ethical issues (i.e., the third weakness of machines in decision-making). For example, digital systems give decision suggestions, usually without explaining the reasons behind the systems' calculation or analysis (Shollo et al., 2015). This can gradually limit human learning ability (Shollo et al., 2015). Digital systems (suggested) decisions may, for example, lead to price or service discrimination against some customer groups (Newell & Marabelli, 2015) as well as to gender discrimination in organizational recruitment (Dastin, 2018).

These three groups of weaknesses of DSSs or machines together help explain practitioners' ongoing worries about relying solely on digital systems that ignore human decision-making capabilities (e.g., tacit knowledge).

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9 For details of machines' weaknesses in decision-making, see section 3.2.

10 More details of tacit knowledge are introduced in section 2.1.2.

1.2.2.1 INVESTIGATING A POSSIBLE SOLUTION

Peer-reviewed papers have been investigated for a possible solution to reduce or mitigate the three groups of weaknesses of machines in decision-making and the one-sided design approach. The solution takes into account two aspects, i.e., designing "hybrid" and "human-centered" DSSs. "Hybrid" indicates that the two groups of weaknesses of machines are addressed, whereas "human-centered" indicates the aim of overcoming the third group of weaknesses.

First, designing human–machine hybrid DSSs that utilize both human and machine capabilities in decision-making has the potential to address the above two groups of weaknesses of machines[11] (i.e., reliance on input data and data analysis algorithms, and inability to acquire tacit knowledge). Some studies have called for the design of human–machine hybrid systems (Demartini, 2015; Demartini et al., 2017; Kamar, 2016), or the like, which will bring "a great opportunity to develop systems that are more powerful than purely machine-based ones" (Demartini, 2015, p. 5). Humans and machines do not have the same capabilities (e.g., Simon, 1978). Humans and machines can be complementary (e.g., Kamar, 2016; Reeves & Ueda, 2016; Simon, 1955; Zheng et al., 2017)[12] or cooperate in human–machine symbiosis (Jarrahi, 2018; Licklider, 1960). Specifically, in human–machine hybrid DSSs, utilizing human capabilities could compensate for machines' weaknesses, for example, reliance on input data (quality and types) and data analysis algorithms and inability to acquire tacit knowledge (i.e., human expertise and experience learned in context). Besides, utilizing machines' capabilities, for example, being efficient and effective when processing large amounts of data (Ghasemaghaei et al., 2018; Hardin et al., 2017; Kulkarni et al., 2017) and being continuously upgradable in memory, algorithms, and computing ability (Sotala, 2012), could compensate for human weaknesses (more details are given in section 3.3).

11 For more details, see section 2.3.

12 Reeves and Ueda (2016) specified that machine capabilities need to be combined with human intelligence in an integrated strategy machine. According to Zheng et al. (2017), humans' cognitive capabilities or human-like cognitive models should be integrated into AI systems, i.e., human–computer collaborative hybrid-augmented intelligence.

Second, giving primacy to human actors, i.e., designing human-centered hybrid DSSs, has the potential to address another weakness of machines, namely, the introduction of unwanted ethical issues. There are suggestions for designing human-centered AI systems or using a human-centered approach to designing AI systems, i.e., human-centered AI (HCAI) (Auernhammer, 2020; Shneiderman, 2020; Xu, 2019; Xu et al., 2023). HCAI aims to amplify humans instead of eroding them (Shneiderman, 2021). In other words, HCAI is intended to "enhance humans rather than replace them" (Xu, 2019, p. 43), leaving humans as the final decision-makers. Therefore, the notion of HCAI provides a possible solution for the "ethical dilemmas now arising in the machine-learning space" (Shneiderman, 2021, p. 57).

Additionally, the suggestions for HCAI embrace the notion of a human–machine hybrid, or human–machine symbiosis, that utilizes the complementary capabilities of humans and machines. In an HCAI framework proposed by Auernhammer (2020, p. 1328), the relationship between humans and technology is labeled "human–technology symbiosis development" (i.e., the development of human–machine hybrid). Similarly, another HCAI framework proposed by Xu et al. (2023, p. 7) implies "integrating human roles into human–machine systems … taking complementary advantages of machine intelligence and human intelligence," i.e., human-controlled hybrid intelligence. Xu et al. (2023, p. 10) advocated that "hybrid intelligence must be developed in a context of 'human–machine' systems by leveraging the complementary advantages of AI and human intelligence."

Therefore, this dissertation proposes designing a type of digital system that is human-centered and utilizes the complementary capabilities of humans and machines in decision-making as a solution to deal with all three identified weaknesses of machines in decision-making and of the one-sided design approach. This study calls these digital systems human-centered hybrid decision support systems (HC-HDSSs). HC-HDSSs are defined as DSSs designed to be human-centered and to utilize the complementary capabilities of humans and machines in decision-making (for more details, see section 3.3).

1.2.2.2 IDENTIFYING THE LACK OF DESIGN KNOWLEDGE FOR THE PROPOSED SOLUTION

Existing studies have been scrutinized for the proposed solution of designing HC-HDSSs. There are studies of DSSs using the term "hybrid." However, the term as used in those studies refers to DSSs that integrate one or more algorithms or data analysis strategies to support human decision-making in solving a single problem, usually a complex decision task (e.g., Bijan & Rustam, 2001; Wang & Benbasat, 2009). In short, "hybrid" in those studies refers to the fusion of different technologies (e.g., algorithms or data analysis strategies). That is, each form of technology has certain advantages and disadvantages; by integrating them, one technology can provide advantages to mitigate the disadvantages of other technologies used in a digital system (Aronson et al., 2005, p. 26).

Moreover, in the last decade, studies using the concept "hybrid" have tried to combine the capabilities (i.e., advantages) of machines with those of humans.[13] Some of these studies are not related to decision-making or DSSs. For example, Dellermann et al. (2019a, 2021) investigated human–artificial hybrid intelligence systems in general and tried to conceptualize what hybrid intelligence and hybrid intelligent systems are. Demartini (2015) and Demartini et al. (2017) investigated hybrid systems by crowdsourcing human intelligence at scale and using computer-based algorithms for a large volume of data to improve the efficiency and effectiveness of data processing. Demartini's two studies consider aspects such as the opportunities and challenges of developing such hybrid systems (Demartini, 2015) and presenting several types of such systems (Demartini et al., 2017) instead of providing any guidance in designing hybrid DSSs. Similarly, van der Aalst (2021) investigated hybrid intelligence systems in business process management but did not focus on decision-making, DSSs, or detailed design guidance.

Several studies using the concept "hybrid" are related to decision-making or DSSs. For instance, Jensen et al. (2011) built a human–computer hybrid system to increase credibility assessment accuracy. The system uti-

13 There were only a few studies of hybrid systems early on in the present research, i.e., in 2017 and 2018, but more have been published since 2019. More details of hybrid systems are provided in section 2.3.

lizes computer-based automated analysis for the structure and content of messages and human observers' perceptual information for those indirect cues that are difficult for computers to analyze. In other words, the hybrid system they built could "perform automated linguistic analysis" and also "elicit and analyze perceptual cues from a human observer" (Jensen et al., 2011, p. 202). They used a controlled laboratory experiment to test the proposed theory-based hypotheses instead of providing any design principles (DPs).[14] Van den Broek et al. (2021) also conducted a DSS study concerning the hybrid of human domain expertise and machine learning, supporting the hiring of job candidates. As an ethnographic study, it does not aim to provide any design guidance.

Furthermore, two studies have tried to provide design guidance in specific fields. Dellermann et al. (2019b) formulated design principles for hybrid DSSs to support managers in making business model design decisions. The proposed DSS supports assessing the validity of managers' assumptions as to business models in early-stage start-ups (i.e., a context with high uncertainty and complexity). The system they designed combines the complementary capabilities of humans and machines, i.e., combining the strength of machines in handling a large amount of information with humans' intuition and creative potential. Dellermann et al. (2019b) provided guidance on how to design such a hybrid DSS, but this guidance applies to the specific context of supporting the assessment of business models in early-stage start-ups. Similarly, Cronholm and Göbel (2022) formulated design principles for designing human–artificial hybrid intelligence to facilitate decision-making in solving complex problems in return management in the retail sector.

Additionally, two studies have tried to provide overall guidance, instead of detailed design guidance, for designing hybrid systems related to decision-making or DSSs. Shrestha et al. (2019) presented two hybrid forms integrating AI into organizational decision-making. Another by Trunk et al. (2020) introduced a conceptual framework that concerns the possibilities of integrating AI into strategic decision-making in organizations.

The above examples provide a sound knowledge base concerning the need to design human–machine hybrid DSSs. However, the research does

14 For design principles (DPs), see section 4.1.1.

not cover the entire range of hybrid DSSs. As stated by Becker et al. (2015, p. 10), "integrating human and machine problem solving" is the second ranking out of 21 challenges relating to integrating the social and technical aspects of system design and use. Moreover, Rai et al. (2019) called for "human–AI hybrids" as next-generation digital platforms. Eriksson-Zetterquist et al. (2020) stated that human actors should "remain an irreducible component of decision-making in the socio-economic realm."

Besides, there is a lack of studies of the design of HC-HDSSs. For example, Xu (2021) claimed that Zheng et al.'s (2017) human–computer collaborative hybrid-augmented intelligence is still a technology-centered design. Similarly, Ostheimer et al.'s (2021) hybrid intelligence systems focus on improving machine-learning algorithms. Dellermann et al. (2019a) pointed out that humans should still be the focus while being augmented by decision capabilities via machine intelligence. Xu et al. (2021) also stated that most of the proposed HCAI approaches take place at a high level. These statements imply that there is still a gap between implementing the proposed solution and existing scientific studies. Specifically, there is a lack of exhaustive support for leveraging the combined capabilities of humans and machines in DSSs. Moreover, there is a specific lack of design knowledge concerning the human-centered design of such digital systems. Consequently, there is a need to identify design knowledge helping researchers and practitioners to develop HC-HDSSs. The problem is summarized as *there is a lack of design knowledge for human-centered hybrid decision support systems*.

1.3 THE RESEARCH AIM, RESEARCH QUESTION, AND SCOPE

This study aims to identify and present knowledge of how to design HC-HDSSs. This design knowledge will provide a solution to the identified problem, i.e., a lack of design knowledge for human-centered hybrid decision support systems. This design knowledge can narrow the gap between expectations of HC-HDSSs and concrete guidelines, leading to a human-centered design that utilizes the complementary capabilities of humans and machines to support humans in making managerial decisions.

Therefore, the research question is formulated as: *How should human-centered hybrid decision support systems be designed?*

The research question is answered in the design knowledge for HC-HDSSs. This design knowledge will consist of two main parts: the lower abstracted design knowledge in the form of a HC-HDSS prototype, and the higher abstracted design knowledge in terms of the goal, meta-design, and five design principles of HC-HDSSs.[15] The prototype, an HC-HDSS instantiation that emerged in the design process, can be developed into a fully fledged tool in the case organizations. By following the goal, meta-design, and design principles, researchers and practitioners could develop other instances of the HC-HDSS class, i.e., other contextualized HC-HDSSs.

The effort made to answer the research question and achieve the research aim sets the delimitations of the dissertation, i.e., the scope of the study. One delimitation is that the study was conducted in one context, i.e., the ITSM (IT service management) context.[16] That is, the HC-HDSS prototype was built and evaluated in an ITSM context, as were the formulated design principles of HC-HDSSs. In other words, the answer to the research question is applicable in the ITSM context. Due to time limitations, the design principles were not evaluated in a context other than ITSM through building other instances of the class of systems. However, as illustrated in the section on external validity (section 10.2.2), generalization of the design knowledge to the HC-HDSS class goes beyond the ITSM context. The design knowledge formulated in this study is intended to support the design of HC-HDSS not only in the ITSM context, but more generally as well. This study tried to formulate the goal, meta-design, and design principles to be as general as possible for the HC-HDSS class. Nevertheless, future research concerning the application and evaluation of the formulated design knowledge in different contexts would be worthwhile.

Another delimitation concerns the theories used in designing the HC-HDSSs. Theories have been selectively used in building the prototype and formulating design principles of HC-HDSSs. Although a given

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15 The design principles, meta-design, and goal will be introduced in section 4.1.2.

16 More details are given in section 4.3.

HC-HDSS should be usable by more than one human (for more details, see chapter 6), theories of group DSSs that focus on the communication between humans located in different places (Arnott & Pervan, 2005, 2014; Aronson et al., 2004) are not considered here. This is because, first, the focus of this study is the hybrid of human and machine capabilities in decision-making instead of the communication between humans located in different places. Second, HC-HDSSs supporting more than one human emphasize utilizing a group of human capacities in decision-making, i.e., knowledge. Therefore, theories of knowledge creation and sharing are prioritized by this study.

1.4 STRUCTURE OF THE DISSERTATION

The remaining part of this dissertation is structured as follows:

Chapter 2 provides this study's theoretical foundation, which consists of theories identified from reference disciplines and the IS discipline. These are theories of human decision-making (in section 2.1), DSSs (in section 2.2), hybrid systems (in section 2.3), and HCAI (in section 2.4). The identified theories have been used to formulate the research problem and question and to design HC-HDSSs.

Chapter 3 elaborates on the proposed solution to the identified problem of designing HC-HDSSs. It first presents this study's identification of the capabilities and weaknesses of humans and machines in decision-making. Based on that, this chapter goes on to explain what "hybrid" and "human-centered" mean in the proposed solution.

Chapters 4 and 5 cover the research approach, methods, and implementation. Chapter 4 presents: the dissertation's philosophy, i.e., the DSR paradigm; the primary research method (i.e., the action design research method); and other supplementary methods or frameworks, such as the FEDS framework for formulation evaluation strategy, qualitative methods for data collection, and data analysis. Chapter 5 provides details on how this study was conducted, mainly following the four phases and seven principles of the ADR method and supplemented with other methods.

Chapters 6 to 9 are the contributions of the study. Chapter 6 gives descriptions of the HC-HDSS prototype (which is one contribution to design knowledge). Chapters 7, 8, and 9 elaborate on another contribution: the formulated goal, meta-design, and design principles of HC-HDSSs. These three chapters present how design knowledge emerged and was revised in three building, intervention, and evaluation iterations, respectively, and how design principles guided the design of the HC-HDSS prototype.

Chapter 10 concludes the dissertation with a summary of the study's contributions, an elaboration on the internal and external validity of the study, and a consideration of ethical considerations and future research opportunities.

CHAPTER 2

THEORETICAL FOUNDATION

This chapter presents the theoretical foundations of the dissertation. The selected theories[17] are from the IS field and reference disciplines such as management science, computer science, and psychology. They are arranged as follows. Section 2.1 focuses on the human actors and presents the selected theories of human decision-making. Section 2.2 focuses on the machine actors, i.e., the selected decision support system (DSS) theories. Section 2.3 brings humans and machines together and presents relevant studies of hybrid systems. Section 2.4 illustrates the theories of HCAI. The details of how the theories emerged and have been used in designing HC-HDSSs are elaborated on in chapters 7, 8, and 9.

17 The term "theory" is used to refer not only to fully developed (also full-blown, full-fledged) theories but also to partial or nascent theories (Gregor & Hevner, 2013; Jones & Gregor, 2007).

2.1 HUMAN DECISION-MAKING

To design HC-HDSSs, it is crucial to investigate how humans make decisions (Adam, 2012). Theories of human decision-making can be normative or descriptive. Normative decision theories are theories about how a decision should be made in order to be rational (Elliott, 2019; Hansson, 1994). For instance, a decision-maker is regarded as rational and can collect information for all options, evaluate them by analysis or calculation, and finally select the optimal one with maximum utility.[18] In contrast, descriptive decision theories, which have been in the mainstream of managerial decision-making[19] since the Second World War (Eriksson-Zetterquist et al., 2020, p. 194), explore how a decision is actually made or how humans actually make decisions. As a representative example, in management science, Simon (1972) viewed decision-makers as boundedly rational instead of rational, which means that decision-makers do not select the optimal option or the one with maximum utility; rather, they usually select the one that they find most satisfactory[20] (March & Simon, 1958, p. 162). In other words, humans have the "ambition to act rationally but factually [are] only … able to do so partially, at best" (Eriksson-Zetterquist at al., 2020, p. 212).

Kahneman (2011) views humans as having two cognitive patterns for decision-making, System 1 and System 2. In System 1, humans apply their intuition. It is a process that is automatic, unconscious, and effortless. Humans make decisions quickly through associations and resemblances. These decisions are made non-statistically and heuristically (Kahneman, 2011). In contrast, System 2 is what economists regard as thinking: it is conscious, slow, controlled, deliberate, effortful, statistical, suspicious, and lazy (i.e., costly to use). If a human can quickly reach a decision, applying

18 Utility is a subjective value assigned by a decision maker to each alternative or option of a decision problem (Elliott, 2019).

19 Based on what Simon said in his Nobel memorial lecture in 1977, Adam (2012, p. 97) stated that the rational view of decision-making is not useful in understanding managerial decision-making. In contrast, other models, such as intuition and bounded rationality, appear to be "the most suitable for understanding how managers apprehend the world."

20 Humans have criteria with which to decide whether an alternative is satisfactory (Campitelli & Gobet, 2010).

only System 1 is enough. If System 1 turns out not to be working well or the human cannot make a quick decision, he/she will use System 2 to analyze the information at hand and collect more information to evaluate options and make a decision, i.e., analytical decision-making. Besides, according to Kahneman (2011), that humans can use System 2 does not mean that System 2 is used in isolation. Humans combine the use of both systems, and the input of System 2 often comes from the output of System 1.

As illustrated by Kahneman's System 1, humans apply intuition in decision-making, i.e., intuitive decision-making. Sadler-Smith and Shefy (2004, p. 81) defined intuition as "a form of knowing that manifests itself as an awareness of thoughts, feelings or bodily sense connected to a deeper perception, understanding, and way of making sense of the world that may not be achieved easily or at all by other means." Intuitive decision-making refers to using intuition, not rational analysis, in a decision-making process. It is a process neither magical nor irrational. On the contrary, applied intuition can be grounded in knowledge and experience (Barnard, 1938). Humans, especially experts in specific fields, gain knowledge of many patterns through their long experience. This knowledge of patterns is stored in human memory and can be extracted rapidly to make decisions (Simon, 1978).

While humans apply intuition to make decisions, they make their decisions relying on heuristics (Dane & Pratt, 2007; Tversky & Kahneman, 1974). As this study does not aim to investigate heuristics further, only one selected definition of the application of heuristics is provided. The application of heuristics is "a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods" (Gigerenzer & Gaissmaier, 2011, p. 454). It is a cognitive process. This ignoring of part of the information can be conscious or unconscious (Gigerenzer & Gaissmaier, 2011).

Kahneman's two cognitive systems focuses on individual decision-making. In contrast, decision-making in an organization[21] can be viewed as a

21 As stated at the beginning of this dissertation, the notion of decision-making is applied here in a specific organizational context, i.e., Swedish companies, and specifies decision-making in IT service management activities (for more details, see section 4.3).

process instead of a single moment of deciding (Simon, 1977, p. 40).[22] This process consists of four principal phases: intelligence, design, choice, and review. In the first phase, intelligence, a manager as the decision-maker identifies a problem or opportunity by gathering information from the environment. In the second phase, design, the decision-maker frames the particular choice in a particular context. In the third phase, choice, the decision-maker compares the alternatives and selects one. The fourth phase, review, assesses past choices made in phase three. Generally, the four phases are conducted sequentially. However, actual decision-making processes can be more complex, as each of the first three phases may itself include another complex decision-making process.

Based on the four-phase view, Simon (1977) pointed out that many studies focus on the third-phase choice, but the first two phases, intelligence and design, actually require more energy and time. This study is aligned with the process view that decision-making in organizations is a thought process of deciding or selecting that consists of four phases (i.e., intelligence, design, choice, and review). The major output of the thought process is the decisions made.

2.1.1 THE VIEW OF KNOWLEDGE AND KNOWLEDGE TYPES

Knowledge is important in decision-making. This study adopts two mainstream views of knowledge in IS. One mainstream view distinguishes between data, information, and knowledge (e.g., Krumay et al., 2019; Schacht et al., 2015). According to this hierarchical view, data are raw numbers and facts, whereas information is processed data. Knowledge, finally, is authenticated information (Miragliotta et al., 2018). In other words, knowledge is "information possessed in the mind of individuals: it is personalized information (which may or may not be new, unique, useful, or accurate) related to facts, procedures, concepts, interpretations, ideas, observations, and judgments" (Alavi & Leidner, 2001, p. 109).

22 Simon is a pioneer of studying human–computer decision-making. His decision-making process considers managerial decision-making in the background of the advancement of digital systems (i.e., "machines" in this study), which suits the emphasis of this study on the human–machine hybrid in decision-making.

Another mainstream view, generally adopted by scholars who study digital systems for organizational knowledge management, distinguishes knowledge as tacit and explicit (Nonaka, 1991), the "tacit" and "explicit" components of knowledge (Polanyi, 1958, 1966), or the tacit, implicit, and explicit components of knowledge (Grant, 2007). The Tacit (component of) knowledge is a "cumulative store of the experiences, mental maps, insights, acumen, expertise, know-how, trade secrets, skill sets, understanding, and learning that an organization has, as well as the organizational culture that has embedded in it the past and present experiences of the organization's people, processes, and values" (Aronson et al., 2005, p. 493). It is highly personal and difficult to capture and formalize. In contrast, the explicit (component of) knowledge is recorded and documented, for example, in filed, organizational documents such as white papers and reports. Not all tacit components can be explicit (Grant, 2007). Digital systems can help make some tacit components more explicit, i.e., implicit (component of) knowledge (Grant, 2007).

This study uses the term "knowledge" in a business organizational context, referring to the knowledge required or applied when making managerial decisions. In summary, on one hand, the knowledge required for decision-making has two sources: 1) decision-makers' expertise and experience, i.e., the knowledge that is vital for the decision task and gained before carrying out a particular decision task; 2) knowledge obtained by decision-makers that is generated from the information given by DSSs through analyzing data (i.e., taking the data, information, and knowledge view). On the other hand, decision-makers' knowledge used in making decisions consists of three components: tacit, implicit, and explicit. The tacit component of knowledge can partly (i.e., the implicit component) be transformed to be explicit. In the remainder of the dissertation, "explicit knowledge" will be used to refer briefly to the "explicit (component of) knowledge"; the same formulation applies to tacit and implicit knowledge.

2.1.2 KNOWLEDGE CREATION AND KNOWLEDGE SHARING

While distinguishing knowledge as tacit, implicit, or explicit, there exists interaction between implicit and explicit knowledge (Nonaka, 1994),[23] which is related to the four modes of knowledge creation (Nonaka & Takeuchi, 1995). Knowledge creation refers to the generation of new insights, ideas, or routines. Table 2.1 lists the four modes of knowledge creation based on the studies of Nonaka and Takeuchi (1995) and Alavi and Leidner (2001). These four modes are highly interdependent and intertwined (Nonaka & Takeuchi, 1995).

The first mode is called *socialization*, representing the conversion of implicit knowledge into new implicit knowledge through social interactions and shared experiences between individuals. For example, there is a project in an organization. Individual B (B for short) observes the behavior of individual A (A for short) during a break from one project meeting, in which B gets to know more about the organizational culture (e.g., the relationships between several decision-makers of the project). Through this socialization, B gains some of A's implicit knowledge. The second mode is called *combination*, referring to the combination of existing explicit knowledge with new explicit knowledge. For instance, A summarizes and documents the project, i.e., A's explicit knowledge. B documents his/her reflections of the project, i.e., B's explicit knowledge. While B shares his/her document with A, A combines it with his/her own summary document, and vice versa. The third mode is called *externalization* and refers to transforming implicit knowledge into new explicit knowledge. For example, A documents his/her reflections on a project. This process illustrates the externalization of A's implicit knowledge to become explicit knowledge. The fourth mode is *internalization*, which refers to the transformation of explicit knowledge into new implicit knowledge. For example, A presents his/her summary in a project meeting. As a participant in the meeting, B learns from what A presents, i.e., B internalizes some (if not all) of A's explicit knowledge to become his/her implicit knowledge.

23 Nonaka (1994) and Nonaka and Takeuchi (1995) view knowledge as only tacit and explicit, i.e., the interaction considered in their studies is between tacit and explicit knowledge. Their studies do not go on to distinguish implicit from tacit knowledge. However, based on what has been pointed out by Grant (2007), the present study uses "implicit" to specify the knowledge component that can be changed or transformed to be explicit.

Table 2.1. Four modes of knowledge creation.

Four modes	Detail	Example
Socialization	From implicit to implicit	B observes and learn A's behavior (e.g., related to organizational culture)
Combination	From explicit to explicit	B shares a document with A, which is combined with A's document.
Externalization	From implicit to explicit	A documents his/her reflections on a project.
Internalization	From explicit to implicit	B learns more about the project by reading A's document.

The knowledge creation modes imply knowledge sharing between individual humans; for example, in the combination mode, there is a knowledge sharing between A and B. Knowledge sharing is affected by organizational culture. There are several studies in this field.[24, 25] Natu and Aparicio (2022) conducted a study to facilitate decision-making processes regarding knowledge sharing within companies. They pointed out that organizational culture plays a crucial role in knowledge sharing because it affects the knowledge-sharing process among knowledge workers. Nisar et al. (2021) investigated big data decision-making capabilities and decision-making effectiveness. They pointed out that organizational culture is vital to improving decision quality. Specifically, organizational culture, together with other aspects such as decision-making capabilities, "significantly contribute toward decision-making effectiveness" (Nisar et al., 2021, p. 1070). Briggs et al. (2008) studied the impacts of organizational culture and personality traits on decision-making in technical organizations. They stated that the nature of the individuals in the group, as well as the culture of the group, heavily impact the decision process and the outcomes. The character and culture of the organization must be considered at the group level because they describe and define "how the group arrives at and accepts

24 This dissertation does not aim to investigate this comprehensively. Instead, it introduces several studies that are relevant to design and will be used as a theoretical basis for formulating the design principles of HC-HDSSs.

25 More details will be given in the building, intervention, and evaluation chapters concerning the formulation of design principle one.

decisions, responds to individual behaviors, and reacts to stresses and challenges" (Briggs et al., 2008, p. 21).

In summary, this section illustrates the adopted descriptive theories of human decision-making, that is: 1) humans use both System 1 and System 2 in making complex decisions, and accompanying these two systems are humans applying their intuitions and knowledge; 2) humans do not make optimal decisions but satisfying ones; and 3) humans follow a decision-making process when making managerial decisions. This dissertation will continue by examining the machine actors in the following section, i.e., decision support systems.

2.2 DECISION SUPPORT SYSTEMS

This section presents studies of DSSs; these studies will be drawn on in defining HC-HDSSs, building the HC-HDSS prototype, and/or formulating the design principles of HC-HDSSs.

The term "decision support system" was first used by Gorry and Scott Morton (1971) for digital systems supporting humans making semi-structured and unstructured decisions (Hosack et al., 2012; Keen & Scott Morton, 1978). Following Gorry and Scott Morton, this term is beginning to be widely used in the IS field, broadly referring to all digital systems support humans make decisions (Aronson et al., 2005, p. 15). Consistent with Gorry and Scott Morton's use, Shim et al. (2002) defined DSSs as computer technology solutions that can be used to support complex decision-making and problem solving. It refers to support for poorly structured and poorly understood solutions or problems, not to support for well-structured and easy problems.

There have been many studies on the design of DSSs since the 1970s. Mills et al. (1977) studied DSSs to support individual managers' decision-making. Pinsonneault and Kraemer (1989), DeSanctis and Gallupe (1987), and Poole and DeSanctis (1990) investigated DSSs to support a group of managers. Burstein and Carlsson (2008) worked on DSSs with a focus on creating, transferring, and applying organizational knowledge to support managers' decision-making. Specific to the ITSM context, a study elaborated on the role of DSSs in ITSM (Mora et al., 2014). Another study built a framework based on simulation modeling to support decision-making in ITSM (Orta et al., 2014). There was also a review on two specific DSS projects in the ITSM (Cater-Steel et al., 2016).

Some authors have explicitly highlighted their contributions as design knowledge[26] for DSSs since the DSR field or community was established in the 2000s.[27, 28] For instance, Beverungen et al. (2015) delivered a design theory for a class of DSSs that could support complex decisions concerning the reuse of electric vehicle batteries. Mackrell et al. (2014) developed an artifact within the conceptual framework of a data warehouse for the non-profit sector, to improve decisions and report performance; they created a set of guidelines for general use in such a sector. Miah et al. (2019) generated a meta-design for tailorable DSSs, i.e., tailoring DSSs in end-user contexts in an agricultural domain. To support decision-making in improving ITSM, Shrestha et al. (2013) and Shrestha et al. (2014b) developed a model to support selecting the most relevant process for improvement. Shrestha et al. (2014a, 2016) designed an approach to automate ITSM processes assessment.

Most of the DSS studies aim to improve decisions and/or decision-making processes instead of providing guidance on secondary design[29] (Miah et al., 2019; Hovorka, 2010). There is a lack of design knowledge "either in the form of generic meta designs or as design principles applicable to new instances of a specific class of DSS problems" (Miah et al., 2019, p. 571).[30]

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26 Concepts related to DSR, such as design knowledge, design theory, and meta-design, will be introduced in section 4.1.

27 DSR is regarded as an important strategy in studies of DSSs (Arnott & Pervan, 2012, 2014; Miah et al., 2016).

28 More efforts have been put into how DSR can be applied to study DSSs (Miah et al., 2016). For example, Miah and McKay (2016) formulated a DSR conceptualization for DSS design, including a set of design dimensions to address the relevance issue of DSS studies.

29 Developing technological rules is the primary design (Hovorka, 2010).

30 Arnott and Pervan (2012) identified that the focus of DSS research between 1990 and 2005 was on instantiations; therefore, they called for "significance attention" on theorizing in DSS studies for the next decades (p. 941). Similarly, Miah et al. (2016) called for more studies on the design knowledge or design theories of DSSs.
The present study also conducted a literature search of the "basket" of eight, the journal of DSSs and the journal of decision sciences, using a combination of keywords such as design principle, design knowledge, design theory, DSS, and decision-making. Only 34 records were identified as of 28 December 2022.

2.2.1 DECISION TYPES OF DECISION SUPPORT SYSTEMS

Gorry and Scott Morton (1971, p. 16, 1989) categorized decisions as structured, semi-structured, and unstructured based on Simon's two polar decision types, the decision-making process view, and Anthony's taxonomy of managerial activities (1965) (see Figure 2.1). First, Anthony (1965) distinguished between managerial activities in terms of strategic planning, managerial control, and operational control. Strategic planning is activities related to organizational objectives. It is "the process of deciding on objectives of the organization, on changes in these objectives, on the resources used to attain these objectives, and on the policies that are to govern the acquisition, use, and disposition of these resources" (Anthony, 1965, p. 24). Strategic planning decisions are usually made by a small number of high-level executives and are often predictions (Gorry & Scott Morton, 1989), for example, decisions for financial management or new product planning. Strategic decisions are characteristically non-repetitive and often very creative, which means there is no routine to follow. Managerial control is activities of managers ensuring that "resources are obtained and used effectively and efficiently in the accomplishment of the organizational objectives" (Anthony, 1965, p. 27) and is mainly concerned with people (Gorry & Scott Morton, 1989). Operational control is activities to ensure that "specific tasks are carried out effectively and efficiently" (Gorry & Scott Morton, 1989, p. 69), such as sales order processing or production scheduling. The major concern of operational control is tasks. A routine can often be followed for making operational control decisions.

Second, the pioneer Simon (1977, p. 45) identified two polar types of managerial decisions anchoring a continuum ranging from programmed to non-programmed decisions, borrowing the term "program" from computer science. Programmed decisions are repetitive and routine decisions. These decisions can be addressed using mathematical analysis, models, and computers. Non-programmed decisions refer to novel, unstructured, and unusually consequential decisions. These decisions have not been made before, are of a complex nature, or need customized treatment. In the early stage of their development, DSSs primarily support programmed, repetitive routine decisions. Along with the advance of information technologies, these systems can automate programmed decisions, and the decision support ability of DSSs is moving towards the non-programmed decision pole.

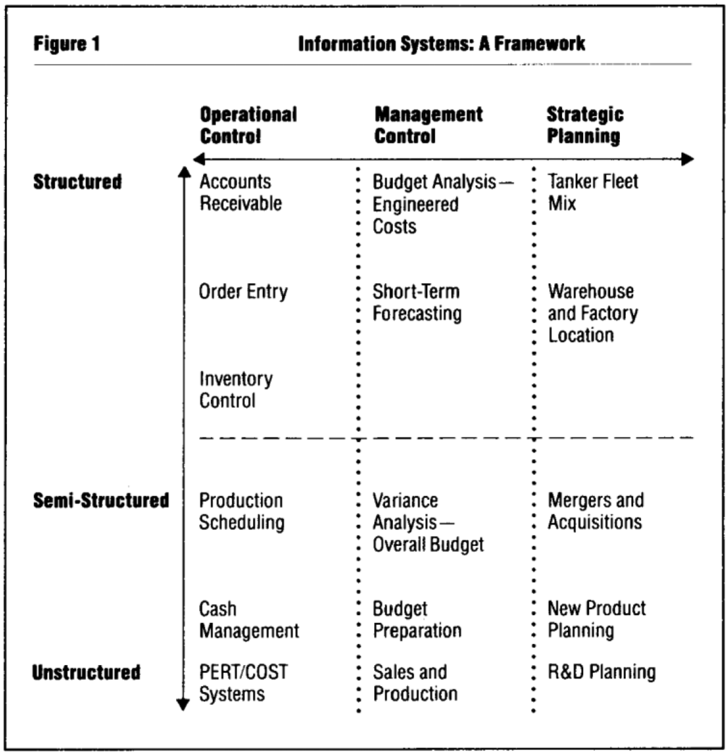

Figure 2.1. A framework of combined managerial activities and decision types (Gorry & Scott Morton, 1989).

In addition, Simon (1977, p. 40) viewed decision-making as a process encompassing intelligence, design, choice, and review. The first three phases are closely related to the stages of problem-solving: What is the problem? What alternatives are the best? Which alternative is the best? (Gorry & Scott Morton, 1989). Meanwhile, according to Gorry and Scott Morton (1971, p. 12), Simon's use of programmed and unprogrammed as the two polar decision types strongly implies dependence on the computer. Therefore, to signal "more dependence on the basic character of the problem-solving activities" and less dependence on the computer, Gorry and Scott

Morton (1971, p. 12) used the terms "structured" and "unstructured" to distinguish problems instead of "programmed" and "unprogrammed."

In detail, Gorry and Scott Morton (1989) identified three types of problems in managerial activities: structured, semi-structured, and unstructured. A fully structured problem is one in which all three decision-making phases—intelligence, design, and choice—are structured (Gorry & Scott Morton, 1989). The common characteristics of structured problems are that they have happened previously and they are easily and completely defined. Algorithms or decision rules can be specified to identify the problem, design alternative solutions, and select the best solution. Unstructured problems are new or unusual, which makes the relevant information ambiguous or incomplete. Also, in unstructured problems, none of the three decision-making phases has been structured. Semi-structured problems are in between, which means that one or two decision-making phases are unstructured. Gorry and Scott Morton's categorization provides a framework through which decision-makers can obtain the necessary assistance for decisions through an easy-to-use menu or command system.

This study focuses on decision-making for managerial control from the point of view of managerial activities. Due to the characteristics of the problems, the decision-making examined in this study is semi-structured. Details and arguments are provided after introducing the case organizations and the study context (in section 3.3).

2.2.2 THREE BASIC COMPONENTS OF DECISION SUPPORT SYSTEMS

As DSSs, HC-HDSSs inherit the general features of DSSs, i.e., HC-HDSSs should be designed with three basic components. A general DSS has three basic components: the data component, the model component, and the user interface (Shim et al., 2002). The data component refers to a database management system in which data from different sources are stored and merged. Users can access data without knowing where the data are physically located in the database.

The model component of a general DSS refers to a model-based management system that keeps track of all of the possible models that might be run during the analysis as well as controlling the running of the models.

Different models use different algorithms to analyze decision alternatives in terms of analyzing the data, and the output of a model is decision suggestions expressed in terms of the values of each alternative. Therefore, users can select one alternative based on the output of the model.

As its name suggests, the user interface component is the interface from which users request data and models and receive the results. It includes all of the input and output screens (for design details, see chapter 6 "The HC-HDSS prototype").

As preexisting design knowledge of DSSs, "three basic components of DSSs" are used in building the HC-HDSS prototype (more details are given in section 7.2.1).

2.2.3 MULTI-CRITERIA DECISION-MAKING

Theories of multi-criteria decision-making (MCDM) emerged in the first iteration[31] of building, intervention, and evaluating HC-HDSSs. This section focuses on introducing the theory. More details of how they are used in building the prototype are given in that iteration.

From the decision-making process view, the third phase, which was named "choice" by Simon (1977, p. 40), refers to the decision-maker comparing the alternatives and selecting one. How to compare and how to decide on one out of several or many alternatives is an issue that needs to be addressed in most, if not all, DSSs. MCDM is a set of approaches to provide solutions to the problem mentioned above and is selected for the evaluation of alternatives in phase three of the HC-HDSS prototype.

Multi-criteria decision-making/multi-attribute utility theory (MCDM/MAUT) was first described by Dyer et al. (1992) and has acquired importance in the field of management since 1998. Later, this theory penetrated other fields, such as finance, engineering, computer science, and artificial intelligence (Wallenius et al., 2008), and has been used in studies of decision-making specifically in the ITSM context (e.g., El Yamami et al., 2017; Encantado Faria et al., 2018; Lima et al., 2018; Göbel, 2019).

31 This study has three iterations of building, intervention, and evaluating HC-HDSSs. They are presented in chapters 7, 8, and 9 respectively.

MCDM/MAUT is based on two assumptions: 1) that an individual decision-maker or a group of decision-makers will choose one (or a subset) of a set of alternatives evaluated on the basis of two or more criteria or attributes; and 2) that the decision-maker(s) will act to maximize a utility that depends on the criteria or attributes (Wallenius et al., 2008). In addition, studies of MCDM/MAUT pay attention to heuristics (Wallenius et al., 2008).

2.2.4 DECISIONAL GUIDANCE

Theories of decisional guidance emerged in the second iteration of building, intervention, and evaluating HC-HDSSs,[32] when they were used in formulating design principles. This section focuses on introducing the underlying theory.

Silver (1991) pioneered using the theory of decisional guidance in studies of designing DSSs. He defined decisional guidance, a design feature of DSSs (including group DSSs) (Silver, 2006, p. 90), as how a DSS "enlightens or sways its users as they structure and execute their decision-making processes—that is, as they choose among and use the system's functional capabilities" (Silver, 1991, p. 107). He suggested three aspects for designers to consider: 1) when and why should a designer build decisional guidance into a DSS? 2) How should decisional guidance be built into a DSS? 3) What are the consequences of building decisional guidance into a DDS? (Silver, 1991). Silver (1991) also provided a specific typology for how to conduct this building, consisting of three dimensions: targets (i.e., what is being guided, structured, or executed by the decision-making process), forms (i.e., the suggestive or informative guidance offered to decision-makers), and modes (i.e., how the guidance is generated, i.e., predefined, dynamic, or participative). Later, Silver (2015), and then Morana et al. (2017), broadened the theory of decisional guidance for DSSs to serve as guidance design features[33] for implementing guidance in various types of information systems (including DSSs).

32 How the theory emerged and how it is used will be presented in BIE iteration two.

33 Morana et al. (2017, p. 33) defined guidance as "the concept of supporting users with their decision-making, problem solving, and task execution during system use by providing

The typologies of decisional guidance (Silver, 1991) and of guidance design features (Morana et al., 2017; Silver, 2015) provide rich resources for designers to consider when building DSSs or other types of information systems. For example, based on Silver's conceptualization of decisional guidance (1991), Limayem and DeSanctis (2000) implemented decisional guidance in a multi-criteria group DSS. Their findings showed that providing decisional guidance improved group users' understanding of the multi-criteria decision-making modeling procedure and increased decision quality. Drawing on four out of ten dimensions suggested by Morana et al. (2017), Dellermann et al. (2019b) implemented decisional guidance in a business model validation DSS. Additionally, Parikh et al. (2001) investigated the effectiveness of decisional guidance in a DSS; they concluded that "providing deliberate decisional guidance is useful because it improves decision quality, increases user satisfaction, helps the user learn more about the decision domain, and shortens the time spent on decision-making" (Parikh et al., 2001, p. 321).

In summary, the theories presented in this section have been used in defining or designing HC-HDSSs. That is, the theories of the decision types of DSSs have been used to set the scope of HC-HDSSs that, as a type of DSS, support human managers in making semi-structured and unstructured decisions. Theories of "three basic components of DSSs" and "multi-criteria decision-making" are used in designing the HC-HDSS prototype. The theory of "decisional guidance" is identified as relevant in the process of building the HC-HDSS prototype and in formulating the design principles of HC-HDSSs. DSSs inherit the capabilities and weaknesses of machines in decision-making. Therefore, as stated in the proposed solution, both their capabilities and weaknesses will be considered when designing HC-HDSSs.

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suggestions and information," whereas guidance design features refer to "the actual implementation of the guidance concept."

2.3 HYBRID SYSTEMS

As introduced in chapter 1, the "hybrid" concept is used in the proposed solution, i.e., designing HC-HDSSs. Designing DSSs with the "hybrid" feature has the potential to address two issues with existing DSSs, i.e., that the outcome of DSSs relies on input data (quality and types) and data analysis algorithms and that DSSs cannot acquire tacit knowledge.

There is no common definition of a hybrid or a hybrid system. This section examines existing studies of digital systems using the term "hybrid" or "hybrid systems."

The term "hybrid" has been used in many IS studies that integrate one or more algorithms or data analysis strategies to support human decision-making. For example, Wang and Benbasat (2009) investigated consumers' perceptions of the utilization and adoption of online decision support in e-commerce. They compared three computer-based decision support strategies, i.e., elimination-based decision support, additive-compensatory-based decision support,[34] and a hybrid strategy mixing the former two types of decision support. Bijan and Rustam (2001) studied the generation of decision alternatives in a DSS, proposing a hybrid approach based on genetic algorithms and fuzzy sets.

This study takes a different view. In recent years, new conceptualizations of hybrid or hybrid systems started appearing in the literature. Increased effort has been put into studies aiming to understand, conceptualize, or define these systems. Hybrid or hybrid systems started to refer to a hybrid of humans and machines because humans and machines can complement[35] each other. Most relevant studies[36] will be presented in roughly chronological order.

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34 Elimination-based decision support refers to a decision support strategy eliminating "product alternatives with unacceptable attribute levels as specified by" the consumers; additive-compensatory–based decision support refers to a decision support strategy that "takes into account the relative importance of a user's attribute preferences and allows for trade-offs among these preferences, fully using all of the information on available alternatives in making choices" (Wang & Benbasat, 2009, p. 294).

35 Regarding what complement refers to in this study, see chapter 3.

36 Many studies of hybrid systems have emerged since 2019. The present study identified relevant studies of hybrid systems using a combination of the keywords "hybrid" and

Jensen et al. (2011) used the term "hybrid" in a study of a DSS aids credibility assessment. They call it "a hybrid decision aid" (Jensen et al., 2011, p. 202), "a hybrid expert system"(p. 203), and "a hybrid human-computer system"(p. 205). "hybrid" is used to mean a hybrid of humans and machines: this digital system combines machines' automated linguistic analysis with humans' perceptual cues to offer more accurate recommendations.

Demartini (2015) and Demartini et al. (2017) used "hybrid human-machine information systems". These systems are intended to improve data processing efficiency and effectiveness through crowdsourcing human intelligence at scale and using computer-based algorithms for a large volume of data. In other words, the "hybrid human–machine information systems" in these two studies combine "human computation and computers" to produce a new breed of hybrid human–machine algorithms (Demartini et al., 2017, p. 6). Demartini et al. (2017, p. 6) defined these systems as "the class of information systems that would involve the crowd at some point in their execution." Additionally, Demartini et al. (2017) examined several types of hybrid systems specific to crowdsourcing, for example, hybrid systems for databases, natural language processing, and multimedia processing.

Some researchers, such as Kamar (2016) and Dellermann et al. (2019a, 2021), used the terms "hybrid intelligence," "hybrid intelligence systems," and "hybrid systems" in their studies. Kamar (2016) called for the development of hybrid intelligence systems that integrate human intelligence into AI systems. Dellermann et al. (2019a) elaborated on hybrid intelligence by clarifying what intelligence, human intelligence, and AI are. They defined intelligence as "the ability to accomplish complex goals, learn, reason, and adaptively perform effective actions within an environment" (Dellermann et al., 2019a, p. 638). Human intelligence is a sub-dimension of intel-

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"decision-making" and searching the Scopus database. Literature review papers on hybrid systems, for example, by Trunk et al. (2020), were also identified and included. In other words, this section selectively presents studies of hybrid systems regarded as the most relevant. These are studies of hybrid systems identified in the early stage of this study that play an essential role in problem formulation and studies that emerged in the later stage of the study that concern hybrid systems mentioning or related to decision-making. These studies cover a wide range of hybrid systems, although they are not exhaustive.

ligence that is related to humans. It refers to "the mental capabilities of human beings," such as humans' capacity to "learn, reason, and adaptively perform effective actions within an environment, based on existing knowledge" (Dellermann et al., 2019a, p. 638). In contrast, AI is a sub-dimension of intelligence but relates to machines that can accomplish complex goals, i.e., "by applying machine learning techniques, a system becomes capable of analyzing its environment and adapting to new circumstances in this environment" (Dellermann et al., 2019a, p. 638). Dellermann et al. (2019a) defined hybrid intelligence as "the ability to achieve complex goals by combining human and artificial intelligence, thereby reaching superior results to those each of them could have accomplished separately, and continuously improve by learning from each other" (p. 640). As in the present study, "hybrid" as used by Dellermann (2019a) is a hybrid of humans and machines. The difference is that the hybrid that this dissertation focuses on is a hybrid of human and machine capabilities, specifically in decision-making, instead of a hybrid of human intelligence, machine intelligence, and AI in general,[37,38] as in Dellermann et al.'s (2019a) study.

Based on Dellermann et al.'s (2019a) definition of hybrid intelligence, Dellermann et al. (2021) elaborated on what hybrid intelligence systems are. Hybrid intelligence systems are defined as "systems that have the ability to accomplish complex goals by combining human and artificial intelligence to collectively achieve superior results than each of them could have done in separation and continuously improve by learning from each other" (Dellermann et al., 2021, related work, para.7).

Like Dellermann et al. (2019a, 2021), van der Aalst (2021, p. 5) stated that hybrid intelligence "blends human intelligence and machine intel-

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37 Dellermann et al. (2019a, p. 638) treated machine and AI as synonyms, stating that "the subfield of intelligence that relates to machines is called artificial intelligence (AI)," which "generally covers the idea of creating machines that can accomplish complex goals." Therefore, from this perspective (i.e., that machine and AI are synonyms), the hybrid this study focuses on is the capabilities of AI in decision-making instead of AI in general.

38 However, this study treats machine and AI differently. "Machine" is used as a broader concept than AI. Machines are digital systems that apply AI and other techniques such as business analytics. Therefore, from this perspective (i.e., that machine differs from AI), the hybrid in this study concerns machines' capabilities in decision-making but is not limited to machines only applying AI in decision-making.

ligence to combine the best of both worlds." Ostheimer et al.'s (2021) "hybrid intelligence system" also relied on the definition of Dellermann et al. (2019a), incorporating human decision-making into machine-learning algorithms (i.e., human-in-the-loop) to improve the accuracy of algorithms. Cronholm and Göbel's (2022) hybrid intelligence design combines human intelligence with AI to facilitate decision-making in solving complex problems in return management in the retail sector.

Additionally, Rai et al. (2019) called for a "human–AI hybrid" as the next-generation digital platform. Van den Broek et al. (2021) used the term "human–ML (machine learning) hybrid" in an ethnographic study of digital systems supporting the hiring of job candidates; the digital system combined human domain expertise with machine learning. Jarrahi (2018) used "human–machine symbiosis" instead of the term "hybrid" in his study, which builds on Licklider's (1960) vision of the human–machine collaborative relationship. As specified by Jarrahi (2018), human–machine symbiosis considers both human and machine capabilities in organizational decision-making (a context characterized by complexity, uncertainty, and equivocality); the utilization of both capabilities results in better decisions.

The above studies use the term "hybrid system" similarly to the way it is used here,[39] i.e., to refer to a hybrid of human and machine. Several of the studies identified early in this work, for example, Demartini (2015), Demartini et al. (2017) and Kamar (2016), have been used as arguments for the proposal to design HC-HDSSs. Others, for example, Jarrahi (2018), Dellermann et al. (2019a, 2021), van den Broek et al. (2021), and van der Aalst (2021), emerged and were identified later in this work, strengthening the proposed solution for bringing "hybrid" into HC-HDSSs.

Existing studies of hybrid systems provide a sound knowledge base for designing HC-HDSSs because, as in this study, those studies highlight that humans and machines have complementary capabilities. Utilizing complementary capabilities could reach better results, as illustrated below.

39 In the remaining part of this dissertation, "hybrid" refers to a hybrid of human and machine. "Hybrid systems" will be used for all digital systems that are a hybrid of human intelligence and machine or artificial intelligence. Section 3.3 will elaborate on what exactly hybrid means in this study.

There are several studies of hybrid systems in general or in specific fields, but they do not focus on decision-making. Dellermann et al. (2019a) examined hybrid intelligence in general, emphasizing the combination of the complementary, heterogeneous intelligence of humans and machines for solving complex problems. Furthermore, they pointed out that human cognitive systems should be considered because highly uncertain contexts require human capabilities, such as intuitive and analytic capabilities, creativity, and empathy. Humans have "proved to be superior in various settings that require System 1 thinking" (Dellermann et al., 2019a, p. 639). Additionally, there should be mutual learning or mutual augmentation between humans and machines.

Dellermann et al.'s (2021) taxonomy of hybrid system design contributes to descriptive knowledge in general. The taxonomy consists of four meta-dimensions (i.e., task characteristics, learning paradigm, human–AI interaction, and AI–human interaction), 16 sub-dimensions, and 50 categories.

Kamar (2016) pointed out that there is a need to involve humans to overcome some limitations or weaknesses of machines, because, without the support of humans, machines (i.e., AI systems in his study) may make mistakes or completely fail.

Rai et al. (2019) highlighted that, on one hand, AI is capable of speed, accuracy, reliability, and scalability, whereas humans have specific competencies such as judgment, creativity, and empathy. Additionally, they also stated that there are different types of human–AI hybrids that range in human–AI interdependence from substitution, through augmentation, to assemblage.

Demartini's (2015) and Demartini et al.'s (2017) hybrid systems concern improving data processes by crowdsourcing human intelligence. Van der Aalst (2021) studied hybrid intelligence in business process management. As they noted, humans are good at tasks that require common sense and contextual knowledge; machines are faster, more efficient, etc., in data analysis. Humans and machines can complement each other to obtain the best results.

Some studies examine hybrid systems related to decision-making. In detail, Jensen et al. (2011) examined hybrid decision aids, highlighting that, on one hand, machines have capabilities for automated analysis of the structure and content of a message. Humans are limited in cognitive capabilities for processing information and have weaknesses in terms of bias when using heuristics. On the other hand, humans are unique or have the capability of perceiving information from indirect cues, which is a limitation of machines. The results of their study (a laboratory experiment) show that, compared with only using the capabilities of either humans or machines, the decision aids that combine machines' automated linguistic analysis with humans' perceptual cues offer more accuracy.

Trunk et al. (2020) conducted a systematic literature review to investigate the possibilities of integrating artificial intelligence (AI) into strategic decision-making in organizations. They used content analysis, the results of which were summarized in a conceptual framework. Trunk et al. (2020) pointed out the benefit of combining humans and machines to improve strategic decisions. Although humans are more capable of making strategic organizational decisions than are machines, machines have capabilities (e.g., being efficient and effective) that support humans in collecting and analyzing data faster. In other words, machines can augment humans in strategic decision-making. Trunk et al. (2020) also stated that humans are necessary to ensure the quality of information and interpretation. Humans' tacit knowledge and explicit knowledge are both essential in making complex decisions.

Van den Broek et al. (2021) suggested a human and machine learning hybrid system for assessing job candidates, i.e., a combination of machine learning and domain expertise. They investigated how developers managed tension between developing machine learning systems that produce knowledge independently (i.e., getting human experts out of the decision support process) and keeping the insights or support from machine learning relevant to the domain knowledge. This tension was caused by claims that the insights from machine learning are superior to those of experts. They concluded that developing machine learning independent of domain experts does not hold in transcending complex knowledge work: "knowledge work cannot be replaced by machine learning technologies or captured in computer systems" (van den Broek et al., 2021, p. 1574), and developers and experts "arrived at a new hybrid practice that relied on a combination of ML and domain expertise" (p. 1557).

Shrestha et al. (2019) presented three forms of organizational structure that consider integrating AI into organizational decision-making. Two of the three[40] are relevant to "hybrid systems." One is hybrid but with a sequential structure, i.e., human decisions are inputted to algorithmic decision-making, and vice versa. Another form, called the aggregated human–AI decision-making structure, treats AI as a decision-maker or a member of a decision-making group. Decision tasks or aspects are allocated to both humans and AI, and humans and AI then make decisions collectively based on aggregation rules such as voting or averaging.

Furthermore, two studies have formulated design principles of DSSs that have hybrid features. Dellermann et al. (2019b) proposed and evaluated a hybrid system to support managers in making business model design decisions. The proposed DSS supports the assessment of the validity of managers' assumptions as to business models in early-stage start-ups (i.e., a highly uncertain and complex context). The system they designed combines the complementary capabilities of human intelligence and machine intelligence, combining the strength of machines handling a large amount of information with human intuition and creative potential. They formulated seven design principles: profile ontology, expertise matching, human feedback, crowd-based classifier, machine feedback, knowledge aggregation repository, and guidance representation.

Cronholm and Göbel (2022) formulated three design principles for developing DSSs that consider both human intelligence and AI. The DSSs they developed are for return management within the retail sector, and the three design principles were developed specifically for that field. The first design principle is design for amplified decision-making, suggesting that developers should "amplify the DSS with procedural support, enabling the exploitation of both human intelligence and AI" (Cronholm & Göbel, 2022, Design principle, para. 2). The second design principle is design for unbiased decision-making, suggesting the development of DSSs to involve several roles, which could provide multiple perspectives to reduce human biases. The third design principle is design for human and AI learning, i.e., enabling mutual learning between humans and machines.

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40 The one called "full human to AI delegation," i.e., that AI-based algorithms make decisions without human intervention, is irrelevant.

As well, there are several studies of hybrid systems, but their emphasis is on the machine actors. For example, Ostheimer et al. (2021) investigated "hybrid intelligence systems" that incorporate human decision-making into machine-learning algorithms, i.e., human-in-the-loop, to improve the accuracy of algorithms. Zheng et al. (2017) developed a new form of AI, "hybrid-augmented intelligence," by introducing human cognitive capabilities or human-like cognitive models into AI systems.

2.4 HUMAN-CENTERED AI

As briefly introduced in the section on problem formulation, the concept of human-centered AI (HCAI) is proposed to address the ethical issues raised by existing DSSs and constitutes part of the solution for designing HC-HDSSs proposed by this study. In other words, the term "human-centered" in HC-HDSSs can be grounded in theories of HCAI. Therefore, this section provides more details on what HCAI is, which supports the proposal to design HC-HDSSs.

HCAI refers to designing AI systems that are human-centered or to using a human-centered approach to designing AI systems (Auernhammer, 2020). It highlights the difference from conventional AI, which has a technology-centered design and autonomous features, i.e., autonomous machines have different levels of autonomy and put autonomy first. HCAI places human users at the center of attention and considers the welfare of human beings and society when designing new technology. In other words, HCAI centers on humans and their "needs, motivations, emotions, behaviour, and perspective in the development of a design" (Auernhammer, 2020, p. 1318). It is a shift from viewing humans as part of a digital system to making humans central to every aspect of a design[41] (Auernhammer, 2020).

Fundamentally, HCAI has a different philosophical stance from that of conventional AI (Auernhammer, 2020; Shneiderman, 2021). The difference concerns the way to gain knowledge (i.e., epistemology). The dominant philosophic stance underlying conventional AI is rationalism, which is based largely on logical–mathematical thinking and focuses on math-

41 HCAI is different from simply involving humans in a design (Auernhammer, 2020).

ematical and technological advancement (Auernhammer, 2020). Algorithms are "treasured for their elegance and measured by their efficiency" (Shneiderman, 2021, p. 57). Developers who adhere to rationalism favor "autonomous designs in which computers operate reliably without human oversight" (Shneiderman, 2021, p. 58). In contrast, HCAI has a basis in empiricism, i.e., that there are multiple realities in the world and that the world (of course including humans) is complex and keeps changing (Shneiderman, 2021). Empiricism that assesses human performance is the basis of much of the work in the HCAI community (Shneiderman, 2021). Shneiderman (2021) elaborated on this difference between the two competing philosophic stances by introducing Aristotle's rationalism versus Leonardo da Vinci's empiricism.[42]

HCAI provides a vision of how machines could augment humans and provide better support (Xu et al., 2023). In other words, HCAI aims to amplify instead of erode humans (Shneiderman, 2021). According to Xu (2019, p. 43), HCAI is to "enhance humans rather than replace them," and humans are the final decision-makers. Therefore, the notion of HCAI provides a possible solution to the "ethical dilemmas now arising in the machine-learning space" (Shneiderman, 2021, p. 57). Furthermore, the underlying philosophy of HCAI, which emphasizes humans' prior experience and irrational decision-making, aligns with the selection of descriptive decision theories introduced in section 2.1.

2.4.1 DESIGN APPROACHES FOR HCAI

Researchers have proposed several overarching design approaches, frameworks, or guidelines for HCAI from different perspectives. First, there are approaches from a human-centered design perspective.[43] For example,

42 More relevant arguments can be found in Shneiderman (2021).

43 The human-centered design approach has "a pivotal role in the development and use of AI technology for the well-being of people" (Auernhammer, 2020, p. 1316). It is an overarching concept covering various research methods that center human value in the design process (Auernhammer, 2020).
Auernhammer (2020) selectively introduced eight approaches with different foci but centering on human values in designing computer systems (especially AI). For instance, *human-centered systems* (Sawyer, 2005) and *social design* (Cooley, 1980) provide a social lens

there are the participatory design of Neuhauser and Kreps (2011), the inclusive design of Spencer et al. (2018), the interactive design of Winograd (2006), and the human-centered computing of Brezillon (2003), Ford et al. (2015), and Hoffman et al. (2004).

More comprehensively, Auernhammer (2020) proposed an overarching design approach, namely, "humanistic design research" (extended by Xu et al., 2023), which integrates different human-centered approaches. In detail, Auernhammer's (2020) approach or framework for HCAI includes "Technology," "Human," and "Policies & guidelines" (see Figure 2.2). In this framework, a double-headed arrow connects "Human (humanistic design)" and "Technology (rationalistic)," showing that the design should promote "human–technology symbiosis development." Meanwhile, "Policies & guidelines" (connected by two double-headed arrows to "Human" and "Technology," respectively) are informed at different design stages. The framework requires the use of experimental designs or prototypes to examine various implications of AI systems to ensure that possible ethical issues are examined and unintended consequences identified faster.

through which to examine changes in social organization caused by the implementation and use of AI. The difference between the two is that the social design approach highlights the designer's role and pays attention to the designer's ideological issues that affect AI system design. *Participatory design* (Bodker, 1996; Ehn & Kyng, 1987) and *inclusive design* (Waller et al., 2015) emphasize the diversity of stakeholders (e.g., end-users, customers, and employees) involved in a design process. The difference is that inclusive design highlights diverse groups in a design instead of diverse individuals. *Interactive design* (Moggridege, 2007), *persuasive technology* (Fogg, 1998), and *human-centered computing* (Winograd, 1997) highlight the interaction of humans and AI systems. The difference is that persuasive technology intends to change humans' attitudes and/or behavior through AI, whereas human-centered computing focuses more on designing "interspaces" that incorporate human lifestyles and system design. The *need-design response* (McKim, 1959, 1980) starts by identifying a human need, and the design responds to that need.

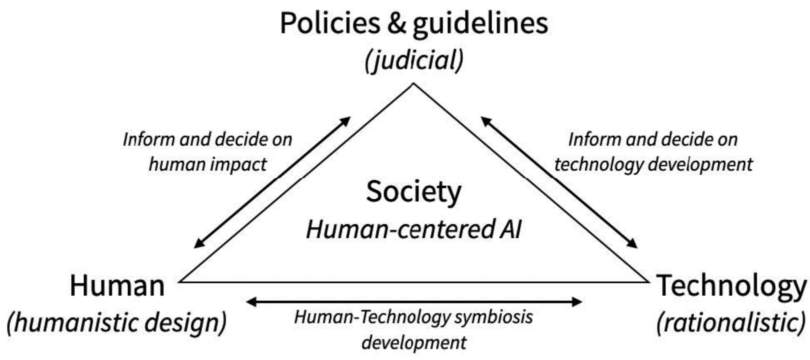

Figure 2.2. A comprehensive design approach to HCAI (Auernhammer, 2020, p. 1328).

Second, and in contrast to the human-centered design view (e.g., the framework of Auernhammer, 2020), Xu et al. (2023) has presented suggestions for the design of HCAI from the human–computer interaction (HCI) perspective. They conducted a holistic literature analysis and proposed a framework that responds to a call for AI that is "ethical and beneficial to humans" (Xu et al., 2023, p. 499) as part of an HCAI strategy, a call issued by HAI: Stanford University Human-Centered Artificial Intelligence. Xu et al.'s framework extends the HCI framework and has three aspects, i.e., "Ethics," "Human," and "Technology" (see Figure 2.3), as well as features that 1) place humans at the center, 2) affirm the interdependence of humans, technology, and ethics, and 3) promote systematic design thinking. Their framework emphasizes that "human intervention is required. Humans must be the ultimate decision maker" (Xu et al., 2023, p. 495), i.e., the AI is human controlled. The framework also requires designing the interface to be "explainable," so that it can show the user what the machine is thinking and can explain to the user why (Xu et al., 2023).

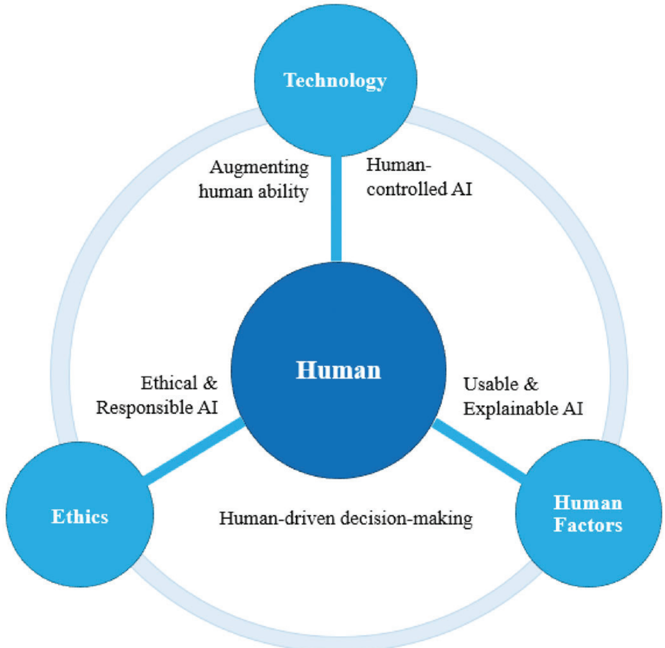

Figure 2.3. A framework with three components (Xu et al., 2023, p. 499).

Third, Shneiderman (2021, p. 60; see also 2020a) has presented three overall HCAI guidelines for policymakers concerning the team, organization, and industry levels: 1) "build reliable and transparent systems based on sound software engineering team practices"; 2) "pursue safety culture through effective business management strategies"; and 3) "increase trust through certification and independent oversight within each industry." Specifically, the first guideline (i.e., the team level) is more relevant than the others to this study. It highlights explainable AI that could enable human users to understand AI-based decisions as well as a visual user interface (e.g., user control panel) "that lets users understand their progress through the process."

The three above approaches to HCAI of Auernhammer (2020), Xu et al. (2023), and Shneiderman (2020a, 2021) are valuable for designing HC-HDSSs. They provide overall guidance from different perspectives: Auernhammer's (2020) approach is from the human-centered design perspective, Xu et al.'s (2022) HCAI framework is from the HCI perspective, and Shneiderman's (2020, 2021) suggestions are aimed at policy-makers. In addition, their studies also give some detailed, though not exhaustive, suggestions about what HCAI should look like. Their overall guidance and detailed suggestions are considered in designing the HC-HDSSs.

2.4.2 TRANSPARENCY AND EXPLAINABLE AI

The two terms "transparency" and "explainable AI" have been frequently mentioned in the HCAI discourse. They will also be used as the theoretical basis of a formulated design principle in this study (more details can be found in section 9.4.2).

Shneiderman (2021, p. 60) stated that "another vital feature [of building reliable and transparent systems] will be to support explainable AI, which enables users to understand AI-based decisions and seek redress for what they see as unfair or incorrect decisions." Xu et al. (2021, p. 38) pointed out that "there is a large body of human factors research work on automation transparency and situation awareness … their comprehensive mitigation solutions may offer possible solutions to explainable AI."

Specifically, Bhaskara et al. (2020, p. 216) have stated that transparency aims to provide operators an awareness of the AI agent's "behavior, reliability, and intention." Achieving transparency refers to "the operator being able to understand why an agent behaves in a particular way, to understand an agent's reliability, its tendency for errors, and its intended action" (Bhaskara et al., 2020, p. 216). Similarly, in Sun et al.'s (2021) study of transparency design, the term "transparency" refers to "the mechanism that can report the behavior and intention of agents, the process of decision making, the reasons behind unexpected errors, and any other information helping users to understand agents" (p. 1).

In summary, the theories presented in this chapter provide a foundation for designing HC-HDSSs. However, design knowledge from earlier DSSs studies is specific to the presented fields, or does not take into account the hybrid and human-centered aspects. Thus, these studies do not provide detailed guidance on how to design HC-HDSSs. The presented theories will be used in building the HC-HDSS prototype and/or formulating the goal, meta-design, and design principles of HC-HDSSs. Some of them are identified when building the initial version of the prototype, for example, human decision-making, DSSs in general, and, specifically, the three basic components of DSSs.

Other theories emerged in the ensuing design process, for example, theories of decisional guidance and HCAI. How the theories presented in this chapter were identified and selected to establish the theoretical foundation is illustrated in section 5.2.4 “Identify contributing theoretical bases and prior technology advances (Task 4).” How theories (presented in this chapter) guided the design of the HC-HDSS prototype and how they were applied in formulating design principles are elaborated on in chapters 7, 8, and 9.

CHAPTER 3

THE PROPOSAL TO DESIGN HC-HDSSS

This chapter aims to elaborate on the proposed solution to the problem, which is designing HC-HDSSs. HC-HDSSs are defined as DSSs designed with humans at the center and utilizing the complementary capabilities of humans and machines in decision-making. In this definition, "designed with humans at the center" is based on theories of HCAI. "Utilizing the complementary capabilities of humans and machines in decision-making" explains the phrase "human–machine hybrid in decision-making"—"hybrid" for short. In other words, the word "hybrid" in HC-HDSSs refers to "utilizing the complementary capabilities of humans and machines in decision-making." "Human-centered" and "hybrid" will be elaborated on after presenting the identified capabilities and weaknesses of humans versus machines in decision-making.[44]

44 Humans and machines are regarded as two actors when discussing their capabilities and weaknesses in decision-making. The capabilities and weaknesses of humans and machines are presented from one angle: that of the characteristics of human actors and machine actors in decision-making. Their capabilities and weaknesses can be viewed from different angles. For example, from the point of view of the characteristics of decision-making tasks, humans are superior in equivocal situations (Jarrahi, 2018). By contrast, machines are superior in complex or uncertain situations (Jarrahi, 2018). This study emphasizes the former.

3.1 HUMAN CAPABILITIES AND WEAKNESSES IN DECISION-MAKING

The term "capability" has been used, without definition, in many studies of hybrid systems and has been applied to both humans and machines. For example, van den Broek et al. (2021, p. 1575) stated that "humans and machines excel in different cognitive capabilities, such as humans in rich and diverse learning, and machines in formal rationality, and have to be brought together to leverage their distinct benefits." Dellermann et al. (2019a, p. 639) pointed out that "the general rationale behind the idea of hybrid intelligence is that humans and machines have complementary capabilities that can be combined to augment each other." Jarrahi (2018, p. 579) stated that "the example of chess proposes a vision for the complementary roles of humans and AI; they offer different yet complementary capabilities needed for effective decision making." Dellermann et al. (2019b, p. 423) stated that their hybrid intelligence DSS "combines the complementary capabilities of human and machine intelligence."

According to the business dictionary, "capability" is used as the measure of an entity's (e.g., department, organization, person, and system) ability to achieve its objectives, especially concerning its overall mission. The capability of humans in this study refers to one or several strengths, advantages, or positive characteristics in achieving the goal of decision tasks. The same applies for machines.

This study identifies two human capabilities and two weaknesses in decision-making. These two identified human capabilities are that humans can apply *intuition* together with *knowledge* (i.e., expertise and experience) in making decisions. Several studies show that humans possess knowledge in terms of expertise and experience, knowledge that is essential for making decisions and that machines lack (Borst, 2016; Demartini, 2015; Kahneman, 2011). Humans gain knowledge at their workplaces by continuously learning or communicating with co-workers (e.g., knowledge of the decision-making context); they comprehensively apply this knowledge in decision-making processes (e.g., identifying problems or opportunities, and discovering and evaluating options). While DSSs are applied to support human decisions, the information presented by those digital systems also requires that humans apply their knowledge as well, to derive, refine, and integrate insights. For instance, information concerning discovered patterns can only be interpreted or made sense of by humans (Frisk et al., 2014; Günther et al., 2017). Likewise, information regarding suggested options for strategic decisions needs to be supplemented, substituted, or reframed by humans (Shollo et al., 2015).

Many studies show that humans can apply intuition in decision-making (e.g., Bannister & Remenyi, 2000), and that when there is a lack of information, humans and machines are limited in making analytical decisions. In this case, human intuition often proves to be useful, effective, and more accurate compared with analytical decisions (e.g., Dane et al., 2012; Dellermann et al., 2019a, 2019b; Gigerenzer & Gaissmaier, 2011; Tallon & Kraemer, 2007). As shown by Hammond, Keeney, and Raiffa (1987), compared with analytical decision-making by humans, human intuition is more suitable for dealing with relatively non-decomposable tasks. Dane et al. (2012) verified that the application of human intuition is more effective than analytical decision-making given a high level of domain expertise.

Additionally, some studies highlight the capabilities of decision-making by groups of humans. For example, Lima et al. (2018, p. 278) listed the advantages of group decision-making: "better performance (results) from a broader base of knowledge and experience; more creativity, wider perspective, and [a] more efficient approach to solving problems; creating accountability in decisions, commitment to common (joint) experience; generating higher quality decisions." Dellermann et al. (2019b) stated in a DSR study of a hybrid intelligence decision support system (HIDSS) that involving several individuals in the HIDSS "aggregates heterogeneous knowledge about a certain problem and allows the capture of a fuller understanding of a decision-making problem" (p. 8). In other words, a group of humans can provide a broader base of knowledge and intuition for making better decisions. Similarly, Trunk et al. (2020) highlighted that a heterogeneous group of humans has better knowledge for decision-making than does a homogeneous group, because the former has more diverse information and experience, which informs better discussions, leading to improved interpretations.

This study identifies two main weaknesses of humans in decision-making: *cognitive constraints* and *biased behaviors*. Here, the term "weaknesses" refers to limitations, disadvantages, or negative characteristics in decision-making; the same definition applies to machines.

Cognitive constraints refer to the limitations of humans in storing and processing information[45] (Maule, 2010; Miller, 1956). Humans need to recall information from their long-term memory when making decisions. Due to limited memory capacity, humans cannot recall all the relevant information, which means that the information retrieved from memory is very likely to be less than the total sum (Maule, 2010). Second, the information is retrieved through a process of association and reconstruction rather than simple recall. This process does not deliver exactly the same information that is present in human memory. If the information retrieved is changed, it can easily lead to human memory bias (Maule, 2010).

Due to humans' limited information processing speed, when humans retrieve information that decisions will draw on, they cannot carry out the mental operations necessary to make decisions according to the rational model (Simon, 1977). Therefore, humans will actually choose the first acceptable alternative rather than look for the best decision (Jalali et al., 2019). In other words, humans make suboptimal decisions. They "reject an alternative as soon as some negative aspect is revealed (even if all the other aspects are brilliant) and evaluation stops as soon as an acceptable alternative is found, even if there are still many other alternatives left unevaluated (including potentially better alternatives than the chosen one)" (Maule, 2010, p. 109).

Due to the above-mentioned cognitive constraints, humans display another weakness called biased behaviors (Ahsen et al., 2019; Khan et al., 2017; Wang et al., 2016). When humans apply heuristics in their System 1 or intuitive decision-making, sometimes heuristics help deal with uncertain conditions, yet sometimes they also lead to severe and systematic errors, referred to as biases.

Tversky and Kahneman (1974) have identified a set of biases corresponding to each of the three heuristics: i.e., representativeness, availability, and anchoring and adjustment biases (for more details, see Tversky & Kahneman, 1974). Apart from Tversky and Kahneman's (1974) preemi-

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45 According to Maule (2010) and Miller (1956), an example of information can be: organization A has 20 departments.

nent study of biases, many other studies have investigated particular human biases (Ahsen et al., 2019; Khan et al., 2017; Wang et al., 2016). For example, Lee and Joshi (2017) explored the role of status quo bias, affecting IS users who tend to stick to the status quo and resist changing to a new IS. Nuijten et al. (2016, p. 535) showed that decision-makers may "fail to heed risk warnings" if the adviser is regarded as an opponent. Lee et al. (2019) studied how the evaluability bias influences individual preferences in decisions concerning an escalation to a software product.

3.2 MACHINE CAPABILITIES AND WEAKNESSES IN DECISION-MAKING

Machine capabilities in decision-making include being *efficient and effective*; *being continuously upgradable in memory, algorithms, and computing ability*; *predicting by pattern recognition*; and *reducing human biases*.

Machines have the capability of making faster and more accurate data calculations than humans can. Therefore, the first capability of machines is *being efficient and effective*[46] (van den Broek et al., 2021; Ghasemaghaei et al., 2018; Kulkarni et al., 2017; Hardin et al., 2017). For example, in the field of marketing, Bucklin et al. (1998) predicted that machine-based decision support and decision automation would bring both efficiency (e.g., management productivity) and effectiveness (e.g., resource allocation decisions). According to Oliveira and Lima-Neto (2010), computers process data faster than humans, and consequently have a higher capacity for quantitative analysis than humans. Brynjolfsson and McElheran (2016) found that decision-makers often use digital systems to make the decision-making process more efficient. Their studies of the US manufacturing sector show that adopters of data-driven decision-making for managerial activities have higher productivity. In a study of DSSs for credibility assessment, Jensen et al. (2011) pointed out that digital systems are more efficient and effective in processing information. More specifically, according to them, digital systems are capable of monitoring multiple communication channels and can operate nearly in real-time.

46 This concept was introduced in chapter 1, but here more details are provided.

The second capability of machines is *being continuously upgradable in memory, algorithms, and computing ability.* According to Sotala (2012), computers can be upgraded to provide more computing power, computer memory can be increased, algorithms can be continuously improved, and computers do not suffer from over- or under-stimulation. In other words, the capability of machines for decision-making can be continually upgraded.

The third capability of machines is *predicting by pattern recognition.* Machines rely on algorithms used for analyzing data. Algorithms can recognize complex patterns from a huge dataset (Newell & Marabelli, 2015). Gunaratne et al. (2018) showed that, compared with humans, algorithms can weigh cues derived from data more appropriately, identify more predictive cues, and are better at assessing emerging patterns.

Reducing human biases is the fourth identified capability of machines in decision-making. Machines have the capability of reducing or mitigating human biases (van den Broek et al., 2021). Hardin et al. (2017) gave the example that some DSSs can help humans to overcome decision-making biases (e.g., by offering them guidance). Shollo et al. (2015) also showed that DSSs can offer more accurate information, which can help humans make less biased decisions. More specifically, Jensen et al. (2011) pointed out that managers have biases in credibility assessment. Managers usually label all incoming messages as truthful, i.e., manifesting truth bias. In contrast, some managers who frequently encounter non-credible sources prefer to label all incoming messages as deceptive, i.e., manifesting lie bias. With the aid of digital systems, these biases could be reduced.

This study identifies three (groups of) weaknesses of machines in decision-making that are, reliance on input data (quality and types) and data analysis algorithms; lack of the human capability of acquiring tacit knowledge; and introducing unwanted ethical issues.

Reliance on input data (quality and types) and data analysis algorithms. In many digital systems, the capability of offering human users valuable insights or making predictions is largely based on the algorithms used for the analysis of large volumes of data (Kulkarni et al., 2017; Lyytinen et al., 2017). Therefore, on one hand, the quality of the predictions or insights is always dependent on the quality of the data analyzed and the algorithms used for the analysis. On the other hand, as Demartini (2015, p. 5) stated, "machine-based solutions for large-scale data processing are limited in the type of data processing tasks they can perform. Examples of tasks where machine-based systems perform poorly include image understanding, detecting opinions or sarcasm in text."

The quality of input data and data analysis algorithms relies on human skills. Humans decide what data to collect, select which group of data is/should be used for analysis, and design the algorithms (Ghasemaghaei et al., 2018). This means, at least so far, that machines cannot independently collect and analyze data without the involvement of humans in making decisions. The quality of machine-based decision-making will be limited if humans are limited in their skills in designing decision-making digital tools. Here are two examples. According to Yampolskiy and Spellchecker (2016), we lack a full understanding of the opportunities and risks of using digital systems for automated decision-making, because only a few human designers in the world have formal training in both computer science and decision theory. According to Chen and Lee (2003, p. 147), most studies of DSSs focus on supporting human behavioral aspects in decision-making, ignoring support for the cognitive aspects; the studied DSSs focused on providing "their users quantitative modeling tools and easy data access."

*Lack of the human capability of acquiring tacit knowledge***.** Several studies report that essential knowledge and competencies that affect decision-making are not represented in digital systems (e.g., Borst, 2016; Demartini, 2015; Kahneman, 2011). Demartini (2015) pointed out that digital systems do not sufficiently include human knowledge and capabilities in the decision-making process. In other words, if human knowledge and competencies are not part of the analysis, there is a risk that the predictions made by a machine might be inexact or even incorrect. More specifically, in a study of building digital systems to support the hiring of job candidates, van den Broek et al. (2021, p. 1560) stated that machines are "incapable of recognizing what is relevant to some particular context of action" and "the broader domain of which they form part." In other words, machines cannot acquire tacit knowledge, such as knowledge about the context. Turpin and Marais (2004) reiterated this weakness. They conducted interviews with six senior decision-makers, and found that DSSs are just used as a supplement: the decision-makers still used the knowledge stored in their memory. For example, they used information concerning the context of a decision-making task: "A strategic decision maker should be aware of his/her environment rather than focusing on the use of decision support tools" (interview, decision-maker 2); "When facilitating group decision-making, sensitivity to people's value systems is more helpful than the use of DSS tools" (interview, decision-maker 3); and "The decision-making context needs to be taken into account when supporting decision-making" (interview, decision-maker 4) (Turpin & Marais, 2004, pp. 149-150).

Introducing unwanted ethical issues. Apart from the two weaknesses mentioned above, this study also identifies one group of weaknesses concerning ethical issues. First, humans learn through their decision-making processes. The knowledge and experience humans gain in this way will be used when making future decisions. However, studies show that intelligent DSSs usually give suggestions without explaining the reasons behind their calculations or analyses, which can gradually limit human learning ability (Shollo et al., 2015). Second, Newell and Marabelli (2015) gave evidence that machine-suggested decisions for organizations may bring profit to the organizations but could also lead to price or service discrimination against customers. Shneiderman (2021, p. 56) pointed out that there is a danger of "hidden biases in algorithms for making decisions." Xu et al. (2023) and Xu (2019) stated that this represents the machines' biased "thinking." Overall, Bannon (2011) has advocated rethinking how we approach issues of humans and technologies, because technologies augment human capabilities but also can cause confusion in humans and disable them.

3.3 THE "HYBRID" AND THE "HUMAN-CENTERED"

Section 2.3 introduces existing studies using the term "hybrid" in a manner similar to how it is used here, that is, to refer to a hybrid of humans and machines, because humans and machines can complement each other. The "hybrid" in this study refers to a hybrid of humans and machines, specifically, a hybrid of their decision-making capabilities, because humans have decision-making capabilities that can complement some machine weaknesses in decision-making, and vice versa.

In detail, several of the above-presented capabilities and weaknesses of humans and machines in decision-making can be complementary (see Table 3.1). Table 3.1 first can be divided into the left and right halves. The left half is for the human actors, listing their capabilities and weaknesses in decision-making. The right half is for the machine actors, listing their capabilities and weaknesses. The green area stands for the capabilities of humans or machines, whereas the white area represents their weaknesses.

Table 3.1. The complementary capabilities and weaknesses of humans and machines in decision-making.

<table>
<tr><td>Humans' capabilities</td><td>- Possessing knowledge (expertise and experience)
- Applying intuition</td><td>- Reliance on input data, and data analysis algorithms;
- Lack of human capabilities (intuition and knowledge)</td><td>Machines' weaknesses</td></tr>
<tr><td rowspan="2">Humans' weaknesses</td><td>- Cognitive constraints</td><td>- Being efficient and effective
- Being continuously upgradable in memory, algorithms, and computing ability
- Predicting by pattern recognition</td><td rowspan="2">Machines' capabilities</td></tr>
<tr><td>- Biased behaviors</td><td>- Reducing human biases</td></tr>
</table>

Table 3.1 can also be divided into the upper and lower halves. On one hand, as shown in the upper part of Table 3.1, humans' capabilities of processing knowledge and applying intuition could complement machines' weaknesses due to their lack of human capabilities in terms of applying intuition and knowledge, and reliance on input data, and data analysis algorithms. Humans apply their intuition and knowledge to collect and select data and to input them to machines. Humans use their intuition and knowledge to develop data analysis algorithms for machines. On the other hand, as indicated in the lower part of Table 3.1, first, machines' capabilities of being efficient and effective; being continuously upgradable in memory, algorithm, computing ability; and predicting by pattern

recognition could complement human cognitive constraints. Second, machines' capability of reducing human biases could mitigate humans' biased behaviors.

Table 3.1 explains what the "hybrid" means in HC-HDSSs, i.e., that utilizing human capacities in decision-making could complement two machine weaknesses (i.e., the upper half of the table). Likewise, utilizing machines' capabilities could complement the weaknesses of humans in decision-making (i.e., the lower half of the table). Combining the capabilities of both could result in better decisions. Meanwhile, the upper part of the table lays the foundation for the proposed solution for designing HC-HDSSs that, through utilizing humans' capabilities in DSSs, could address the two weaknesses of machines.

Table 3.1 only lists two, instead of all three, identified weaknesses of machines in decision-making, because these two weaknesses can be complemented by human capabilities. Addressing the remaining weakness of machines (i.e., introducing unwanted ethical issues) requires a different strategy or solution. In other words, only adding the "hybrid" feature in DSSs, or only utilizing the complementary capabilities of humans and machines in decision-making, is not enough to address all three identified weaknesses of machines. The third weakness could be addressed by involving humans in a decision-making process, and designing DDSs with humans at the center, i.e., making them "human-centered."

The term "human-centered" used in HC-HDSSs is based on the theories of HCAI, which aim to amplify human abilities instead of eroding them (Shneiderman, 2021), offering a possible solution to the unwanted ethical issues engendered by machines. As mentioned earlier, first, machines or DSSs applying AI give suggestions to humans without explaining the reasons behind the associated calculations or analyses (i.e., one example of the machine weakness introducing unwanted ethical issues). In the long term, human learning ability will be limited by this (Bannon, 2011; Shollo et al., 2015). Unlike conventional AI, HCAI provides a vision of how machines could augment humans (Xu et al., 2023). HCAI focuses on "amplifying, augmenting, and enhancing human performance in ways that make systems reliable, safe, and trustworthy" (Shneiderman, 2020). In other words, HCAI highlights that human performance could be augmented by continuously enhancing their abilities, such as learning abilities.

Second, as another example of this machine weakness, a machine's (suggested) decisions for organizations may lead to price or service discrimination against customers (Newell & Marabelli, 2015), i.e., "hidden biases in algorithms for making decisions" (Shneiderman, 2021, p. 56) or biased thinking (Xu et al., 2019, 2023). HCAI considers the welfare of human beings when designing new technology. HCAI centers on humans and their needs, motivations, emotions, etc., in the development of a design (Auernhammer, 2020).

Third, HCAI embraces the "hybrid" notion featured in this dissertation. Overall, the relationship between humans and technology, i.e., "human–technology symbiosis development" (Auernhammer, 2020, p. 1328), is consistent with what "hybrid" means in this study. Similarly, Xu et al. (2023) have made two statements aligned with what "hybrid" means in this study: "integrating human roles into human–machine systems … taking complementary advantages of machine intelligence and human intelligence" (p. 7) and "hybrid intelligence must be developed in a context of 'human–machine' systems by leveraging the complementary advantages of AI and human intelligence" (p. 10). Both statements highlight utilizing the complementary capabilities of humans and machines, i.e., "hybrid" as used in this dissertation. Furthermore, and in greater detail, as pointed out by Auernhammer (2020, p. 1318), HCAI values the "different prior experience, needs, desires, ambitions, interests, irrational decision making, and lifestyles embedded within specific cultural contexts" of humans. The "different prior experience" is what has been highlighted in "hybrids" that utilize humans' capabilities, i.e., prior experience, in HC-HDSSs. The "irrational decision making" can be related to the weaknesses of humans, who have biased behaviors in decision-making. Therefore, adding "human-centered" to "hybrid" DSSs has the potential to address the machine weakness "bringing unwanted ethical issues."

In summary, first, humans and machines have complementary capacities that can be utilized to mitigate several of their weaknesses in decision-making, i.e., the proposed "hybrid" in HC-HDSSs. Second, machines have one more weakness that requires the involvement of humans in decision tasks and in designing digital systems to be human-centered, i.e., the proposed "human-centered" in HC-HDSSs. Therefore, designing HC-HDSSs has the potential to address all three weaknesses of machines.

CHAPTER 4
THE RESEARCH PARADIGM AND METHODOLOGY

This chapter presents the underlying research paradigm of this doctoral study, outlining the applicable ontology, epistemology, and methodology. This study adopts the DSR paradigm. The ontology and epistemology are illustrated in section 4.1. The methodology, presented in section 4.2, consists of multiple methods (Mingers, 2003), including the action design research (ADR) method as well as qualitative methods for data collection and data analysis. The study was conducted in organizations. Section 4.3 introduces the study context and the two organizations. Section 4.4 concludes this chapter with a summary, including Figure 4.4, which provides an overview of the chapter by connecting its main elements.

4.1 THE DESIGN SCIENCE RESEARCH PARADIGM

In IS, a research paradigm is a device used to classify theories and approaches (Iivari, 1991, p. 255). Underpinning a research paradigm are "the philosophic assumptions regarding the nature of the phenomena studied by IS researchers, and what constitutes valid knowledge about those phenomena" (Orlikowski & Baroudi, 1991, p. 1). In other words, a research paradigm is the basis that underlies all research. It implies or conveys: the researchers' assumptions about the world's reality (i.e., ontology); the ways in which people can know about reality or how people can gain knowledge (i.e., epistemology); and the methods that can be used to obtain knowledge (i.e., methodology) (Johannesson & Perjons, 2014, p. 167). Paradigms guide researchers toward understanding research problems, framing research questions, and selecting research methods.

Positivism, interpretivism, and the DSR paradigm (Baskerville et al., 2018; Goldkuhl, 2020; Hevner et al., 2004; Iivari, 2007; Peffers et al., 2018) are often adopted by IS researchers.[47] Positivism is the main underlying paradigm of natural science, and was the main underlying paradigm of the IS discipline in its early era (Orlikowski & Baroudi, 1991). Ontologically, it views world reality (i.e., physical and social reality) as single, knowable, objective, and independent of humans. In contrast, interpretivism, the major paradigm underlying social science, views the world as subjective, socially constructed, and comprising multiple realities (i.e., social realities can only be interpreted).

The DSR paradigm is another "lens" or perspective that complements the positivist and interpretive perspectives when performing research in IS (Vaishnavi & Kuechler, 2004). It is rooted in engineering and the science of the artificial (Simon, 1996) and views multiple realities, contextually situated in alternative world-states (Vaishnavi & Kuechler, 2004). The DSR paradigm seeks to "extend the boundaries of human and organizational capabilities by creating new and innovative artifacts" (Hevner et al., 2004, p. 75). It is essentially pragmatic with a focus on practical utility (Iivari, 2007), but also delivers distinct prescriptive knowledge of IT artifacts (Hevner, 2007).

This study adopts the DSR paradigm because it strives to formulate relevant design knowledge to solve the identified problem (i.e., there is a lack

47 The IS discipline's research paradigms have been evolving along with the development of the discipline, which currently appears to be in a state of pluralism (Iivari, 1991; Iivari et al., 1998; Chen & Hirschheim, 2004; Frank, 2006).

of design knowledge for HC-HDSSs). The innovative artifacts providing practical utility to the problem are examples of design knowledge.

Ontologically, this study agrees with Vaishnavi and Kuechler (2004, p. 9) that there are "multiple, contextually situated alternative world-states" or world realities, the multiplicity of which is constrained in a single, stable underlying physical reality. This ontological view differs from positivism, which posits a single reality; it also differs from interpretivism, which holds a similar view of multiple realities and is socially constructed (Vaishnavi & Kuechler, 2004) but does not emphasize that these realities are also technologically enabled. Epistemologically, this study upholds "knowing through making" (Vaishnavi & Kuechler, 2004, p. 9) or "learning through building" (p. 6), according to which knowledge is gained through "construction within a context" as "iterative circumscription reveals meaning" (p. 9).

4.1.1 ARTIFACT, IT ARTIFACT, DESIGN PRINCIPLE AND DESIGN THEORY

The DSR paradigm provides several key concepts for knowledge communication within and outside the DSR community. The DSR concepts used in this dissertation include artifact, IT artifact, design knowledge, design theory, design principle, and others. Several of these concepts, for example, artifact and IT artifact as the core matter of DSR research (Benbasat & Zmud, 2003; Hevner et al., 2004; Orlikowski & Iacono, 2001), have been used or interpreted differently in various DSR studies. Therefore, this section focuses on clarifying the key concepts of artifact, IT artifact, design principle, and design theory that will be used in the ensuing parts of this dissertation.

4.1.1.1 ARTIFACT

Simon (1966) pioneered the concept of artifact in The Science of Design: Creating the Artificial. Artifact "describe[s] something that is artificial, or constructed by humans, as opposed to something that occurs naturally" (Gregor & Jones, 2007, p. 313). For example, a digital tool, a piece of software, and a DSR method are artifacts because they are created by humans.

An artifact has three levels of abstraction, from the DSR contribution view (Gregor & Hevner, 2013) (see the first column of Table 4.1). The lowest abstract level (i.e., contribution level 1) is the situated implementation of artifacts, for example, the prototype of HC-HDSSs in this study. Level 2 is nascent design theory. Design theory is a prescriptive theory stating how to do something (Gregor, 2006; Gregor & Jones, 2007) or describing "how a design process can be carried out in a way which is both effective and feasible" (Walls et al., 1992, p. 37). As type V theory,[48] that theory for design and action (Gregor, 2006), it differs from the explanatory and predictive theories often found in natural or physical science. Nascent design theory is a narrower use of design theory. It refers to knowledge in terms of constructs, methods, models, and technological rules, as well as the design principles that this study aims to formulate for HC-HDSSs. Level 3 refers to well-developed design theories about embedded phenomena, which are usually mid-range and grand theories. In other words, design theory as used in this study includes both nascent and well-developed design theory.

Table 4.1 (on page 77) is adapted from Gregor and Hevner (2013, Table 1) to show the different abstract levels of artifacts from a DSR contribution view, extending their table by adding the column on the right, namely, "Artifacts in this study." The newly added column highlights the key concepts used in this study and connects them to different contribution abstract levels, as articulated in this thesis. The prototype and the design principles of HC-HDSSs, which this study aims to contribute, are artifacts. Of these, the prototype HC-HDSS belongs to abstract level 1. The design principles of HC-HDSSs belong to abstract level 2, as they are nascent design theories. (This study does not aim to contribute a level 3 artifact, that is, a well-developed design theory, which could be a future research opportunity. Chapter 10 presents more details about this matter.)

48 The other four types are: theory for analyzing (type I), theory for explaining (type II), theory for predicting (type III), and theory for explanation and prediction (Type IV) (Gregor, 2006).

4.1.1.2 IT ARTIFACT

The concept of IT artifact has been used in both broader and narrower ways. Based on March and Smith (1995), Hevner et al. (2004, p. 77) gave a broad definition of IT artifacts as "constructs (vocabulary and symbols), models (abstractions and representations), methods (algorithms and practices), and instantiations (implemented and prototype systems)." This definition includes abstract levels 1 and 2 from the DSR contribution view. Level 1 IT artifacts could be algorithms, human/computer interfaces, and DSSs. Examples of level 2 IT artifacts are system design methodologies (Hevner & Chatterjee, 2010) and methods for IS evaluation (Gregor & Hevner, 2013).

This study applies Orlikowski and Iacono's (2001) narrower view or definition to remain consistent with the selected ADR method.[49] Orlikowski and Iacono (2001), the researchers who popularized the term "IT artifact" within the IS research community, defined IT artifacts as "bundles of material and cultural properties packaged in some socially recognizable form such as hardware and/or software" (p. 121). Sein et al. (2011) also applied this view in their ADR method, instead calling the IT artifact an "ensemble artifact," which specifies "the material and organizational features that are socially recognized as bundles of hardware and/or software" (p. 8). IT artifacts in the present study are a type of artifact that is designed and constructed based on information technologies. Meanwhile, they are socially recognized as bundles of hardware and/or software. According to Gregor and Hevner's (2013) three abstract levels, the IT artifact in this study belongs to the level 1 situated implementation of the artifact (see the right column of Table 4.1).

Table 4.1. Key concepts used in this study (the grey area is adapted from Gregor & Hevner, 2013).

Contribution Types of DSR	**Artifacts in this study**		
Level 3. Well-developed design theory about embedded phenomena	-	**Design theory**	**Design knowledge**
Level 2. Nascent design theory - knowledge as operational principles/architecture	**Design principles** of HC-HDSSs		
Level 1. Situated implementation of artifact	The **prototype** of HC-HDSSs	**IT artifact**	

49 Sein et al.'s (2011) ADR method is the research method used in this study (for arguments, see section 4.2.1).

4.1.1.3 DESIGN PRINCIPLE

As level 2 artifacts, nascent design theory design principles are among the main contributions of this study, i.e., design principles for HC-HDSSs. The design principles delivered by a DSR project are also features that distinguish design science knowledge from other forms of knowledge (Gregor et al., 2020). They are artifacts that belong to Gregor and Hevner's (2013) contribution, which is on abstract level 2, i.e., nascent design theory, and are principles of form and function that define "the structure, organization, and functioning of the design product or design method" (Gregor & Jones 2007, p. 325), and allow "abstracting away from singular settings and thus generalizing prescriptive knowledge" (Chandra et al., 2015, p. 4040). Design principles are stated to be "prescriptive statements that show how to do something to achieve a goal" (Chandra et al., 2015, p. 4040), i.e., knowledge about "know-how." In other words, the purpose of design principles is to guide the design and evaluation of artifacts (Sein et al., 2011). They are used "by implementers who apply them in practice and theorizers who use them to capture knowledge" (Gregor et al., 2020, p. 18).

There are some guidelines for how to formulate design principles in DSR projects. For example, Walls et al. (1992, p. 41) suggested that "if you want to achieve goal X, then make Y happen"; Aken (2004, p. 227), said that "if you want to achieve Y in situation Z, then something like action X will help"; and Chandra et al. (2015) suggested that effective design principles should be formulated to contain three kinds of information: 1) information about the actions made possible through the use of an artifact; 2) information about the material properties that make those actions possible, and 3) information about the boundary conditions of the design work.

However, Chandra et al. (2015) claimed that existing guidelines are inconsistent and imprecise, displaying wild variation and lack of precision (Gregor et al., 2020). Existing guidelines vary in structure, content, and level of abstraction (both between different studies and within the same study), which hampers the reuse of design principles (Cronholm & Göbel, 2018).

Therefore, this study follows the guidance of Cronholm and Göbel (2018),[50] who summarized and synthesized existing guidelines for formulating design principles. In detail, each design principle in this dissertation is given a short name and a description. The short name supports the identification of the design principle (Cronholm & Göbel, 2018), enhancing memorability and capturing its essence in a convenient way (Gregor et al., 2020). The description provides support for understanding how to apply the design principle. It includes four elements, i.e., the purpose/goal of the design principle, the action/process concerning the building of the artifact, the boundary/context, and the artifact's properties,[51] all of which should be justified through argumentation. In addition, all the formulated design principles in this dissertation are presented in the same structure (for congruency, logically continuity, and consistency)[52] and should be considered as creating a whole set of design principles (Cronholm & Göbel, 2018).

4.1.1.4 DESIGN THEORY

This dissertation uses two terms, "goal" and "meta-design," which are two concepts in well-developed design theory in IS or IS design theory (ISDT). Gregor and Jones (2007) and Wall et al. (1992) have discussed the components of ISDT. According to Gregor and Jones (2007), an ISDT consists of eight components: 1) purpose and scope, 2) constructs, 3) principles of form and function, 4) artifact mutability, 5) testable propositions, 6) justificatory knowledge, 7) principles of implementation, and 8) expository instantiation. The first six are core components, whereas the remaining two are additional components. Two of these components that will be frequently used in this dissertation are defined below.[53]

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50 The tables presenting design principles in this dissertation are also affected by the multi-grounded theory method used (see section 4.2.3.2), which adds two rows for the theoretical and/or empirical grounding of a design principle.

51 These constitute meta-design principle 1 of Cronholm and Göbel (2018).

52 This constitutes meta-design principle 2 of Cronholm and Göbel (2018).

53 The remaining six components will be discussed as a future research opportunity in chapter 10.

The first ISDT component is the goal(s) of a class of IT artifacts—"purpose and scope"[54] according to Gregor and Jones (2007) or meta-requirement[55] according to Walls et al. (1992)—telling what the systems/tools are for and setting the scope of the IT artifacts. It describes the overall requirement of designing the IT artifact.

The second ISDT component is meta-design. It refers to a class of IT artifacts hypothesized to meet their goals (Gregor & Jones, 2007; Walls et al., 1992). According to Iivari (2015), meta-design is "a general solution concept to address a class of problem." Sein et al.'s (2011, p. 44) seminal work on the ADR method mentions meta-design while introducing the principle of guided emergence in stage 3: reflection and learning. The guided emergence of the IT artifact "include[s] not only trivial fixes but also substantial changes to the design, meta-design, and meta requirements" (Walls et al., 1992). A meta-design could be a new, innovative concept for a software–hardware system, method, system development approach, or innovative design principle (Walls et al., 1992).

4.1.2 A DSR CONCEPTUAL FRAMEWORK

Hevner's (2007) conceptual framework for DSR has epistemologically guided the overall conducting of this study. The framework consists of three cycles, shown in Figure 4.1, which provides an overview of DSR and its relationship to a broader environment and knowledge base. The relationship among DSR, the environment, and the knowledge base highlights the rigor and relevance of a DSR project, providing an epistemological guide for the overall conducting of this study.

The DSR framework has been formulated by borrowing the IS research framework of Hevner et al. (2004). In the framework, the DSR box is situated in the middle, with the Environment box on the left and the

54 Purpose and scope specify "the type of system to which the [design] theory applies and in conjunction also … [define] the scope, or boundaries, of the theory" (Gregor & Jones, 2007, p. 325).

55 Meta-requirements "describe the class of goals to which the theory applies" (Walls et al., 1992, p. 42), emphasizing that the requirements are for addressing a class of problems instead of a particular one.

Knowledge Base box on the right. The word "design" in DSR has a twofold meaning. It represents both the process of design (used as a verb) and the product of a design process, a designed artifact (used as a noun).

While design refers to a design process, it consists of two processes, building and evaluation. Through a building process, an artifact is created. Conversely, evaluating the artifact provides feedback helping us understand the research problem and improve the design product and the whole design process. Accordingly, a build–evaluate loop (i.e., the Design Cycle in Figure 4.1) iterates several times until a final designed artifact is generated. In the loop, research activities iterate between the construction of an artifact, its evaluation, and the refinement of the design based on feedback. Both the design process and the designed artifact are evolving in this loop.

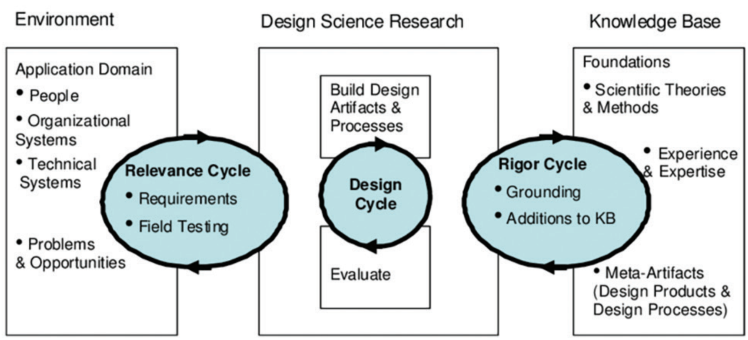

Figure 4.1. Design science research cycle (Hevner, 2007, p. 88).

The Environment box in the framework defines the DSR context (e.g., organization, people, and technical systems), the problem that needs to be solved, or the opportunity for a DSR project. The relevant cycle "bridges the contextual environment of the research project with the design science activities" (Hevner, 2007, p. 88). In this study, the research context and the research problem as components of the Environment box have been specified in section 1.2.

The Knowledge Base box in the framework provides the knowledge foundations of a DSR project, such as scientific theories and methods, experience and expertise from prior studies, and meta artifacts.[56] By grounding the design process theoretically and empirically, the rigor cycle "connects the design science activities with the knowledge base of scientific foundations, experience, and expertise that informs the research project" (Hevner, 200, p. 88). Furthermore, the output of the design process contributes to the knowledge base through the rigor cycle.

In this study, on one hand, the knowledge base connected through the rigor cycle to the designed artifacts consists of the decision-making theories, and other theories presented in chapters 2 and 3, and the knowledge and experience of researchers and practitioners that contributed to the design process. On the other hand, the design knowledge produced by this study, for example, design principles and the prototype, contribute to the knowledge base through the rigor cycle.

In detail, building the HC-HDSS prototype starts with a search for relevant theories in the knowledge base, which is where the rigor cycle begins. The initially identified theories guide the building of the initial version of the prototype and are used in formulating design principles. Here the rigor cycle moves from the Knowledge Base box to the DSR box. Evaluating the initial version of the prototype generates empirical data. Analyzing the empirical data should verify the utility of the prototype and also the utility of the formulated design principles. The outcome of the evaluation should be "something new" in the early design phases. Here "something new" comes from empirical data, but leads to 1) looking for other related theories in the knowledge base with which to revise the formulated design principles or 2) formulating new design principles that could contribute to the knowledge base. The rigor cycle moves from the DSR box to the Knowledge Base box.

56 Meta-artifacts could be design products and design processes, such as prototypes, abstract models and principles, systems development approaches, methods, techniques, and tools. They could be used for the development of IS artifacts (Iivari, 2003).

4.1.3 DSR CONTRIBUTIONS

The primary contribution of this study is in terms of DSR contributions, so this section presents forms of DSR contributions

To advance DSR studies and for a shared common language within the DSR community, DSR researchers have been working on clarifying or assessing the degrees of DSR contributions (e.g., Chandra et al., 2015; Gregor & Hevner, 2013; Gregor & Jones, 2007; Hevner et al., 2004). This dissertation will also emphasize the contributions of this study (in the final chapter) by using the following three DSR contribution frameworks.

First, Gregor and Hevner (2013) proposed a three-level abstraction framework to indicate three maturity levels of DSR contributions or artifacts. Level 1, with the lowest abstraction, refers to more specific artifacts, for example, instantiations. Level 3 represents more general or abstract artifacts, for example, well-developed design theories. Artifacts in level 2, at the middle level of abstraction, are regarded as nascent design theory, for example, constructs, design principles, and methods. The framework is presented in the first column of Table 4.1 and is elaborated on in section 4.1.1.1.

Second, Gregor and Hevner (2013) also formulated a knowledge contribution framework in a 2 × 2 matrix by considering the maturity of the application domain and the solution (see Figure 4.2). The application domain can be a research problem or a research opportunity. In the figure, the maturity of the application domain or problem context (i.e., the x-axis) decreases from left to right. The maturity of the solution (i.e., the y-axis) decreases from bottom to top. Therefore, by considering the starting point of a research project context in terms of the maturity of the research problem and the solution, potential DSR contributions can be located in four different quadrants: Routine Design, Improvement, Exaptation, and Invention.

Routine design refers to the quadrant with the highest maturity of the problem and application domains, for example, applying known solutions to known problems. Studies located in this quadrant are considered to be lacking major DSR knowledge contributions. Improvement represents the quadrant with high maturity of the problem and low maturity of the solution, for example, contributing a newly identified solution to a known problem. Conversely, exaptation represents the quadrant with low maturity of the problem and high maturity of the solution, for example, applying a known solution from other fields to a newly identified problem. The invention quadrant represents DSR contributions with the lowest maturity of both the application and solution domains. Chapter 10 will illustrate the contributions of this study by using this matrix.

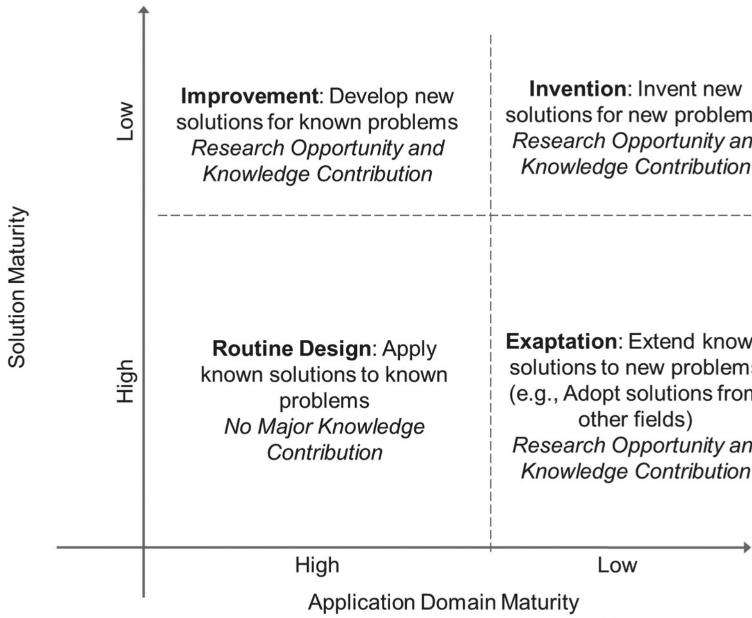

Figure 4.2. DSR knowledge contribution framework (Gregor & Hevner, 2013, p. 345).

Third, Hevner et al. (2004) explained that a DSR project should make both practical and theoretical contributions. As mentioned earlier when introducing the three cycles of DSR shown in Figure 4.1, the knowledge generated by a DSR project should contribute to both theory (i.e., the Knowledge box of Figure 4.1) and practice (i.e., the Environment box of Figure 4.1).

4.2 RESEARCH METHODOLOGY

Research methodology is "the combination of research strategies and data generation methods" for solving a research problem (Oates, 2005, p. 112). In other words, the adoption of a particular research methodology is based on the characteristics of a research problem and the resources that could be applied to solving the problem. Meanwhile, it is also affected by the underlying ontology and epistemology of a researcher.

As stated earlier in this dissertation, the proposed solution to solve the identified problem is to design HC-HDSSs. The outcome of this study, the answer to the research question, should be design knowledge of HC-HDSSs. Therefore, this study's methodology, which consists of the selected research methods,[57] should serve to generate design knowledge of HC-HDSSs.

In brief, the primary research method for generating design knowledge is the ADR method, which is a method of conducting DSR that emphasizes the context and encourages organizational intervention. The FEDS framework (Venable et al., 2016) supplements the ADR method for formulating an evaluation strategy. Aligning with the overall evaluation strategy, which is naturalistic; qualitative methods are used for data collection and data analysis.

4.2.1 THE ADR METHOD

For generating design knowledge to answer the research question, the ADR method has been selected from among several other well-known DSR methods. Arguments for this choice are provided following a list of existing well-known DSR methods.

There are several research methods for conducting a DSR project. For example, Peffers et al. (2007) demonstrated and evaluated a DSR process that consists of six steps (i.e., problem identification and motivation; definition of the objectives for a solution; design and development; demonstration; evaluation; and communication) in a study named design science research methodology (DSRM). Pries-Heje et al. (2007) and Baskerville

57 In this study, a research method is regarded as that which provides detailed guidance for conducting research.

et al. (2009) proposed soft design science methodology (SDSM) by incorporating soft system methodology into a typical DSR process (i.e., design, build artifact, and evaluation). It incorporates seven activities (i.e., identification of a specific problem; expression of the specific problem; deriving the general problem; a general solution design; comparison between the general solution design and the specific problem; search for a specific solution; and construct solutions). Participatory action design research (PADR), formulated by Bilandzic and Venable (2011), includes five stages (i.e., diagnosing and problem formulation; action planning; action taking: design; impact evaluation; and reflection and learning). One more example is the action design research (ADR) method (Sein et al., 2011), which includes four stages (i.e., problem formulation; building intervention and evaluation; reflection and learning; and formalization of learning).

The ADR method was chosen because, first, it emphasizes the context and encourages organizational intervention. As claimed in the seminal work on the ADR method, it emphasizes not only the core of the subject, i.e., the artifact, but also the organizational context where the artifact is built and evaluated. It is a response to Benbasat et al.'s (1999) commentary that there should be a much better balance between rigor (in research methodology) and relevance (to practice) in IS research. As claimed by Sein et al. (2011), ADR stems from the integration of design research (DR) and action research (AR). DR methods focus on building the artifact, positioning the artifact at the core of the information systems discipline, but barely considers its shaping by the organizational context (Sein et al., 2011). Action research is a popular method within the IS community and investigates a phenomenon through intervention (i.e., a course of action) in a problematic situation. It is used to improve the problematic situation while researching the phenomenon or phenomena of interest (Bilandzic & Venable, 2011).

The ADR method integrates both AR and DR and generates prescriptive design knowledge through building and evaluating IT artifacts in an organizational setting. A key tenet of the method is that new information systems should not be developed in isolation from their environments. In other words, the artifacts should emerge from interaction with their organizational contexts (Sein et al., 2011). There should be a tight coupling between the research activities of building, intervention, and evaluation in a cycle, with extensive participation by key stakeholders (e.g., researchers, problem owners, and system users) (Bilandzic & Venable, 2011).

Second, the ADR method takes on a more subjective and interpretive stance to treat the problems, stakeholders, and evaluation compared with several other DSR methodologies (e.g., DSRM)[58] (Venable et al., 2017). The objectivist and positivist treat problems "as coming from the literature and focuses (positivist) evaluation using experiments"; in contrast, the subjectivist and interpretive stance formulates problems based on "local needs (not only literature-based) and the working with client stakeholders in doing so, as well as in the evaluation" (Venable et al., 2017, p. 9).

Third, several studies of DSSs that had already applied the ADR method strengthened the adoption of the ADR method in this doctoral study. These studies applied the ADR method to develop artifacts intended to improve decision-making in different sectors and draw out design theories or principles for a class of similar issues in those fields. For instance, based on Simon's (1977) organizational decision-making process, Beverungen et al. (2015) applied the ADR method and delivered a design theory for a class of DSSs that would support complex decisions concerning the reuse of electric vehicle batteries. Mackrell et al. (2014) adopted the ADR method and developed an artifact with a conceptual framework of a data warehouse for the non-profit sector to improve decisions and report performance; meanwhile, they created a set of guidelines for general use in such a sector. Miah et al. (2019) utilized the ADR method and generated a meta-design for tailorable DSSs.

Therefore, this dissertation has selected the ADR method to guide the development of the HC-HDSS prototype and generate design knowledge of HC-HDSSs. There are three reasons for this choice: 1) the ADR method highlights the relevance of a DSR project, i.e., the organizational context where the artifact is built and evaluated and the intervention of organizations; 2) the ADR method takes a more subjective and interpretive stance; and 3) several studies of DSSs that display both relevance and rigor have applied the ADR method.

58 The PADR method (Bilandzic & Venable, 2011) also applies subjective and interpretive perspectives, but it has been applied specifically in the product and urban informatics domain. Therefore, the ADR method, without a specific application domain, is more suitable for this study than the PADR method.

4.2.1.1 FOUR STAGES AND SEVEN PRINCIPLES OF THE ADR METHOD

The ADR method consists of four stages (i.e., problem formulation; building, intervention, and evaluation; reflection and learning; and formalization of learning) and seven principles (Sein et al., 2011). As the four stages and seven principles have guided the conducting of the entire study, this section presents them in overview. Regarding how the four stages of the ADR method are conducted in this study, see chapter 5 for details.

In the first stage, problem formulation, research opportunities are identified and conceptualized, and research questions are formulated. Problem formulation is the entry point of an ADR study (Sein & Rossi, 2019). A person has a current state; however, he or she is not satisfied with it. If a desired state has not been achieved, this means that there is a gap (i.e., a problem that needs to be solved) between the current state and the desired state. Sein et al. (2011) formulated six tasks for confronting the gap in this stage: 1) identify and conceptualize the research opportunity; 2) formulate initial research questions; 3) cast the problem as an instance of a class of problems; (4) identify contributing theoretical bases and prior technology advances; 5) secure long-term organizational commitment; and 6) set up roles and responsibilities.

Stage two, building, intervention, and evaluation (BIE), is about using the problem framing and theoretical premises identified and adopted in stage one, as well as knowledge from researchers and practitioners about organizational work practice, to generate an initial design of an IT artifact, which will be further shaped by organizational use and subsequent design cycles. Two tasks for this stage are: Task 1: reflect on the design and redesign during the project; and Task 2: evaluate adherence to the principles.

Stage three is about reflection and learning, paralleling the first two stages and drawing on the principle of guided emergence. It includes three tasks: 1) reflecting on the design and redesign during the project; 2) evaluating adherence to the principles; and 3) analyzing intervention results according to the stated goals (Sein et al., 2011). This stage is about conscious reflection on the design and redesign during the study, the problem framing, the theories chosen, and the emerging artifact. It is critical to ensure that contributions to knowledge are identified. Through continuing reflection and learning, initial design knowledge (e.g., design principles for the IT artifact) is identified and revised further. The scope of the IT artifact is extended from the initial design, as more functions are added to the earlier design.

Stage four of the ADR method is about formalizing the learning, which is a conceptual move from the problem instance to a general solution to a class of problems. This stage includes five tasks: (1) abstract the learning into concepts for a class of field problems; (2) share outcomes and assessments with practitioners; (3) articulate outcomes as design principles; (4) articulate learning in light of the theories selected; and (5) formalize results for dissemination (Sein et al., 2011). In this stage, the situated learning in the case organization is further developed into general solution concepts for a class of field problems. The output of this stage is characterized as design knowledge (e.g., design principles) for a class of such problems and, with further reflection, as refinements to theories that contributed to the initial design. These outputs are shared and assessed with practitioners.

Each stage is guided by one or several principles (Sein et al., 2011). The seven principles are shown in Table 4.2. Figure 4.3 is borrowed from Sein et al. (2011) and shows the stages and corresponding principles of the ADR process.

Table 4.2. The seven principles of the ADR method.

Principle	**Name of principle**	**Brief illustrations**
Principle 1	Practice-inspired research	This highlights "viewing field problems (as opposed to the theoretical puzzles) as knowledge-creation opportunities." (Sein et al., 2011, p. 40)
Principle 2	Theory-ingrained artifact	This emphasizes that the ensemble artifacts "created and evaluated via ADR are informed by theories." (Sein et al., 2011, p. 40)
Principle 3	Reciprocal shaping	This emphasizes the "inseparable influences mutually exerted by the two domains: the IT artefact and the organizational context." (Sein et al., 2011, p. 43)
Principle 4	Mutually influential roles	This points to "the importance of mutual learning among the different project participants." (Sein et al., 2011, p. 43)
Principle 5	Authentic and concurrent evaluation	This emphasizes that "evaluation is not a separate stage of the research process that follows building." (Sein et al., 2011, p. 43)
Principle 6	Guided emergence	This emphasizes that "the ensemble artifact will reflect not only the preliminary design created by the researchers (principle 2) but also its ongoing shaping by organizational use, perspectives, and participants (principles 3 and 4), and by outcomes of authentic, concurrent evaluation (principle 5)." (Sein et al., 2011, p. 44)
Principle 7	Generalized outcomes	This requires moving the problem, solution, and design principles from specific-and-unique to generic-and-abstract. (Sein et al., 2011)

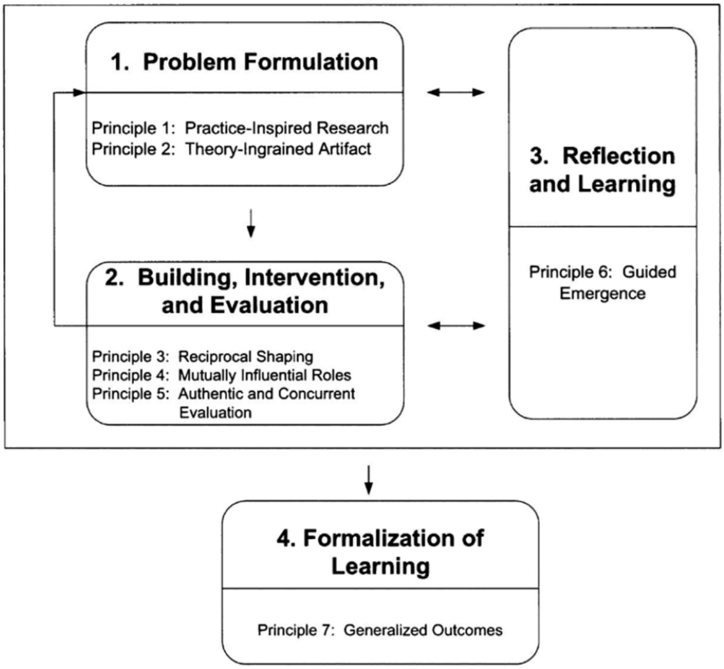

Figure 4.3. Stages and principles of the ADR method (Sein et al., 2011, p. 41).

4.2.1.2 THE NEED FOR OTHER SUPPLEMENTARY METHODS

The ADR method (Sein et al., 2011) provides overall guidance (i.e., the four stages and seven principles introduced above) for conducting an ADR study. The framework is at a high level of abstraction, which provides general knowledge instead of detailed information on guiding the conducting of an ADR study to a greater extent. For instance, the different stages of the ADR method "do not go into details" (Sein & Rossi, 2019, p. 21), and how the principles could be manifested is not specified (Cronholm & Göbel, 2018). The BIE stage of the ADR is "in large part left open to interpretation by the researcher" (Mullarkey & Hevner, 2019, p. 8). Specifically, there is a lack of detailed guidance for the evaluation activities in the BIE stage.

Evaluating artifacts is one of the two key activities (the other one is building) of a DSR project (Hevner et al., 2004), which is a "process of determining how well the artifact performs" (March & Smith, 1995, p. 254). It is central and critical for DSR (Hevner et al, 2004; March & Smith, 1995; Pries-Heje et al., 2008). It primarily evaluates artifacts' utility in solving the identified problem(s) (i.e., the relevance cycle in Figure 4.1) and in contributing to the knowledge base (the rigor cycle in Figure 4.1) (Hevner et al., 2004; Venable et al., 2016). In Sein et al.'s (2011) seminal work, the authors mentioned utility several times, for example: "later evaluation of the beta versions … assessing value and utility outcomes" (p. 44); "ensemble specific knowledge and user utility are also important contributions of an ADR project" (p. 50); and "ADR … seeking utility in the ensemble they represent" (p. 53).

In detail, Sein et al.'s (2011) seminal work on the ADR method provides one guiding principle related to evaluation activities, i.e., authentic and concurrent evaluation. This principle gives general guidance for when evaluation activity should take place. Specifically, the principle highlights that evaluation should be an ongoing activity interwoven with other activities in the BIE stage, i.e., building and intervention. In other words, the ADR method views building the IT artifact and evaluating it in a way that is not sequential, i.e., not separating building and evaluating. Evaluation is not an activity following the building, as in many design types of research; instead, building the IT artifact, intervention in the organization, and evaluation are interwoven (Sein et al., 2011).

Second, Sein et al. (2011, p. 43) stated that "evaluation cycles for the alpha version are formative, contributing to the refinement of the artifact and surfacing anticipated as well as unanticipated consequences. Later evaluation of the beta versions is summative, assessing value and utility outcomes." The BIE stage is usually conducted in more than one cycle in an ADR project, as in the example of Volvo IT cited by Sein et al. (2011) or the example of service innovation cited by Cronholm and Göbel (2019). This means that there is usually an alpha version in BIE cycle one and a beta version in BIE cycle two. Different evaluation methods for artifacts could be selected and utilized in different research stages or cycles (Cronholm & Goldkuhl, 2003; Venable et al., 2016). Venable et al. (2016) called this an evaluation strategy consisting of different evaluation episodes. However, Sein et al. (2011) implicitly mentioned the evaluation strategy in terms of formative evaluation of the alpha version (i.e., in an early stage) and summative evaluation of the beta version (i.e., in a later stage). No further details are given about creating an evaluation strategy.

In summary, the ADR method does not provide concrete guidelines for creating an evaluation strategy (concerning formative and/or summative) (Göbel, 2019) or for how to evaluate utility. Neither does the method provide exhaustive information that explicitly and concretely specifies why, how, and when to evaluate (Venable et al., 2016). Therefore, there is a need for more concrete ways of working with the ADR method (Haj-Bolouri et al., 2018), especially for evaluation. Other methods related to evaluation should supplement the ADR method (Göbel, 2019).

4.2.2 THE FEDS FRAMEWORK FOR FORMULATING AN EVALUATION STRATEGY

DSR requires rigorous methods for evaluation (as well as for building), which should be derived from "the effective use of the knowledge base, theoretical foundations and research methodologies" (Hevner et al., 2004, p. 88). There are several studies of evaluation methods (e.g., Hevner et al., 2004; March & Smith, 1995; Peffers et al., 2012), strategies for DSR (e.g., Pries-Heje et al., 2008), and evaluation frameworks and strategies for DSR (e.g., Venable et al., 2016).

Pries-Heje et al.'s (2008) and Venable et al.'s (2016) Framework for Evaluation in Design Science (FEDS) was selected to guide the formulation of the evaluation strategy of this doctoral study. The reasons for this choice are as follows: 1) its evaluation strategies are designed specifically for DSR; 2) the FEDS framework (i.e., formative and summative evaluation) is implicitly mentioned in the seminal work on the ADR method; 3) FEDS shares a common language (e.g., terms and concepts) with traditional evaluation theories (e.g., Remenyi, 1999); and 4) it has been selected and applied effectively in several ADR studies (e.g., Cronholm & Göbel, 2019; Göbel, 2019; Shrestha et al., 2020).

4.2.2.1 THE OVERALL EVALUATION STRATEGY

The evaluands in this study are the HC-HDSS prototype and the design principles of HC-HDSSs. The prototype and the design principles should provide utility to address the identified problem (i.e., there is a lack of design knowledge for HC-HDSSs). The prototype can be directly evaluated by the ADR group. The build of the prototype is guided by existing theories in reference disciplines, design knowledge, and the design principles newly formulated in this study. Therefore, the utility of the formulated design principles that are effective for guiding the build of HC-HDSSs is indirectly evaluated while evaluating the prototype.

According to the FEDS framework, there are two basic dimensions when considering an evaluation strategy (Pries-Heje et al., 2008; Venable et al., 2016). The first dimension concerns the functional purpose of the evaluation (i.e., why to evaluate), whether formative or summative (Venable et al., 2016). Formative evaluations are used for improving the characteristics or performance of the evaluand, while summative evaluations are used for creating shared meaning about the evaluand when faced with different contexts (that will influence the selection of the evaluand in future application)(Venable et al., 2016; William & Black, 1996). Formative and summative evaluations can be viewed as the two ends of a continuum where an evaluation may be located. As suggested by Sein et al. (2011), this study plans to use both formative and summative evaluations in different BIE cycles, respectively. Formative evaluation intended to improve the characteristics and performance of the HC-HDSS prototype is the main focus of early evaluation; later, the evaluations progressively become summative, emphasizing the utility of the prototype.

The second dimension concerns the evaluation method's paradigm[59] (i.e., how to evaluate), which can be artificial or naturalistic (Venable, 2006; Venable et al., 2016). The artificial evaluation (e.g., laboratory experiments, simulations, criteria-based analyses, and mathematical proofs) "is nearly always positivist and reductionist," being used for improving or disproving the design theory and/or the utility of the IT artifacts (Venable et al., 2016, p. 80). The naturalistic evaluation "explores the performance of

59 Here, the term "paradigm" has a meaning similar to its meaning in scientific paradigms such as positivism, interpretivism, or the DSR paradigm (Venable et al., 2016).

a solution technology in its real environment, typically within an organisation" (Venable et al., 2016, p. 81). This study adopts the ADR method, the evaluation of which is concurrent with building the IT artifact, i.e., building and evaluation are intervened in the organization. In other words, the evaluations are conducted in a real organizational environment from the early stage of the design process to its end. The naturalistic paradigm is in line with the underlying paradigm of the ADR method. From this paradigm perspective, the evaluation is conducted in real organizations, so the evaluation method is close to naturalistic.

To sum up, the overall evaluation strategy in this study is naturalistic; through the design process, there is a progression from formative to summative evaluation. Guided by the overall evaluation strategy, an evaluation plan was made at an early stage (i.e., in BIE iteration one). In implementing the research, the plan was first revised within the research group and later within the ADR group (including researchers and practitioners). Table 4.3 presents the final evaluation strategy with four episodes. Evaluation episode 1 is for BIE iteration one. Evaluation episodes 2a and 2b are for BIE iteration two. Evaluation episode 3 is for BIE iteration three. The table includes information about when, why, and how to evaluate. Regarding what to evaluate (i.e., evaluation properties such as utility), details are presented in section 4.2.2.2.

In Table 4.3, evaluation episode 1 is formative. It focuses on evaluating components of the HC-HDSS prototype. This episode aims to get feedback from the ADR team to improve the components and to evaluate whether the components are designed to reach the goal of solving the identified problem. Episode one is semi-naturalistic/artificial because the evaluation is conducted by a researcher (i.e., the author of the dissertation), presenting the prototype to one representative of each case organization.

Episode 2a is similar to episode 1, that is, formative and semi-naturalistic/artificial. The difference is that episode 2a focuses on evaluating the alpha version of the HC-HDSS prototype. It aims to improve the characteristics of the prototype continuously. The evaluation is still conducted by a researcher (i.e., the author of the dissertation) presenting the prototype to a representative of the case organization as in episode 1.

Episode 2b is formative and summative because it aims to improve the characteristics of the prototype, as in Episode 2a, as well as the utility of the prototype (the alpha version). Episode 2b is still semi-naturalistic/artificial because it is conducted by presenting the prototype to one representative of each case organization as in episodes 1 and 2a. In addition, interview questions related to evaluating the utility are put to practitioners.

Episode 3 is summative and naturalistic. It evaluates the utility of the beta version of the prototype. It is naturalistic because end users (i.e., practitioners from case organizations) use the prototype instead of a researcher presenting it.

Table 4.3. The evaluation strategy with four episodes.

When to evaluate	**Why to evaluate**	**How to evaluate**
Episode 1 (in BIE iteration one)	**Formative** Evaluating components of the HC-HDSS prototype, aiming to improve the characteristics of the prototype based on the objective of HC-HDSSs	**Semi-naturalistic/artificial** The evaluation activities are conducted within research group first, then within the ADR group, including one representative of each case organization, through workshops
Episode 2a (in BIE iteration two)	**Formative** Evaluating the alpha version of the HC-HDSS prototype, aiming to continue improving the characteristics and performance of the prototype	**Semi-naturalistic/artificial** The evaluation activities are conducted within the research group first, then within the ADR group, including one or two representatives of each case organization, through workshops; a researcher presents the prototype to practitioners in the workshops
Episode 2b (in BIE iteration two)	**Formative and summative** Evaluating the alpha version of the HC-HDSS prototype, aiming to continue improving the characteristics, performance, and also the utility of the prototype	**Semi-naturalistic/artificial** The evaluation activities are conducted within the ADR group, including one representative of each case organization, through workshops and interviews; a researcher presents the prototype to practitioners in workshops; interviews are conducted
Episode 3 (in BIE iteration three)	**Summative** Evaluating the beta version of the HC-HDSS prototype, aiming to evaluate the utility of the prototype	**Naturalistic** The evaluation is conducted with end users in the case organizations through workshops and interviews

4.2.2.2 EVALUATION PROPERTIES

Regarding what to evaluate (i.e., evaluation properties), DSR researchers give general suggestions such as evaluating the utility, quality, and efficacy of the artifacts (e.g., Hevner et al., 2004; Peffers et al., 2007); "IT artifacts can be evaluated in terms of functionality, completeness, consistency, accuracy, performance, reliability, usability, fit with the organisation, and other relevant quality attributes" (Hevner et al., 2004, p. 85). Moreover, "evaluation of a designed IT artifact requires the definition of appropriate metrics" (Hevner et al., 2004, p. 85); evaluation properties that are "unique to the artefact, its purpose(s), and its situation during evaluation" should be defined (Venable et al., 2016, p. 83). Therefore, drawing on the primary property of utility, together with the defined goal of HC-HDSSs, and the contextual characteristics, six evaluation properties specific to the HC-HDSS prototype are selected and discussed within the ADR research group. Column 1 in Table 4.4 shows the final six evaluation properties. The reasons why they are selected are the following.

As a DSR study, this study's evaluation goal is utility (i.e., the first item in the column "Evaluation properties"), i.e., determining that the HC-HDSS prototype is effective for the identified problem. Therefore, the first evaluation property is utility.

Second, considering that "the new artifact may have deficiencies in functionality or in its inherent qualities (e.g., performance, usability) that may limit its utility in practice" (Hevner, 2007, p. 89), the quality of the HC-HDSS prototype that affects its utility should also be evaluated. Therefore, the remaining properties in Table 4.4 concern evaluating quality.

For example, property Functionality is contextualized as evaluating the main functionalities of the HC-HDSS prototype, such as, the functionality of utilizing both human and machine capabilities in decision-making. Main functionalities directly affect the utility of the prototype. Another example, property Fit with the organization is contextualized as evaluating the relevance of the prototype in relation to the organization's purpose and context.

Table 4.4. Six evaluation properties for evaluating the HC-HDSS.

Evaluation Properties	**Properties contextualized for the HC-HDSS**
1. Utility (Hevner et al., 2004; Peffers et al., 2007; Venable et al., 2016)	The HC-HDSS is effective for solving the identified problem (a lack of design knowledge for HC-HDSSs)
2. Functionality (Hevner et al., 2004)	The function of the HC-HDSS 1) is designed to be human centered and 2) combines both human and machine capabilities
3. Usability (ease of use) (Hevner et al., 2004; Venable et al., 2016)	The HC-HDSS is easy to use
4. Comprehensibility (Venable et al., 2016)	Understandability of the content of HC-HDSS (e.g., labels, statements formation, and work flow)
5. Fit with the organization (Hevner et al., 2004)	The relevance of the HC-HDSS in relation to the organization's purpose and context (e.g., the statements for assessment are contextualized)
6. Perceived decision quality (Jarupathirun & Zahedi, 2007; Parikh et al., 2001; Shrestha et al., 2016)	Quality of the outcome (the decisions made)

As mentioned earlier, evaluating quality could mean evaluating "functionality, completeness, consistency, accuracy, performance, reliability, usability, fit with the organization, and other relevant quality attributes" (Hevner et al., 2004, p. 85) as well as efficiency and comprehensibility (Venable et al., 2016), etc. Based on the project context, the properties functionality, usability, comprehensibility, and fit with the organization are selected from among many, and have been contextualized for this study (see descriptions in column 2 of Table 4.4). For example, the property functionality is contextualized as evaluating the specific functionalities of the HC-HDSS prototype that utilize both human and machine capabilities in a decision-making process. The functionalities directly affect the utility of the prototype. Another example, the property fit with the organization, is contextualized as evaluating the relevance of the prototype in relation to the organization's purpose and context.

The outcomes of the HC-HDSS prototype are, undoubtedly, the decisions made, the quality of which affects the utility of the prototype. Therefore, the perceived decision quality has been used for evaluating digital decision-making systems in DSR and is included as a quality attribute.

This selection of six evaluation properties should not be interpreted as the only relevant properties worth evaluating. However, they have been selected mainly because they are considered the major properties that serve to evaluate the utility of the HC-HDSS prototype within a limited time. For example, perceived decision efficiency (e.g., Jarupathirun & Zahedi, 2007; Shrestha et al., 2016) or efficiency (e.g., Mettler et al., 2014) used as a quality attribute is excluded from this study as it is not the main factor that affects utility. Reliability, which is often used as an evaluation property (e.g., Hevner et al., 2004; Venable et al., 2016), is not included because the property attribute perceived decision quality covers assessing the reliability of the prototype, i.e., the decision made by the prototype is reliable.

4.2.3 METHODS OF DATA COLLECTION AND ANALYSIS

In following the formulated evaluation strategy to conduct formative and summative evaluation activities, data are collected and analyzed. It is worth noting, first, that according to the ADR method, the three activities building, intervention, and evaluation are inseparable and take place concurrently. Although the data are collected guided by the formulated evaluation strategy, the collected data are used to build and evaluate. Second, the data are collected from the ADR team, including researchers and practitioners.

Table 4.5 summarizes the methods for data collection corresponding to the formative and summative evaluations, the type of data collected by each method, and the method of data analysis. The methods selected for collecting empirical data are introduced in section 4.2.3.1. The method for analyzing those data is illustrated in section 4.2.3.2.

Table 4.5. Methods for data collection and data analysis.

Evaluation strategy	Methods for data collection	Data collected	Method for data analysis
Formative	Presenting the tool to researchers and practitioners	Qualitative data (comments from researchers and practitioners)	Inspired by the multi-grounded theory (MGT) method
Summative	Interviewing practitioners using semi-structured questions (questions related to the six evaluation properties are given in section 4.2.3.1)	Qualitative data (answers from practitioners)	

4.2.3.1 THE METHOD OF DATA COLLECTION

As presented in section 4.2.2.1, the evaluation of this study is a combination of formative and summative, which implies that the data should be collected in two correspondingly different ways. This data collection strategy aligns well with Goldkuhl's (2019) study of methods for data collection/generation in IS, which found that DSR researchers usually use several different methods for data collection.

In detail, for formative evaluation, data is collected by the author of the dissertation, who presents the prototype to researchers and practitioners. Their feedback or comments are audio-recorded and transcribed into text.

For summative evaluation, which explicitly targets the utility of the prototype (implicitly targeting the utility of the design principles), interviews with semi-structured questions are carried out with practitioners. Table 4.6 gives examples of questions relating to each evaluation property. Initially, open-ended interview questions are formulated before an interview. In the interview, more questions triggered by pre-formulated questions are asked. The interviews are also audio-recorded and transcribed into text. For both formative and summative evaluations, one other researcher in the ADR group takes notes while collecting data.

Table 4.6. Example questions asked about each evaluation property (used for BIE iteration three).

ID	Property name	Examples of questions asked
1	Utility (i.e., effectiveness)	What are the strengths of this tool?
2	Functionality	The tool tries to utilize human capabilities (i.e., intuition and knowledge) in decision-making. What do you think about this? The tool tries to utilize a machine's capabilities in decision-making. What do you think about this? The tool tries to combine human and machine capabilities in a guided decision-making process. What do you think about this?
3	Usability (ease of use)	What do you think about the tool related to its ease of use?
4	Comprehensibility	What do you think about the tool (e.g., the labels, statement formulations, and workflow) related to its understandability?
5	Fit with the organization	What do you think about the statements assessing the selected ITIL [i.e., IT infrastructure library] practice? What is their relevance to the organization?
6	Perceived decision quality	What do you think about the quality of the decision you made by using this tool? (e.g., Are you satisfied? Is the decision good enough?)

4.2.3.2 THE METHOD OF DATA ANALYSIS

As illustrated above, the data collected are in two different forms, enabling data triangulation (Yin, 2014). However, they should be analyzed as one set of data because they share the overall aim of evaluating the utility of the prototype and corresponding design principles. The multi-grounded theory (MGT) method inspires the data analysis of this study. Illustrations and arguments follow.

The data collected are transcribed into texts, i.e., non-numerical, qualitative data in contrast with numerical, quantitative data. Although quantitative analysis could be adopted for analyzing qualitative data, qualitative data analysis should be considered due to the overall aim of the evaluation. The overall aim of the evaluation is to make sense of the collected data and find codes or categories from the data that could trigger the revision of the prototype directly, revising or formulating design principles (i.e., the theory-building of this study) indirectly. Therefore, the MGT method, based on and transformed from the grounded theory method (GTM) [60](Glaser, 1978; Glaser & Strauss, 1967; Strauss & Corbin, 1990) especially for generating design theory (Goldkuhl & Cronholm, 2010, 2018), inspires the method of data analysis and theory building used in this dissertation. Other qualitative data analysis methods, such as thematic analysis (Braun & Clarke, 2012) and content analysis, are excluded because the aim of those methods is not to generate theories.

MGT consists of four phases: inductive coding, conceptual refinement, pattern coding, and theory condensation. Inductive coding corresponds to open coding in GTM and refers to open-mindedly and inductively coding the raw data and generating categories by identifying and grouping concepts, attributes, and dimensions. Conceptual refinement refers to critically and constructively working with the categories from inductive coding. Researchers should "take a critical stance toward what has been expressed by different informants" (Goldkuhl & Cronholm, 2010, p. 194). Pattern coding mainly corresponds to axial coding in GTM and entails combining categories into theoretical statements. Theory condensation corresponds to selective coding in GTM and is the concluding stage of MGT. At this stage, a theory is generated.

"Multi-grounded" in MGT refers to empirical grounding (i.e., grounded in empirical data), theoretical grounding (i.e., grounded in preexisting theories), and internal grounding (i.e., the theory is internally coherent). In other words, MGT explicitly grounds theory building in empirical data and preexisting theories. This feature aligns well with the design process in this study and with the rigor cycle of the DSR framework in Figure 4.1.

60 The GTM, aiming to build theory from data, was originally developed by Glaser and Strauss (1967). Now it has evolved into a family of methods (Bryant & Charmaz, 2007; Goldkuhl & Cronholm, 2019; Matavire & Brown, 2013; Seidel & Urquhart, 2013). The GTM can be used in different research paradigms (Birks et al., 2013; Lanamäki & Haj-Bolouri, 2019). It has been used flexibly and adaptively with other research methodologies (Birks et al., 2013; Goldkuhl & Cronholm, 2019; Matavire & Brown, 2013).

As introduced in section 4.1.2, the knowledge base shown in the DSR framework should be cyclically referred to until the prototype and the design principles are validated in terms of utility. Specific to the revision or formulation of design principles, i.e., theory building, collecting data from practitioners utilizes their experience and expertise in the knowledge base. Analyzing the collected empirical data for revising or formulating new design principles provides empirical grounding, or the grounding of design principles in empirical data. Some of the codes extracted by analyzing data could be linked to preexisting theories in the knowledge base. Referring to preexisting theories in the knowledge base grounds the revision or formulation of design principles in theories. Therefore, MGT inspires the method of data analysis. For how data are analyzed in each BIE iteration, section 5.3.3 gives details.

This study analyzes data by means of empirical data coding, explicit empirical validation, and theoretical matching. In detail, coding the empirical data in this study means reading the transcribed empirical data collected in one organization with an open mind. Codes are extracted from practitioners' statements; they are grouped and selectively used to improve the prototype's characteristics and/or utility. The improved prototype is used for collecting data from another organization (i.e., explicit empirical validation).

Meanwhile, the prototype is built guided by the design knowledge shown in the meta-design,[61] especially by the design principles formulated in this study. The improvement of the prototype is based on selected and validated codes from the empirical data. For the selected codes, other preexisting theories are searched (i.e., theoretical matching) to improve the corresponding design knowledge in the meta-design, especially the formulated design principles of this study.

For example, in BIE iteration one, a practitioner commented that "more than one human should join the assessment of the statement, because …" (i.e., coding). Based on this selected "code," the prototype was revised by adding the functionality to support the participation of more than one human in the decision-making process. This functionality inscribed in a revised prototype was presented to the representative from

61 Regarding what meta-design is, see section 4.1.1.4: Design theory.

another case organization. The revised functionality was validated (i.e., explicit empirical validation). Meanwhile, theories related to supporting a group of humans making decisions were searched (i.e., theoretical matching).

The above description of the data analysis has been written sequentially. However, empirical data coding, explicit empirical validation, and theoretical matching are conducted iteratively while more data related to evaluation are collected from different BIE iterations. The evaluation stops when the results of data analysis from the latest BIE iteration show the utility of the prototype, which implicitly indicates the utility of the formulated design principles.

4.3 THE STUDY CONTEXT AND THE TWO SELECTED ORGANIZATIONS

The ADR method that this study follows highlights that the building and evaluation are being carried out concurrently with researchers intervening in real organizations, which means that having one or more real organizations is inherently a requirement for adopting the ADR method. This study selected two organizations. On one hand, the two organizations share the broader context of ITSM, specifically concerning decision-making to improve practices in the ITIL service operation of ITSM. On the other hand, the two organizations contribute knowledge in practice from different perspectives (i.e., data triangulation).

4.3.1 THE STUDY CONTEXT

ITSM is the overall context of this study. ITSM is a well-known concept, subject, or discipline[62] in the IT sector and refers to all the activities involved in designing, creating, delivering, supporting, and managing the entire lifecycle of IT services. Service is regarded as "a means of deliver-

62 ITSM is also known as a framework for aligning "IT operations-related activities and the interactions of IT technical personnel with business customer and user processes" (Galup et al., 2009, p. 125)To distinguish ITSM from the framework ITIL, this study applies concept or discipline to ITSM.

ing value to customers by facilitating outcomes customers want to achieve without the ownership of specific costs and risks" (Vicente et al., 2013, p. 148). Service management refers to "a set of specialized organizational capabilities for providing value to customers in the form of services" (Cartlidge et al., 2007, p. 6).

In contrast with traditional technology-oriented approaches to IT, the development of ITSM has been influenced by the concepts of organization, quality, and service (van Bon et al., 2005, p. 15). ITSM helps align IT with organizational goals and delivers value by providing "a framework to align IT operations-related activities and the interactions of IT technical personnel with business customer and user processes" (Galup et al., 2009, p. 125). According to ITSM, IT service providers need to consider the quality of their services and focus on the relationship with customers.

ITIL, which was previously named as IT infrastructure library, is the most commonly used framework that describes best practices in ITSM (Vicente et al., 2013). ITIL 3 [63] is organized around a service lifecycle that includes five stages: service strategy, service design, service transition, service operation, and continual service improvement (Arraj, 2010). The service strategy stage, located in the core layer of the lifecycle, deals with the initial definition and analysis of business requirements, and the defined strategy guides the conducting of the four other stages. The service design, service transition, and service operation stages, located in the second layer, deal with tasks ranging from designing the service and migrating the designed service to the live environment, to live operation. The continual service improvement stage, situated in the outermost layer, covers all the other four stages. It envelops the service lifecycle and offers a mechanism for the IT organization to measure and improve the service (Arraj, 2010), i.e., improving service in terms of service design, service transition, and service operation (Cartlidge et al.,

63 The most recently released version was ITIL 4 in 2019. However, this study started in 2017, when ITIL 3 was being used by organizations. No new fundamental ideas were introduced in ITIL 4 compared with ITIL 3 (ITIL 4, 2019). One change related to this study is that ITIL 4 uses the term "practice," instead of "process" in ITIL 3. For example, the event management process in ITIL 3 is called the event management practice in ITIL 4. Therefore, to align with the latest terminology in ITIL 4, the rest of this dissertation will stick to the term "practice."

2007, p. 9). Giving a brief summary, ITIL provides a holistic perspective on different IT practices that cover the five stages of the service lifecycle. It facilitates the governance of IT and focuses on "the continual measurement and improvement of the quality of IT service delivered, from both a business and a customer perspective" (Cartlidge et al., 2007, p. 8).

Improving service operation is the specific context of this study. In the service operation of ITIL 3, there are three (and not only three) closely related but different main terms, i.e., incident, problem, and event. ITIL defines an incident as an unplanned interruption to an IT service or a reduction in the quality of an IT service (Cartlidge et al., 2007, p. 30) that could lead to loss of, or disruption to, an organization's operations, services, or functions. In ITIL, a problem is a cause of one or more incidents not usually known at the time when the problem is recorded (Cartlidge et al., 2007, p. 31). An event is defined as a change of state that has significance for the management of an IT service or other configuration items (Cartlidge et al., 2007, p. 29). It can be an incident, but not always.

Correspondingly, there are incident management, problem management, and event management practices, respectively. Taking the event management practice as an example (because it is the related practice implemented in the HC-HDSS prototype), the general process starts with events detected. Some informational events (e.g., user login and device power-up) are filtered and recorded in a log. Other events are categorized as warnings (/alerts) or exceptions (/errors), which are responded to by selecting from a number of options. Then, these events are closed when they are handed on to another practice, for instance, incident management practice.

Companies store data related to the service operation practices mentioned above in databases. Applying and analyzing those data have the potential to help improve those practices, i.e., identifying problems in service operation processes and deciding on corresponding improvement solutions.

The activities for improving service operation practices are managerial activities. On one hand, these activities are a type of managerial control (the other two types of control are strategic planning control and operational control).[64]

64 For more details of decision types, see section 2.2.1.

This is because, first, these activities are not about setting strategic objectives within the organization (i.e., strategic planning); conversely, the conducting of these activities is guided by organizational objectives. Second, these activities are not operational control concerns about specific tasks.

As in any managerial activity, the activities to improve practices in service operation involve decision-making. For example, there are decisions regarding which problem to prioritize and which solution to select for implementation. The activities to improve practices align with Simon's (1977, p. 40) three main phases of the managerial decision-making process. In phase one, intelligence, problems or improvement opportunities in service operation practices should be identified. In phase two, design, possible solutions (e.g., decision options/alternatives) for the identified problem(s) or opportunity(ies) are formulated. In phase three, choice, the final solutions to improve practice should be selected or decided from among several options.

On the other hand, the managerial decisions made to improve practices in service operation are semi-structured. This is because improving service operation practices usually starts with assessing the current state of a certain practice based on a predefined metric, benchmark, etc. According to Shrestha et al. (2020), the assessment is mostly done by humans from a third party through interviews and the qualitative analysis of interview answers, which implies that there are unstructured elements in such a decision-making process. In other words, the decision-making process to improve service operation practices is not structured, and because machines cannot automatically conduct the whole process, the outcome of a machine-made decision would have to be based on prewritten algorithms. Instead, machines can support humans by providing suggestions for opportunity/problem identification, choice formulation, and decisions.

4.3.2 THE TWO SELECTED ORGANIZATIONS

Two companies were selected as the organizational setting for collecting data to design the HC-HDSS prototype. The reasons for this choice are the following. First, as introduced in chapter 1, this study is part of a bigger project, DDI, involving researchers and practitioners from several IT departments of organizations in Sweden. Before the start of this study, the two companies were already members of the DDI project and shared the initially perceived problem related to DSSs with other DDI partner companies. In other words, both companies had experienced the perceived problem mentioned at the beginning of problem formulation. Second, the two companies showed interest in participating in the design of HC-HDSSs before the launch of this study. Third, they share a similar context, i.e., ITSM, but are of different sizes and offer different services, which means that the two companies could contribute to the design of HC-HDSSs for the same context but with complementary knowledge.

Company A is medium-sized and mainly offers customer companies IT services in terms of hardware, software, and networking. For instance, it offers data centers, application monitoring, workplace services, service desks, and remote operation. Like most IT companies, organization A applies the ITIL framework to its ITSM. The IT department of company A (referred to organization A in the remainder of this dissertation) that participated in this study of HC-HDSSs is a department responsible for IT service live operation as well as service operation improvement. Organization A uses various DSSs to support their service operation, for example, an application reminding operators of an incident that needs to be addressed in real-time. In addition, digital data are generated by different practices of service operation (e.g., monitoring and event management, and incident management practices) and are stored in the databases of organization A. This large volume of data has not been well utilized to improve those processes. Therefore, the representative of organization A was willing to make better use of Company A's stored data in DSSs to identify problems and further improve the service operation processes. This would be done by applying and analyzing data as well as analyzing more data types, extracting valuable information to help identify problems in the service operation processes, and deciding on corresponding improvement solutions.

Organization A's participation helps to set the broader study context of the HC-HDSS prototype relative to ITSM, i.e., the HC-HDSS prototype is a DSS used in ITSM; decisions supported by the HC-HDSS are managerial decisions for improving IT services. Participants from organization A contributed knowledge gained from their daily ITSM activities.

Organization B is a small-sized private consulting agency. It helps organizations with leadership development, change work, process improvement, communication, business relationships, etc.—in other words, managerial issues. Organization B has an extensive IT and service delivery background and many years of experience in leadership, change work, and coaching in ITSM. On one hand, organization B is familiar with ITSM. On the other hand, its participation helped narrow the broader ITSM context, specifically to improve IT services. The participant from organization B contributed knowledge of ITSM in general and specific knowledge of improving IT services.

To sum up, first, organizations A and B, together with the researchers' group, co-set the context of the HC-HDSS prototype: broadly, a DSS for ITSM; specifically, a DSS for improving practices in service operation. Second, the specific decision support context of improving practices in service operation consists of both structured and unstructured elements, which matches the hypothesis that an HC-HDSS is a DSS that utilizes the capabilities of both humans and machines.

Ten meetings (including interviews or workshops) were conducted with the representatives of the two organizations involved in designing HC-HDSSs.[65] The first two meetings were to collect data for problem formulation. The remaining eight were arranged to collect data for building and evaluating the HC-HDSS prototype in three BIE iterations and for intervening in the two organizations. As mentioned in the section on the method of data collection, interviews were conducted in BIE iterations two and three.[66] The collected data have been analyzed by following the method introduced in the section on research methodology. The results of the data analysis are presented in the sections on reflection and learning in BIE iterations two and three.

65 For more details, see Table 5.2 in section 5.1: Timetable for the research implementation.

66 For the interview questions used in BIE iteration two, see Appendix 2. For the interview questions used in BIE iteration three, see Appendix 3.

4.4 SUMMARY

This study adopts the DSR paradigm due to the claimed multiple, contextually situated alternative world-states, the socially technologically enabled ontologies, and the "knowing through making" or "learning through building" epistemology. The ADR, a method of DSR, is adopted mainly due to its emphasis on the context and its encouragement of organizational intervention.

The FEDS framework supplements the ADR method, providing detailed guidance on formulating evaluation strategies and evaluation properties. Qualitative methods are used for collecting data in evaluation activities. MGT, a method of qualitative data analysis, inspires the method for analyzing the data collected.

Figure 4.4 summarizes and visualizes the research paradigm and research methods. The BIE stage of the ADR is conducted in three iterations.[67] There are three dashed lines between the three BIE iterations and the FEDS framework box. They represent the link between the evaluation strategy shown in the FEDS framework box and the evaluation activities in each BIE iteration.

67 Section 5.3.3 illustrates the three BIE iterations.

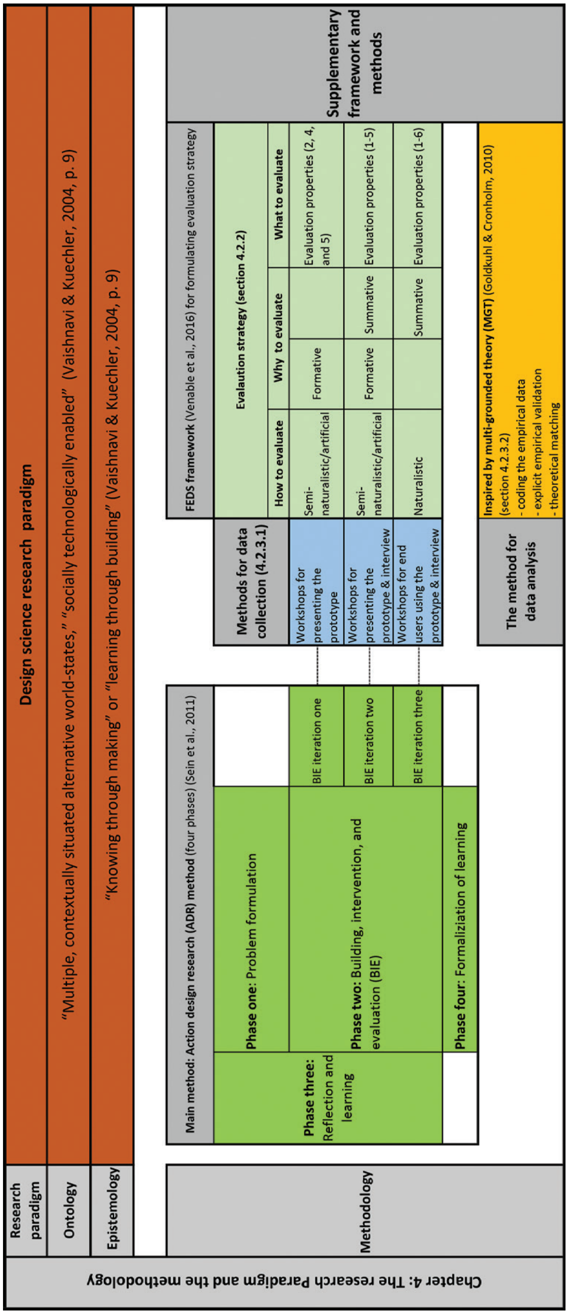

Figure 4.4. A summary of the research paradigms and research methods.

CHAPTER 5
RESEARCH IMPLEMENTATION

This chapter focuses on how the study was conducted by following the ADR method (i.e., the four stages and seven principles), the supplementary FEDS framework, and qualitative data collection and analysis methods. The implementation of the four stages is described in a sequential way. However, stage three, reflection and learning, was undertaken in parallel with stages one and two; the four stages were performed iteratively.

5.1 TIMETABLE FOR THE RESEARCH IMPLEMENTATION

Table 5.1 shows the overall schedule of the research implementation, which was planned and organized based on the four stages of the ADR method. The study started with problem formulation in 2018, i.e., the box in blue. The three yellow boxes spanning 2019 and 2022 represent the three BIE iterations. “BIE 1” refers to “building, intervention, and evaluation” iteration one. The box (in yellow) for each BIE iteration also shows the progression of the study’s main contributions, i.e., the version of the prototype and the formulated design principles. For instance, DP1(v1) represents the first version of design principle 1, which was formulated in BIE iteration one. DP1(v2), listed in the box of BIE 2, refers to DP1(v1) formulated in BIE iteration one that has been developed into a second version in BIE iteration two, i.e., DP1(v2). The content of all the design principles and their evolution will be presented in chapters 7, 8, and 9.

"R&L," which appears in four of the five boxes, stands for the third stage of the ADR method, "reflection and learning." It was carried out in parallel with the stage one problem formulation and the stage two BIE.

This study ends with the green box in 2023, i.e., formalization of the learning, in which the study is finalized and packaged into this monograph and disseminated. The monograph presents the whole research process, which ranges from problem formulation to articulating research outcomes in terms of generalized design knowledge.

There are overlaps between the boxes. The overlaps indicate that the next stage or iteration began before the previous stage or iteration ended. Take boxes BIE 1 and BIE 2, for example. The main activities at the end of BIE iteration one were reflection and learning, and formulating design principles. However, empirical data, i.e., practitioners' comments or suggestions on the prototype, were already collected. They were used in building the prototype in BIE iteration 2. Therefore, BIE 2 starts before the end of BIE 1.

Table 5.1. The schedule of the research implementation.

2018			2019				2020				2021				2022				2023
Q 2	Q 3	Q 4	Q 1	Q 2	Q 3	Q 4	Q 1	Q 2	Q 3	Q 4	Q 1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1
Problem formulation; Reflection & learning (R&L)																			
			BIE 1 (R&L): **Prototype (Initial version)**; **DP1(v1)** Design for utilizing human capabilities; **DP2(v1)** Design for utilizing machine capabilities; **DP3(v1)** Design for combining human and machine capabilities; **DP4(v1)** Design for humans at the center.																
							BIE 2 (R&L): **Prototype (Alpha version);** **DP1(v2)** Design for utilizing human capabilities (intuition and knowledge); **DP2(v1)** Design for utilizing machine capabilities; **DP3(v2)** Design for guided combination; **DP4(v2)** Design for humans at the center; **DP5(v1)** Design for complementary capabilities.												
														BIE 3 (R&L): **Prototype (Beta version);** **DP1(v3)** Design for utilizing human capabilities (intuition and knowledge); **DP2(v2)** Design for utilizing machine capabilities; **DP3(v3)** Design for guided combination; **DP4(v3)** Design for humans at the center; **DP5(v2)** Design for complementary capabilities.					
																Formalization of Learning			

Table 5.2 lists all the meetings (including workshops or interviews) arranged with the two organizations for this study. There were ten meetings in total. Most meetings were limited to two hours.[68]

Table 5.2 Meetings with practitioners.

No.	Meetings (workshop/ interview)	Year & Month	Purpose	Organizations	Stages
1	Meeting & interview	2018.10	Confirm collaboration; identify research problem	A	Stage 1
2	Meeting	2019.1	Confirm collaboration; identify research problem	B	
3	Meeting	2020.2	Discuss main components of the initial design of the prototype, for example, the statements for assessing event management practice, and collect feedback	B	Stage 2 (BIE iteration one) & Stage 3
4	Meeting	2020.3	Discuss main components of the initial design of the prototype, for example, the statements for assessing event management practice, and collect feedback	A	
5	Workshop	2020.4	Discuss the HC-HDSS prototype (alpha version) and collect feedback	B	Stage 2 (BIE iteration two) & Stage 3
6	Workshop	2020.5	Discuss the HC-HDSS prototype (Alpha version) and collect feedback	B	
7	Workshop & interview	2021.9	Present and evaluate the HC-HDSS prototype (Alpha version)	B	
8	Workshop & interview	2021.9	Present and evaluate the HC-HDSS prototype (Alpha version)	A	
9	Workshop & interview	2022.8	Evaluate the HC-HDSS prototype (Beta version)	B	Stage 2 (BIE iteration three) & Stage 3
10	Workshop & interview	2022.9	Evaluate the HC-HDSS prototype (Beta version)	A	

68 As an exception, the first meeting with organization A lasted about one hour. To effectively utilize the practitioners' time, this meeting shared time with another study in the DDI project.

In detail, the first two meetings listed in the table were for confirming the collaboration with the two organizations and collecting information for problem formulation, respectively. The following two meetings (i.e., meetings No. 3 and 4) were conducted in BIE iteration one. These meetings were organized mainly to present the components (e.g., statements of the monitoring and event management practice) of the initial design of the HC-HDSS prototype and of the interfaces with practitioners from the two organizations, respectively. Practitioners evaluated and gave feedback. BIE iteration two held four workshops (i.e., meetings No. 5 to 8) in 2020 and 2021. They were used for presenting and evaluating the alpha version of the designed HC-HDSS prototype, which was improved based on the feedback from the earlier meetings in iteration one and relevant knowledge recently identified through research. In BIE iteration three, two workshops were conducted to evaluate the beta version of the HC-HDSS prototype. It is worth noting that besides the meetings with practitioners, the ADR researchers' group also met regularly to discuss the designed prototype, the generalized design principles, etc.

5.2 ADR STAGE ONE: PROBLEM FORMULATION

Stage one, problem formulation, consisted of six tasks and was guided by two principles, practice-inspired research and theory-ingrained artifact (Sein et al., 2011). The six tasks are listed in Table 5.3. This stage has four primary outcomes: understanding the research opportunity, formulating an initial research question, identifying the knowledge base, and securing long-term knowledge contributions from practitioners and researchers.

Table 5.3 Tasks in ADR stage one (Sein et al., 2011).

The ADR stage	Tasks in the ADR stage
ADR stage one: Problem formulation	Task 1: Identify and conceptualize the research opportunity
	Task 2: Formulate initial research questions
	Task 3: Cast the problem as an instance of a class of problems
	Task 4: Identify contributing theoretical bases and prior technology advances
	Task 5: Secure long-term organizational commitment
	Task 6: Set up roles and responsibilities

5.2.1 IDENTIFY AND CONCEPTUALIZE THE RESEARCH OPPORTUNITY (TASK 1)

Identifying a research opportunity or a problem is the first step of research. Following the principle of practice-inspired research, the problem initially emerged in meetings of the DDI project.[69] Then the problem was discussed in a meeting with more than 50 participants (including representatives of public and private Swedish organizations, researchers, and students). The initially perceived problem was related to existing digital systems used for decision-making.

The identified problem was initially vague, so the author started an investigation to understand it better. An interview was conducted in 2018 with a representative of case organization A. The interview consisted of open-ended questions. These questions were related to the current state of using digital systems to support decision-making in the organization, including whether the respondent was satisfied with those digital systems and expectations of innovative digital systems related to decision-making. In that interview, the research group also narrowed the study context to ITSM[70] (for further about ITSM, see section 4.3.1).

69 The DDI project participants were university researchers and practitioners. The practitioners came from several Swedish public and private organizations of diverse sizes (i.e., small, medium, and large). The researchers and practitioners met regularly.

70 The specific study context of decision-making in improving ITIL practices was decided on with practitioners in following meetings.

Following that, another meeting was conducted with the representative of organization B. Open discussions were carried out about the status of using existing digital systems for decision-making and the expectations of practitioners.

The author reflected on what had been answered or discussed and what practitioners thought was missing or important in such systems. In the end, the author summarized what had been learned from the meetings: practitioners have concerns about the decisions supported by existing digital systems; they expect human capabilities to be utilized.

Guided by the theory-ingrained artifact principle, first, DSSs were identified as the digital systems used in supporting managerial decision-making and, second, possible scientific solutions were sought in the literature. This dissertation identified the capabilities and weaknesses of humans and machines in decision-making. Following this, the initial solution to the problem was proposed as designing a digital system that combines the capabilities of humans and machines for better decisions.

The outcome of Task 1 was a research gap identified between existing design knowledge of DSSs and the design knowledge needed for the proposed solution.

5.2.2 FORMULATE INITIAL RESEARCH QUESTIONS (TASK 2)

Guided by the theory-ingrained artifact principle of ADR stage one, the proposed digital system was initially called a "hybrid decision-making system." The term "hybrid" was initially conceptualized as describing a combination of human and machine capabilities in decision-making based on the identified capabilities and weaknesses of humans and machines in decision-making.

The research gap identified in Task 1 was formulated as a research problem. As the outcome of Task 2, the research problem is: There is a lack of design knowledge for developing hybrid decision-making systems. Therefore, the research question was initially formulated as: How should a hybrid decision-making system be built?[71]

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71 The research question was further developed into what has been presented in chapter 1: How should HC-HDSSs be built?

5.2.3 CAST THE PROBLEM AS AN INSTANCE OF A CLASS OF PROBLEMS (TASK 3)

Following the ADR method, this study "generates knowledge that can be applied to the class of problems that the specific problem exemplifies" (Sein et al., 2011, p. 40). The specific problem (or the instance problem) is that there is a lack of design knowledge for developing a hybrid decision-making system to improve ITIL practice. The class of problems is that there is a lack of design knowledge for HC-HDSSs. This can be illustrated as follows.

The efforts put into tasks 1 and 2 support casting the problem as an instance of a class of problems (Task 3). Guided by the principle of theory-ingrained artifact, preexisting theories, for example, concerning human decision-making, decision types, and DSSs, were searched to help understand and conceptualize the specific problem.

This study initially proposed designing a hybrid decision-making system (i.e., an instance digital system). Correspondingly, the identified problem is a lack of design knowledge for such a digital system (i.e., the instance problem). According to the identified theories, the "decision-making system" is a DSS because it is used to support humans in making decisions. The decision type exemplified by "improving ITIL practice" (in the specific problem) is semi-structured managerial decisions. Together with the "hybrid" and lately identified "human-centered" features, the class of digital systems is HC-HDSSs. HC-HDSSs are a sub-class of the DSS class that inherits several features of the DSS class. Correspondingly, the class of problems is identified as a lack of design knowledge for HC-HDSSs.

5.2.4 IDENTIFY CONTRIBUTING THEORETICAL BASES AND PRIOR TECHNOLOGY ADVANCES (TASK 4)

As introduced in the section on the DSR paradigm, Hevner's (2007) DSR conceptual framework illustrates the relationship between DSR and a relevant knowledge base. The scientific theories and engineering methods (or prior technology advances) in the knowledge base provide "the foundations for rigorous design science research" (Hevner, 2007, p. 89). Similarly, Webster and Watson (2002, p. xiii) claimed that the knowledge base "facilitates theory development, closes areas where a plethora of research exists and uncovers areas where research is needed." Therefore, guided by the principle of theory-ingrained artifact, Task 4 aims to identify a solid theoretical foundation that could serve as a basis for the study. Task 4 also helps target the theoretical contributions of this study to a specific theoretical base.

The theories were initially identified by conducting a literature review. The search strategy was inspired by Levy and Ellis (2006) and Webster and Watson (2002). According to Levy and Ellis (2006), in general, a keyword search is used to find relevant literature to review. However, this approach has some general limitations in the IS field. First, IS is a multidisciplinary field. Researchers are drawing on references from several fields, not only IS but also from fields such as business, management science, or education. It is thus difficult to identify "the applicable key words for an unknown domain" (Levy & Ellis, 2006, p. 190). Second, in the IS field, new technologies are frequently appearing. New concepts or terms for new technologies are emerging, and concepts or terms for old technologies may disappear. This nature of the IS field means that IS studies of similar or related technologies may use different words or phrases, which means that a search sticking to specific keywords may limit the depth and breadth of a literature review (Levy & Ellis, 2006).

Based on Levy and Ellis (2006), this study started the search with the keyword "decision-making" to identify contributing theoretical bases and prior technological advances. The search covered leading peer-reviewed journals and conference proceedings in the IS discipline. The leading peer-reviewed journals in IS, also known as the "basket" of eight (AIS, 2016), are the eight top journals in IS.[72,73] In addition to journals specific to decision-making, Decision support systems and Decision sciences, were added. Apart from journals, conference proceedings sometimes also

72 The eight journals are Information Systems Research (ISR), European Journal of Information Systems (EJIS), Journal of Management Information Systems (JMIS), Journal of AIS (JAIS), Information Systems Journal (ISJ), Journal of Strategic Information Systems (JSIS), MIS Quarterly (MISQ), and Journal of Information Technology (JIT).

73 Three more journals have been added to this list based on the meeting of the college of senior scholars held post-ICIS in Copenhagen (2022). These are Decision Support Systems (DSS), Information & Management (I&M), and Information and Organization (I&O).

deliver high-quality peer-reviewed articles that should not be neglected (Webster & Watson, 2002), so the author extended the search to include the top eight conference proceedings.[74]

Then, the search was complemented by backward and forward searches (Webster & Watson, 2002), called “snowball searches” by Wohlin (2014). Backward search means searching for references in the identified literature, whereas forward search means searching for papers that cite the identified literature. The snowball search (Wohlin, 2014) broadened the searched IS field to encompass other disciplines, for example, business, management science, and computer science.

The searches in the leading peer-reviewed journals and in conference proceedings began in the Scopus database. The keyword string “decision-making” was searched in titles, abstracts, and keywords. The results returned by searching with “decision-making” or “decision making” did not differ. Google Scholar and university libraries (of both Gothenburg University and the University of Borås) were used to acquire articles while conducting the forward and backward searches.

As suggested by the rigor cycle in Hevner’s (2007) DSR conceptual framework, on one hand, the knowledge identified through the above search strategy was used as the theoretical base that this study started with or is positioned on. For example, Simon’s (1977, p. 40) decision-making process view, Kahneman’s (2011) two cognitive patterns of decision-making, and studies of hybrid systems by Demartini (2015) and Demartini et al. (2017) were used to formulate the initial research question and to revise it later on, as well as for the initial design of the HC-HDSS. The knowledge identified is presented in chapters 2 and 3. On the other hand, the contributions made by this study are design knowledge, i.e., theory type V (Gregor, 2006), which will contribute to the design knowledge base in IS.

74 These are International Conference on Information Systems (ICIS), European Conference on Information Systems (ECIS), Hawaii International Conference on System Sciences (HICSS), Americas Conference on Information Systems (AMCIS), Pacific Asia Conference on Information Systems (PACIS), Australasian Conference on Information Systems (ACIS), The Scandinavian Conference on Information Systems/Information Systems Research Seminar in Scandinavia (SCIS/IRIS), and International Conference on Design Science Research in Information Systems and Technology (DESRIST).

5.2.5 SECURE LONG-TERM ORGANIZATIONAL COMMITMENT (TASK 5)

As introduced in section 1.2, this study is part of the bigger DDI project, which means that, before the start of this study, the practitioners and the research group had already established a four-year collaboration agreement. In other words, the two organizations selected for this study already had a long-term research collaboration relationship with the research group before the study began. Second, even though the two organizations showed interest in participating in the study of HC-HDSSs, two meetings were conducted separately with representatives; a primary purpose of these two meetings was to confirm the collaboration and possible contributions in designing HC-HDSSs.

5.2.6 SET UP ROLES AND RESPONSIBILITIES (TASK 6)

The ADR team consists of two stakeholder groups, i.e., the researcher and practitioners' groups. The researchers' group consists of the author of the dissertation, three researchers, and a program/web developer, all of whom are from the University of Borås. The author works as a doctoral student and has taken primary responsibility for the research tasks, for instance, building and evaluating the HC-HDSS prototype, intervening in the organizations, presenting the HC-HDSS prototype, reflecting and learning, and formulating design knowledge of HC-HDSSs. The three researchers, two of whom are supervisors of the doctoral student, supported conducting the research. For example, they helped initiate the first two meetings with the two organizations. They joined in and followed the meetings with practitioners and gave feedback on the design of HC-HDSSs. Their suggestions and comments inspired the author in the design process and affected the formalized learning outcomes. The program/web developer was responsible for implementing the HC-HDSS prototype. The implementation was based on specified design requirements identified by the author, together with the researchers and practitioners. The developer also contributed suggestions on the interfaces of the HC-HDSS prototype from a developer's perspective (i.e., the knowledge and experience of know-how).

Table 5.4 The ADR team.

The ADR team	Participants (and roles)	Responsibilities
The researchers' group	The author of the dissertation	Being primarily responsible for all the ADR tasks
	Three researchers	Supporting the conducting of the research Contributing knowledge about the building, intervening in, and evaluating of HC-HDSSs
	A program/web developer	Implementing the HC-HDSS prototype Giving suggestions for building the prototype from a developer's perspective
The practitioners' group	An ITIL practice manager from organization A	Contributing knowledge about the building and evaluation of HC-HDSSs
	ITIL practice performers/ operators from organization A	
	The owner of organization B and a certified ITIL expert help customers improve their ITSM	
	Customers of organization B	

The practitioners' group consists of representatives of organization A and a representative of organization B. They are also potential end users. Two types of roles for organization A are involved. One role is that of the practice manager, who manages the operation of ITIL practices. Another role is that of the practice performer/operator, who operates ITIL practices. There are also two roles involved in organization B. The first role is the owner of organization B, a certified ITIL expert involved in many successful and unsuccessful IT service improvement projects. The second role represents the customers of organization B, who can use the prototype to improve their ITIL practices. These four roles encapsulate a whole operational and management view of ITIL practices. All the representatives are responsible for contributing their contextualized knowledge to the study (i.e., expertise and experience) and for giving feedback on different versions of the designed HC-HDSS prototype. Additionally, organization A provides digital data stored in a database (e.g., documentation of their ITSM and stored digital data from the tool used for ITSM) for building the HC-HDSS prototype. Table 5.4 summarizes the ADR team.

Tasks 4 and 5, securing long-term organizational commitment and setting up roles and responsibilities, established and clarified the expertise and experience in the knowledge base of the DSR framework (introduced in section 4.1.2). Both groups' knowledge was used for designing the HC-HDSSs.

5.3 ADR STAGE TWO: BUILDING, INTERVENTION, AND EVALUATION (BIE)

Stage two BIE is about building, intervening in, and evaluating the HC-HDSSs. This stage has four tasks (see Table 5.5) and draws on three principles of the ADR method[75]: 1) reciprocal shaping, 2) mutually influential roles, and 3) authentic and concurrent evaluation. This stage used the outcome of stage one, especially the identified knowledge base and dataset shared by organization A, to generate an initial design of HC-HDSSs, which was further shaped by organizational use and subsequent design cycles.

Table 5.5 Tasks in ADR stage two (Sein et al., 2011).

The ADR stage	Tasks in the ADR stage
ADR stage two: Building, intervention, and evaluation (BIE)	Task 1: Discover initial knowledge-creation target
	Task 2: Select or customize BIE form
	Task 3: Execute BIE cycle(s)
	Task 4: Assess need for additional cycles, repeat

75 For the principles of the ADR method, see section 4.2.1.

5.3.1 DISCOVER INITIAL KNOWLEDGE-CREATION TARGET (TASK 1)

The rigor cycle in the DSR conceptual framework (Hevner, 2007) shows that a DSR project should contribute to the knowledge base.[76] Based on the identified problem and research question (introduced in sections 1.2 and 1.3), the theories (introduced in chapters 2 and 3), and the research approach (introduced in chapter 4), an initial knowledge-creation target of this study was established by this task. This means that this study aims to create design knowledge (i.e., a prototype and design principles of HC-HDSSs) concerning how to design HC-HDSSs. Specifically, the design knowledge should expand the DSS knowledge base in the IS community.

5.3.2 SELECT OR CUSTOMIZE BIE FORM (TASK 2)

Sein et al. (2011) presented two endpoints for the research design continuum in a BIE stage, IT-dominant BIE and organization-dominant BIE. The IT-dominant BIE endpoint suits the ADR effort, which "emphasize[s] creating an innovative technological design at the outset" with the influence of practitioners having first-hand experience (Sein et al., 2011, p. 42). In contrast, the organization-dominant BIE endpoint suits "ADR efforts to generate design knowledge where the primary source of innovation is organizational intervention" (Sein et al., 2011, p. 42), with several points being possible between the two endpoints.

This study adopted the generic schema of IT-dominant BIE because it was to design an innovative IT artifact HC-HDSS that did not exist in organizations at the start of the study.[77] That is to say, the innovative IT artifact HC-HDSS was first articulated by the ADR research group. Practitioners' first-hand experience influenced the design throughout the design process to follow. The adapted IT-dominant BIE is shown in Figure 5.1.

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76 See section 4.1.2: A DSR conceptual framework.

77 Organization A uses a DSS to support decision-making in managing ITIL practices. It is a complex digital system. Therefore, the ADR team together decided to develop an independent prototype, i.e., the HC-HDSS, to support decision-making for improving ITIL practices.

In the adapted schema, the ADR team consisted of researchers and practitioners. Details of the ADR team are described in Task 6 of ADR stage one (section 5.2.6). The starting point in the schema is that the researchers' group articulated an initial design of an HC-HDSS based on the knowledge base identified in Task 4 in stage one (section 5.2.4). Following this, the practitioners' group contributed their knowledge and experience to refine and evaluate the IT artifact in the ensuing design process.

5.3.3 EXECUTE BIE CYCLE(S) AND ASSESS NEED FOR ADDITIONAL CYCLES, REPEAT (TASK 3 AND 4)

Executing the BIE cycle(s) is performed through three activities: building the IT artifact, intervention in the organization, and evaluation. The three activities were interwoven in each BIE cycle (Sein et al., 2011).

In an ADR project, executing the BIE cycle(s) and assessing the need for additional cycles are assigned to tasks 3 and 4 (Sein et al., 2011). Before carrying out the first BIE cycle, this study was designed with more than one BIE cycle or iteration. This decision was initially made based on the researcher group's rich experience of applying the ADR method, experience suggesting that an ADR project requires more than one BIE iteration. Second, the established long-term relationship with practitioners in the DDI project ensured the possibility of carrying out more than one iteration of the BIE.

Conducting the BIE activities, especially the evaluations of the designed artifact in BIE iteration two, indicated that a third BIE iteration was required. In the third iteration, saturation was assessed to have been reached when the designed artifact matched the evaluation goal. Therefore, the BIE cycle was executed in three iterations in total (see Figure 5.1). The remaining part of this section focuses on describing how the three ADR principles (i.e., reciprocal shaping, mutually influential roles, and authentic and concurrent evaluation), the overall evaluation strategy (presented in section 4.2.2), and the methods of data collection and data analysis (presented in section 4.2.3) guided the execution of the BIE cycle in the three iterations, respectively.

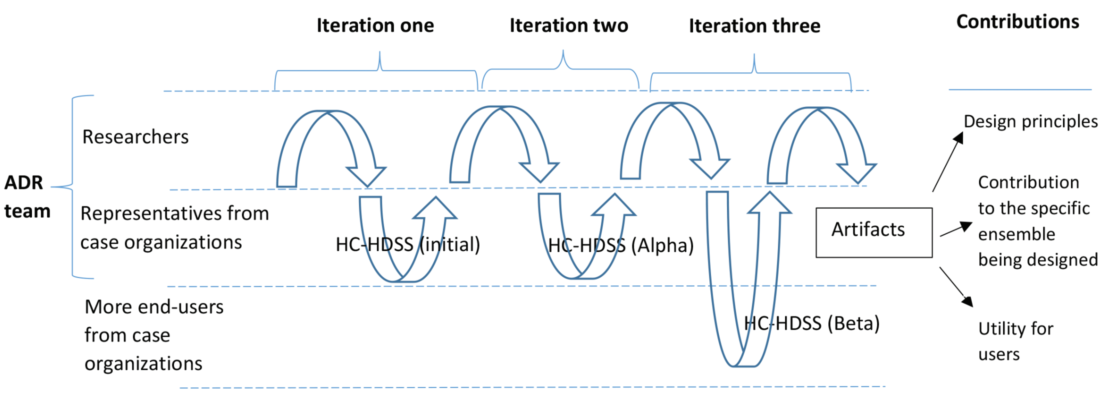


Figure 5.1. The IT-dominant BIE stage with three BIE iterations.

5.3.3.1 BIE ITERATION ONE

BIE iteration one aims to build, intervene in, and evaluate an initial version of the HC-HDSS prototype, which includes several main components of the implemented prototype. These components are the database, user interfaces, and statements for assessing a selected ITIL practice. Meanwhile, this iteration also aims to start the formulation of the design principles of HC-HDSSs.

One main focus of BIE iteration one is developing the statements for assessing a selected ITIL practice in the prototype. As introduced in section 4.3, the HC-HDSS prototype is designed to support decision-making tasks for improving ITIL practices (introduced in section 4.3). Assessing the current state of an ITIL practice, i.e., assessing the statements of an ITIL practice, can help identify potential problems or improvement opportunities.

Guided by the ADR principle of reciprocal shaping, the monitoring and event management practice was selected as the ITIL practice to be implemented in the prototype. This selection was based on the dataset shared by organization A, which is related to the monitoring and event management practice. The statements of the practice were also initially formulated based on the shared dataset in BIE iteration one.[78]

In addition, the initial requirements of the prototype were derived from theories within the ADR researchers' group. This is because the prototype this study was going to build did not exist in organizations (as introduced in Task 2). The theories were identified from design knowledge from the IS discipline and reference disciplines, i.e., the initially identified knowledge base (in Task 4 of stage one). For instance, the prototype should be built of three components (i.e., database, model, and interface), be built to utilize both human and machine capabilities in decision-making, and support decision-making as a process.

The initially defined requirements, together with a small set of data (in the format of an Excel file) from organization A, guided the drawing of mockups of the prototype. The mockups were presented and discussed several times in the researchers' group. This was followed by the programmer of the ADR group developing the prototype based on the mockups. Figure 5.2 gives an example of the requirements and mockups sent to the programmer. The requirement that "the prototype should support decision-making as a process" was extracted from the theory of the decision-making process.

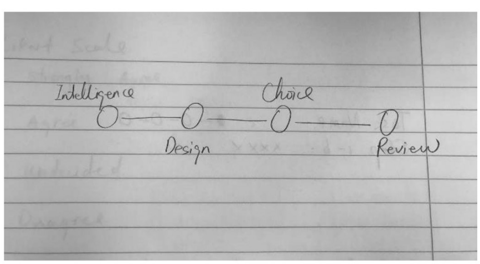
Done	Requirements
Yes	The prototype should support decision-making as a process, including four stages: intelligence, design, choice, and review. 

Figure 5.2. An example of requirements and mockups.

78 More details are given in section 7.2.3: Building to fit the organization.

Guided by the ADR principle of mutually influential roles, two meetings with the practitioners' representatives were carried out respectively by presenting the initial design of the prototype to collect feedback. The researcher's group contributed their theoretical knowledge. The presented prototype, inscribed with theories, triggered the reflection and learning of practitioners related to decision-making in their organization. Meanwhile, the practitioners contributed their knowledge gained from practice to help build the prototype. The initial version of the HC-HDSS prototype served as a lightweight intervention.

Guided by the ADR principle of authentic and concurrent evaluation, the evaluation, which was formative, took place in the same two meetings. In other words, by presenting the initial design to the practitioners, empirical data in the form of practitioners' feedback were collected.

The MGT method[79] inspired the method of data analysis. Relevant words, phrases, or statements from researchers or practitioners were captured as signals (suggested by the ADR method). Selected signals were further used to revise the prototype and/or search for other possible relevant theories. For example, one practitioner commented that "the statements [i.e., about assessing the monitoring and event management practice] could be formulated by considering critical success factors and key performance indicators." Therefore, critical success factors and key performance indicators documents were searched after the meeting; they were used to refine the statements about monitoring and event management practice in the prototype.

The outcome of the data analysis was an initial design of the prototype, an initially formulated goal, and a meta-design for HC-HDSSs. The meta-design consists of the formulated design principles of HC-HDSSs.

To summarize BIE iteration one: the input of BIE iteration one was identified as preexisting theories related to decision-making and designing DSSs, the experience and expertise of the ADR group, and the dataset provided by organization A. In the iteration, these were used to build the prototype and formulate design knowledge about HC-HDSSs. Building, intervention, and evaluation took place concurrently. The primary outcome of BIE iteration one was 1) an initial version of the prototype, 2)

79 For MGT, see section 4.2.3.2: The method of data analysis.

an initial version of the goal of HC-HDSSs, and 3) an initial meta-design including the design principles of HC-HDSSs.[80]

5.3.3.2 BIE ITERATION TWO

Based on the outcome of BIE iteration one, BIE iteration two built, intervened in, and evaluated an alpha version of the HC-HDSS prototype, further refining the goal and the meta-design (including the formulated design principles) of HC-HDSSs. As in BIE iteration one, the three ADR principles related to BIE guided this iteration.

In BIE iteration two, the prototype was revised. The revision was based on the design knowledge outcome (e.g., the formulated design principles) of BIE iteration one. Then the prototype was evaluated by the ADR group. The revised prototype (i.e., the alpha version) was first discussed with researchers of the ADR group. It was improved. Then the prototype was used in two meetings with practitioners from the two organizations, respectively. Corresponding to evaluation episode 2a (in Table 4.3), the functional purpose of evaluation in the two meetings was formative in order to improve the characteristics and performance of the prototype. The author of this dissertation presented the prototype and collected feedback from practitioners.

The continually revised prototype was used in two following meetings with practitioners from the two organizations. Corresponding to evaluation episode 2b (in Table 4.3), the functional purpose of evaluation in the two meetings was formative and summative in order to improve the characteristics and performance of the prototype, and to assess its utility. Therefore, the author of this dissertation collected empirical data by presenting the prototype and asking interview questions.

Similarly, as in BIE iteration one, the alpha version of the HC-HDSS prototype served as a lightweight intervention (as suggested by the ADR method). The collected data were analyzed. For example,[81] in the intervention, one practitioner pointed out that when selecting human participants,

80 The details of BIE iteration one are given in chapter 7.

81 The details of this example are given in section 8.4.1: Reflection and learning about DP1(v1).

the culture or environment of the organization should be considered. In other words, the organizational culture affects the willingness to share knowledge between different human roles. The role of human participants (e.g., managers) may hinder knowledge sharing among other human participants, or other participants may feel afraid to give rational scores.

Signals related to knowledge sharing and culture were captured. The following are theories of organizational culture affecting knowledge sharing (see section 2.1.2) searched. Based on the empirical data and the identified theories, DP1(v1) was revised into DP1(v2). In BIE iteration one, DP1 reads "for …, the digital system should utilize human intuition and knowledge by externalizing humans' implicit knowledge, combining explicit knowledge, socializing between humans, and internalizing the explicit knowledge." In BIE iteration two, DP1 was revised to "for…, the digital system should support the selection of different organizational roles of human participants based on the organizational context. Moreover, the system should externalize the implicit component of human knowledge, combine explicit knowledge between humans, socialize the knowledge between humans and internalize the explicit component of knowledge."

The outcome of BIE iteration two is an alpha version of the prototype, the refined goal, and the meta-design of HC-HDSSs. The refined meta-design includes the newly formulated DP5(v1) and three refined design principles of HC-HDSSs, i.e., DP1(v2), DP3(v2), and DP4(v2). They were used as input for BIE iteration three.

5.3.3.3 BIE ITERATION THREE

BIE iteration three aimed to continue implementing the prototype to make a beta version, revising the corresponding design knowledge, especially the design principles, intervening in the organizations, and evaluating the prototype and corresponding design principles that guided the build.

The outcome of BIE Iteration two was used as input for this iteration. The DP2(v1) outcomes of BIE iteration one, the revised design principles, i.e., DP1(v2), DP3(v2), and DP4(v2), and the newly formulated DP5(v1) from BIE iteration two guided the revision of the prototype.

The prototype was evaluated according to episode 3 in the overall evaluation strategy, i.e., the evaluation was summative and naturalistic. More end users from organizations A and B used the prototype in two workshops, respectively. In each workshop, practitioners were also interviewed. More details are given in the presentation of BIE iteration three in chapter 9.

The collected empirical data were analyzed as in the previous BIE iterations. The results of data analysis showed that the design had reached saturation according the researchers' group of the ADR team. Therefore, the BIE iteration stopped there. The outcome of BIE iteration three is the finalized meta-design of HC-HDSSs, the explicitly or directly evaluated beta version of the HC-HDSS prototype, and the five implicitly or indirectly evaluated design principles of HC-HDSSs.

5.4 ADR STAGE THREE: REFLECTION AND LEARNING

Stage three is reflection and learning. This stage parallels the first two stages. It draws on the ADR principle of guided emergence. This principle emphasizes that "the ADR team should be sensitive to signals that indicate such ongoing refinement" (Sein et al., 2011, p. 44). The signals perceived by the author of this dissertation when meeting the ADR group (presenting the prototype to researchers and practitioners, intervening in organizations) triggered reflection and learning. The reflection was mainly carried out by the author. Discussion with other researchers in the ADR group inspired the reflection and helped formalize the reflection and learning.

The refinement includes trivial adjustments to the prototype and substantial changes to the design, meta-design, and goal of HC-HDSSs. Therefore, this stage supports an improved understanding of HC-HDSSs, further contributing to the conceptual movement "from building a solution for a particular instance to applying that learning to a broader class of problem" (Sein et al., 2011, p. 44).

Stage three includes three tasks (see Table 5.6). The three tasks were also carried out in parallel.

Table 5.6 Tasks in ADR stage three (Sein et al., 2011).

The ADR stage	Tasks in the ADR stage
ADR stage three: Reflection and learning	Task 1: Reflect on the design and redesign during the project
	Task 2: Evaluate adherence to principles
	Task 3: Analyze intervention results according to stated goals

Task 1: Reflecting on the design and redesign during the project

Guided by the principle of guided emergence, signals were perceived indicating anticipated and unanticipated results. Anticipated results confirmed the previous design, for example, the selection of preexisting theories. Unanticipated results showed the need for redesign, for instance, reframing the problem, refining the goal and meta-design of HC-HDSSs, removing selected theories, searching for other theories that could be used in redesigning HC-HDSSs, further revising the formulated design principles of HC-HDSSs, and redesigning the correspondingly implemented functions in the prototype. The details of the anticipated and unanticipated results of each BIE iteration are presented in sections 7.4, 8.4, and 9.4, respectively.

Task 2: Evaluating adherence to principles

Building the prototype of HC-HDSSs (later versions) was guided by the earlier formulated design principles of HC-HDSSs. Specific to evaluation, the reflection and learning emphasized checking the adherence of the HC-HDSS prototype building to the formulated design principles. The anticipated results confirmed the previous design, whereas the unanticipated results indicated a need to revise the design principles.

Task 3: Analyzing intervention results according to stated goals

As will be introduced later in this dissertation, the goal of HC-HDSSs[82] sets the scope of HC-HDSSs and tell what they are for; it describes the overall requirements for designing HC-HDSSs. This task highlights that the stated goal of HC-HDSSs guides the overall data analysis. In other

82 The goal of HC-HDSSs is "a contextualized easy-to-use web-based IT artifact that is designed with humans at the center, and utilizes both human and machine capabilities to make semi-structured managerial decisions."

words, the empirical data directly collected while intervening in the organizations and the indirectly generated anticipated and unanticipated results were analyzed based on the formulated goal of HC-HDSSs.

The data were analyzed and reflected on by the author of this dissertation. The results of the data analysis and the reflection were discussed with the whole ADR team.

5.5 ADR STAGE FOUR: FORMALIZATION OF LEARNING

Stage four of the ADR method is about formalizing the learning and draws on the ADR principle generalized outcomes. That is, there is a conceptual move from the specific solution to generalized solutions. In other words, the situated learning in the case organizations was further developed into general solution concepts for a class of field problems in this stage. The outcome of this stage was design knowledge in terms of finalized goal, meta-design, and design principles as a class of solutions for a class of problems. The output was shared and assessed with practitioners.

This stage includes five tasks (see Table 5.7):

Table 5.7 Tasks in ADR stage four (Sein et al., 2011).

The ADR stage	Tasks in the ADR stage
ADR stage four: Formalization of learning	Task 1: Abstract the learning into concepts for a class of field problems
	Task 2: Share outcomes and assessment with practitioners
	Task 3: Articulate outcomes as design principles
	Task 4: Articulate learning in light of theories selected
	Task 5: Formalize results for dissemination

Task 1: Abstract the learning into concepts for a class of field problems

The learning in this stage results in abstract concepts related to the class of problems. For instance, the concepts of "complementary capabilities," "hybrid," and "human-centered" are articulated and presented in section 3.3; what exactly the HC-HDSSs are is clearly defined in section 3.3.

Task 2: Share outcomes and assessment with practitioners

The outcomes and assessment were shared in meetings with practitioners starting from BIE iteration two. The author presented the prototype to practitioners. The functionalities of the prototype, which were implemented or refined based on practitioners' suggestions in the previous BIE iteration, were highlighted in the meetings. For example, the 12 statements about monitoring and event management practice were highlighted in the meetings of BIE iteration two, and these statements were refined based on practitioners' suggestions in BIE iteration one.

Task 3: Articulate outcomes as design principles

As will be presented in chapters 7, 8, and 9, the design principles of HC-HDSSs started to be formulated at the end of each BIE iteration. The design principles were formulated following the guidance of Cronholm and Göbel (2018). In this final stage of the ADR method, those design principles were fully formulated and articulated as presented in this dissertation.

Task 4: Articulate learning in light of theories selected

As indicated by the rigor cycle of the DSR framework (Hevner, 2007), the outcome of this ADR study should feed back to the knowledge base. This study started by building upon the selected theories, for example, the theory of DSSs. The feedback, i.e., the learning or the outcome of this study, is articulated to connect back to the selected knowledge base. In detail, the HC-HDSS prototype was initially built based on design knowledge of the DSS class (and theories from other reference disciplines). The HC-HDSS class (which contains generalized design knowledge of this class) extends the DSS class. That is, an HC-HDSS has the features of a DSS as well as other features specific to the HC-HDSS class, which can be built through the guidance of the formulated design principles.

Task 5: Formalize results for dissemination

The results of this study have all been formalized in this dissertation. The dissertation is a monograph instead of a compilation of papers. This form allows the evolution of the contributions to be presented, i.e., how the goal, meta-design, and design principles of HC-HDSSs have evolved from initial to final versions, instead of only presenting the final version of the contributions. The results will also be further disseminated in conferences and journals after the defense.

CHAPTER 6
THE HC-HDSS PROTOTYPE

This chapter presents the final version of the HC-HDSS prototype[83], an instance of HC-HDSSs implemented in the ITSM context. The build of the prototype was guided by theories identified from existing studies and from design knowledge emerging in the three BIE iterations. Presenting the prototype (the final version) before introducing how it was built was done in anticipation that the prototype could provide a complete and concrete picture of what an HC-HDSS might be like. How the functionalities of the prototype were built (i.e., how design knowledge guided the building) will be introduced in chapters 7, 8, and 9.

83 The language work is unpolished as it is a prototype instead of a fully fledged digital tool.

6.1 THE MAIN PROCESS AND ROLES OF ACTORS

Figure 6.1 provides a brief overview of the main process in the prototype, which consists of four main activities, i.e., four main steps. Step 1, *preparation*, refers to preparing for a decision-making project by naming a project, selecting an ITIL practice, selecting participants, etc. On one hand, this step provides an interface for entering the prototype. On the other hand, it aims to contextualize a decision-making project based on an actual situation. Step 2, *intelligence*, aims to identify a problem or opportunity by gathering information from the environment (e.g., organization). Step 3, *design,* is for framing the particular choices in terms of the possible solution(s) for the identified problem or opportunity from step 2. Step 4, *choice,* is about evaluating and deciding on a solution. Decision-makers could compare the possible solutions from step 3 and select one of several.

The main process shown in Figure 6.1 was drawn using Business Process Modeling Notation (BPMN) 2.0 (Object Management Group, 2021), which is a standardized graphical notation widely used to model business processes[84] for business process management.[85] Each main activity/step contains sub-steps, and the details will be presented in the following sections.

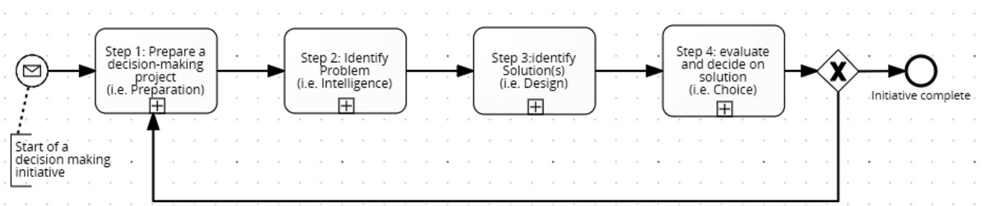


Figure 6.1. The main process of the designed prototype (by BPMN 2.0).

The prototype was implemented as a web-based tool consisting of several webpages. Each webpage represents a step or sub-step in the process. The main process in the prototype is displayed in terms of a process map (see

84 A business process is "a set of logically-related tasks performed to achieve a defined business outcome" (Davenport & Short, 1990, p. 4).

85 Business process management "includes concepts, methods, and techniques to support the design, administration, configuration, enactment, and analysis of business processes" (Weske, 2019, p. 5).

Figure 6.2) in the upper right corner of each webpage. It aims to provide users with a brief overview of the whole process and to indicate which step the user is currently in by highlighting the step in a darker color. For example, step 1 is highlighted in Figure 6.2, which means that the user is in step 1. Besides displaying the main steps, sub-steps are also shown in Figure 6.2. For instance, there are four sub-steps in step 2. The "2A" in Figure 6.2 indicates the first sub-step in step 2.

Figure 6.2. Process map in the HC-HDSS prototype.

Before moving on to describing each step, the actors in the prototype should be introduced. The HC-HDSS prototype is designed for two types of actors, humans and machines (see the first column in Table 6.1). Different roles can be distinguished among the actors; an actor can take on several roles (see the second column in Table 6.1).

The first role of the human actor is that of facilitator. The facilitator is familiar with the designed HC-HDSS prototype and is responsible for facilitating its use. For example, the facilitator creates a decision-making project/task, uploads relevant text or image documents that could be used for human assessment, and uploads initial data for the machine actor to analyze. This role could be played by a researcher, an IT service manager, or a knowledgeable operator in an organization. This role only participates in "step 1," shown in Figure 6.3. In other words, this role does not participate in making decisions (from steps 2 to 4 in Figure 6.2).

The other three roles of the human actor are participating in the decision-making process and jointly making final decisions. These are the roles of the practice manager, who manages the operation of ITIL practices, the practice operator, who operates ITIL practices, and other practice stakeholders, such as the operators of other connecting practices. For example, if the selected practice in a decision-making project/task is event management practice, operators of incident or problem management practice could act in this role. There are three key roles in which human actors can apply human capability in a decision-making task. They contribute knowledge in different steps, for instance, assessing practice-relevant statements individually and/or collaboratively, identifying problems and solutions, and evaluating and deciding on the problem–solution pair for implementation in the future.

Table 6.1. Actors and roles in the HC-HDSS prototype.

Actors in the HC-HDSS prototype	Roles	Description	Main responsibilities
The human actor	Facilitator	Supporting the use of the HC-HDSS prototype; could be a researcher or IT service manager	Facilitating the use of the HC-HDSS prototype throughout the decision-making process
	Practice manager	Participates in decision-making tasks	Assessing a selected practice; making decisions
	Practice operator	Participates in decision-making tasks	Assessing a selected practice; making decisions
	Other practice stakeholders	Participates in decision-making tasks	Assessing a selected practice; making decisions
The machine actor	Intelligent machine	Participates in decision-making tasks	Analyzing datasets; providing information (e.g., displaying example datasets and statistical information) for each practice statement; suggesting possible solutions for the identified problem or improvement opportunity
	DSS	A digital tool/system	Supporting the decision-making process, for example, by providing data storage and data management, users interfaces

The machine actor has two roles, as a DSS and as an intelligent machine. The role of a DSS supports the whole decision-making process as an ease-of-use web-based digital tool by storing data, displaying statements for assessment, and presenting the results of data analysis, etc. The role of the intelligent machine is also the key role that participates in the decision-making process by analyzing datasets. It is the role of providing the capabilities of machines. In detail, it provides information in terms of statistical data to help human decision-making participants make final decisions or suggest solutions to the identified problem. It could be any data-analysis technology such as data mining and/or machine learning.

In summary, four roles participate in the decision-making process (i.e., steps 2 to 4 in Figure 6.2). Three of the four are played by humans taking part in the whole decision-making process and making the final decisions. One role is played by a machine taking part in the intelligence and design phases of the decision-making process. The four roles and their responsibilities are shown in the grey area of Table 6.1. Notably, a human actor can have more than one role in the tool.

6.2 STEP 1: PREPARE A DECISION-MAKING PROJECT/PREPARATION

As introduced earlier, step 1 provides an interface for users entering the designed prototype, as shown in Figure 6.3. The interface lists all the existing created projects when a user logs in to the system. The interface is also implemented to incorporate the functionalities of *creating* a new decision-making project, and of *editing*, *launching*, and *deleting* an existing project.

The "+Create Project" button is used to create a new decision-making project. Clicking on the button opens a webpage called "Create." The screenshot of the "Create" page is shown in Figure 6.4. This page provides functionalities for users to give contextual information related, for example, to the project's name, objective, description, and expected outcome.

In detail, a functionality called "Select an ITIL management practice" is used to contextualize a decision-making project based on a real situation (see #1 in Figure 6.4). As an example to illustrate the prototype, the operation practice of event management, i.e., monitoring and event management practice, is selected from the drop-down list "Select an ITIL management practice." Twelve tailored statements[86] about assessing the event management practice are inscribed (see Appendix 1). They are extracted from ITIL-relevant documents initially discussed and decided on together with two representatives of the two case organizations.

86 A statement here refers to something that is written and conveys information or an opinion.

The functionality "Upload text or image documents for human assessment" (see #2 of Figure 6.4) is designed so that a user creating a project can upload text or image documents for human assessment in these steps. When humans assess a statement in the ensuing steps, they may need to seek information to support their assessments. The information may come from documents uploaded on the "Create" page. These documents can be in the .doc, .docx, .pdf, and .jpg formats. Organization A provided several documents relevant to event management practice for the prototype, for example, the Service Level Agreement (SLA) document.

The functionality "Upload dataset for machine assessment" (see #3 of Figure 6.4) is for uploading an event management practice-relevant dataset for machine analysis. It is in the .xlsx or.xls format with fixed structures. Organization A provided an example dataset that this functionality could use.

The functionalities shown in the box #4 in Figure 6.4 are designed for adding one or more humans to a decision-making project.

In Figure 6.3, the "Launch" functionality is for a user entering the next step, i.e., step 2: Intelligence. The "Edit" functionality allows users to edit an existing project before "launching" it. For instance, the user can edit the project by adding or deleting a human participant. The webpage for "Edit" is similar to the "Create" page introduced above. Right next to the "Edit" functionality is the "Send emails" functionality, by clicking on which emails containing the links to individual assessments will be sent to the selected participants, respectively. The "Delete" functionality allows users to delete a selected decision-making project. Usually, the role of manager or facilitator is applied in this step.

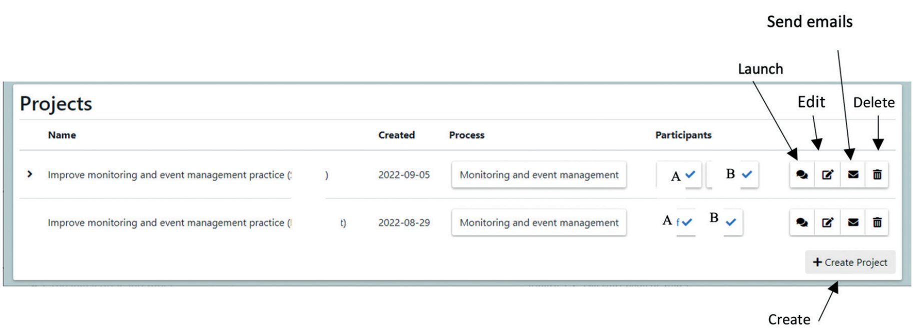


Figure 6.3. The start page of Step 1: preparation.

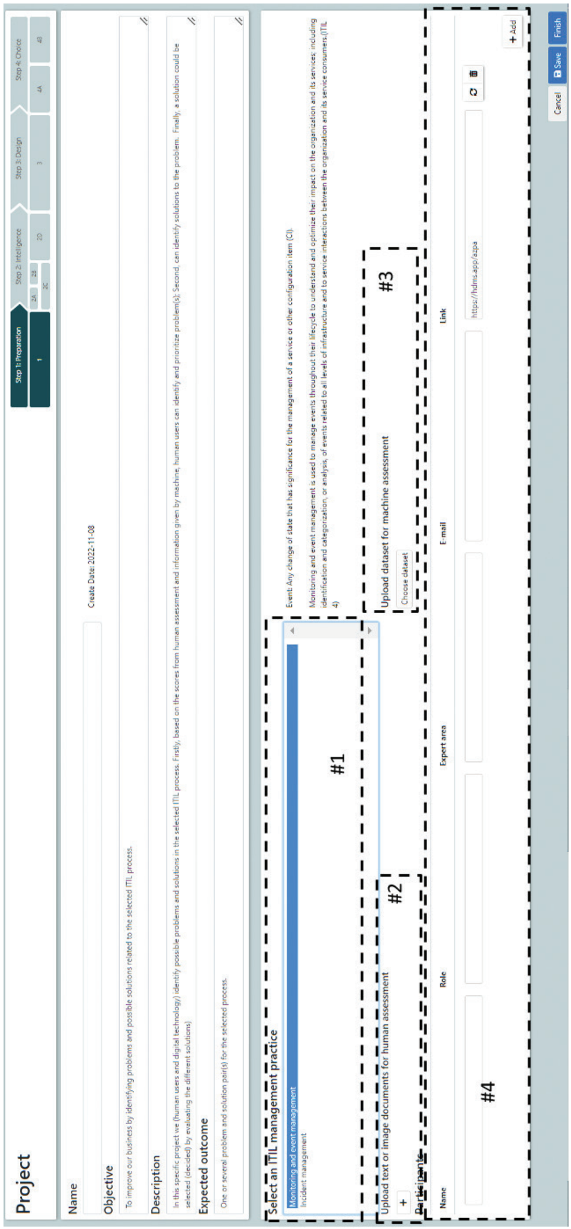


Figure 6.4. Screenshot of creating a decision-making project.

6.3 STEP 2: IDENTIFY PROBLEM/INTELLIGENCE

Step 2 corresponds to the "intelligence" phase of Simon's decision-making process (see section 2.1). It aims to identify problems or opportunities by assessing the selected ITIL practice statements. The process map drawn by BPMN 2.0 is shown in Figure 6.5. Step 2 is divided into human assessment (steps 2A and 2B) and machine assessment (step 2C). The two actors, humans and machines, start the activities of this step in parallel, i.e., first, humans assess individually in step 2A and then collaboratively in step 2B; meanwhile, the machine actor assesses in step 2C. When both actors finish their assessments, they meet in step 2D to consolidate both assessments.

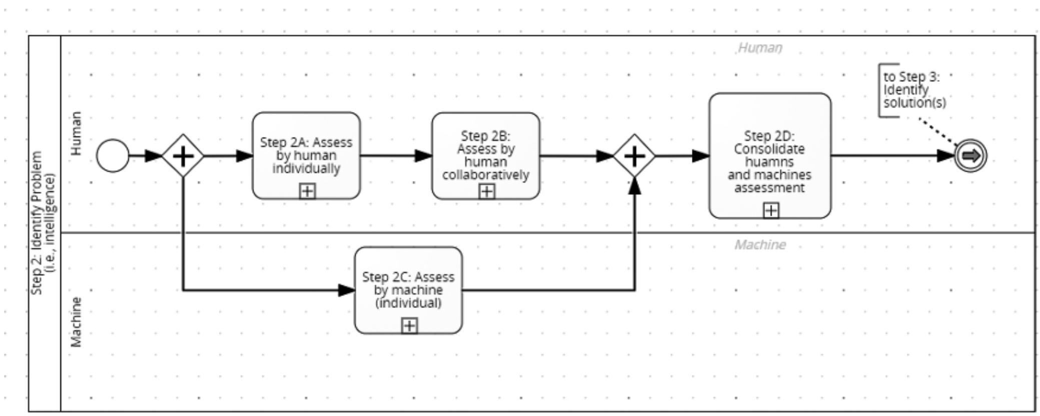


Figure 6.5. Process map of step 2: Identify problem (i.e., intelligence) (by BPMN 2.0).

In step 2A: *Individual assessment* (see Figure 6.6), an individual human participant assesses statements by scoring them (see box #1 in Figure 6.6). In detail, for a selected statement, an individual human participant selects a score from among 0 (Do not know), 1 (Do not agree), 2 (Partly agree), 3 (Mostly agree), and 4 (fully agree) to indicate the degree of agreement with the selected statement. The five different scores are inspired by a 5-point Likert scale (Albaum, 1997) to support communication between human participants and support prioritizing a statement about a potential problem that needs to be solved.

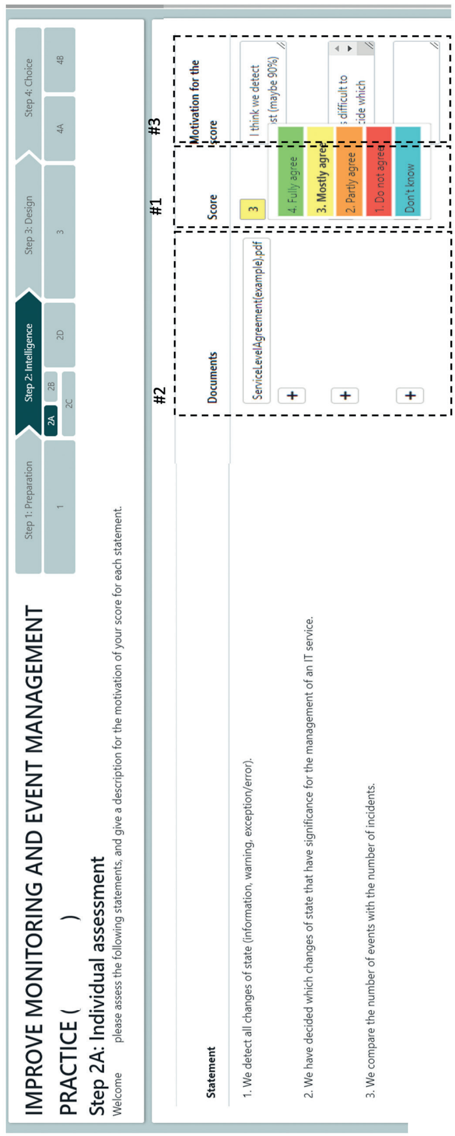


Figure 6.6. Screenshot of Step 2A: Individual assessment.

As one or several document(s) uploaded in step 1 may be relevant when assessing a statement, these documents can be selected and used by the human participant for the selected statement (see box #2 in Figure 6.6). If there are other relevant documents that have not been uploaded in step 1, the human participant can upload them in this step.

The document(s) selected or uploaded in this step are stored in the knowledge database and can be used to support the scoring and/or for further identification of the problem implied by the statement and of the solution(s) to the identified problem (i.e., they will be displayed in the following steps). This document uploading functionality is also incorporated in steps 2B and 2D to allow human participants to continue uploading other relevant documents that come to mind when they are involved in those steps.

The "Motivation for the score" functionality (see box #3 in Figure 6.6) is for humans specifying the motivation for a given score, which is important knowledge and will be stored in the knowledge database for future knowledge sharing.

Following step 2A is step 2B (see the screenshot in Figure 6.7). It is designed to allow human actors to compare and discuss individual assessments and supply an agreed-on score for a selected statement. Therefore, individual scores, motivations, and/or uploaded documents from step 2A are also shown under each statement. After comparison and discussion, earlier individual scores are allowed to change (see box #1 in Figure 6.7). An agreed-on score may be added if all the human participants reach agreement (see box #2 in Figure 6.7). Arguments for an agreed-on score or for failing to reach agreement should be provided and are also stored in the knowledge database for further knowledge sharing and seeking. These arguments represent knowledge created in step 1D (see box #3 in Figure 6.7).

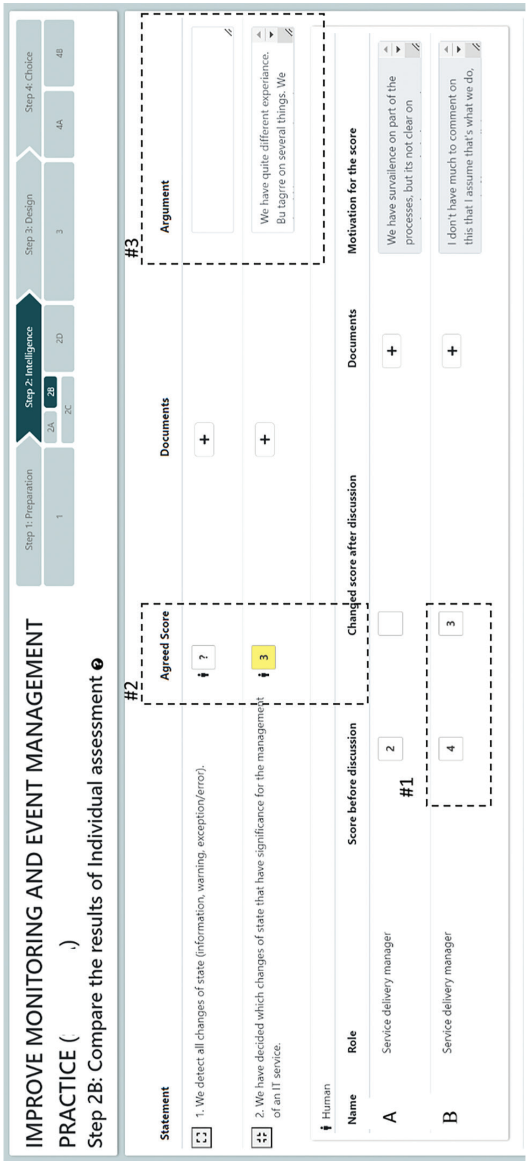


Figure 6.7. Screenshot of step 2B: Comparing the results of individual assessments.

Step 2C: Machine assessment is shown in Figure 6.8. It is designed to allow the machine actor to analyze datasets and present the analysis results for use in step 2D: Human and machine assessment comparison. For each statement, the assessment results given by the machine actor differ in three ways (see box #1 in Figure 6.8). They take the form of statistical information extracted by analyzing datasets, extracted example datasets, and/or documents (uploaded by human actors in steps 1, 2A, and/or 2B). These three forms were derived from the data types provided by organization A and later confirmed with the representatives of the two organizations. A statement about which type(s) of information the HC-HDSS could provide is marked by a " ✓ ." Details of a marked type of information are given when expanding a statement by clicking on button "⛶," which is positioned on the left side of a statement (see box #2 in Figure 6.8).

For example, the data provided by organization A can be calculated and provide statistical information for statement "9. All tickets are assigned a priority." Therefore, there is a " ✓ " for this statement in the "Statistical information" column in Figure 6.8. The statistical information reads: "There are totally 20 tickets records; 20.0% are assigned a priority type 'Medium'; 80.0% without priority." Based on this information, a pie graph is given for a brief overview of the analysis results in the following steps. This example is shown in Figure 6.9.

Step 2C is conducted automatically by the machine actor, so the human user of the HC-HDSS can skip this step and move directly to step 2D.

Figure 6.8. Screenshot of step 2C: Machine assessment.

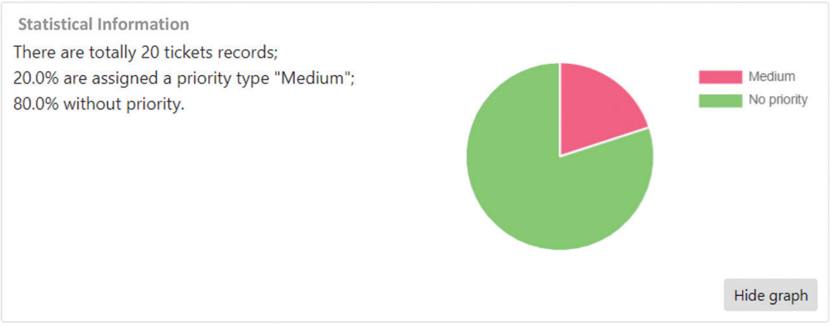


Figure 6.9. Statistical information for assessing statement No. 9.

Step 2D: Human and machine assessment comparison (see Figure 6.10) aims to identify potential problems or opportunities by comparing the assessments made by human actors and machine actors. Under each statement, the machine actor's assessment is displayed on the left-hand side and the human actors' assessment is displayed on the right-hand side.

After comparing the assessments from both humans and machines, a final score, as well as a priority, should be given for the selected statement. In general, the lower the score a statement gets, the higher the priority it should be given (i.e., selecting from highest, high, low, or lowest). In other words, a statement with a lower score indicates that there exists a more severe potential problem or a high opportunity relating to this statement. Therefore, a statement with a lower score will usually be prioritized (see the "Prio" column in Figure 6.10). The justification of the prioritization should be given in the column labeled "Justification" in Figure 6.10. For the prioritized statement, a potential problem or opportunity should be formulated and added in the column labeled "Identified problem" in Figure 6.10. After prioritization, one or several identified problems with high priority should be selected for the identification of solutions in step 3.

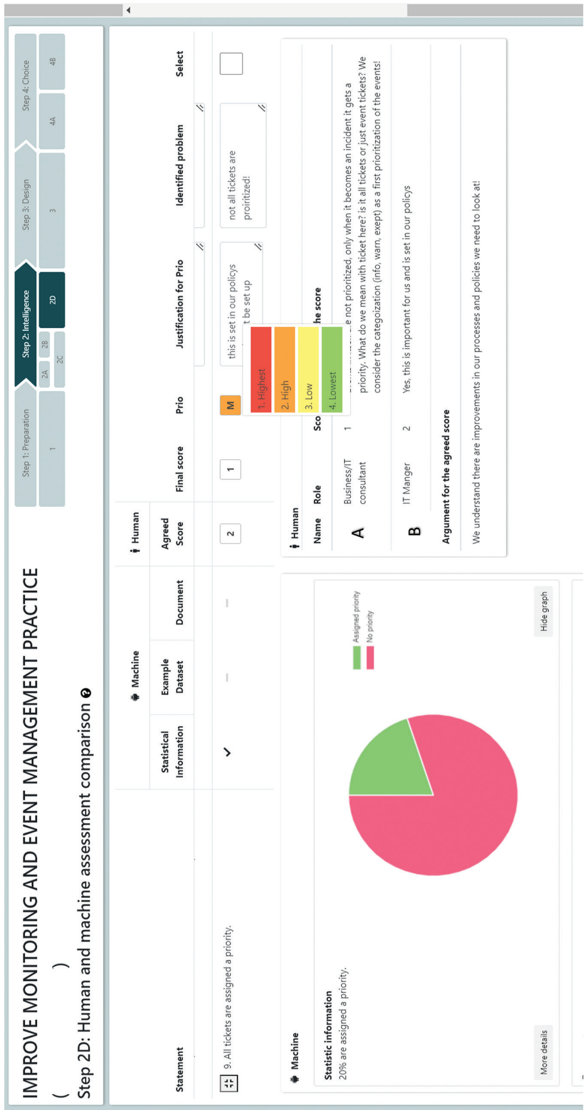


Figure 6.10. Screenshot of step 2D: Human and machine assessment comparison.

6.4 STEP 3: IDENTIFY SOLUTION(S)/DESIGN

Step 3 is designed to formulate ideas and identify solutions to the selected problem(s) from step 2. The process map of step 3 is displayed in Figure 6.11. As indicated in the figure, human actors start this step by selecting one problem (more than one problem may be selected in step 2D). Next, they check the information and knowledge generated in the previous steps. Meanwhile, the machine actor also generates an idea/ideas based on AI. Then, the human actors can use all the information and knowledge and the ideas suggested by the machine actor to generate ideas by brainstorming. The implicit component of knowledge stored in human actors' memory is rendered explicit and stored in the database of the prototype.

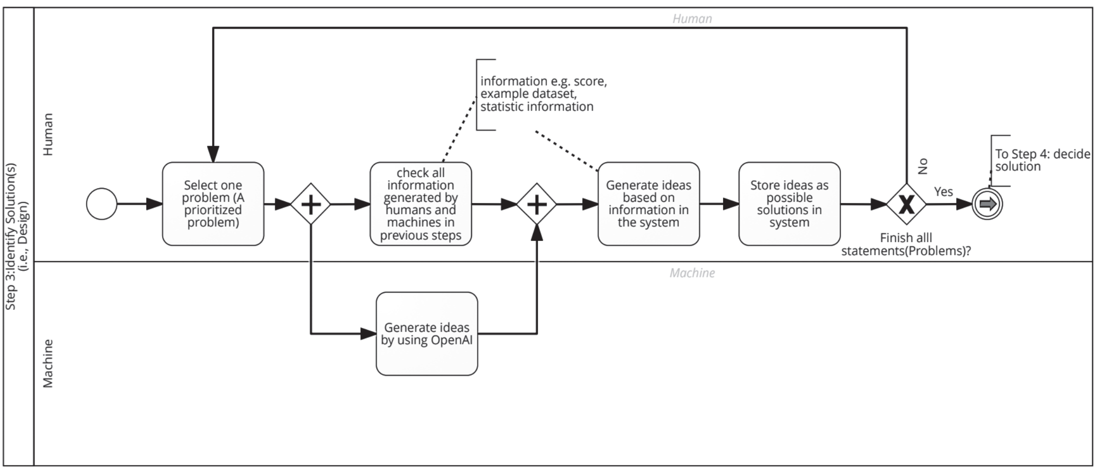


Figure 6.11. Process map of step 3: Identify solution(s) (i.e., choice) (by BPMN 2.0).

In detail, the functionality "Assessment details from human and machine" in box #1 of Figure 6.12 displays all the knowledge produced in previous steps by both humans (the right-hand side in the box) and machines (the left-hand side in the box). It aims to support humans in generating ideas for a solution to the identified problem. Additionally, human actors can also click on the button "Ask machine" (displayed in box #2 of the figure) to check the machine's ideas. The idea(s) generated by human actors should be written down (in box #3 of the figure).

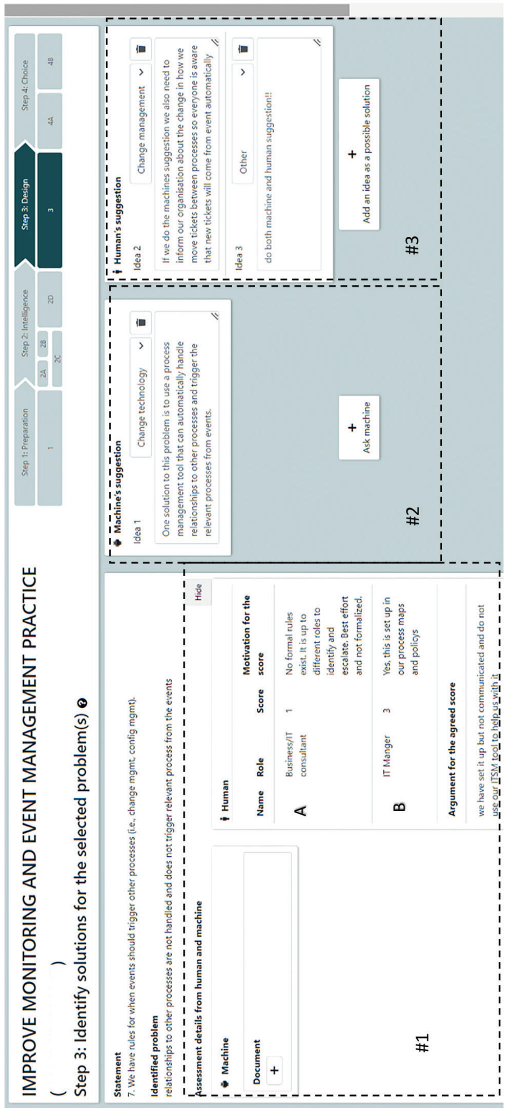


Figure 6.12. Screenshot of step 3: Design.

6.5 STEP 4: EVALUATE AND DECIDE ON SOLUTION/CHOICE

Step 4 is the last step in the prototype and is designed for evaluating the ideas generated in step 3. It consists of two sub-steps, step 4A: Valuation and step 4B: Visualization and decision made. The output of step 4 is one or more problem–solution pairs decided on using the HC-HDSS. Figure 6.13 shows the activities and their flow in this step.

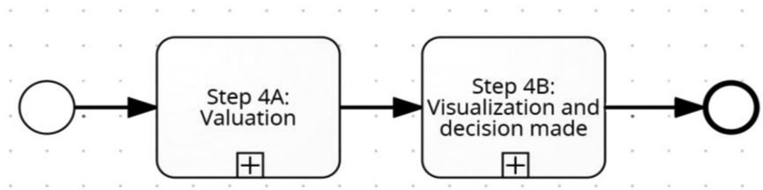


Figure 6.13. Process map of step 4: Valuate and decide on a solution (i.e., choice) (by BPMN 2.0).

In detail, all the ideas generated by humans and machines are listed in step 4A of the prototype (see Figure 6.14). Each idea should be evaluated according to three criteria, i.e., feasibility, desirability, and risk (see box #1 of the figure). Humans value or rate the criteria (see box #2 of the figure) from 1 to 5. For example, the feasibility of "idea 1" is rated 5, meaning that human actors think their organization has the competencies for implementing it. The organization has resources for implementing this idea, so "idea 1" is assigned the highest feasibility. In contrast, the feasibility of "idea 2" is rated 4, which means that "idea 2" is less feasible than "idea 1." In the end, the most desirable and feasible idea with a low degree of risk should be considered the optimal option for addressing the problem identified in step 4B (see Figure 6.15).

In step 4B, humans can compare the three desirability/feasibility, desirability/risk, and feasibility/risk pairs. These are visualized in the upper part of step 4B (see box #1 in Figure 6.15). Humans can also compare these three pairs through the scores for feasibility, desirability, and risk displayed in the table shown in the lower part of step 4B (see box #2 of Figure 6.15).

Meanwhile, the machine actor also suggests an idea, such as the decision based on calculations (see box #3 of Figure 6.15).

Ultimately, as the final decision-maker, humans decide on or select a solution from among the ideas (see box #4 of Figure 6.15). Figure 6.16 displays the window for inputting information into the decided solution, for example, setting the responsible person and the due date.

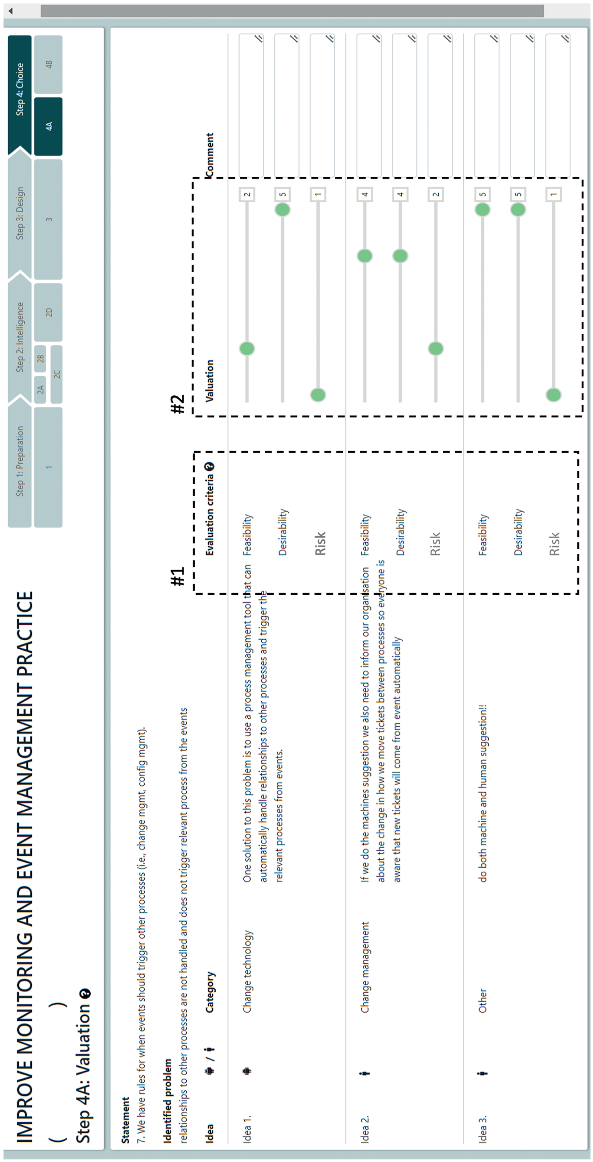


Figure 6.14. Screenshot of step 4.A: Valuation

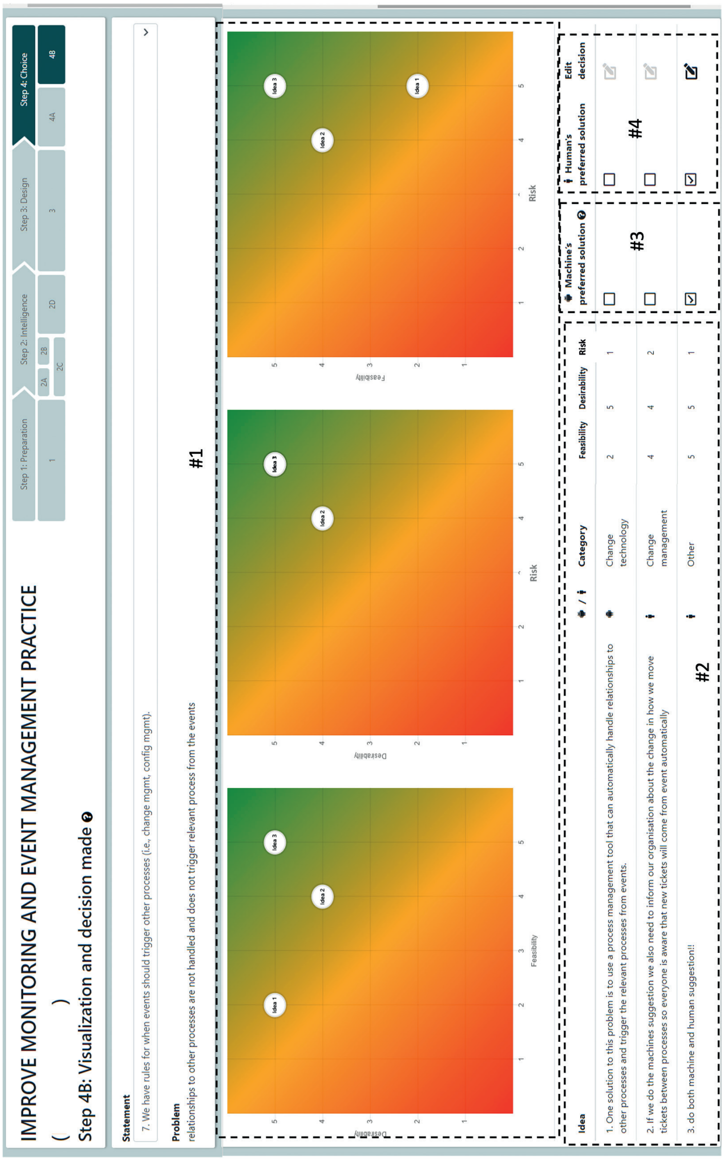


Figure 6.15. Step 4B: Visualization and decision made.

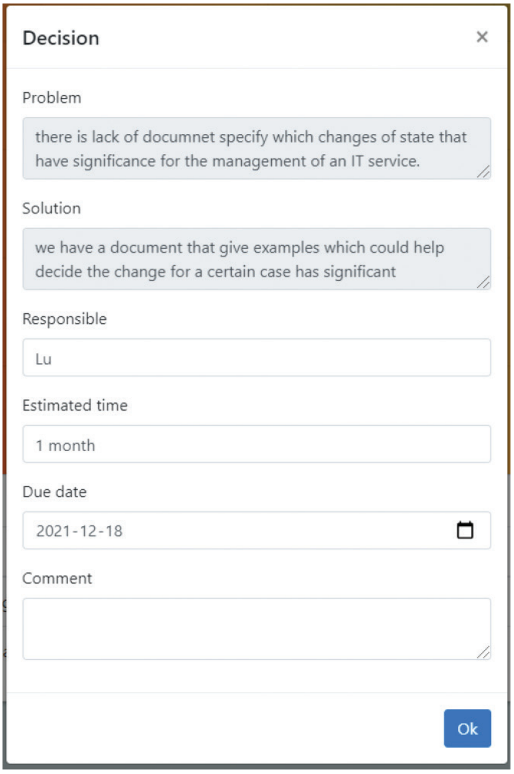


Figure 6.16. Screenshot of a finally made decision

CHAPTER 7

THE BUILDING, INTERVENTION, AND EVALUATION: ITERATION ONE

As introduced in the section on research implementation, the ADR project was conducted with three BIE iterations. The ADR "reflection and learning" phase paralleled the BIE phase. This chapter focuses on BIE iteration one and the corresponding reflection and learning. It begins by presenting the initially formulated goal and meta-design of HC-HDSSs in section 7.1. Section 7.2 shows how preexisting design knowledge guided the building of the HC-HDSS prototype (the initial version). Section 7.3 examines the intervention and evaluation. Section 7.4 presents the reflection and learning in this BIE iteration, the outcomes of which are the four articulated design principles presented in section 7.5. Section 7.6 ends this chapter with a summary of this iteration.

It is worth noting, first, that presenting the goal and meta-design prior to the building, reflection, and learning is useful for readers who often wish to get an overview of the selected or emerging design knowledge prior to the details of how it emerged. This does not mean that the goal and meta-design of HC-HDSSs were formulated before building the initial version of the HC-HDSS prototype. As stated by Iivari (2015), this study, following the ADR method, uses strategy 2 of DSR, which starts with solving a specific problem (i.e., building the prototype), then distills a generalized solution, i.e., the HC-HDSSs, for the class of problems.[87] In other words, the goal and meta-design are formulated based on the continuous reflection and learning in BIE iteration one and are formulated approximately in parallel with, if not later than, the BIE stage. Besides, there is mutual influence or reciprocal shaping between the formulation of the goal and the meta-design of HC-HDSSs (i.e., the generalized solution) and the building of the specific solution (i.e., the HC-HDSS prototype).

Second, the formulated overall evaluation strategy is also a sample of design knowledge emerging in BIE iteration one. However, it is presented in section 4.2.2 of chapter 4: The research paradigm and methodology, instead of here, because the author prefers to give readers a full picture of the research methodology.

7.1 THE INITIAL GOAL AND META-DESIGN OF HC-HDSSS

As mentioned earlier in this dissertation, possible relevant studies were searched to address the research problem because there is a lack of design knowledge for HC-HDSSs. Based on the identified theories, the goal of HC-HDSSs, generalized design knowledge for the class of systems was initially formulated in BIE iteration one, as follows: "a contextualized easy-to-use web-based IT artifact that utilizes both human and machine capabilities to make semi-structured managerial decisions."

"Contextualized" indicates that the IT artifact should suit the organizational context (Franz & Robey, 1986; Hevner et al., 2004). In other words, the characteristics of the organizations and available resources that can be used for decision-making should be considered. Specific to the two

87 According to Iivari (2015), strategy 1 of DSR starts a DSR study with a generalized problem and solution. The ensuing built specific system, an instantiation of the generalized solution, is used for proofing the generalized solution that is hypothesized to address the generalized problem.

organizations participating in this study, the context of this study is decision-making in order to improve service operation practices in ITSM.

"Easy-to-use web-based" defines the physical features of the IT artifact as a "physical existence in the real world" (Gregor & Jones, 2007, p. 23), and "easy-to-use" specifically encourages trust in human users when adopting certain information technologies (Bartlett & McCarley, 2019; Davis, 1989).

"Semi-structured managerial decisions" continues setting the scope, indicating that an IT artifact is applicable in making semi-structured managerial decisions instead of the other two types of decisions (i.e., structured and unstructured). It is grounded in the decision types for DSSs discussed in section 2.2.1, according to which decisions need HC-HDSSs that are not structured, or need one or more unstructured phases in the decision-making process of HC-HDSSs. This also means that the decisions cannot be made by machines (i.e., the decisions require the involvement of humans). Meanwhile, the structured phase(s) could utilize a machine's capabilities.

"Utilizes both human and machine capabilities" is supported by claims introduced in section 1.2.2, for example: humans and computers can be complementary (Simon, 1955); there is human–computer symbiosis (Licklider, 1960); and there can be a combination or hybrid of human intelligence and machine intelligence (Demartini, 2015; Demartini et al., 2017; Reeves & Ueda, 2016; Zheng et al., 2017).

In addition to the goal of HC-HDSSs, this study formulates a meta-design of HC-HDSSs, which consists of generalized design principles concerning how to design HC-HDSSs that are hypothesized to meet the goal introduced above. The initial version of the meta-design is presented in Figure 7.1.

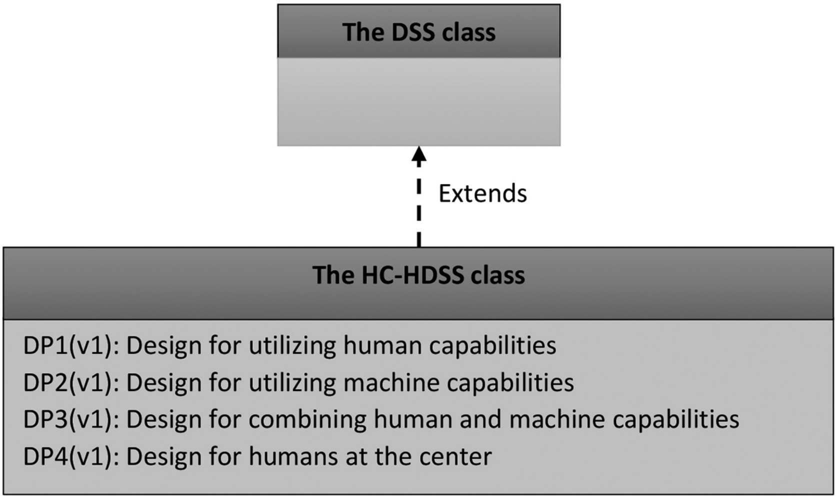


Figure 7.1. The initial meta-design of HC-HDSSs.

Figure 7.1 is inspired by the graphical notations of a Unified Modeling Language (UML) class diagram. UML is widely known and used in software engineering or systems analysis and design (Dobing & Parsons, 2006). The class diagram is a key component of UML (Berardi et al., 2005; Dobing & Parsons, 2006) and is used to describe the structure of a system/application by showing its classes and their relationships (Jacobson & Booch, 2021, p. 25). A class in the diagram is drawn as a rectangle (Jacobson & Booch, 2021, p. 25). As in a UML class diagram, a rectangle in the meta-design represents a class (of systems). The name of the class is in bold and centered in the top compartment.

Existing IS studies that may share a similar goal with the HC-HDSSs have been looked for. A familiar class of digital systems called DSSs was identified as having a similar overall goal as that of HC-HDSSs, i.e., to support humans in making managerial decisions without replacing humans in the decision-making process. Therefore, several preexisting theoretical statements concerning DSS design have been extracted from theories presented in the section on DSSs. For example, based on studies showing that DSSs have three basic components, i.e., database, model, and user interface (Aronson et al., 2005, p. 109; Shim et al., 2002), the prototype was built based on the same three components. Based on the underlying emphasis of DSSs studies dealing with how technologies can effectively support managerial decision-making, the prototype was built to utilize the capabilities of machines in decision-making. Drawing on studies using multi-criteria decision-making (MCDM) to evaluate alternatives in a decision task (e.g., El Yamami et al., 2017; Encantado Faria et al., 2018; Lima et al., 2018), the prototype was built to evaluate alternatives using multiple criteria. Arguments and details about how these theories guided the building will be given in the following sections.

The DSS class is shown in the upper box of Figure 7.1. The HC-HDSS class, which extends the DSS class, is represented by the lower box of Figure 7.1. It includes four design principles formulated for the HC-HDSS class in BIE iteration one. The four design principles will be examined in this chapter. In the figure, "v1" stands for version one of a design principle.

7.2 BUILDING THE INITIAL VERSION

Preexisting studies of DSSs and studies in other fields (e.g., human decision-making) identified as potentially offering design knowledge relevant to HC-HDSSs have been used when building the initial version of the prototype.

7.2.1 BUILDING THE PROTOTYPE BASED ON THREE COMPONENTS (I.E., DATA, MODEL, AND USER INTERFACE)

An HC-HDSS should be built based on three components, i.e., data, model, and user interface, as these are the three basic components of DSSs (Aronson et al., 2005, p. 109; Shim et al., 2002), which share a goal similar to that HC-HDSSs.

The data component refers to a database management system in which data from different sources are stored and merged. Users can access these data without knowing where they are physically located in the database.

The model component of a general DSS refers to a model-based management system that keeps track of all possible models that might be run during the analysis and that controls the running of the models. Different models use different algorithms to analyze decision alternatives in terms of analyzing data, and the output of a model is decision suggestions expressed in terms of the values of each alternative. Therefore, users can select one alternative based on the output of the model.

As its name suggests, the third component, the user interface, is the interface through which users request data and models and receive the results. It includes all of the input and output screens. (For design details of all the user interfaces, see chapter 6: The HC-HDSS prototype).

The prototype is built as a web-based tool consisting of webpages as user interfaces. Through the webpages/interfaces, users input the prototype (e.g., a dataset for machine analysis, and users' knowledge) and receive output (i.e., a decision made). The database is designed to store information such as: information about participants (e.g., name, expertise, and email address); general information about a decision-making task/project (e.g., project name, date created, project objectives, and expected outcomes); and dataset for the machine actor's data analysis. The prototype is designed with only one model as the model component, because it is not a fully fledged system.

7.2.2 BUILDING TO SUPPORT DECISION-MAKING AS A PROCESS

The HC-HDSS prototype is designed to support decision-making as a process. This is based on Simon (1977, p. 40), who found that humans make managerial or analytical decisions following a process that consists of several phases. Second, a semi-structured decision refers to one or two decision-making phases that are unstructured (Gorry & Scott Morton, 1989). The HC-HDSS prototype deals with semi-structured decisions, so it is designed to support decision-making as a process.

In detail, Simon's (1977) first three phases are implemented (see the area surrounded by a dotted line in Figure 7.2). These are numbered starting from 2 because step 1 is assigned to the step of preparing a decision-making task. Step 2 "Intelligence" aims to identify a problem or opportunity by gathering information from the environment. Step 3 "Design" frames the particular choice in terms of one or more possible solutions for the identified problem or opportunity from step 2. Step 4 "Choice" is designed to allow decision-makers to compare the choices (i.e., solutions) from step 3 and to select one of several.

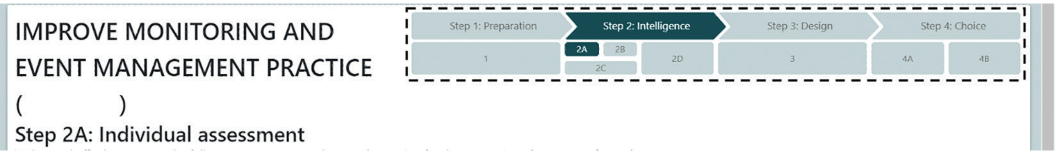


Figure 7.2. The HC-HDSS prototype supports human decisions through a process.

7.2.3 BUILDING TO FIT THE ORGANIZATION

The prototype should be built to fit the organization because, as stated by Hevner et al. (2004, p. 83), "we acknowledge that perceptions and fit with an organization are crucial to the successful development and implementation of an information system." Similarly, as pointed out by Franz and Robey (1986, p. 330), there is "a need to fit MIS [i.e., management information system] and MIS-development efforts to the organization's context."

The specific decision context of the prototype is improving the monitoring and event management practice of ITSM (see section 4.3: The study context and the two selected organizations). Therefore, twelve monitoring and event management-related statements are extracted from ITSM practice-relevant documents and discussed with practitioners in BIE iteration one. These are shown in Figure 7.3a.

In addition, to build the prototype to fit the organization, the functionalities "Select an ITIL management practice," "Upload text or image documents for human assessment," and "Upload dataset for machine assessment" are implemented in step 1 of the prototype (see boxes #1, #2, and #3 in Figure 7.3b). They provide functionalities allowing the user who creates a decision project to select an ITIL practice for assessment, to upload relevant text or image documents that human participants can use in the following decision-making steps, and to upload customized datasets corresponding to the twelve statements for machines.

Statement
1. We detect all changes of state (information, warning, exception/error).
2. We have decided which changes of state that have significance for the management of an IT service.
3. We compare the number of events with the number of incidents.
4. We monitor software licences to ensure that licences are valid.
5. We ensure that events are communicated to relevant function/department/people that need to be informed or take further contrc actions.
6. We monitor the number of incidents that occurred and the percentage of these that were triggered without a corresponding event.
7. We have rules for when events should trigger other processes (i.e., change mgmt, config mgmt).
8. We monitor the number and the percentage of events that required human intervention and whether this was performed.
9. All tickets are assigned a priority.
10. We provide the means to compare actual operating performance and behaviour against design standards and SLAs.
11. We provide a basis for service assurance, reporting and service improvement.
12. We monitor the number of events/alerts generated without actual degradation of service/ functionality (false positives – indication of the accuracy of the instrumentation parameters, important for CSI).

Figure 7.3a. The twelve customized statements for assessing the monitoring and event management practice.

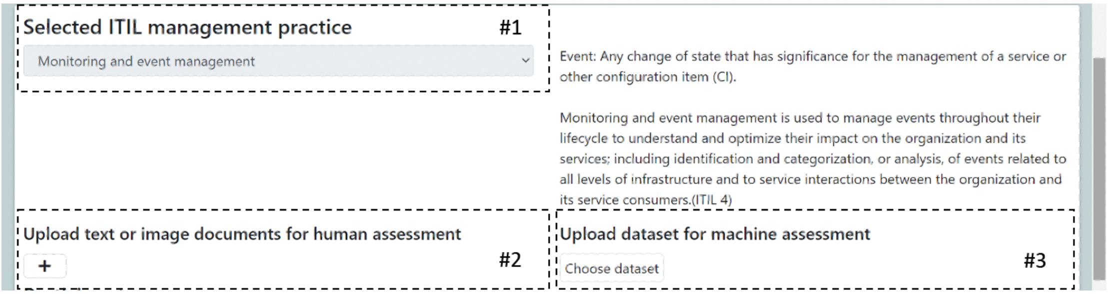


Figure 7.3b. Functionalities built to fit the organization in step 1: Preparation.

7.2.4 BUILDING TO UTILIZE MACHINE CAPABILITIES

An HC-HDSS should utilize machine capabilities in decision-making because, as in most, if not all, studies of DSSs, machine capabilities are utilized explicitly in different ways to support humans in different aspects.

Section 3.2 introduces the four identified types of machine capabilities: "being efficient and effective," "being continuously upgradable in memory, algorithm, and computing ability," "predicting by pattern recognition," and "reducing human biases." Organization A provided a dataset of event management information. It is a small set of data in two sheets of a Microsoft Excel document. Based on this dataset, three machine capabilities, i.e., "being efficient and effective," "being continuously upgradable in memory, algorithm, and computing ability," and "reducing human biases," are mainly considered while building the prototype in this iteration.

Figure 7.4a provides a screenshot of step 2C: Machine assessment, in the prototype. The area surrounded by a dotted line indicates the functionalities of utilizing machine capabilities. In the prototype, the machine capabilities of "being efficient and effective" and "being continuously upgradable in memory, algorithm, and computing ability" are utilized to provide statistical information about each statement based on calculating the dataset provided by organization A and uploaded in step 1. The statistical information, which is based on calculation, also aims to reduce human biases, i.e., utilizing the machine capability of "reducing human biases." The statistical information is given in both text and figure formats, providing additional brief information about the comparison between different components of the statistical information for humans. An example of these functionalities is shown in Figure 7.4b.

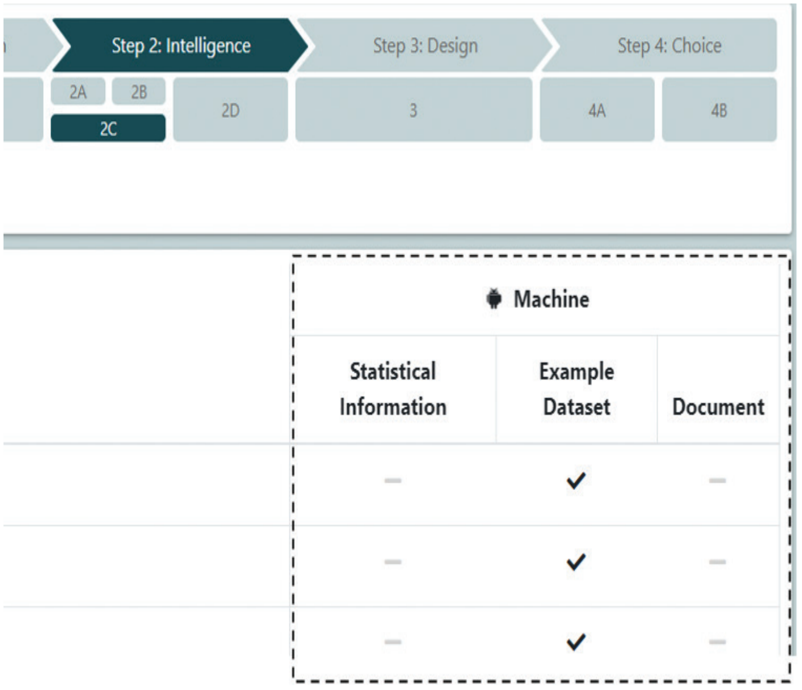


Figure 7.4a. Functionalities of utilizing machine capabilities in step 2C: Machine assessment.

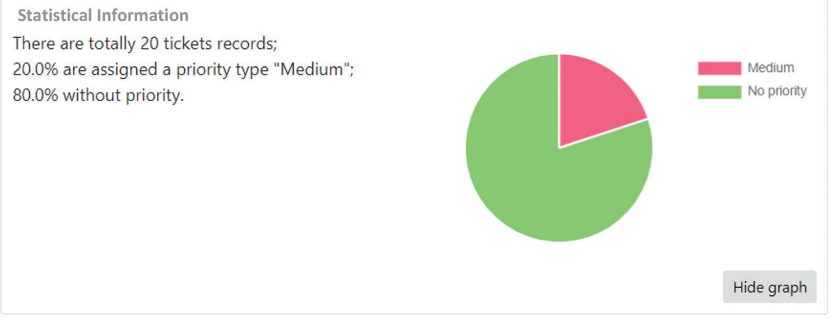


Figure 7.4b. Statistical information for statement No. 9 "All tickets are assigned a priority."

7.2.5 BUILDING TO EVALUATE ALTERNATIVES USING MULTIPLE CRITERIA

Based on the decision-making process view, the third phase, i.e., "choice" (Simon, 1977, p. 40), refers to the decision-maker comparing the alternatives or options and selecting one. Furthermore, drawing on studies of evaluating alternatives in the ITSM context by El Yamami et al. (2017), Encantado Faria et al. (2018), and Lima et al. (2018), the prototype is designed to evaluate alternatives using multiple criteria (i.e., the MCDM introduced in section 2.2.3).

Researchers of the ADR group suggested three criteria for implementing the functionalities of MCDM in the prototype, i.e., the criteria feasibility, desirability, and risk. These three suggested criteria are based on the researchers' previous empirical experience of decision-making in ITSM (e.g., Göbel, 2019) and digital options theory (Sandberg et al., 2014). Digital options theory draws on general options theory but is specific to digital options related to IT capability[88] investments. Digital options are "potential investments—enabled by existing IT capabilities and addressing relevant business opportunities" (Sandberg et al., 2014, p. 425). Being supported by the prototype, the decision to improve ITSM by addressing an identified problem or an improvement opportunity in ITSM is an investment in an organization's IT capabilities. The decision that is to be taken needs to be made actionable by the organization.

According to Sandberg et al. (2014), digital options "may be systematically examined in terms of desirability and feasibility and to recognize the most suitable as actionable digital options. Eventually, if a decision is made to invest in the proposed IT capability, the digital option is activated and becomes a realized digital option" (p. 425). "During a process improvement effort, available options may be systematically examined in terms of desirability and feasibility and to recognize the most suitable as actionable

88 IT capability is defined as a firm's "ability to mobilize and deploy IT-based resources in combination or copresent with other resources and capabilities" (Bharadwaj, 2000, p. 171). IT-based resources include "tangible resource comprising the physical IT infrastructure components," human IT resources, and "intangible IT-enabled resources such as knowledge assets, customer orientation, and synergy" (Bharadwaj, 2000, p. 171).

digital options" (Sandberg et al., 2014, p. 426). Furthermore, the most desirable and feasible option, with a low degree of risk, i.e., uncertainty (Sandberg et al., 2014), should be considered an actionable option (Göbel, 2019, p. 179). Therefore, the three criteria have been implemented in the prototype (see Figure 7.5).

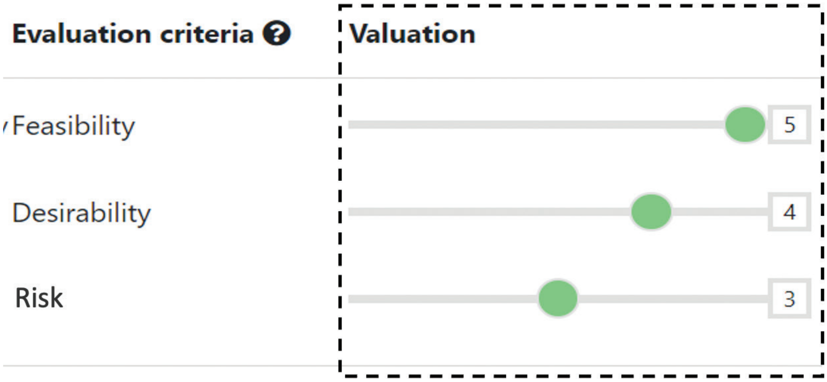


Figure 7.5. Three criteria for evaluating the ideas generated in step 4A.

The feasibility criterion refers to the degree to which the option is easily implemented (Göbel, 2019; Sandberg et al., 2014). The prototype provides information to bolster practitioners' understanding of the feasibility criterion. For example, does the organization have enough competencies to implement the option? Does the organization have the resources to implement the option? The desirability criterion refers to the degree to which organizations are willing to choose the option (Göbel, 2019; Sandberg et al., 2014). Inspiring questions such as "Can cost be reduced by implementing the option?" are provided for practitioners. The risk criterion refers to the risk of implementing the option.

As shown in the area surrounded by a dotted line in Figure 7.5, practitioners score the three criteria between 0 and 5, the higher the value, the higher the rating of the criteria. For example, assigning feasibility a value of 5 means that the option is easier to implement than an option assigned a value of 4.

7.2.6 BUILDING TO UTILIZE HUMAN CAPABILITIES

As pointed out in the problem formulation, the HC-HDSS prototype should utilize humans' decision-making capabilities. The identified human capabilities useful in decision-making are intuition and knowledge, which are human strengths in making decisions that machines lack. [89]Below are the arguments for this.

First, an HC-HDSS is designed for making semi-structured managerial decisions, which means that the decisions are complex, and machines are unable to automatically make decisions due to the unstructured part of the decision task. The involvement of humans and utilization of human capabilities in an HC-HDSS are mandatory. Second, the support (e.g., analytical information) provided by machines needs human knowledge to "derive, refine and integrate insights" (see section 3.1). Third, the decision support provided by machines is based on data analysis, which relies on data quality, data types, and algorithms (see machine weaknesses in section 3.2). From this perspective, human involvement in an HC-HDSS and the utilization of human capabilities can complement machines. Fourth, a DSS that relies solely on machines may introduce unwanted ethical issues, such as human fear of being replaced (Jarrahi, 2018), the limiting of human learning ability (Shollo et al., 2015), and discrimination against different stakeholders (Newell & Marabelli, 2015). Therefore, an HC-HDSS should utilize human capabilities for the unstructured part of a decision task as well as for interpreting and understanding the support from machines.

In addition, the ADR researchers' group suggested that the HC-HDSS prototype should support the involvement of more than one human in a decision task, because there are advantages to group decision-making compared with individual decision-making (e.g., Lima et al., 2018; for more details, see section 3.1). Therefore, the prototype is built to support a group of humans and to utilize their joint capabilities in decision-making.

In step 1 of the prototype, at least two human participants should be involved in a decision-making project (see Figure 7.6a). Figure 7.6a shows

89 For humans' capabilities in decision-making, see section 3.1.

that two humans have been added; more humans can be added by clicking on the "+Add" button.

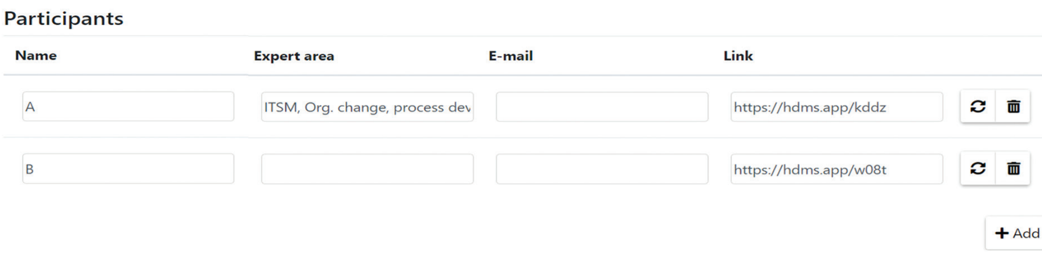


Figure 7.6a. More than one human can be added to a decision-making task in step 1.

In step 2A, the functionalities of utilizing individual human capabilities are implemented. Individual humans can select or add relevant documents to an ITIL statement, and give scores for a statement (see boxes #1 and #2 in Figure 7.6b). Individual humans have knowledge that there may be certain documents that might be useful for scoring a statement. Besides, individual humans have knowledge of how to assess an ITIL statement (i.e., scoring a statement).

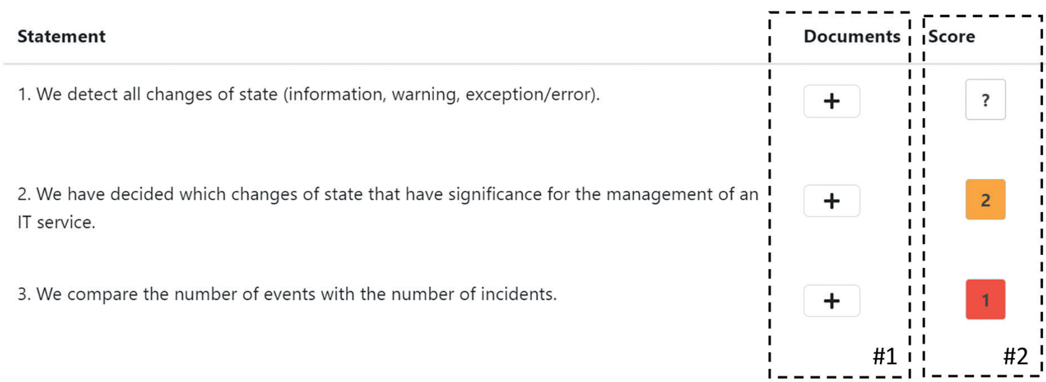


Figure 7.6b. Utilizing individual human capabilities in step 2A.

Similarly, step 2B implements two functionalities to utilize the capabilities of a group of humans (i.e., at least two humans) instead of an individual. When multiple humans meet and hold a discussion in step 2B, they apply their intuition and knowledge to select or add other missing but relevant documents to a selected ITIL statement (see box #1 in Figure 7.6c), giving an "agreed-on score" (see box #2 in Figure 7.6c).

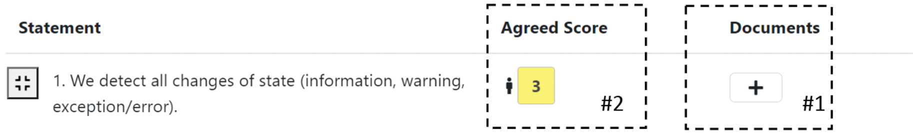


Figure 7.6c Functionalities of utilizing human capabilities in step 2B.

Figure 7.6d shows the implemented functionalities of utilizing human capabilities in step 2D, which aims to identify and prioritize a problem. The humans in the group use their joint intuition and knowledge to assign a final score to an ITIL statement, which gives the prioritization (see box #1 of the figure). Furthermore, they may utilize their intuition and knowledge to identify a problem (see box #2 of the figure). At the end of this step, they use their intuition and knowledge to select an identified problem for the next step (see box #3 of the figure).

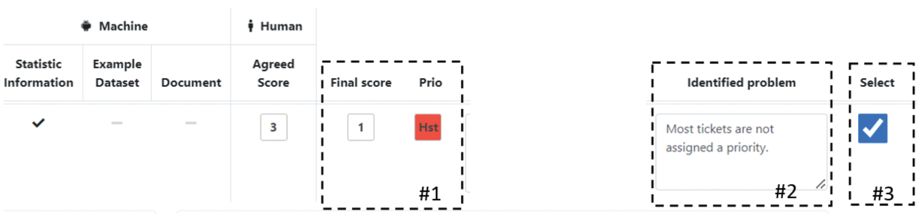


Figure 7.6d. Functionalities of utilizing human capabilities in step 2D.

Step 3 utilizes human capabilities by implementing functionalities for humans adding ideas as possible solutions (see Figure 7.6e).

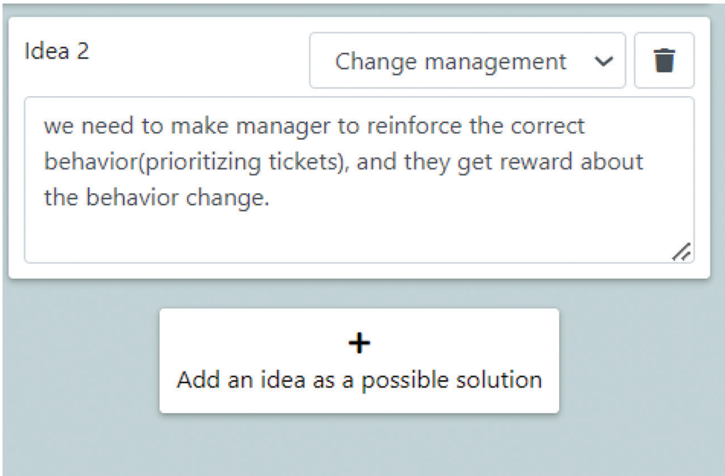


Figure 7.6e. Functionalities of utilizing human capabilities in step 3.

Step 4A utilizes human capabilities by functionalities for humans scoring the evaluation criteria for the formulated ideas (see Figure 7.6f). In the last step, step 4B, humans are enabled to utilize their capabilities to decide on an idea as the final solution.

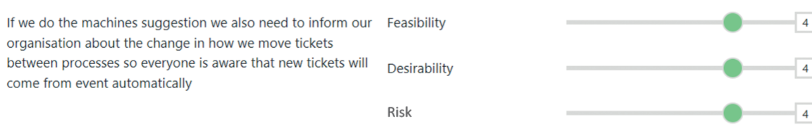


Figure 7.6f. Functionalities of utilizing human capabilities in step 4A.

7.3 INTERVENTION AND EVALUATION

As mentioned at the beginning of the chapter, an overall evaluation strategy, including strategies for each BIE iteration, was formulated in BIE iteration one. Guided by this, the evaluation of the initial version of the prototype built in BIE iteration one is formative and semi-naturalistic/artificial.

Several meetings with the researchers' group were first carried out, in which the author presented components of the prototype and the researchers gave feedback based on their theoretical knowledge. Two meetings with the practitioners' representatives followed, in which the initial design was presented and suggestions and feedback were collected (i.e., semi-naturalistic/artificial evaluation), respectively.

As introduced in the section on research implementation, the main focus of evaluation in BIE iteration one was on the statements concerning monitoring and event management practice. Practitioners contributed their knowledge gained from practice, and their suggestions and feedback constituted the data collected for analysis.

The initial version of the HC-HDSSs prototype served as a lightweight intervention.

7.4 REFLECTION AND LEARNING

As illustrated in the chapter on research implementation, reflection and learning will be achieved by presenting the prototype to researchers and practitioners in BIE iteration one. This means that the anticipated and unanticipated results come from empirical data and the conversations within the researchers' group. The reflections and learning concerning the four tentative design principles are summarized in Table 7.1, and are presented in detail in sections 7.4.1 to 7.4.4. Additionally, there are also reflections and learning about preexisting design knowledge used in building the prototype (see Table 7.2 in section 7.4.5) and reflections and learning about the problem formulation (in section 7.4.6).

Table 7.1. Anticipated and unanticipated results of tentative design principles.

Tentative design principles	**Anticipated results**	**Unanticipated results**	**Reflection and learning**
Design for utilizing humans capabilities (DP1)	1) Building for a group of humans making decisions is supported by practitioners. 2) Needs further work on how to utilize human capabilities.	Involving more than one human in a decision task can minimize human biases, i.e., make better decisions.	1) Building to support a group of humans, instead of one individual, making decisions utilizes human capabilities in a better way. This is because different humans have different forms of knowledge. Supporting a group of humans could also minimize individual human biases, i.e., utilizing the capabilities of a group of humans could reduce the weaknesses of individual humans. 2) In HC-HDSSs, human capabilities are identified as intuition and knowledge. For a tentative design principle more knowledge is needed of how to utilize human intuition and knowledge.
Design for utilizing machine capabilities (DP2)	Building to utilize machine capabilities requires more work.	Section 3.2 introduces the four identified machine capabilities. In this study, organization A provided too small a dataset, so the machine capability "predicting by pattern" cannot be utilized.	The choice of which one of several machine capabilities can be utilized should be based on the context (of the case).
Design for combining human and machine capabilities (DP3)	Building to support decision-making as a process should work.	1) The decision-making process combines the capabilities of both humans and machines. 2) The fourth phase cannot be implemented.	1) The decision-making process combines both human and machine capabilities, which can be a tentative design principle (DP3). 2) Simon (1977, p. 44) views decision-making as a process that consists of four principal phases: intelligence, design, choice, and review. The fourth phase cannot be implemented in the prototype, like in several other DSS studies, because the review activity can only be conducted after a decision is implemented in an actual situation. This requires a long time, which is not realistic for this study. However, it will be studied in a future follow-up project.
Design for humans at the center (DP4)	To center human needs and behavior, the selected descriptive decision theories used in building the prototype should align with considering both human capabilities and weaknesses in decision-making.	The decision task in the prototype can only be made by humans.	1) The prototype should support humans' actual decision-making process. 2) The decision supported by the prototype should be made by humans. 3) Designing for humans at the center can be implemented in the prototype by supporting humans' actual decision-making process and letting humans be the final decision-makers.

7.4.1 REFLECTION AND LEARNING ON A TENTATIVE DP1

The prototype was designed to utilize a group of humans' capabilities in decision-making. There are anticipated and unanticipated results. First, as anticipated, practitioners agreed on implementing the prototype to support more than one human. The author suggested that involving more than one human could create a more extensive knowledge base for a decision task. Practitioners expressed appreciation of this idea by saying, for example, "Yes, it is very good."

Second, as anticipated, continuous learning and a deeper understanding of how to utilize human capabilities (i.e., intuition and knowledge) are required. Based on this, theories of intuition (e.g., Barnard, 1938; Dane & Pratt, 2007) and knowledge (e.g., Grant, 2007; Nonaka, 1991; Polanyi, 1958, 1966) were identified. They are used in articulating the initial version of DP1, which is presented in section 7.5.1.

One unanticipated result relates to building the prototype to support the decision-making of a group of humans. The original idea of supporting a group of humans, instead of an individual, making decisions aimed at aggregating heterogeneous knowledge. However, supporting a group of humans could also minimize the biases of individual humans, i.e., utilizing the capabilities of a group of humans could reduce the weaknesses of an individual human in decision-making (for biases, see section 3.1). This unanticipated result aligns with what was stated by Dellermann et al. (2019b), namely, that involving several individuals in their designed hybrid intelligence DSS could minimize biases, which is a weakness of individual humans.

On one hand, the HC-HDSS prototype in this study aims to utilize human capabilities in decision-making, i.e., knowledge. A group of humans can contribute heterogeneous knowledge to a decision-making process, which is an advantage compared with an individual decision-maker. On the other hand, as introduced in section 3.1, biases are human weaknesses in decision-making, leading to severe and systematic errors. A group of humans could minimize these biases. Therefore, there is a tentative design principle that HC-HDSSs should be built in order to utilize the capabilities of a group of humans in a decision-making project/task.

7.4.2 REFLECTION AND LEARNING ON A TENTATIVE DP2

There is an unanticipated result of utilizing machine capabilities (see the third row of Table 7.1). As exemplified in the table, this study identifies four forms of machine capabilities. However, the data provided by organization A could only utilize three of these capabilities: being efficient and effective; being continuously upgradable in memory, algorithm, and computing ability; and reducing human biases. A machine's capability of predicting by pattern recognition could not be utilized. Therefore, a reflection of this unanticipated result is that one or several machine capabilities could be utilized based on the context (i.e., the case). A tentative deign principle (i.e., DP2) related to utilizing machine capabilities is articulated and presented in section 7.5.2.

7.4.3 REFLECTION AND LEARNING ON A TENTATIVE DP3

As anticipated, building the prototype to support decision-making as a process was agreed on with practitioners. However, there are two unanticipated results, one of which could become a tentative design principle, i.e., DP3 in Table 7.5.

In detail, the ADR researchers' group noticed that the prototype supporting a decision-making task in a process brings together both human and machine capabilities in decision-making. In other words, these capabilities in decision-making are combined in the process. Therefore, DP3 is articulated and presented in section 7.5.3.

The second unanticipated result is that the fourth phase of Simon's (1977, p. 44) decision-making process cannot be implemented in the prototype. According to Simon (1977, p. 44), the decision-making process consists of four principal phases: intelligence, design, choice, and review. However, the fourth phase cannot be implemented, like in several other DSS studies, because the review activity can only be conducted after a decision is implemented in an actual situation. This would require a time span that is not realistic to include in this study; however, it could be studied in a future follow-up project.

7.4.4 REFLECTION AND LEARNING ON A TENTATIVE DP4

Reflection and learning occurred when designing the prototype centering on humans, leading to the tentative formulation of DP4: Design for humans at the center.

First, the design of the prototype is centered on human needs. As stated in the problem formulation, practitioners "do not want to rely solely on technologies or existing digital systems when making decisions. To some extent, they still rely more on human experts' experience and expertise." In other words, there is a need expressed by practitioners that a digital system should rely more on human experts' experience and expertise when making decisions. Therefore, to meet practitioners' needs, the design in this study places humans at the center and starts with involving humans, identifying and utilizing human capabilities in a decision task.

Second, the design of the prototype takes into account human behavior. As illustrated in chapter 3, aside from having capabilities in decision-making, humans also have weaknesses. Additionally, humans are only boundedly rational. Therefore, taking into account human behavior, descriptive decision theories, which investigate how humans actually make decisions, for example, Kahneman's (2011) theory of humans' two cognitive systems, were adopted for designing the prototype. In other words, the selection of theories in this dissertation was driven by practitioners' needs and was based on human behavior, which can be used in designing the prototype for humans at the center.

As expected, by centering on human needs and considering human behavior, the selected descriptive decision theories embrace both human capabilities and weaknesses in decision-making. In detail, as stated by Kahneman (2011), the actual decision-making process used by humans making complex decisions involves using both cognitive systems 1 and 2. Humans applying cognitive System 1 are using their intuition, whereas humans apply cognitive System 2 to make analytical decisions. The outcome of System 1 is the input of System 2. On one hand, Kahneman's two cognitive systems embrace human capabilities, especially intuition; on the other hand, Kahneman's two cognitive systems, especially System 1, do not exclude human weaknesses. As stated in the section on human weaknesses in decision-making, humans apply heuristics in their System 1 or intuitive decision-making, which may also lead to severe and systematic errors, i.e., biases.

As an unanticipated result of the design process, the author noticed that humans should be the final decision-makers in the prototype. According to the theories of three decision types, i.e., structured, semi-structured, and unstructured, machines cannot make semi-structured or unstructured decisions, but humans can. In other words, humans should be the final decision-makers for semi-structured or unstructured decisions.

Therefore, a tentative design principle (DP4) exists related to centering on human needs and behavior in HC-HDSSs. DP4 is articulated in section 7.5.4.

7.4.5 REFLECTION AND LEARNING ON OTHER SELECTED PREEXISTING FORMS OF DESIGN KNOWLEDGE

Besides the reflection and learning on four tentative design principles, there is also reflection and learning on the selected preexisting design knowledge used in building the prototype. Table 7.2 provides a summary. First, there are no unanticipated results related to building the prototype based on three components (i.e., data, model, and user interface). Practitioners only gave detailed suggestions for designing the interface. In other words, as anticipated, building the prototype with the three components works.

Second, there is an unanticipated result of designing to fit the organization. One practitioner commented on the formulated statements about monitoring and event management practice: "the statements [i.e., assessing the monitoring and event management practice] could be formulated by considering critical success factors and key performance indicators." Therefore, critical success factors and key performance indicators documents were searched after the meeting. They were used to refine the statements about monitoring and event management practice in the prototype.

Third, there is an unanticipated result of building to evaluate alternatives using multiple criteria. The prototype applied the theory of fuzzy logic and implemented corresponding functionalities. Practitioners need to set both the values of the criteria and their weights. Unexpectedly, practitioners pointed out that these functionalities are too complex and need to be simplified. Therefore, after a discussion within the ADR researchers' group, the MCDM functionality was simplified by giving the same default weights to all criteria. Practitioners only need to value each criterion instead of both its value and weight.

Table 7.2. Anticipated and unanticipated results of the selected preexisting design knowledge.

Preexisting design knowledge	**Anticipated results**	**Unanticipated results**	**Reflection and learning**
Build the prototype with three components	The prototype built on three components works.	-	Designing the prototype based on three components works. Practitioners gave detailed suggestions for designing the interface.
Build to fit the organization	-	Critical success factors and key performance indicators can be used in formulating the statements about monitoring and event management practice.	critical success factors and key performance indicators documents should be searched and used to refine the formulated statements about monitoring and event management practice.
Build to evaluate alternatives using multiple criteria	-	It is complex for practitioners to set both the values of the criteria and their weights.	The prototype should be simplified for easy use, as stated in the goal of HC-HDSSs. The MCDM functionality is simplified by providing the same default weights to all criteria.

7.4.6 REFLECTION AND LEARNING ON PROBLEM FORMULATION

As stated in the ADR method (Sein et al., 2011), reflection and learning constitute a continuous stage paralleling the stage of problem formulation and the stage of building, intervention, and evaluation. There is a "conscious reflection on the problem framing, the theories chosen, and the emerging ensemble" (Sein et al., 2011, p. 44). In other words, except for the revision of design knowledge as presented in the above sections, the research problem formulated and the theories selected early in the study have also been refined based on reflection and learning in BIE iteration one. The formulated research problem changed from designing hybrid decision-making systems in the ITSM to designing hybrid decision support systems for semi-structured decisions after the reflection and learning parallel to this iteration. Elaboration on this matter follows below.

The initial scientific problem identified by the DDI research group was that existing digital systems were developed driven by technology, or developed from a strictly technical perspective, neglecting or insufficiently utilizing the knowledge and skills of humans, which are important since they affect decision-making (e.g., Borst, 2016; Demartini, 2015; Demartini et al., 2017; Kahneman, 2011). Such knowledge and competence are not based on technical algorithms or mathematical calculations using large volumes of data. Instead, they are stored in organizational structures, personal memories, and cognitive thought patterns (Göranzon, 2009). The knowledge is often based on professional experiences, personal reflections, branch-specific events, contextual factors, relationships with other involved actors, and organizational culture (Göranzon, 2009). The type of competencies that digital systems lack consists of the specific capability of humans to apply intelligent cognitive processes (e.g., Kahneman, 2011). Demartini (2015) and Demartini et al. (2017) called such combinations of humans and machines hybrid systems. Therefore, on one hand, the research problem was initially formulated as there being a lack of support for designing such a hybrid decision-making system, integrating the benefits of technology with human experience-based knowledge and cognitive skills that can improve the decision-making of digital systems. On the other hand, the research problem arose in the specific context of ITSM, because the representatives of the two organizations work with ITSM and the shared input data are also a dataset in ITSM.

Furthermore, in this study, a hybrid decision-making system was defined as a digital system that utilizes both human and machine capabilities for decision-making. Both humans and machines can be the final decision-makers. This dissertation initially focused on studying the scenario in which humans are the final decision-makers. Another scenario in which machines can be the end decision-makers can be studied in future projects.

In this iteration, first, the author gained more knowledge of digital systems related to decision-making. Digital systems in which humans are the final decision-makers or digital systems take the role of supporting humans' decision-making instead of automatically making decisions should be called DSSs. Therefore, design knowledge of DSSs has been added to chapter 2: Theoretical foundation.

Second, the author tried to generalize the specific research problem to a class of problems and identified theories of three decision types (Simon, 1977, p. 44; Gorry & Scott Morton, 1971, 1989) and the decision-making process view (Simon, 1977, p. 44). The research problem concerning decision-making specific to ITSM was generalized as concerning semi-structured managerial decisions. Because the decisions in the selected specific context are semi-structured from the perspective of the three decision types and the decision-making process view, machines cannot automatically take action in all of the first three steps of the decision-making process (i.e., intelligence, design, and choice).

Therefore, the research problem has been refined as there being a lack of design knowledge of hybrid decision support systems for making semi-structured decisions, instead of decision-making systems in ITSM. The term "hybrid" highlights a combination of human and machine capabilities in decision-making.

7.5 THE INITIALLY ARTICULATED DESIGN PRINCIPLES

Based on reflection and learning, four design principles were articulated in BIE iteration one and outputted to the next BIE iteration. They are DP1(v1), DP2(v1),DP3(v1), and DP4(v1) (see the first column in Table 7.3).

Table 7.3. Design principles articulated in BIE iteration one.

DPs articulated in BIE iteration 1	**DPs articulated in BIE iteration 2**	**DPs articulated in BIE iteration 3**
DP1(v1) Design for utilizing human capabilities	DP1(v2)	DP1(v3)
DP2(v1) Design for utilizing machine capabilities	-	DP2(v2)
DP3(v1) Design for combining human and machine capabilities	DP3(v2)	DP3(v3)
DP4(v1) Design for humans at the center	DP4(v2)	DP4(v3)
-	DP5(v1)	DP5(v2)

As stated earlier in this dissertation, the articulated design principles have evolved through the three BIE iterations—that is, there is more than one version of each articulated design principle. Table 7.3 presents a summarized evolution process of all the design principles formulated in the three BIE iterations. The first column of the table shows the design principles initially articulated in BIE iteration one, which are highlighted because this chapter focuses on BIE iteration one. The other two columns list the design principles articulated in the following two BIE iterations, which are presented in the following two chapters.

7.5.1 DP1(V1): DESIGN FOR UTILIZING HUMAN CAPABILITIES

Based on reflection and learning on the implemented functionalities of utilizing human capabilities, design principle 1 (DP1), "design for utilizing human capabilities," was formulated. Section 4.1.1 defines design principles and introduces the guidelines for formulating them. Therefore, following the selected guidelines, DP1(v1) is given a short name, description, and rationale or justification (see Table 7.4). The theoretical grounding and/or empirical grounding of the design principle are also provided in the table.

DP1 reads, "*for developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should utilize human intuition and knowledge by externalizing humans' implicit knowledge, combining explicit knowledge, socializing between humans, and internalizing the explicit knowledge*."

The text at the beginning of the description of DP1, "for developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions," provides the overall aim and context of designing HC-HDSSs. It is aligned with the identified goal of HC-HDSSs introduced in section 7.1, specifies who can use the design principle, and sets the context that the design principle is for digital systems "making semi-structured managerial decisions." Other design principles formulated in this study will also start with the same text.

Table 7.4. DP1(v1): Design for utilizing human capabilities (intuition and knowledge).[90]

ID & title	DP1(v1): Design for utilizing human capabilities
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should utilize human intuition and knowledge by externalizing human implicit knowledge, combining explicit knowledge, socializing between humans, and internalizing the explicit knowledge.
Rationale	Because humans utilize intuition and knowledge in combination and because knowledge is created by these four modes.
Theoretical grounding	- Intuition (e.g., Barnard, 1938; Dane & Pratt, 2007) - Knowledge (e.g., Grant, 2007; Nonaka, 1991; Polanyi, 1958, 1966) - Human capabilities in decision-making, i.e., intuition and knowledge (e.g., Dellermann et al., 2019a; 2019b; Demartini, 2015) - Group decision-making (e.g., Lima et al., 2018; Dellermann et al., 2019b)
Empirical grounding	Practitioners agree with building the HC-HDSS to involve more than one human.

DP1(v1) is theoretically grounded in theories of intuition (e.g., Barnard, 1938; Dane & Pratt, 2007), human knowledge for decision-making (e.g., Grant, 2007; Nonaka, 1991; Polanyi, 1958, 1966), human capabilities in decision-making, and group decision-making (e.g., Dellermann et al., 2019b; Lima et al., 2018). Elaboration on this matter follows. In addition, DP1(v1) has the empirical grounding that the practitioners agreed with, namely, building the HC-HDSS for more than one human.

First, the two identified human decision-making capabilities are intuition and knowledge (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015). Humans can apply intuition by relying on heuristics (Dane & Pratt, 2007; Tversky & Kahneman, 1974). The intuition applied by humans can be grounded in their knowledge and experience (Barnard, 1938). Human experts gain knowledge of many patterns through their long experience. Their knowledge of patterns is stored in humans' memory and is quickly extracted by them when making decisions (Simon, 1987). Dane and Pratt (2007) claimed that, in intuitive decisions, humans use

90 How DP1(v1) guides the building will be presented in BIE iteration two.

intuition or judgment instead of rational analysis, interpreted as humans applying their intuition together with their previously stored knowledge in an unconscious way. In other words, *humans apply their intuition and knowledge in combination.*

Second, human knowledge has tacit, implicit, and explicit components; the tacit knowledge can be partly transformed to be more explicit, i.e., implicit knowledge. Furthermore, there are four highly interdependent and intertwined modes of interplay between the tacit and explicit components (Nonaka & Takeuchi, 1995). The *socialization* mode is about transforming implicit knowledge into new implicit knowledge through individuals' social interactions and shared experiences. The *combination* mode is about transforming existing explicit knowledge of individual A into new explicit knowledge of individual B. *Externalization* refers to an individual's implicit knowledge being externalized to form that individual's new explicit knowledge. *Internalization* refers to the transformation of an individual's explicit knowledge into new implicit knowledge. In summary, knowledge is created through the four modes of interplay, of which the *socialization* and *combination* modes require more than one human being. Therefore, HC-HDSSs should utilize human intuition and knowledge by externalizing the implicit knowledge, and by socializing (between humans), combining (existing explicit knowledge), and internalizing the explicit knowledge.

7.5.2 DP2(V1): DESIGN FOR UTILIZING MACHINE CAPABILITIES

Through reflection and learning in BIE iteration one, a more profound understanding of the utilizing of machine capabilities in HC-HDSSs was gained. Therefore, design principle DP2(v1), "Design for utilizing machine capabilities," is formulated for the HC-HDSS class. It reads, "*for developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, machine capabilities should be identified and utilized based on the decision context"* (see Table 7.4).

Table 7.4. DP2(v1): Design for utilizing machine capabilities.[91]

ID & title	**DP2(v1) : Design for utilizing machine capabilities**
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, machine capabilities should be identified and utilized based on the decision context.
Rationale	Because 1) machines have capabilities that humans lack in general and 2) the specific decision context affects the utilization of machine capabilities.
Theoretical grounding	- Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine capabilities in decision-making (e.g., van den Broek et al., 2021; Gunaratne et al., 2018; Sotala, 2012)

DP2(v1) is grounded in the identified weaknesses of humans in decision-making and in machine capabilities in decision-making. As introduced in section 3.1, humans have certain cognitive constraints (i.e., limited information processing speed and limited memory) as well as biases. As introduced in section 3.2, machines have decision-making capabilities that could generally complement human weaknesses. For example, a machine's capabilities of "being efficient and effective," "being continuously upgradable in memory, algorithms, and computing ability," and "predicting by pattern recognition" could complement human weaknesses of limited information processing speed and limited memory. The machine capability of reducing human biases could complement the human weakness of being biased in decision-making tasks.

Furthermore, on one hand, the specific decision context affects the utilization of machine capabilities. The context may limit the capabilities of certain machines. For example, according to the decision types introduced in section 2.2.1, a semi-structured decision consists of structured and unstructured problems in a decision-making process. The more unstructured the decision problems, the less autonomously machines can make the decisions. On the other hand, based on a specific decision context, the decision-making task of an HC-HDSS has a specific focus, which means

91 How DP2(v1) guides the building will be presented in BIE iteration two.

that an HC-HDSS could emphasize one or several machine capabilities instead of utilizing all of them. Therefore, in designing an HC-HDSS, "developers should identify and utilize machine capabilities based on the decision context."

7.5.3 DP3(V1): DESIGN FOR COMBINING HUMAN AND MACHINE CAPABILITIES

The design principle "design for combining human and machine capabilities" is formulated based on one of the unanticipated results of building the prototype to support decision-making as a process. This is because designing a tool to support a decision-making process provides a means to combine human and machine capabilities in decision-making. Therefore, DP3(v1) is formulated as "f*or developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should combine the capabilities of humans and machines in a decision-making process" (see Table 7.5).*

DP3(v1) was initially grounded in theories of the decision-making process (Simon, 1977, p. 44) and of decision types. On one hand, the decision-making process view considers both human and machine capabilities in decision-making. When Simon (1977) proposed a view of the decision-making process in The New Science of Management Decision, he was thinking about computers' implications for business management. The purpose of his book was "to examine how the processes of management, and especially management decision making, have changed and continue to change under the impact of the new technology of the computer" (Simon, 1977, p. 1). This can be interpreted as a proposal to view decision-making as a process considering both humans and machines (i.e., "computers" in Simon's study) as elements of management decision-making.

Table 7.5. DP3(v1): Design for combining human and machine capabilities.[92]

ID & title	**DP3(v1) : Design for combining human and machine capabilities**
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should combine the capabilities of humans and machines in a decision-making process.
Rationale	Because 1) humans apply both cognitive patterns for making complex decisions, of which the cognitive pattern System 2 links to analytic decisions, carried out as a process, and 2) one of the machine's roles, as well as displaying machine capabilities, is supporting humans making analytical decisions.
Theoretical grounding	- Kahneman's systems 1 and 2 (Kahneman, 2011) - The decision-making process (Simon, 1977, p. 44) - Human capabilities in decision-making (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine capabilities in decision-making (e.g., van den Broek et al., 2021; Gunaratne et al., 2018; Sotala, 2012) - Machine weaknesses in decision-making (e.g., Demartini, 2015; Kulkarni et al., 2017; Shollo et al., 2015)

On the other hand, as argued earlier, HC-HDSSs are used for making semi-structured managerial decisions. This means that there are structured parts of the decision-making process in which machine capabilities could complement human weaknesses; there are also unstructured parts in which human capabilities could complement machine weaknesses. Therefore, grounded in theories of the decision-making process and decision types, HC-HDSSs should be designed to bring both human and machine capabilities into the decision-making process.

Second, DP3(v1) is also grounded in the theory that humans have two cognitive systems (Kahneman, 2011). As stated earlier, based on Kahneman's (2011) study, introduced in section 2.1, HC-HDSSs should support both human cognitive patterns because humans use both systems to make

92 How DP3(v1) guides the building will be presented in BIE iteration two.

complex decisions. Supporting System 1 refers to supporting humans to make intuition or intuitive decisions, whereas supporting System 2 refers to supporting logical, analytical, and statistical decision-making. Kahneman's two cognitive systems can be linked to Simon's study, because Simon regards managers or decision-makers as boundedly rational, i.e., they use both systems 1 and 2, making analytical decisions in a process. In other words, designing HC-HDSSs for a decision-making process supports both human cognitive patterns. Therefore, the theory of humans' two cognitive systems is also used as the theoretical grounding of DP3(v1).

7.5.4 DP4(V1): DESIGN FOR HUMANS AT THE CENTER

Based on the previous reflection and learning, DP4(v1): Design for humans at the center is formulated for HC-HDSSs. It reads, "*for developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, humans' actual decision-making process should be supported and human users, instead of machines, should be the final decision-makers*" (see Table 7.6).

DP4(v1) is first grounded in theories of humans' two cognitive systems (Kahneman, 2011), human capabilities and weaknesses in decision-making, and human-centered design. That is, centering on human needs in designing HC-HDSSs should take account of human behavior, i.e., humans' actual decision-making and human capabilities and weaknesses in decision-making. Second, it is grounded in the decision types of DSSs and in machine weaknesses in decision-making, which mean that machines cannot make semi- or unstructured decisions. Third, DP4(v1) is grounded in theories of knowledge (e.g., Grant, 2007; Nonaka, 1991; Polanyi, 1958, 1966) stating that, while implicit knowledge can be transformed to be explicit, tacit knowledge cannot be transformed to be explicit. Therefore, humans need to be involved in the decision-making process to apply their tacit knowledge.

Table 7.6. DP4(v1) Design for humans at the center in BIE iteration one.[93]

ID & title	**DP4(v1): Design for humans at the center**
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, humans' actual decision-making process should be supported and human users, instead of machines, should be the final decision-makers.
Rationale	Because design for humans at the center should take account of human needs and behavior, and machines cannot make semi-structured decisions.
Theoretical grounding	- Humans' two cognitive systems (Kahneman, 2011) - Tacit, implicit, and explicit knowledge (e.g., Grant, 2007; Nonaka, 1991; Polanyi, 1958, 1966) - Decision types of DSSs (Gorry & Scott Morton, 1971, 1989) - Human capabilities in decision-making (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine weaknesses in decision-making (e.g., Demartini, 2015; Kulkarni et al., 2017; Shollo et al., 2015)

7.6 SUMMARY

This chapter primarily presents how preexisting design knowledge has been used in building the initial version of the HC-HDSS prototype in BIE iteration one. The built prototype was evaluated by researchers and practitioners. Through analyzing the collected empirical data, reflections, and learning, the primary outcomes were the initial version of the prototype, an initial version of the goal of HC-HDSSs, and an initial meta-design of HC-HDSSs, including DP1(v1), DP2(v1), DP3(v1), and DP4(v1). These are used as input to BIE iteration two.

The initial version of the goal and meta-design (including design principles) of HC-HDSSs will evolve in the following BIE iterations. The final

93 How DP4(v1) guides the building will be presented in BIE iteration two.

version of the goal will be presented in BIE iteration two. The goal evolves along with the evolution of the research problem from HDMSs to HC-HDSSs. There is no change in the goal in BIE iteration three. The final version of the meta-design will be presented in BIE iteration three.

CHAPTER 8

THE BUILDING, INTERVENTION, AND EVALUATION: ITERATION TWO

This chapter presents the design knowledge that emerged, and was identified and used in BIE iteration two, including: the revised goal and meta-design of HC-HDSSs in section 8.1; building the alpha version of the prototype in section 8.2; intervention in organizations and evaluation of the alpha version of the prototype in section 8.3; reflection and learning on BIE iteration two in section 8.4; and revised or newly articulated design principles resulting from reflection and learning in section 8.5. Section 8.6 summarizes the chapter.

8.1 THE REVISED GOAL AND META-DESIGN OF HC-HDSSS

The initially identified goal of HC-HDSSs has been revised in BIE iteration two. Now, the statement that the IT artifact should be "designed with humans at the center" has been added as part of the goal. The revised goal reads, “a contextualized easy-to-use web-based IT artifact that is ***designed with humans at the center,*** and utilizes both human and machine capabilities to make semi-structured managerial decisions” (the change is emphasized). This change was made because theories of HCAI are identified as relevant to the study in this iteration. More details are given in section 8.4.4.

Meanwhile, the initial meta-design of HC-HDSSs has also been revised in BIE iteration two (see Figure 8.1). The main changes have been highlighted in the HC-HDSS class of Figure 8.1. Briefly, DP1(v1), DP3(v1), and DP4(v1) have been revised into new versions, DP1(v2), DP3(v2), and DP4(v2). There is no change in DP2(v1) in this iteration. DP5(v1) is a newly formulated DP. Revised or newly emerged design principles are formulated by following the same guidelines used for formulating DP1(v1) in BIE iteration one. Details are given in the following sections.

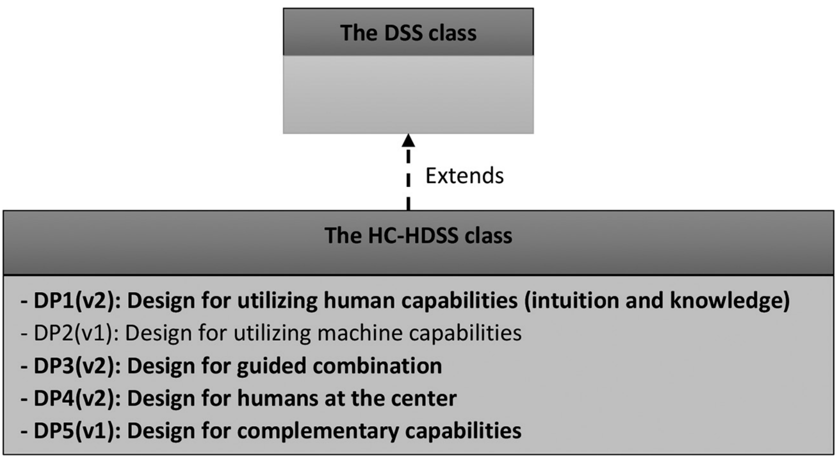


Figure 8.1. The revised meta-design of HC-HDSSs.

8.2 BUILDING THE ALPHA VERSION

The four design principles of the HC-HDSS class articulated in BIE iteration one are used to build the alpha version of the prototype in BIE iteration two.

8.2.1 DP1(V1) GUIDES THE BUILDING

DP1(v1), "Design for utilizing human capabilities," guided the building of the alpha version of the prototype. The following illustration of several functionalities in the prototype provides a more concrete description of how DP1(v1) guides the building of the prototype.

In step 2A: Individual assessment, the functionality "Motivation for the score" (see the area surrounded by a dotted line in Figure 8.2a) is implemented so that an individual human can justify the score given to a selected statement. This functionality is primarily guided by the aim to "externalize the tacit component of human knowledge" in DP1(v1). The externalized knowledge, i.e., the motivation, is one of the outputs of this step and will be used as one of the inputs in the following steps of the prototype.

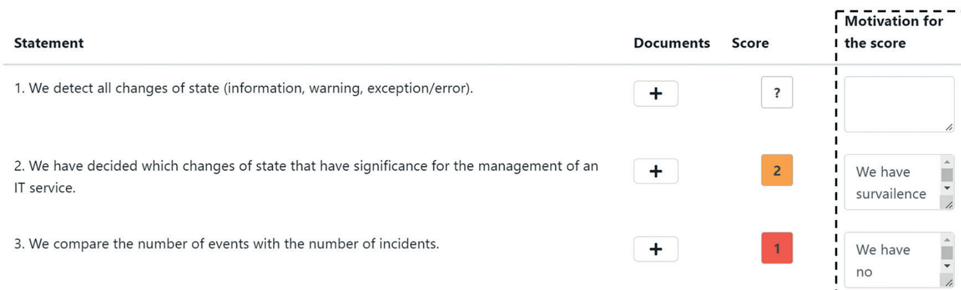


Figure 8.2a. The functionality guided by DP1(v1) in step 2A.

Step 2B: Compare the results of individual assessment (see Figure 8.2b) is guided by "socialize the knowledge between humans" in DP1(v1) in general. The aim is for more than one individual human to meet in this step to share their knowledge and experience. The social interaction in this step promotes the transferring of tacit components between humans.

Specifically, the functionality "Changed score after discussion" in step 2B (see area surrounded by a dotted line #1 in Figure 8.2b) is implemented and guided by "internalize the explicit component" of DP1(v1), describing how an individual human could internalize the explicit knowledge in this step after discussing it with other humans. This internalized knowledge is reflected in terms of a changed score. The "Argument" functionality of step 2B (see the area surrounded by a dotted line #2 in Figure 8.2b) is guided by the aim to "externalize the tacit component of human knowledge" in DP1(v1). The aim is for humans to externalize the tacit component of their knowledge by explicitly giving arguments supporting the agreed-on or not agreed-on score.

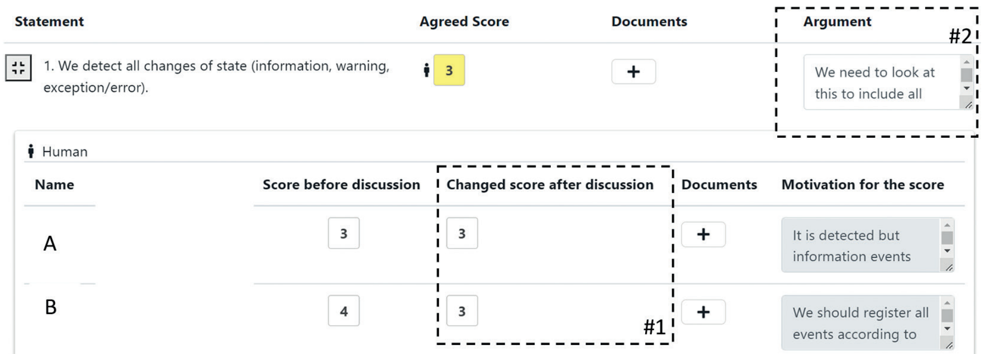


Figure 8.2b. Functionalities guided by DP1(v1) in step 2B.

In step 2D: Human and machine assessment comparison, the "Justification for Prio" and "Identified problem" functionalities (areas #1 and #2 surrounded by dotted lines in Figure 8.2c) are also guided by the direction to "externalize the tacit component of human knowledge" in DP1(v1). In detail, the "Justification" functionality is for externalizing knowledge in terms of justifying the prioritization of one or several statements after humans compare the information or score provided by machines in step 2C. The "Identified problem" functionality is for externalizing knowledge in terms of a formulated problem for the selected statement.

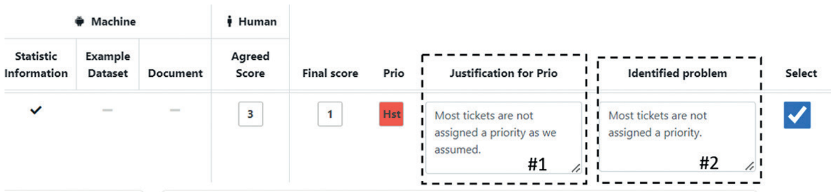


Figure 8.2c. Functionalities guided by DP1(v1) in step 2D.

Step 3: Identify solutions to the selected problem(s) in general is guided by "combine explicit knowledge" of DP1(v1). In this step, all the implicit and explicit knowledge generated in earlier steps (see box #1 in Figure 8.2d) converges and is combined into ideas that could be solutions to an identified problem to be addressed in a decision-making process (see box #2 in Figure 8.2d).

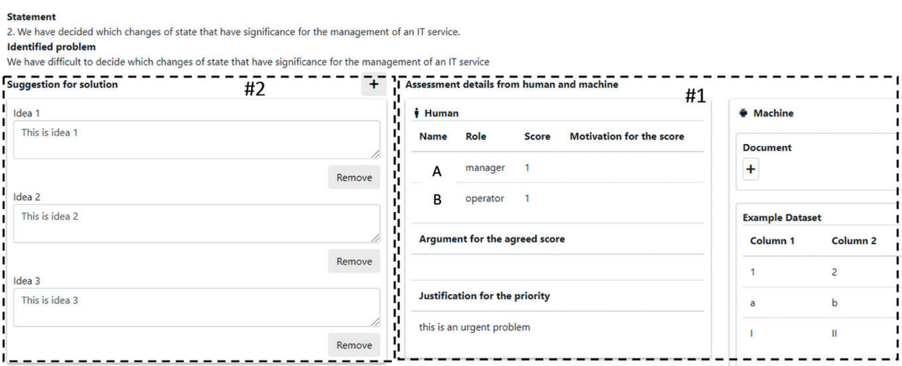


Figure 8.2d. Functionalities guided by DP1(v1) in step 3.

8.2.2 DP2(V1) GUIDES THE BUILDING

Guided by "machine capabilities should be utilized based on the decision context" in DP2(v1), "Design for utilizing machine capabilities," the machine capability of pattern recognition cannot be utilized in the prototype. This is because organization A did not provide a large enough volume of data for the machines to calculate and give scores for each statement. Although a large volume of data could have been provided by organization

A, the machine's capability to calculate the score is uncertain in such a highly unstructured problem. Therefore, in this case, the machine's capability, in terms of pattern recognition relying on technologies such as data mining and machine learning, could not be utilized.

8.2.3 DP3(V1) GUIDES THE BUILDING

Guided by DP3(v1), "Design for combining human and machine capabilities," the prototype is designed to combine human and machine capabilities in steps 2 and 3 of the prototype.

In detail, in step 2D (see area surrounded by a dotted line in Figure 8.3), humans and machines have already finished separately assessing the statements about monitoring and event management practice in the earlier step. The capabilities of humans and machines are brought together in this sub-step, for human users to identify and prioritize one or more problems. In step 3: Identify solutions to the selected problem(s), human and machine capabilities are also brought together for human users to find solutions to the identified problem(s) (see box #1 in Figure 8.2d).

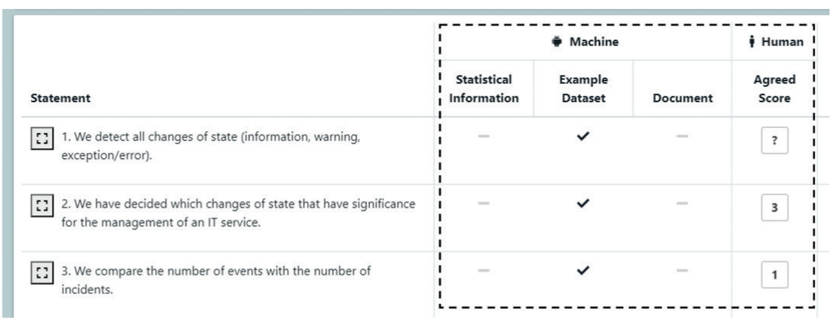


Figure 8.3. DP3(v1) guides the functionality in Step 2D.

8.2.4 DP4(V1) GUIDES THE BUILDING

DP4(v1), "Design for humans at the center," guided the building of functionality in the last step of the prototype (i.e., step 4B). In step 4B, human users are the final decision-makers, comparing the ideas and selecting one as the “preferred solution,” which is the decision made (see the area surrounded by a dotted line in Figure 8.4). Next, human users edit the decision by adding information such as who will be responsible for implementing the decision, the due date of the implementation, etc.

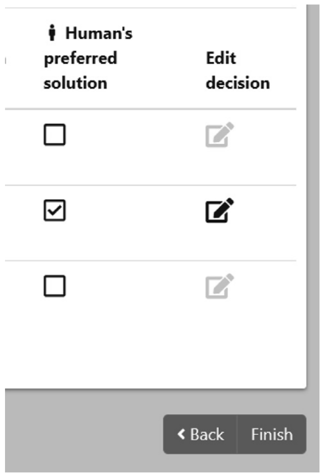


Figure 8.4. DP4(v1) guides the positioning of the human user as the final decision-maker in step 4B.

8.3 INTERVENTION AND EVALUATION

Following the overall evaluation strategy, the prototype (alpha version) evaluation in BIE iteration two has two episodes: formative and semi-naturalistic/artificial evaluation in episode 2a and summative and semi-naturalistic/artificial evaluation in episode 2b.

As already introduced, episode 2a aims to improve the characteristics of the prototype. The prototype was first discussed with researchers of the ADR group. Comments from researchers were transformed into requirements for the developer of the ADR team. Then the author presented the revised prototype to representatives of the two organizations; the representatives gave feedback (i.e., formative and semi-naturalistic/artificial evaluation). The feedback was reformulated as new requirements. The developer is continuing to implement those requirements.

Episode 2b aims to improve the characteristics of the prototype, as in episode 2a, and to assess its utility. Initially, the prototype was presented to representatives of the two organizations, as in episode 2a, who were free to give comments. Later, interview questions related to evaluating the prototype were put to practitioners in the same meeting.

Table 8.1 lists the interview questions concerning the property of functionality and corresponding design principles.[94] Four questions were formulated especially for DP1. The first one is a question concerning DP1 in general; the next three questions are sub-questions of the first one and aim to collect more detailed comments from practitioners.

As in BIE iteration one, the alpha version of the HC-HDSS prototype served as a lightweight intervention. The collected data were analyzed.

Table 8.1. Interview questions concerning the property of functionality related to design principles.

Design principles	**Interview questions concerning the property functionality**
DP1: Design for utilizing human capabilities (intuition and knowledge)	The tool tries to utilize human capabilities (i.e., intuition and knowledge) in decision-making. What are your thoughts about that?
	Different people have different experiences and skills. The tool tries to support making use of different experiences and skills of humans. What are your thoughts about that?
	The tool tries to support humans sharing their knowledge and learning from one another. What are your thoughts about that?
	The tool tries to support humans to express their experiences and skills. What are your thoughts about that?
DP2: Design for utilizing machine capabilities	The tool tries to utilize the capabilities of machines in decision-making. What are your thoughts about that?
DP3: Design for combining human and machine capabilities	The tool tries to combine human and machine capabilities in a decision-making process. What are your thoughts about that?
DP4: Design for humans at the center	In what way do you think the design is centered on humans?

94 The interview questions used in episode 2b are given in Appendix 2.

8.4 REFLECTION AND LEARNING

Table 8.2 provides a summary of the reflection and learning specific to each formulated or tentative design principle. Details are given in the following sections.

Table 8.2. Anticipated and unanticipated results of BIE iteration two.

Design principles	**Anticipated results**	**Unanticipated results**	**Reflection and learning**
DP1(v1): Design for utilizing human capabilities (intuition and knowledge)	Building to utilize human capabilities (intuition and knowledge) should work but may need some improvement.	Consider the organizational context, which affects the selected roles and further affects decision-making.	The tool facilitates human intuition and knowledge, which is good. However, the context should be formally considered because it affects the selection of human participants. The roles of human participants (e.g., managers) may hinder the knowledge-sharing of other human participants, who may be reluctant to give rational scores.
DP2(v1): Design for utilizing machine capabilities	More intelligent machine capabilities should be implemented.	-	More intelligent machine capabilities that suit the context should be implemented.
DP3(v1): Design for combining human and machine capabilities	Building to combine human and machine capabilities in a decision-making process should work.	The prototype provides a guided decision-making process.	Design the tool to support decision-making as a process, not only bringing together human and machine capabilities. A guided process with several mandatory steps is needed to address complex decisions.
DP4(v1): Design for humans at the center	Building to center humans should work but may need some improvement.	Theories of HCAI may suit this study.	The HCAI philosophy matches the previous design process of this study, i.e., a human-centered design process. DP4 could be revised based on HCAI theories.
A tentative new design principle, DP5(v1)	-	The functionality related to uploading relevant documents for human users to review during the decision-making process supports human intuition.	Machine capabilities are utilized not only to complement human weaknesses, but also to enable human capabilities.

8.4.1 REFLECTION AND LEARNING ON DP1(V1)

The anticipated result of DP1(v1), "Design for utilizing human capabilities (intuition and knowledge)," is that it works but may need improvement. There was one unanticipated result of DP1(v1): one practitioner mentioned that, to utilize human capabilities in the digital tool, the organizational context or management style has to be considered when selecting human participants. In other words, the organizational culture affects the willingness to share knowledge between different human roles. The roles of human participants (e.g., managers) may hinder knowledge sharing with other human participants, or other participants may be reluctant to give rational scores. The following are several relevant quotations from the practitioners:

> The department members don't always say what they think when it is the manager who asks the question.

> Depending on the manager and the management culture, you don't always get the answers. Sometimes you get the correct answer. Sometimes, when the manager doesn't run this assessment, you might get more honest answers.

> It is not always the best option for the manager to perform the assessment.

> The manager's role—depending on the management style, organizational culture, the manager may think he/she is the manager, the one running the department. "This is my area—the score is 4." They will convince the operator the score is 4.

> Management styles and roles are important.

Therefore, signals related to organizational culture affecting decision-making were captured and used to revise DP1(v1). Meanwhile, studies of organizational culture affecting knowledge sharing and/or decision-making were identified and used as the theoretical grounding of a new version of DP1, i.e., DP1(v2). The identified studies, for example, by Natu and Aparicio (2022), Nisar et al. (2021), and Briggs et al. (2008), are presented in section 2.1.2. The revised DP1(v2) is presented in section 8.5.1.

8.4.2 REFLECTION AND LEARNING ON DP2(V1)

The evaluation in BIE iteration two confirmed the implemented functionalities based on the context guided by DP2(v1), "Design for utilizing machine capabilities." The anticipated result of DP2(v1) is that more intelligent machine capabilities should be implemented in the prototype. There were no unanticipated results. Therefore, there is no change to DP2(v1) based on reflection and learning in this iteration. However, the prototype should be continually revised by providing more intelligent machine capabilities.

8.4.3 REFLECTION AND LEARNING ON DP3(V1)

The anticipated result of DP3(v1), "Design for combining human and machine capabilities," is that it works. One of the practitioners confirmed in an interview during BIE iteration two that the decision-making process brings in the capabilities of both humans and machines. Additionally, practitioners gave unanticipated comments about "a guided decision-making process."

One practitioner said: "[For] complex problems, statements, issues, then you need a guided decision-making process … a guided tool that helps me in some mandatory steps to work through a decision-making process. Yes, really good. Because we [i.e., humans] are known to take shortcuts." Similarly, another practitioner in a different meeting pointed out that "[the four steps in a decision-making process] keep a structure."

Practitioners' comments implied that designing the digital tool supports a decision-making process through several mandatory steps, not only by bringing together human and machine capabilities for making decisions. However, the functionality also ensures that humans contribute or apply their knowledge through the mandatory guided steps. Furthermore, the comments confirmed that designing HC-HDSSs to incorporate a decision-making process is suited for semi-structured decisions.

Based on the signal captured from the empirical data (i.e., practitioners' answers), the author looked for relevant theories and found the theory of decisional guidance, which is presented in section 2.2.4, of chapter 2: Theoretical foundation. According to Silver (1991), the signal of a guided decision-making process captured from practitioners in this study would refer to the prototype providing decisional guidance on executing rather than structuring the decision-making process. Guidance for executing the decision-making process "affects how decision makers perform the evaluative and predictive judgments necessary when executing the chosen operators," whereas guidance for structuring the decision-making process "affects how users choose which operators to invoke and the order in which to invoke them" (Silver, 1991, p. 107). The prototype guides human users by following the mandatory steps until a decision is made. Human users do not need to structure a decision-making process.

Additionally, the identified theory of decisional guidance also strengthens several other implemented functionalities that provide guidance in different dimensions. For example, the prototype provides informative guidance (i.e., the dimension of forms). Informative guidance provides "pertinent information that enlightens the decision maker's judgment without suggesting how to act" (Silver, 1991, p. 112). In step 2D, the capabilities of machines are utilized to provide statistical information for statement No. 9 to humans.

In the same example, the prototype also inscribes dynamic guidance (i.e., the dimension of modes). The information displayed by the machine in step 2D is not predefined; rather, it is based on the input dataset in step 1, creating a decision-making project. The information will be different if another set of data provides input into the calculations of a machine. Therefore, the prototype also provides dynamic decisional guidance given that the information from machines is generated "by the mechanism dynamically, not by the designer in advance" (Silver, 1991, p. 116).

Finally, as mentioned earlier, providing decisional guidance can improve group users' understanding of the multi-criteria decision-making modeling procedure and can increase decision quality (Limayem & DeSanctis, 2000). The prototype in this study is also a multi-criteria DSS used by more than one human participant. Therefore, decisional guidance theory strengthens several implemented functionalities of the prototype. Decisional guidance theory is added as one theoretical grounding of DP3(v2) in section 8.5.2. Guided by this theory, more functionalities can be implemented in BIE iteration three, in the same or differing dimensions.

8.4.4 REFLECTION AND LEARNING ON DP4(V1)

The anticipated result related to DP4(v1) in BIE iteration two is that practitioners agreed that humans should be the final decision-makers for making semi-structured (and also unstructured) decisions.

The unanticipated result is that the researchers' group of the ADR team identified studies of HCAI highly relevant to the design process of HC-HDSSs. Therefore, the author searched for more HCAI studies and found that statements about HCAI from the identified studies aligned well with DP4(v1), especially with its implied philosophy. The theory of HCAI is presented in section 2.4 of chapter 2: Theoretical foundation.

Philosophically, HCAI differs from traditional AI, which highlights the autonomy of machines or machines' autonomy-first design. In contrast, HCAI places human users at the center of attention, as in the process of designing the HC-HDSS prototype. First, the prototype values human knowledge and intuition, i.e., the prior knowledge and irrational decision-making of humans embedded within specific cultural contexts (Auernhammer, 2020), because these two are identified as human capabilities in decision-making in this study. Utilizing the two capabilities is one focus when designing the prototype. In each step of the decision-making process, human knowledge and intuition are considered. More details are given in the sections related to DP1, "design for utilizing human capabilities."

Second, the prototype highlights that humans can learn from a decision-making task instead of only using the prototype to make a decision. In other words, in addition to the decision made as one outcome of using the prototype, increased knowledge of humans is another outcome, i.e., augmenting human capabilities (Shneiderman, 2020). Examples of this can be found in the sections related to DP1, "design for utilizing human knowledge and intuition."

Third, Auernhammer (2020) mentioned that HCAI centers on human needs, which is aligned with the reflection and learning about DP4 in BIE iteration one (for more details, see section 7.4.4).

Fourth, Shneiderman (2021, p. 58) stated that "humans choose which action to carry out." In all the steps of the prototype, humans instead of machines take action: machines only give information and suggestions based on the input data and rewritten algorithms.

Fifth, as pointed out by Xu et al. (2022, p. 10), HCAI is "ensuring the final decision of humans on the system control." Humans are designated the final decision-makers in the prototype. In the final step of the prototype, step 4D, humans decide which idea is the solution to the identified problem, who is responsible for implementing the decision, and what the due date is.

Based on learning and reflection on studies of HCAI, the revised version DP4(v2) is articulated in section 8.5.3.

8.4.5 REFLECTION AND LEARNING ON A TENTATIVE DESIGN PRINCIPLE (DP5)

There is an unanticipated result that corresponds to the tentative new design principle shown in the last row of Table 8.2. One practitioner mentioned that the functionality of uploading relevant documents for human users to review in the decision-making process supports human intuition. This comment triggered the author's reflection on the relationship between humans and machines in HC-HDSSs.

The functionality of uploading relevant documents has been implemented in several steps of the prototype/ the decision-making process. The documents could be uploaded by the person who creates a decision-making task; then the document could be utilized by human users who join the decision-making process in the following steps. Documents could also be uploaded by human users in the decision-making process to be used as evidence of user choice in a specific step.

The original rationale for implementing this functionality was to utilize machine capabilities (as guided by DP2: Design for utilizing machine capabilities). However, utilizing machine capabilities could complement human weaknesses in terms of cognitive constraints and biased behaviors. Furthermore, utilizing machine capabilities also facilitate human intuition, i.e., utilizing human capabilities, as the uploaded documents could trigger a human user to apply intuition to a decision-making task.

Based on the above-captured signal, papers using the term "complement" or similar expressions were identified. For example, Humans and AI play complementary roles (Jarrahi, 2018). Humans and machines have *complementary capabilities* that can be combined to augment each other (Dellermann et al., 2019a). Following, a hybrid intelligence decision support system that "combines the *complementary* capabilities of human and machine intelligence" is designed (Dellermann et al., 2019b, p. 423). Auernhammer (2020, p. 1323) mentioned that "it complements rather than substitutes human intelligence in systems." Xu et al. (2022) pointed out that "develop[ing] the complementarity of machine intelligence and human intelligence" (p. 7) entails "emphasizing the complementarity of human and machine intelligence" (p. 7) and "optimiz[ing] the human–machine collaboration and performance of AI systems by taking advantage of the functional complementarity and adaptability between humans and AI systems" (p. 18) (all emphasis in these quotations is the present author's).

In summary, designers should design the tool to complement the capabilities of humans and machines. The tentative new design principle is formulated as DP5(v1), "Design for complementary capabilities," in BIE iteration three; details are given in section 8.5.4.

8.4.6 REFLECTION AND LEARNING ON EVALUATION PROPERTY UTILITY

As introduced in the section on evaluation properties[95], the property utility is the primary evaluation property. The property utility is affected by the property quality, i.e., the five properties or quality attributes (functionality, usability, comprehensibility, fit with the organization, and perceived decision quality). Questions related to these properties have been asked of practitioners to evaluate the prototype.[96]

Based on the practitioners' answers, the prototype has strengths and weaknesses. Concerning the strengths of the prototype, practitioners gave comments in general, such as "impressed", "as a whole [human-machine] is very interesting", "[the tool] makes a difficult thing more neutral". They also comment on specific, such as, "the graph in the human-machine part is very good", "simple to understand the process because you see the process from the start", "[the tool] helps to collect different perspectives",

95 See section 4.2.2.2.

96 For interview questions used in BIE iteration two, see appendix 2.

”very good that many humans work together so this system can be used on several different practices (knowledge sharing and team building)”.

Concerning the weaknesses of the prototype, practitioners gave practical suggestions on how to improve the prototype (both when the author presented the prototype and asked them questions related to the weaknesses of the prototype). For example, there are suggestions that the layout could be improved, e.g., by adding colors. There needs to be more space between the labels (e.g., name, objective, description, and expected outcome on the project page).

The comments or answers related to the weaknesses of the prototype imply that there is a need to refine the prototype to achieve its utility continually.

8.4.7 REFLECTION AND LEARNING ON PROBLEM FORMULATION

The refined research problem output from BIE iteration one concerns the lack of design knowledge about hybrid decision support systems for making semi-structured managerial decisions. The research problem has continually been refined as there is a lack of design knowledge about human-centered hybrid decision support systems for making semi-structured managerial decisions.

The refinement is triggered by the HCAI theory identified in BIE iteration two. As mentioned earlier, after reading studies of HCAI, the author realized that designing hybrid decision support systems is not enough when seeking to address all three identified underlying problem causes. Designing hybrid decision support systems can address the two machine weaknesses, i.e., that DSSs rely on input data (quality and types) and data analysis algorithms, and that DSSs cannot acquire tacit knowledge. Human capabilities can complement the two machine weaknesses. The third machine weakness, i.e., that DSSs introduce unwanted ethical issues, cannot be addressed by designing hybrid decision support systems. However, as elaborated on in chapter 1, inscribing HCAI in the prototype is a solution to the third problem cause.

Therefore, the research question is refined as presented in chapter 1, and HCAI theory is added in chapter 2.

8.5 THE FURTHER ARTICULATED DESIGN PRINCIPLES

The second column in Table 8.3 lists all the design principles articulated in BIE iteration two. Three design principles have been revised to new versions in this iteration. They are DP1(v2), DP3(v2), and DP4(v2). No change is made to DP2. In addition, DP5(v1) is a newly articulated design principle as an outcome of BIE iteration two.

Table 8.3. Design principles articulated in BIE iteration one.

DPs articulated in BIE iteration 1	DPs articulated in BIE iteration 2	DPs articulated in BIE iteration 3
DP1(v1) Design for utilizing human capabilities	DP1(v2) Design for utilizing human capabilities (intuition and knowledge)	DP1(v3)
DP2(v1) Design for utilizing machine capabilities	-	DP2(v2)
DP3(v1) Design for combining human and machine capabilities	DP3(v2) Design for guided combination	DP3(v3)
DP4(v1) Design for humans at the center	DP4(v2) Design for humans at the center	DP4(v3)
	DP5(v1) Design for complementary capabilities	DP5(v2)

8.5.1 DP1(V2): DESIGN FOR UTILIZING HUMAN CAPABILITIES (INTUITION AND KNOWLEDGE)

DP1(v1) is revised based on the reflection and learning in BIE iteration two. Table 8.4 presents DP1(v2) and highlights the changes from DP1(v1).

The signal regarding organizational culture affecting decision-making captured from the empirical data is added as the empirical grounding of DP1(v2) (see the last row of Table 8.4). Theories of organizational culture affecting decision-making (e.g., Briggs et al., 2008; Nisar et al., 2021) and knowledge sharing (e.g., Natu & Aparicio, 2022) have been added as the theoretical grounding of DP1(v2).

Table 8.4. Articulated DP1(v2): Design for utilizing human capabilities (intuition and knowledge); changes are bolded.

ID & title	**DP1(v2):** Design for utilizing human capabilities **(intuition and knowledge)**
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should **support the selection of different organizational roles of human participants based on the organizational context**. Moreover, the system should externalize the implicit human knowledge, combine explicit knowledge between humans, socialize the knowledge between humans, and internalize the explicit knowledge.
Rationale	Because **organizational contexts affect knowledge creation**, and because knowledge is created through the four modes.
Theoretical grounding	- Intuition (e.g., Barnard, 1938; Dane & Pratt, 2007) - Knowledge (e.g., Grant, 2007; Nonaka, 1991; Polanyi, 1958, 1966) - Human capabilities in decision-making, i.e., intuition and knowledge (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Group decision-making (e.g., Dellermann et al., 2019b; Lima et al., 2018;) **- Theories of organizational culture affecting decision-making (e.g., Briggs et al., 2008; Nisar et al., 2021) and knowledge sharing (e.g., Natu & Aparicio, 2022).**
Empirical grounding	- Practitioners agree to build the HC-HDSS to involve more than one human. **- A captured signal suggests that the organizational context should be considered, as it affects the selection of the role, for example: "Depending on the manager and the management culture, you don't always get the answers. Sometimes you get the correct answer. Sometimes, when a manager doesn't run this assessment, you might get more honest answers."**

8.5.2 DP3(V2): DESIGN FOR GUIDED COMBINATION

DP3(v1) is revised based on the reflection and learning in BIE iteration two. The new version, DP3(v2), reads, "For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should bring the capabilities of humans and machines together in a **guided** decision-making process" (see Table 8.5). Meanwhile, the name of DP3 is revised to "Design for guided combination."

The changes compared with DP3(v1) are highlighted in Table 8.5. The collected empirical data strengthening DP3(v1) have been added as the empirical grounding of DP3 in general. The captured signal of a guided decision-making process has been added as the empirical grounding of DP3(v2) (see the last row of Table 8.5). The identified theory of decisional guidance (Dellermann et al., 2019b; Limayem & DeSanctis, 2000; Morana et al., 2017; Parikh et al., 2001; Silver, 1991) has been added as the theoretical grounding of DP3(v2).

Table 8.5. Articulated DP3(v2): Design for guided combination; changes are bolded.

ID & title	**DP3(v2): Design for guided combination**
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should bring the capabilities of humans and machines together in a **guided** decision-making process.
Rationale	Because 1) humans apply both cognitive patterns for making complex decisions, of which the cognitive pattern System 2 links to analytic decisions, carried out as a process; 2) one of a machine's roles and capabilities is supporting humans when making analytical decisions; and **3) a guided decision-making process will support users to make more effective, better, or faster decisions.**
Theoretical grounding	- Kahneman's systems 1 and 2 (Kahneman, 2011) - The decision-making process (Simon, 1977, p. 44) - Human capabilities in decision-making (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine capabilities in decision-making (e.g., van den Broek et al., 2021; Gunaratne et al., 2018; Sotala, 2012) - Machine weaknesses in decision-making (e.g., Demartini, 2015; Kulkarni et al., 2017; Shollo et al., 2015) **- Theory of decisional guidance (Silver, 1991) or guidance design features (Morana et al., 2017; Silver, 2015). E.g., Dellermann et al., 2019b; Limayem & DeSanctis, 2000; Parikh et al., 2001).**
Empirical grounding	**- Empirical data strengthening DP3(v1), for example: "It [i.e., the decision-making process] absolutely helps me."** **- A captured signal about a guided decision-making process, for example: "[For] complex problems, statements, issues, then you need a guided decision-making process." "A guided tool that helps me in some mandatory steps to work through a decision-making process. Yes, really good. Because we [humans] are known to take shortcuts."**

8.5.3 DP4(V2): DESIGN FOR HUMANS AT THE CENTER

DP4(v2) reads, "For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, humans' actual decision-making process should be supported, human capabilities should be augmented by machines, and human users must have the overall control of the decision-making process and be the final decision-makers instead of machines."

Table 8.6. Articulated DP4(v2): Design for humans at the center; changes are bolded.

ID & title	**DP4(v2) :** Design for humans at the center
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, humans' actual decision-making process should be supported, **human capabilities should be augmented by machines, and human users must have the overall control of the decision-making process** and be the final decision-makers instead of machines.
Rationale	Because, 1) design for humans at the center should take account of human needs and behaviour;2) machines cannot make semi-structured decisions**; 3) machines take on the role of supporting humans and enhancing human capabilities, instead of replacing humans or eroding human capabilities; and 4) humans should learn in a decision-making process.**
Theoretical grounding	- Humans' two cognitive systems (Kahneman, 2011) - Tacit, implicit, and explicit knowledge (e.g., Grant, 2007; Nonaka, 1991; Polanyi, 1958, 1966) - Decision types of DSSs (Gorry & Scott Morton, 1971, 1898) - Human capabilities in decision-making (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine weaknesses in decision-making (e.g., Demartini, 2015; Kulkarni et al., 2017; Shollo et al., 2015) **- Theories of HCAI (e.g., Auernhammer, 2020; Shneiderman, 2021; Xu, 2022)**
Empirical grounding	**Empirical data strengthening DP4, for example: "It [i.e., the tool] directs you to focus on what to think about."**

As illustrated in section 2.4 of chapter 2: Theoretical foundation, HCAI includes several aspects, such as: designers should design the tool with humans as the final decision-makers (Xu et al., 2022); "humans choose which action to carry out" (Shneiderman, 2021, p. 58). Therefore, design knowledge related to HCAI has been extracted from existing studies for revising DP4(v1). The revised DP4(v2) is presented in Table 8.6 and guides the build of the beta version of the prototype. The changes in DP4(v2) are highlighted.

8.5.4 DP5(V1): DESIGN FOR COMPLEMENTARY CAPABILITIES

DP5, "Design for complementary capabilities," is formulated based on reflection and learning in BIE iteration two (see section 8.4.5). It reads, "for developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should utilize the complementary capabilities of humans and machines in decision-making in which human capabilities complement machine weaknesses and machine capabilities complement human weaknesses and augment human capabilities." DP5(v1) is grounded both in empirical data and theories. Table 8.7 is a summary of DP5(v1).

Additionally, DP5(v1) is an abstraction of DP1 and DP2. According to Gregor et al. (2020), there could be multiple abstraction levels of design principles in a study. In this study, DP1 and DP2 are identified as subordinate to DP5. DP5 has a higher abstraction, whereas the subordinated DP1 and DP2 have lower abstraction.

Table 8.7. Articulated DP5(v1): Design for complementary capabilities.

ID & title	**DP5(v1):** Design for complementary capabilities
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should utilize the complementary capabilities of humans and machines in decision-making so that human capabilities complement machine weaknesses and machine capabilities complement human weaknesses.
Rationale	Because humans and machines have different capabilities in decision-making, and these capabilities can complement each other's weaknesses in decision-making.
Theoretical grounding	- Human capabilities in decision-making (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine capabilities in decision-making (e.g., van den Broek et al., 2021; Gunaratne et al., 2018; Sotala, 2012) - Machine weaknesses in decision-making (e.g., Demartini, 2015; Kulkarni et al., 2017; Shollo et al., 2015) - Designers should design the tool so that it complements human and machine capabilities (Auernhammer, 2020; Dellermann et al., 2019b; Xu et al., 2022)
Empirical grounding	Captured signal of "complement."

8.6 SUMMARY

This chapter focuses on elaborating on the design knowledge that was used or emerged in BIE iteration two, including: 1) the revised goals of HC-HDSSs; 2) the revised meta-design of HC-HDSSs; 3) the design principles used in building the alpha version of the prototype; and 4) the design knowledge emerging from reflection and learning based on the intervention in organizations and evaluation of the prototype. The relevant design principles are DP1(v2), DP3(v2), DP4(v2), and DP5(v1). The above design knowledge and the evaluated alpha version of the prototype are used as input to BIE iteration three.

CHAPTER 9

THE BUILDING, INTERVENTION, AND EVALUATION: ITERATION THREE

This chapter aims to illustrate BIE iteration three and the corresponding reflection and learning. It follows a structure similar to the presentations of the previous two BIE iterations, starting with displaying the finalized meta-design of HC-HDSSs in section 9.1.[97] Section 9.2 concerns building the beta version of the prototype, which is guided by the newly formulated or revised design principles, which are outputs of BIE iteration two. Section 9.3 primarily illustrates the reflection and learning on each formulated design principle by analyzing the collected empirical data in this BIE iteration. Based on the reflection and learning, section 9.4 presents the articulated design principles, constituting the final version of all the design principles. Section 9.5 ends this chapter with a summary.

97 No changes were made to the goal of HC-HDSSs in this iteration.

9.1 THE FINAL META-DESIGN OF HC-HDSSS

The meta-design of HC-HDSSs is finalized in BIE iteration three (see Figure 9.1). Compared with the meta-design presented in BIE iteration two, all five design principles have been revised into new versions. The changes are highlighted under "The HC-HDSS class" in Figure 9.1.

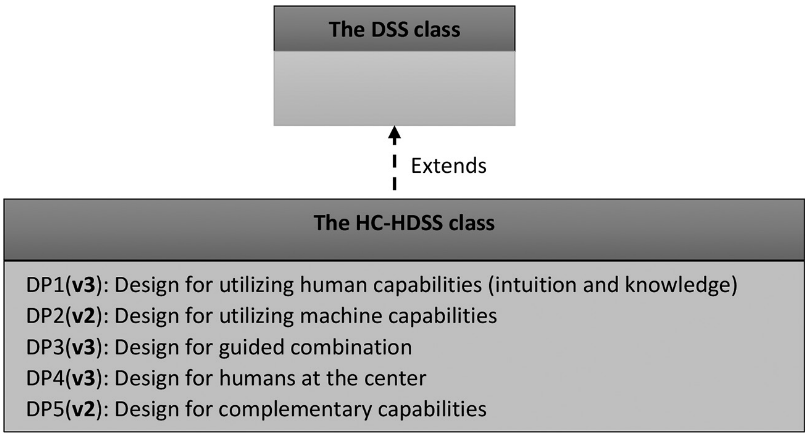


Figure 9.1. The final meta-design of HC-HDSSs.

9.2 BUILDING THE BETA VERSION

The five formulated design principles, outputs of BIE iteration two, guide the building of a beta version of the prototype in BIE iteration three.

9.2.1 DP1(V2) GUIDES THE BUILDING

The screenshots shown in figures 9.2a, b, and c are the newly implemented functionalities guided by DP1(v2) in BIE iteration three. The functionality marked by the area surrounded by a dotted line in Figure 9.2a is especially guided by the revised part of DP1(v2).[98] It aims to trigger the human

98 The changes made in DP1(v2): "digital system should support the selection of different organizational roles of human participants based on the organizational context."

user creating a decision-making project to consider the different roles of human participants that may affect their decision-making.

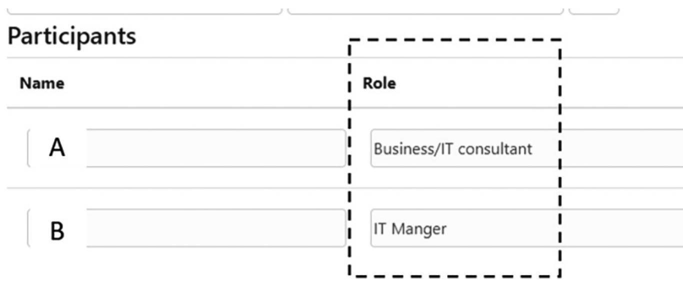


Figure 9.2a. The functionality of considering the roles of human participants in step 1 guided by DP1(v2).

The functionalities shown in the areas surrounded by dotted lines in figures 9.2b and c are implemented based on practitioners' suggestions collected in BIE iteration two. They are two related functionalities. The first functionality is implemented in step 3. It enables humans to apply their knowledge to categorize the generated ideas/possible solutions by assigning the category "change technology," "change behavior," "change management," or "other" to each idea. The second functionality, implemented in step 4b, enables humans to apply their knowledge to decide on a solution to the identified problem. In these two cases, humans, instead of machines, have the knowledge needed to categorize the generated ideas and compare the ideas with different categories, even if the solutions are in different categories.

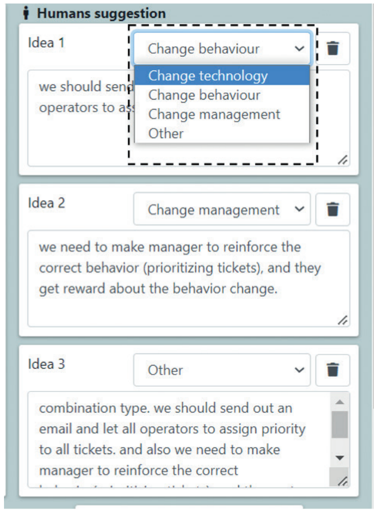
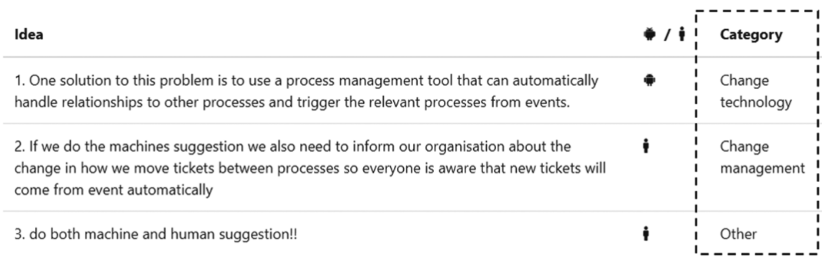


Figure 9.2b. The functionality of categorizing ideas in step 3 guided by DP1(v2).



Idea	/	Category
1. One solution to this problem is to use a process management tool that can automatically handle relationships to other processes and trigger the relevant processes from events.		Change technology
2. If we do the machines suggestion we also need to inform our organisation about the change in how we move tickets between processes so everyone is aware that new tickets will come from event automatically		Change management
3. do both machine and human suggestion!!		Other

Figure 9.2c. The functionality of utilizing human capabilities by presenting the category for each idea in step 4b, guided by DP1(v2).

9.2.2 DP2(V1) GUIDES THE BUILDING

There is no change made to DP2(v1) in BIE iteration two. However, DP2(v1) continues to guide the implementation of more functionalities related to machines in the prototype. Specifically, as anticipated in BIE iteration one, more intelligent functionalities utilizing machine capabilities should be implemented.

The area surrounded by a dotted line in Figure 9.3 shows the functionality newly implemented in Step 3 of the prototype. This functionality uses OpenAI (OpenAI API) and could provide several ideas for a possible solution to the problem selected in step 2D. OpenAI is an online open-source AI that can be applied to virtually any task that involves understanding or generating natural language or code. In the prototype, the problem identified in step 2D is input to OpenAI in step 3. OpenAI returns one or more AI-generated ideas to address the identified problem.

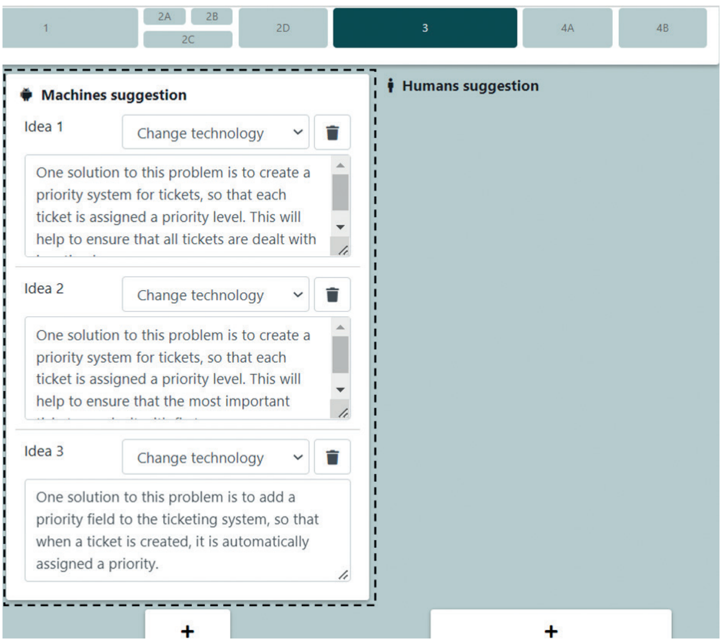
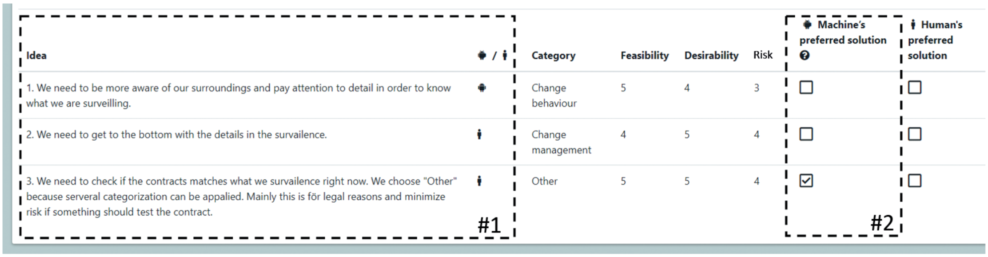


Figure 9.3. The intelligent functionality utilizing machine capabilities in step 3 guided by DP2(v1).

9.2.3 DP3(V2) GUIDES THE BUILDING

DP3(v2), "Design for guided combination," guides the revision of the prototype. First, based on "a guided decision-making process" in DP3(v2), steps from step 2B in the prototype become mandatory. Human users cannot skip a step. Second, the functionality of machines suggesting solutions to the problem identified in step 3 (already presented in Figure 9.3) provides suggestive guidance. Suggestive guidance "makes judgmental recommendations (what to do, what input values to use) to the decision maker" (Silver, 1991, p. 112). The same applies to functionality #2 shown in Figure 9.4b. The machine provides suggestive guidance in step 4b while suggesting its preferred solution based on a calculation of the decision-making criteria. Third, based on "to bring the capabilities of humans and machines together in a guided decision-making process" in DP3(v2), more functionalities related to bringing together human and machine capabilities have been added in steps 3 and 4b. See the areas surrounded by dotted lines in figures 9.4a and 9.4b (#1), respectively. In detail, both humans and machines formulate possible ideas for addressing the problem identified in step 3 (as shown in Figure 9.4a). Both human and machine ideas are listed and compared by the human users in step 4 (as given by box #1 in Figure 9.4b).

Figure 9.4a. Bringing together both human and machine capabilities in step 3.



Idea	/	Category	Feasibility	Desirability	Risk	Machine's preferred solution	Human's preferred solution
1. We need to be more aware of our surroundings and pay attention to detail in order to know what we are surveilling.		Change behaviour	5	4	3	☐	☐
2. We need to get to the bottom with the details in the survalence.		Change management	4	5	4	☐	☐
3. We need to check if the contracts matches what we survailence right now. We choose "Other" because serveral categorization can be appalied. Mainly this is för legal reasons and minimize risk if something should test the contract.		Other	5	5	4	☑	☐

Figure 9.4b. Bringing together both human and machine capabilities in step 4b.

9.2.4 DP4(V2) GUIDES THE BUILDING

Figure 9.5 shows the functionality guided by DP4(v2), "Design for humans at the center," built in BIE iteration three. Machine capabilities are used for augmenting humans. The highlighted text in the area surrounded by a dotted line of Figure 9.5 is an example.

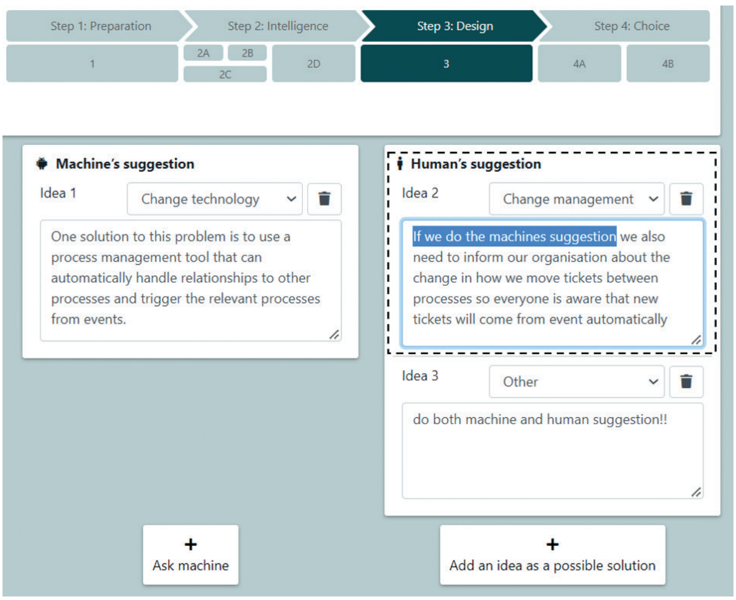


Figure 9.5. Functionality inscribed in DP4(v2).

9.2.5 DP5(V1) GUIDES THE BUILDING

The areas surrounded by dotted lines in figures 9.6a–c are screenshots of functionalities related to DP5(v1), “Design for complementary capabilities.” Figure 9.6a illustrates the functionalities implemented in previous BIE iterations.

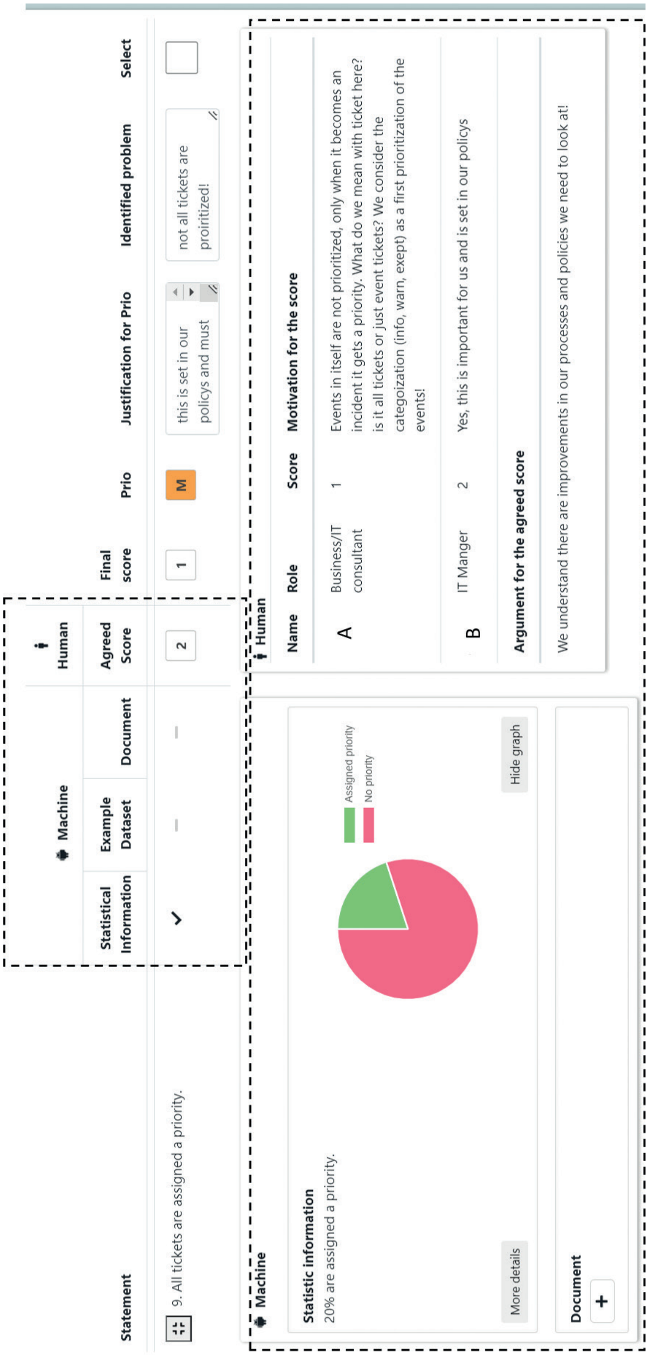


Figure 9.6a. Functionalities in step 2 guided by DP5(v1).

The areas surrounded by dotted lines in figures 9.6b and c are functionalities newly implemented in BIE iteration three. The machine generates ideas as possible solutions to the problem identified in step 3 (see box #1 in Figure 9.6b). This functionality utilizes machine capabilities to support humans. Meanwhile, box #2 in the same figure requires humans to apply their knowledge to assign a type to a machine's suggested idea. Human capabilities are utilized here to complement machine capabilities. In step 4b (see Figure 9.6c), machines give suggestions for a choice based on algorithms and calculations, according to which humans apply their knowledge to make a final decision.

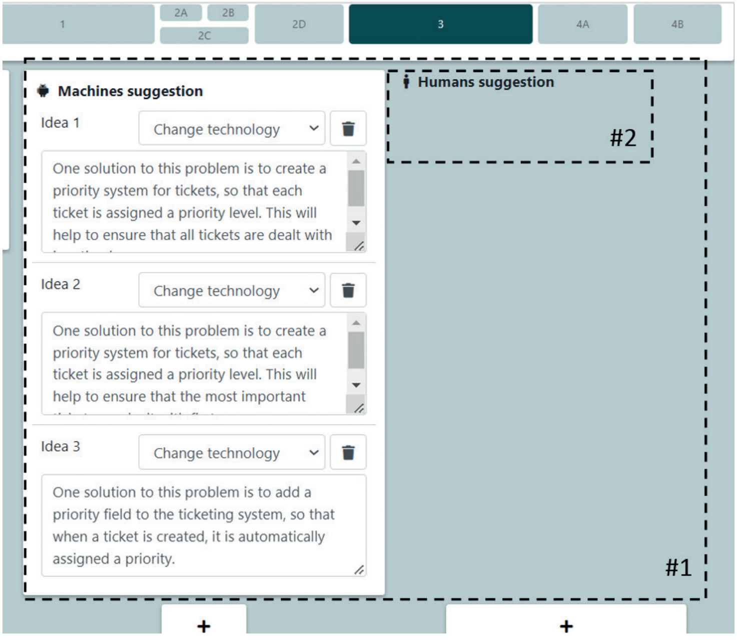


Figure 9.6b. Functionalities in step 3 guided by DP5(v1).

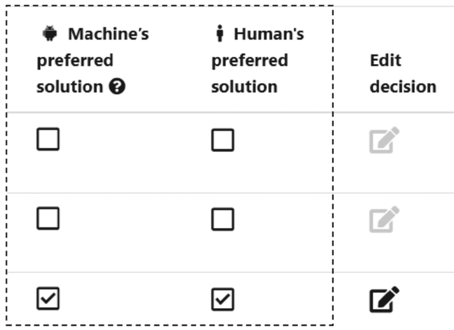


Figure 9.6c. Functionality in step 4b guided by DP5(v1).

9.3 INTERVENTION AND EVALUATION

The evaluation strategy presented in section 4.2: Research methodology guides the evaluation of the prototype in this BIE iteration. The evaluation is summative and naturalistic. Two workshops were conducted with potential end users from organizations A and B, respectively, each lasting about two hours. First, the end users used the prototype (i.e., naturalistic evaluation); after that, they were interviewed by the author (i.e., summative evaluation).

There were two participants from organization A. They first used the prototype (in step 2a) individually, then collaboratively worked as a pair in the remaining steps of the prototype. There was one participant from organization B. That participant played two roles based on previous rich consulting experience in improving ITIL practices.[99]

99 Only one practitioner from organization B could attend the workshop. Initially, the workshop was arranged to skip step 2b because it requires that two humans collaboratively assess the statements. However, the participant preferred to play two roles because he/she had plenty of experience of customers having different opinions about improving ITSM practice.

As HC-HDSSs emphasize a hybrid of humans and machines, having more than one human use the prototype was not a necessary condition. Besides, two participants from organization A had already provided empirical data related to the scenario in which more

As mentioned earlier in this dissertation, the prototype has twelve statements regarding monitoring and event management practice. Three statements were selected and used in the workshops for reasonable control of the workshop duration (details are given below). Additionally, and more importantly, the evaluation purpose in BIE iteration three was to evaluate the prototype rather than the components (i.e., statements). All twelve statements were evaluated in BIE iteration one.

In detail, the author decided on statement No. 9, "All tickets are assigned a priority." This is because this statement provides a scenario in which both human and machine capabilities can be utilized when assessing the statement regarding the intelligence step (i.e., step 2 in the prototype).[100] This study highlights the hybrid of both human and machine capabilities in each step. Therefore, statement No. 9, as a representative statement, was chosen by the author to guarantee that at least one statement would provide such a scenario.

Concerning the remaining two statements, the two practitioners of organization A individually decided on statements No. 2 and 3 in the workshop.[101] They quickly browsed through all twelve statements at the beginning of the workshop. Each practitioner selected one statement that interested him/her. Statements No. 1 and 6 were selected by the practitioner in the workshop with organization B because they were attractive to the practitioner.

In the interview session, the practitioners answered all the questions, and their answers constitute the collected empirical data for analysis. The results of the data analysis are presented in the following sections.

There is a slight change in the interview questions compared with those used in evaluation episode 2b in BIE iteration two. In particular, there were questions concerning property functionality because new functionalities were implemented in the beta version of the prototype, guided by the revised design principles and the newly formulated DP5(v1).

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than one human uses the prototype. The ADR researchers' group thought that this was workable.

100 Another scenario is that only human capabilities can be utilized, or only humans can make the assessment in step 2.

101 For these statements, see Appendix 1.

In detail, the question concerning DP1 in general was kept (see the first row in Table 9.1). The other questions, which sought more details related to DP1 and specific to its previous version, were removed, because the author had already got answers to them in BIE iteration two. Three questions were added to evaluate the implemented functionalities guided by the newly articulated DP5(v1) outcome of BIE iteration two (see the last row in Table 9.1). Table 9.1 provides the interview questions related to the property functionalities and their corresponding design principles.[102]

The author also intervened in the organizations through the two workshops, both when practitioners were using the prototype and when they were being interviewed.

Table 9.1. Interview questions concerning the properties of functionalities related to design principls.

Design principles	**Interview questions concerning the property functionality**
DP1: Design for utilizing human capabilities (intuition and knowledge)	The tool tries to utilize human capabilities (i.e., intuition and knowledge) in decision-making. What do you think about that?
DP2: Design for utilizing machine capabilities	The tool tries to utilize machines' capabilities in decision-making. What are your thoughts about that?
DP3: Design for guided combination	The tool tries to combine human and machine capabilities in a decision-making process. What are your thoughts about that?
DP4: Design for humans at the center	In what way do you think the design is centered on humans?
DP5: Design for complementary capabilities	The tool tries to utilize human capabilities to complement machine weaknesses. What do you think about that?
	The tool tries to utilize machine capabilities to complement human weaknesses. What do you think about that?
	The tool tries to utilize machine capabilities to augment human capabilities. What do you think about that?

102 The interview questions used in episode 3 are given in Appendix 3.

9.4 REFLECTION AND LEARNING

The beta version of the prototype is evaluated by practitioners in BIE iteration three. Practitioners gave positive responses or comments on the prototype. The analysis of the collected empirical data shows that all the formulated design principles work as expected. Additionally, the unanticipated results provide a deeper understanding of the formulated design principles by offering more examples or insights regarding different aspects. Table 9.2 summarizes the reflection and learning results corresponding to the five design principles formulated in BIE iteration three. These results are illustrated in the ensuing sections. Additionally, these sections also present the reflection and learning about the utility of the prototype and the ADR method.

The reflection and learning do not produce any need to revise the formulated problem, goal, and meta-design of HC-HDSSs because there are only minor changes in the five formulated design principles. These minor changes concern adding more empirical evidence to support the design principles. Therefore, the research problem formulated in BIE iteration two is the final version, as presented in the section on problem formulation (in chapter 1). The goal of HC-HDSSs stays as it is in BIE iteration two. The meta-design presented earlier in this chapter is the final version.

Table 9.2. Anticipated and unanticipated results of design principles.

Design principles	Anticipated results	Unanticipated results	Reflection and learning
DP1: Design for utilizing human capabilities (intuition and knowledge)	The functionalities of utilizing human intuition and knowledge work.	None	Saturation reached; more empirical evidence is collected.
DP2: Design for utilizing machine capabilities	The functionalities of utilizing machine capabilities should work.	Transparency	When utilizing machine capabilities, one should be aware of transparency.
DP3: Design for guided combination	The implemented functionalities guide the combination of human and machine capabilities in a decision-making process.	None	Saturation reached but more insights were gained: - step 3 combines both human and machine capabilities in a good way - machine suggestions (i.e., machine capabilities) augment human capabilities
DP4: Design for humans at the center	The prototype is designed with humans at the center.	None	Saturation reached; more empirical evidence is collected.
DP5: Design for complementary capabilities	The implemented functionalities utilize human and machine capabilities to complement one another.	None	Saturation reached but more insights were gained. Machines can provide generic solutions. Humans have knowledge specific to their organizations. Human capabilities complement the weakness of machines, which lack specific knowledge.

9.4.1 REFLECTION AND LEARNING ON DP1(V2)

As shown in Table 9.2, there are no unanticipated results related to DP1(v2). The anticipated result is that the functionalities guided by DP1(v2) utilize the intuition and knowledge of humans. The collected empirical data strengthen this. For example, when answering the question related to the functionalities guided by DP1 (i.e., "The tool tries to utilize human capabilities in decision-making. What do you think about that?"), one practitioner said, "It is really good from the human perspective that there are a number of people involved with different roles." That answer shows that having the prototype involve more than one human enables better utilization of human capabilities. In a similar but more specific example, one practitioner highlighted the functionalities related to human group discussion in his/her answer, suggesting that human group discussion during a decision-making task enables the better utilization of human capabilities. Another practitioner in the same meeting agreed with this point of view.

DP1 reached saturation in this iteration. The revised DP1, i.e., DP1(v3), is given in Table 9.4.

9.4.2 REFLECTION AND LEARNING ON DP2(V1)

As anticipated, the practitioners' answers strengthen the functionalities guided by DP2(v1) in the prototype. More empirical evidence is collected for DP2(v1). For example, one practitioner commented, "I think the visualization is good and makes humans quickly understand the results through diagrams and colors." This is an example of utilizing machine capabilities in terms of efficiency and effectiveness, because machines can provide diagrams based on efficient and effective calculation. Another practitioner reiterated DP2(v1) by commenting, "Yes, it is great."

Additionally, the practitioner pointed out the importance of transparency, mentioning that it "is really important to understand each decision, each visualization." This is a captured signal about transparency. However, the author realized that the ADR team had suggested transparency or explainable AI in previous BIE iterations. Therefore, the prototype had already implemented functionalities related to this signal, but DP2(v1) had not been revised to include the term "transparency." For example, the area surrounded by a dotted line in Figure 9.7a is a functionality of transparency giving details of how the machine calculates. This functionality was implemented in BIE iteration two. The area surrounded by a dotted line in Figure 9.7b shows the functionality of transparency implemented in BIE iteration three before the intervention and evaluation. This functionality provides more details about why machines suggest certain decisions.

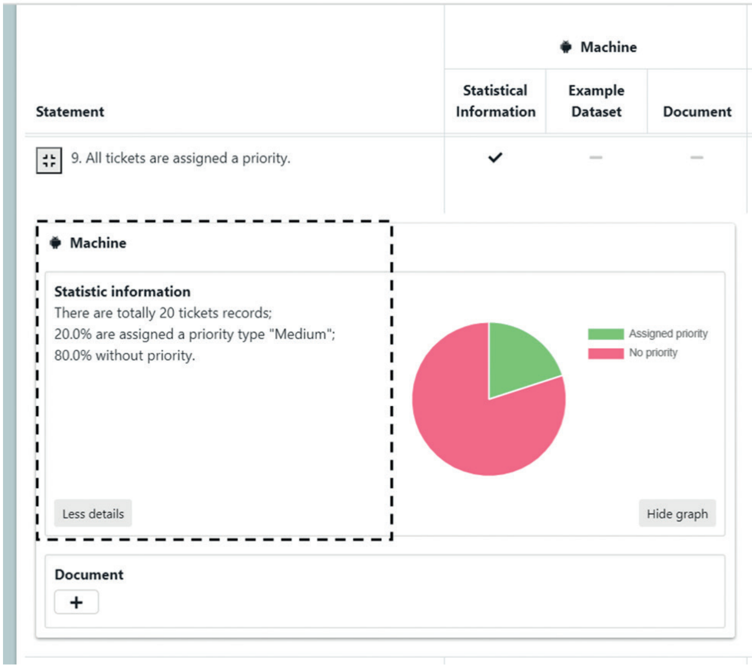

Figure 9.7a. Functionalities of transparency or explainable AI related to DP2.

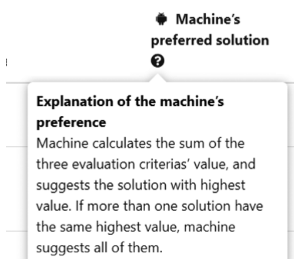

Figure 9.7b. Functionalities of transparency or explainable AI related to DP2.

When the practitioner pointed out the importance of transparency in the workshop, the author displayed the functionalities ignored by the practitioner concerning transparency (shown in figures 9.7a and b). The practitioner appreciated them. Therefore, theories related to transparency or explainable AI have been used to refine DP2(v1). The ADR researchers' group agreed that there is no need for one more BIE iteration to evaluate the functionalities related to DP2(v2). The practitioner appreciated that the author had already presented the relevant functionalities. The final version of DP2, i.e., DP2(v2) is presented in Table 9.5.

9.4.3 REFLECTION AND LEARNING ON DP3(V2)

Similar to DP1 and DP2, the data analysis shows no unanticipated results related to DP3(v2). As anticipated, the functionalities guided by DP3(v2) support the combination of human and machine capabilities in a guided decision-making process. More insights or samples of empirical evidence are gained in this iteration.

For instance, one practitioner answered a question about DP3(v2) by saying, "It is user friendly, it is good." Another practitioner said, "Yes, I think it guided very well. It combines both capabilities [i.e., of humans and machines]." The latter practitioner also emphasized that the machine's suggested possible solutions could be used as input for humans to think about (in step 3), i.e., humans could analyze the consequences of the machine's suggestions and then suggest an improved solution. This example illustrates the usefulness of combining both human and machine capabilities, especially in step 3 of the prototype.

One more practitioner added, "even though we as human beings can do this ourselves, it is hard to keep many thoughts, to balance all the thoughts you have. This machine [tool] helps us to structure [our thoughts]—yeah, get a good structure." This comment was strongly agreed with by the other practitioner in the same meeting.

DP3 reached saturation in this iteration. Table 9.6 presents the finally revised DP3, i.e., DP3(v3), and highlights the changes made.

9.4.4 REFLECTION AND LEARNING ON DP4(V2)

There were no unanticipated results related to DP4(v2) in BIE iteration three, except that more empirical evidence was found in the collected data. The practitioners strengthened the anticipated result, which was that the functionality guided by DP4(v2) works, i.e., that the prototype is designed with humans at the center.

For example, one practitioner gave a very positive answer to the question related to DP4 (i.e., "How do you think the design of the tool is centered on humans?"): "Yes, yes, yes. I think so [i.e., the tool is centered on humans]." Another practitioner commented, "It is centered on humans. It is the humans who drive the process and have the overall control and [make] the final decisions." This comment is also aligned with what Xu et al. (2022, p. 9) stated about "human-driven decision-making." Moreover, as stated by another practitioner, "It [i.e., human-centered AI] is important and good, I believe. Because we as humans want to get results out of it [i.e., the tool]. So we use the AI, the machine, the data to make a good decision. It is not the computer who wants the answers, it is us [i.e., humans]."

The collected empirical data show that DP4 reached saturation in this iteration. Table 9.7 gives the finally revised DP4 and highlights the changes made.

9.4.5 REFLECTION AND LEARNING ON DP5(V1)

There were no unanticipated results related to DP5(v1). Practitioners confirmed the design of the tool for complementary capabilities guided by DP5(v1) in general. For example, an answer from one practitioner was, "Yes! It is both ways," meaning that humans complement machines in decision-making, and vice versa.

More specifically, three quotations illustrate how machines complement humans in decision-making. First, "It [i.e., the machine] absolutely helps us … all the calculations and visualizations done in the software [i.e., the prototype] complement us. We don't need to calculate them. It takes time. More automatic there. It is really good." This statement describes how machine capabilities, being efficient and effective, complement humans' cognitive constraints.

In the second example**,** one practitioner said that "humans do have thoughts about rows [and] columns of data, but we can't handle that much information. We base our decisions on our assumptions. We get facts from computers." This statement describes how machine capabilities complement human weaknesses in terms of human bias and cognitive constraints. Because humans have limited memory and information processing speed, they may be biased in decision-making, for example, making incorrect assumptions in this example.

A third example illustrates how machines complement humans: "For example, the statements we worked on, the machine suggested two solutions. And one of them was not applicable, but the first one provided us with some perspectives we didn't think about." This practitioner's comment illustrates how humans have weaknesses in terms of cognitive constraints in decision-making. Machine capabilities, in terms of being efficient and effective, and being continuously upgradable in memory, algorithm, and computing capabilities, complement humans by providing different but useful suggestions.

Conversely, one practitioner illustrated how human capabilities complement machine weaknesses: "It is very important, that question you asked. The computer might answer the question very correctly, but humans can realize that it is not important. But a computer gives you the correct answer to a question, even if you ask the wrong question." In this case, the practitioner meant that machines can give a correct answer if the answer is based on calculations using input data. However, first, machines do not have the knowledge to identify whether the question is asked in a good way or is an important question. A correct answer to a wrong question does not help advance decision-making. Second, machines do not have the knowledge to identify whether or not the issue addressed is essential: "The computer can't know if the right answer has a good impact or not, even if it is correct." However, humans can complement machines because humans have more knowledge in this case. In the same meeting, another practitioner agreed with this comment, stating that "what [he/she] said is very good." In summary, the practitioners' comments can be interpreted as claiming that machines lack some of the knowledge required to make satisfactory decisions, which is a weakness of machines and can be complemented by humans.

The collected empirical data show that DP5 reached saturation in this iteration. Table 9.8 gives the final version of DP5, i.e., DP5(v2), and highlights the changes made.

9.4.6 REFLECTION AND LEARNING ON EVALUATION PROPERTY UTILITY

As illustrated in the section on the evaluation strategy, this study primarily evaluates the utility of the HC-HDSS prototype based on whether or not it is effective in solving the identified problem (i.e., there is a lack of design knowledge for human-centered hybrid decision support systems) in BIE iteration three. The utility property is affected by the quality of the HC-HDSS prototype, which is evaluated by asking practitioners questions related to the functionality, usability, comprehensibility, fit with the organization, and perceived decision quality properties.

First, practitioners' answers related to the functionality property have been presented in previous sections. Practitioners confirmed that the implemented functionalities related to the critical features of HC-HDSSs, for example: the prototype utilizes the complementary capacities of humans and machines in decision-making (related to the reflection and learning on DP1, DP2, and DP5); the prototype supports combining human and machine capabilities in a guided decision-making process (related to the reflection and learning on DP3); and the prototype is designed with humans at the center (related to the reflection and learning on DP4).

Second, the evaluation related to the usability, comprehensibility, and fit with the organization properties also supports the conclusion that the prototype reached saturation. The prototype has been built using input from practitioners and evaluated by practitioners in three BIE iterations. In other words, the prototype has been continuously improved in terms of the three properties from BIE iterations one to three. The interfaces have been improved to make sure they are easy to use (i.e., the usability property). One practitioner said in the final workshop that "it [i.e., the interface] is fairly easy to use now." The labels in the prototype have been revised to be easy to understand (i.e., the comprehensibility property). For instance, one practitioner once pointed out that the label "Low risk" in step 4B was confusing, given that the label "Risk" was used instead of "Low risk" in the prototype. The affected functionalities related to that label have also been changed. The twelve statements used for assessing the ITIL practice have also been refined based on what the practitioners suggested (i.e., the fit with the organization property). As one practitioner commented, "It is absolutely relevant. Look at it from the human side. It is relevant. We had a long time for statement analysis. That's not enough. When we add machine capabilities, it adds new perspectives, makes it more relevant."

Third, concerning the perceived decision quality property, practitioners were satisfied with the decisions made using the prototype. For example, one practitioner said, "the quality is good, absolutely—it is of good quality."

In summary, practitioners' answers confirmed the quality of the prototype. The prototype and the formulated design principles (which emerged in and guided the building of the prototype) provide guidance concerning how to design HC-HDSSs. Therefore, the conclusion can be made that the prototype and the formulated design principles effectively solve the identified problem.

9.4.7 REFLECTION AND LEARNING ON THE ADR METHOD

There was both reflection and learning regarding principle 4 (i.e., mutually influential roles) of the ADR method, which points out "the importance of mutual learning among the different project participants" (Sein et al., 2011, p. 43). Moreover, "action design researchers bring their knowledge of theory and technological advances, while the practitioners bring practical hypotheses and knowledge of organizational work practices" (Sein et al., 2011, p. 43).

This study provides empirical evidence concerning the guidance offered by principle 4. There was mutual learning between the researchers and between the researchers and practitioners. For example, the author shared her knowledge of HCAI that was inscribed in the prototype with practitioners who immediately became very interested. The practitioners shared their knowledge of the importance of organizational context as influencing decision-making, an influence that the author had ignored before the intervention in organization B. Furthermore, there was also mutual learning between the practitioners. For example, it emerged during the intervention in organization A in BIE iteration three that one human participant had been more recently hired than with the other. After using the prototype, both practitioners mentioned that they now knew more about each other. One practitioner said, "I didn't know that you didn't know this [i.e., the surveillance in the event management practice of the organization]"; conversely, the other practitioner said, "Now I know more about the surveillance [i.e., in the event management practice of the organization]."

9.5 THE FINALLY ARTICULATED DESIGN PRINCIPLES

The third column in Table 9.3 lists all the design principles articulated in BIE iteration three. DP1(v2), DP3(v2), DP4(v2), and DP5(v1), as articulated in BIE iteration two, have been refined to DP1(v3), DP3(v3), DP4(v3), and DP5(v2), respectively. DP2(v1), formulated in BIE iteration one, has been changed to a second version.

Based on the reflection and learning illustrated in the above sections, some minor changes have been made in DP1, DP3, DP4, and DP5 by adding more empirical evidence. The changes to the four DPs are bolded in tables 9.4, 9.6, 9.7, and 9.8. Exceptionally, in DP2, which is presented in Table 9.5, the changes made are in the description of this design principle.

Table 9.3. Design principles articulated in BIE iteration three.

DPs articulated in BIE iteration 1	**DPs articulated in BIE iteration 2**	**DPs articulated in BIE iteration 3**
DP1(v1) Design for utilizing human capabilities	DP1(v2) Design for utilizing human capabilities (intuition and knowledge)	DP1(v3) Design for utilizing human capabilities (intuition and knowledge)
DP2(v1) Design for utilizing machine capabilities	-	DP2(v2) Design for utilizing machine capabilities
DP3(v1) Design for combining human and machine capabilities	DP3(v2) Design for guided combination	DP3(v3) Design for guided combination
DP4(v1) Design for humans at the center	DP4(v2) Design for humans at the center	DP4(v3) Design for humans at the center
	DP5(v1) Design for complementary capabilities	DP5(v2) Design for complementary capabilities

9.5.1 DP1(V3) DESIGN FOR UTILIZING HUMAN CAPABILITIES (INTUITION AND KNOWLEDGE)

DP1(v3), "Design for utilizing human capabilities (intuition and knowledge)," is presented in Table 9.4. It is the final version of DP1. Based on reflection and learning, empirical data that strengthen DP1 have been added. The changes are bolded in the "Empirical grounding" row of the table.

Table 9.4. The final version of DP1: Design for utilizing human capabilities (intuition and knowledge); changes are bolded.

ID & title	DP1(v3): Design for utilizing human capabilities (intuition and knowledge)
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should support the selection of different organizational roles of human participants based on the organizational context. Moreover, the system should externalize the implicit human knowledge, combine explicit knowledge between humans, socialize the knowledge between humans, and internalize the explicit knowledge.
Rationale	Because organizational context affects knowledge creation, and knowledge is created by these four modes.
Theoretical grounding	- Intuition (e.g., Barnard, 1938; Dane & Pratt, 2007) - Knowledge (e.g., Grant, 2007; Nonaka, 1991; Polanyi, 1958, 1966) - Human capabilities in decision-making, i.e., intuition and knowledge (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Group decision-making (e.g., Dellermann et al., 2019b; Lima et al., 2018) - Theories of organizational culture affecting decision-making (e.g., Briggs et al., 2008; Nisar et al., 2021) and knowledge sharing (e.g., Natu & Aparicio, 2022)
Empirical grounding	- Practitioners agree with building the HC-HDSS to involve more than one human. - A captured signal suggests that the organizational context should be considered, as it affects the selection of the role, for example: "Depending on the manager and the management culture, you don't always get the answers. Sometimes you get the correct answer. Sometimes, when a manager isn't running this assessment, you might get more honest answers." **- Empirical data strengthening DP1, for example: "It is really good from the human perspective that there are a number of people involved with different roles"; "The tool allowed us, the discussion part, also the function that we could change our scores afterwards and write in comments."**

9.5.2 DP2(V2) DESIGN FOR UTILIZING MACHINE CAPABILITIES

Based on the reflection and learning of DP2(v1), 'be utilized with transparency ' has been added to the description of DP2(v2). Theories related to transparency or explainable AI have been added as DP2(v2)'s theoretical grounding. For instance, as mentioned by Shneiderman (2021, p. 60),"AI systems must be transparent and explainable"; Xu et al. (2022, p.11) pointed out that "explainable AI intends to provide the user what the machine is thinking and can explain to the user why." The final version of DP2 is given in table 9.5. The changes are bolded.

Table 9.5. The final version of DP2: Design for utilizing machine capabilities; changes are bolded.

ID & title	DP2(v2): Design for utilizing machine capabilities
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, machine capabilities should be identified based on the decision context and **be utilized with transparency**.
Rationale	Because 1) machines have capabilities that could complement human weaknesses in general and 2) the specific decision context affects the utilization of machine capability.
Theoretical grounding	- Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine capabilities in decision-making (e.g., van den Broek et al., 2021; Gunaratne et al., 2018; Sotala, 2012) **- Theories related to transparency or explainable AI** **(e.g., Shneiderman, 2021; Sun et al., 2021; Xu et al., 2022)**
Empirical grounding	**- Captured signal of transparency, for example: "Transparency is really important when using this kind of tool."** **- Empirical data strengthening DP2, for example: "That is really an important issue to understand regarding each decision, each visualization, [to show] where these data come from, what algorithm, why it is showing me something like this";** **"I think the visualization is good and makes humans quickly understand the results through diagrams and colors."**

Based on the reflection and learning of DP2(v1), "be utilized with transparency" has been added to the description of DP2(v2). Theories related to transparency or explainable AI have been added as the theoretical grounding of DP2(v2). For instance, as mentioned by Shneiderman (2021, p. 60), "AI systems must be transparent and explainable"; Xu et al. (2022, p. 11) pointed out that "explainable AI intends to provide the user what the machine is thinking and can explain to the user why." The final version of DP2 is given in Table 9.5. The changes are bolded.

9.5.3 DP3(V3) DESIGN FOR GUIDED COMBINATION

According to the reflection and learning of DP3, "Design for guided combination," one more example has been added as empirical evidence of DP3. The final version of DP3 is given in Table 9.6 with the change shown in bold in the last row of the table.

Table 9.6. The final version of DP3: Design for guided combination; changes are bolded.

ID & title	DP3(v3): Design for guided combination
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should combine the capabilities of humans and machines in a guided decision-making process.
Rationale	Because 1) humans apply both cognitive patterns for making complex decisions, of which the cognitive pattern system 2 links to analytic decisions is carried out as a process, and 2) one of machines' role as well as machine capability is supporting humans making analytic decisions.
Theoretical grounding	- Kahneman's systems 1 and 2 (Kahneman, 2011) - The decision-making process (Simon, 1977, p. 44) - Human capabilities in decision-making (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine capabilities in decision-making (e.g., van den Broek et al., 2021; Gunaratne et al., 2018; Sotala, 2012) - Machine weaknesses in decision-making (e.g., Demartini, 2015; Kulkarni et al., 2017; Shollo et al., 2015) - Theory of decisional guidance (Silver, 1991) or guidance design features (Morana et al., 2017; Silver, 2015). E.g., Dellermann et al., 2019b; Limayem & DeSanctis, 2000; Parikh et al., 2001).
Empirical grounding	- Empirical data strengthening DP3(v1), for example: "It [i.e., the decision-making process] absolutely helps me." - A captured signal about a guided decision-making process, for example: "[For] complex problems, statements, issues, then you need a guided decision-making process." "A guided tool that helps me in some mandatory steps to work through a decision-making process. Yes, really good. Because we [humans] are known to take shortcuts." - Empirical data strengthening DP3, for example: **"[The four steps in a decision-making process] keep a structure"; "This machine [tool] helps us to structure [our thoughts]—yeah, get a good structure."**

9.5.4 DP4(V3) DESIGN FOR HUMANS AT THE CENTER

The final version of DP4 is given in Table 9.7. There is no change in the title, description, rationale, and theoretical grounding, but two more examples have been added as empirical grounding.

Table 9.7. The final version of DP4: Design for humans at the center; changes are bolded.

ID & title	DP4(v3) : Design for humans at the center
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, humans' actual decision-making process should be supported, human capabilities should be augmented by machines, and human users must have the overall control of the decision-making process and be the final decision-makers instead of machines.
Rationale	Because, 1) design for humans at the center should take account of human needs and behaviour; 2) machines cannot make semi-structured decisions; 3) machines take on the role of supporting humans and enhancing human capabilities, instead of replacing humans or eroding human capabilities; and 4) humans should learn in a decision-making process.
Theoretical grounding	- Humans' two cognitive systems (Kahneman, 2011) - Tacit, implicit, and explicit knowledge (e.g., Grant, 2007; Nonaka, 1991; Polanyi, 1958, 1966) - Decision types of DSSs (Gorry & Scott Morton, 1971, 1898) - Human capabilities in decision-making (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine weaknesses in decision-making (e.g., Demartini, 2015; Kulkarni et al., 2017; Shollo et al., 2015) - Theories of HCAI (e.g., Auernhammer, 2020; Shneiderman, 2021; Xu, 2019)
Empirical grounding	- Empirical data strengthening DP4, for example: "It [i.e., the tool] directs you to focus on what to think about." **"It is centered on humans. It is the humans who drive the process and have the overall control and [make] the final decisions."** **"It [i.e., human-centered AI] is important and good, I believe. Because we as humans want to get results out of it [i.e., the tool]. So we use the AI, the machine, the data to make a good decision. It is not the computer who wants the answers, it is us [i.e., humans]."**

9.5.5 DP5(V2) DESIGN FOR COMPLEMENTARY CAPABILITIES

The final version of DP5 is presented in Table 9.8. The only change made is adding two more examples as empirical grounding.

Table 9.8. The final version of DP5: Design for complementary capabilities; changes are bolded.

ID & title	DP5(v2): Design for complementary capabilities
Description	For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should utilize the complementary capabilities of humans and machines in decision-making so that human capabilities complement machine weaknesses and machine capabilities complement human weaknesses.
Rationale	Because humans and machines have different capabilities in decision-making, and these capabilities can complement each other's weaknesses in decision-making.
Theoretical grounding	- Human capabilities in decision-making (e.g., Dellermann et al., 2019a, 2019b; Demartini, 2015) - Human weaknesses in decision-making (e.g., Ahsen et al., 2019; Khan et al., 2017; Maule, 2010) - Machine capabilities in decision-making (e.g., van den Broek et al., 2021; Gunaratne et al., 2018; Sotala, 2012) - Machine weaknesses in decision-making (e.g., Demartini, 2015; Kulkarni et al., 2017; Shollo et al., 2015) - Designers should design the tool so that it complements human and machine capabilities (Auernhammer, 2020; Dellermann et al., 2019b; Xu et al., 2022)
Empirical grounding	- Captured signal of "complement" **- Empirical data strengthening DP5(v1), for example: (regarding machines complementing humans) "All the calculations and visualizations done in the software [i.e., the prototype] complement us. We don't need to calculate them. It takes time. More automatic there. It is really good"; (regarding humans complementing machines) "Yes! It is both ways." The practitioner means that humans and machines complement each other in the prototype.**

9.6 SUMMARY

This chapter presents design knowledge that emerged in BIE iteration three. The outcome of this iteration is an evaluated beta version of the prototype, the finalization of five design principles, and the meta-design of HC-HDSSs.

CHAPTER 10

FORMALIZATION OF LEARNING

The purpose of this chapter is to conclude the dissertation by presenting the outcome of the formalized learning in this doctoral study. It presents the summarized contributions of the study in section 10.1, the internal and external validity of the study in section 10.2, the ethical considerations in section 10.3, and future research opportunities in section 10.4.

10.1 CONTRIBUTIONS TO RESEARCH AND PRACTICE

As a DSR study, this study mainly contributes to design knowledge in five forms: 1) the prototype, 2) the DPs, 3) the meta-design, 4) the goal of HC-HDSSs, and 5) a detailed description of the prototype and the design process. This section will first summarize the five forms of design knowledge, then illustrate them from three DSR contribution frameworks (introduced in chapter 4).

The primary contribution of this study is prescriptive design knowledge in the form of five DPs concerning how to design HC-HDSSs, the meta-design and goal of HC-HDSSs, and a prototype of HC-HDSSs. The secondary contribution is design knowledge in terms of an exhaustive description of the prototype and the design process (Sein & Rossi, 2019).

As the primary design knowledge contribution, the five design principles of HC-HDSSs are listed in Table 10.1 by giving their numbers and titles.

Table 10.1. The five formulated DPs of HC-HDSSs.

ID	**Title of design principles**
DP1	Design for utilizing human capabilities (intuition and knowledge)
DP2	Design for utilizing machine capabilities
DP3	Design for guided combination
DP4	Design for humans at the center
DP5	Design for complementary capabilities

The title of the first design principle (i.e., DP1) is "Design for utilizing human capabilities (intuition and knowledge)." It aims to guide developers to utilize human intuition and knowledge in HC-HDSSs. The short description is:

For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should support the selection of different organizational roles of human participants based on the organizational context. Moreover, the system should externalize the implicit human knowledge, combine explicit knowledge between humans, socialize the knowledge between humans, and internalize the explicit knowledge.

The title of second design principle (i.e., DP2) is "Design for utilizing machine capabilities." It is for guiding developers to design HC-HDSSs to utilize machine capabilities in decision-making. The short description is:

For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, machine capabilities should be identified based on the decision context and be utilized with transparency.

The title of the third design principle (i.e., DP3) is "Design for guided combination," which is a principle concerning how to combine the capabilities of humans and machines in a decision task when designing HC-HDSSs. The short description is:

For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should combine the capabilities of humans and machines in a guided decision-making process.

The title of design principle 4 (i.e., DP4) is "Design for humans at the center." It is a principle concerning how to center the value of humans in the design process. The short description is:

For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, humans' actual decision-making process should be supported, human capabilities should be augmented by machines, and human users must have the overall control of the decision-making process and be the final decision-makers instead of machines.

The title of design principle 5 (i.e., DP5) is "Design for complementary capabilities." This design principle aims to guide developers in how to utilize the complementary capabilities of humans and machines in HC-HDSSs. The short description is:

For developers to design an HC-HDSS (human-centered hybrid decision support system) for making semi-structured managerial decisions, the digital system should utilize the complementary capabilities of humans and machines in decision-making so that human capabilities complement machine weaknesses, and machine capabilities complement human weaknesses.

The five design principles are packaged in the meta-design of HC-HDSSs, which is class of systems extending the DSS class. The final version of the meta-design is presented in Figure 10.1.

The goal of the HC-HDSS class sets the boundary of where the design principles of HC-HDSSs can be applied. The generalized goal of the HC-HDSS class is *a contextualized easy-to-use web-based IT artifact that is designed with humans at the center, and utilizes both human and machine capabilities to make semi-structured managerial decisions.* The goal sets the scope of the design principles so that they can be applied 1) for designing a DSS for making semi-structured decisions 2) with humans at the center and 3) for combining both human and machine capabilities in decision-making.

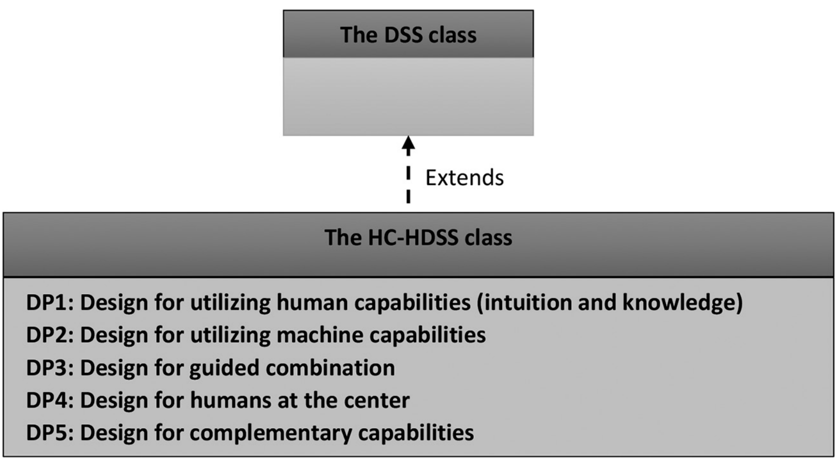

Figure 10.1. The final meta-design of HC-HDSSs.

The secondary design knowledge contribution is a detailed description of the prototype and the design process that is difficult to deliver in a journal or conference paper. Chapter 6 illustrates the final version of the prototype, including a description of the whole process of the prototype, the sub-processes in each step, and the functionalities implemented in each step.

Concerning the design process, this dissertation presents the research implementation process by following the four steps of the ADR method in chapter 5 as a starting point. Then, in chapters 7, 8, and 9, the dissertation provides an exhaustive description of the evolution of the design knowledge in the three BIE iterations. The description includes the evolution of the five formulated DPs, the goal, and the meta-design. How the identified design knowledge or formulated DPs guided the building of the prototype is also presented. The description also covers the evolution of the formulated problem based on reflection and learning.

The remaining part of this section elaborates on the contributions of this study based on the three DSR contribution frameworks (introduced in chapter 4). First, the contribution of this study can be distinguished in terms of two abstract levels of design knowledge based on Gregor and Hevner's (2013) contribution types (see the first column in Table 10.2). The design knowledge contributed by this study is shown in the second column of Table 10.2. The design knowledge in terms of a prototype of HC-HDSSs is an instantiation of the HC-HDSS class. The designed prototype and its detailed descriptions belong to contribution level 1, according to Gregor and Hevner (2013). In addition, the detailed description of the design process also belongs to contribution level 1. The design knowledge in terms of the five design principles, meta-design, and goal of HC-HDSSs belongs to contribution level 2, which refers to constructs, methods, models, design principles, and technological rules, according to Gregor and Hevner (2013).

Table 10.2. Contributions of this study (the grey area is adapted from Gregor & Hevner, 2013).

Contribution types of DSR	Contributions of this study
Level 3. Well-developed design theory about embedded phenomena	-
Level 2. Nascent design theory—knowledge as operational principles/architecture	Five design principles of HC-HDSSs The meta-design of HC-HDSSs The goal of HC-HDSSs
Level 1. Situated implementation of artifact	The prototype of HC-HDSSs Detailed description of the prototype and the design process

Second, there is broad consensus in the IS discipline that DSR contributions are twofold, being both practical and theoretical (Hevner et al., 2004). Such is the case in this study. The design knowledge emerged from interaction with organizations. It is expected to solve the real problem in practice that there is a lack of design knowledge for HC-HDSSs. The prototype can be continually developed into a fully fledged tool used by the case organizations to make better decisions. Other organizations could apply the design principles, meta-design, and goal to develop new HC-HDSSs in a similar context but specific to their organizations. Besides, the design principles can also be used selectively by practitioners to guide the implementation of specific functionalities and integrate them into their existing tools.

The design knowledge has a scientific impact. Gregor and Jones (2007, p. 325) stated that design principles "define the structure, organization, and functioning of the design product or design method." The present design principles aim to make recommendations about how such an HC-HDSS, which is human-centered and combines human and machine capabilities, could be developed. The prototype was built according to the formulated design principles. It is an instantiation of the HC-HDSS class. Researchers could use this prototype (and its description) to understand the formulated design principles better. The detailed description of the design process enhances the study's rigor and has the potential to inspire other researchers.

Third, according to Gregor and Hevner's (2013) DSR knowledge contribution framework, the contribution of this study has low maturity in terms of the research problem and solution. Therefore, it should be positioned in the *invention* quadrant (see Figure 10.2) because designing HC-HDSSs is an innovative solution proposed by this study to address the identified problem. The research problem that there is a lack of design knowledge for HC-HDSSs was formulated by scrutinizing existing studies. As presented in chapter 1, on one hand, several studies of hybrid DSSs are not enough to cover the full range of hybrid DSSs. On the other hand, there is a lack of detailed design knowledge of HCAIs. In combination and specifically, there is a lack of design knowledge for HC-HDSSs.

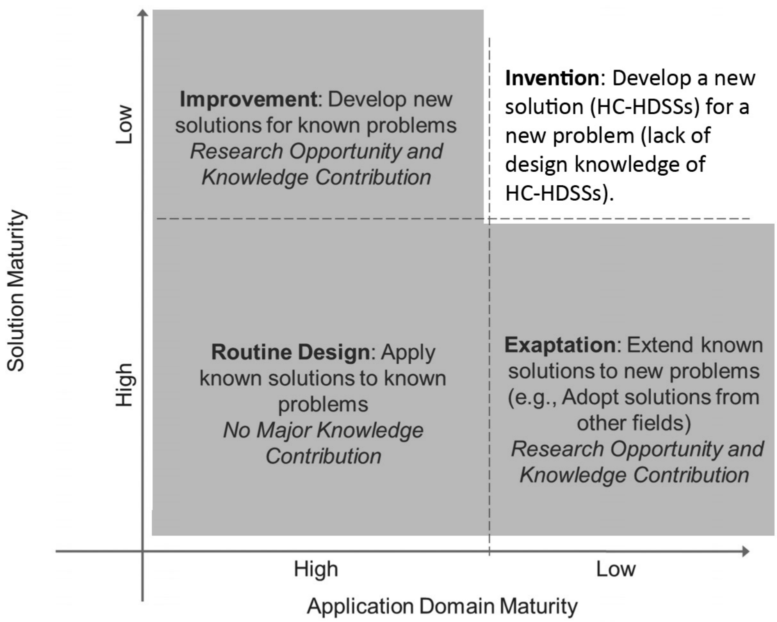

Figure 10.2. DSR knowledge contribution as invention (the grey area is adapted from Gregor & Hevner, 2013).

10.2 THE INTERNAL AND EXTERNAL VALIDITY OF THE STUDY

As validity affects the rigor and quality of scientific research, it must be considered in scientific research (Larsen et al., 2020). Concerning DSR, Larsen et al. (2020, p. 276) defined validity as "formalized procedures for justifying arguments and conclusions of a research study involving the design, development and/or evaluation of IT artifacts to solve identified problems." There are many types of validity in IS or DSR research worth considering. For example, content validity, construct validity (Straub et al., 2004; Boudreau et al., 2001; Larsen et al., 2020), and internal and external validity (Johannesson & Perjons, 2014). This dissertation covers the two most frequently discussed forms of validity: internal and external.

10.2.1 THE INTERNAL VALIDITY OF THE STUDY

Internal validity refers to "the extent to which the internal components of an IT artifact are consistent, transparent, and explainable" (Larsen et al., 2020, p. 277). It is about rigorously selected research methods supported by arguments that are followed through.

For the rigor of this study, chapter 4 elaborates on the selection of the research approach to effectively address the research problem and answer the research question. First, an illustration of why the study follows a DSR paradigm is given. Second, arguments for why the ADR method is selected from among several DSR methods or methodologies are provided. Third, arguments for why the FEDS framework is selected for developing the evaluation strategy of this study are presented. Fourth, the choice of methods for data collection and analysis is given.

For the transparency of this study, chapter 5 presents the research process in detail. Chapters 7, 8, and 9 illustrate the evolution of design knowledge in the three BIE iterations.

10.2.2 THE EXTERNAL VALIDITY OF THE STUDY

External validity is related to the generalizability of research results (Johannesson & Perjons, 2014). As introduced earlier in this chapter, this dissertation makes two main contributions: a prototype of HC-HDSSs and five design principles concerning how to design HC-HDSSs. The prototype is designed in a specific context, i.e., decision-making in improving IT service practices. However, the design principles of HC-HDSSs are an abstraction and generalization of the design knowledge gained in the design process of the HC-HDSS prototype.

In detail, the formulated design principles target a class of digital systems that share the same features. First, as users of digital systems, humans are the final decision-makers. The digital systems are used to support human decision-makers instead of replacing them. Second, the decisions supported by the digital systems are semi-structured managerial decisions instead of structured and unstructured decisions. Third, the decision-making task supported by the digital systems starts from identifying a problem or opportunity, formulating solutions as choices, to selecting one choice instead of only the moment of selecting one choice among several. Fourth, the design of the digital systems centers on human values because digital systems are used to augment human capabilities in decision-making instead of letting them erode.

10.3 ETHICAL CONSIDERATIONS

The ethical considerations of the dissertation can be summarized on two levels: level one covers the whole dissertation (i.e., the overall ethical consideration), and level two focuses on several details encountered when collecting and analyzing the empirical data.

Level one and the overall ethical consideration: The proposal for designing HC-HDSSs takes account of the ethical issue brought about by existing DSSs (i.e., the third weakness of machines). This study emphasizes human-centered design and pays attention to human needs when designing the system. It puts human values at the core of the design process.

Level two, first, from the point of view of data collection, organization A provided digital data related to ITSM stored in the organization for designing the prototype. Consent concerning the responsibility not to disclose the data to others not connected to the project was signed between the organization and the project. Furthermore, the data collection for evaluating the prototype was conducted in real organizations. The discussions and interviews with practitioners were audio recorded. Permission for audio recording was explicitly requested and granted before each meeting or workshop.

Second, from the point of view of data analysis, the author's individual bias was mitigated by letting one more researcher from the ADR researchers' group help take notes in several interviews with practitioners. Moreover, a supervisor supervised the data analysis process.

10.4 FUTURE RESEARCH OPPORTUNITIES

Through reflection and learning (i.e., the third phase of the ADR method), this section presents four research opportunities.

The first research opportunity concerns formulating a design theory of HC-HDSSs by investigating or explicitly elaborating on the eight components of an ISDT. This dissertation contains most of the eight components but needs more elaboration to explicitly turn them into the components of an ISDT in a future study. For example, the component *purpose and scope* sets the scope, or boundaries, of the theory. The purpose and scope of HC-HDSSs sets the boundaries of a class of systems named HC-HDSSs, instead of an instance of HC-HDSSs. The five formulated design principles of HC-HDSSs are the component *principle of form and function,* which defines "the structure, organization, and functioning of the design product" (Gregor & Jones, 2007, p. 325). The prototype of HC-HDSSs (presented in chapter 6) is an *expository instantiation*, which is the component that provides "a physical implementation of the artifact that can assist in representing the theory both as an expository device and for purposes of testing" (Gregor & Jones, 2007, p. 322). The sections of building the prototype in each BIE iteration constitute the component *principles of implementation*, which describe the process of implementing the theory in a specific context, i.e., ITSM, in this study.

The component *constructs* of the ISDT, representing the entities of interest in the theory, need to be defined in the future. An entity can be a physical phenomenon or an abstract theoretical concept (Gregor & Jones, 2007). Constructs, "at the most basic level in any theory," should be defined as clearly as possible. Possible constructs of the HC-HDSS theory could be hybrid, complementary capabilities, etc. This study already elaborates on these two possible constructs. In future research, in addition to these two, which need to be explicitly defined as clearly as possible, more constructs should be identified and defined for an ISDT.

The component *justificatory knowledge*, according to the kernel theory of Wall et al. (1992), is "the underlying knowledge or theory from the natural or social or design sciences that gives a basis and explanation for the design" (Gregor & Jones, 2007, p. 322). This study provides the theoretical foundations for designing HC-HDSSs, including theories of design-making, design theories of DSSs, and HCAI. A future study could elaborate on the selected theories in terms of justificatory knowledge or kernel theory.

The components *artifact mutability* and *testable propositions* of the ISDT need to be worked out in the future. According to Gregor and Jones (2007), *artifact mutability* refers to "the changes in state of the artifact anticipated in the theory, that is, what degree of artifact change is encompassed by the theory," while *testable propositions* or *hypotheses* refer to the "truth statements about the design theory" that can be demonstrated by constructing an instantiation (Gregor & Jones, 2007, p. 322). Following the general form suggested by Gregor and Jones (2007), one testable proposition of the HC-HDSS theory could be "if a digital system that follows design principle five of the HC-HDSSs is instantiated, then the digital system can utilize the complementary capabilities of human and machine for making better semi-structured managerial decisions."

The second research opportunity concerns formulating two possible design principles for the future study of human–machine collaboration or human–machine hybrid decision-making systems (i.e., digital systems in which either humans or machines can be the final decision-makers).

One emphasis of HC-HDSSs is on a human-centered design that focuses on augmenting human capabilities instead of machine capabilities or both. In other words, humans can be augmented by machines; for example, humans can learn from each other and can also learn from machines.

In BIE iteration three, a signal related to machines that can learn from humans was captured by the author when performing the data analysis. This unanticipated result implies that a new design principle of (human and machine) mutual learning could be formulated. This design principle is interesting but not an essential design principle of HC-HDSSs, but it could be an important principle for designing human–machine collaboration or hybrid human–machine decision-making systems.

Furthermore, learning between humans and machines could augment the capabilities of both. Therefore, another possible new design principle, i.e., (human and machine) mutual augmentation, could be formulated for designing human–machine collaboration or hybrid human–machine decision-making systems. The principle of (human and machine) mutual learning could be subordinate to the principle of (human and machine) mutual augmentation because mutual augmentation can be decomposed. Mutual learning can be a component of mutual augmentation.

The third research opportunity concerns evaluating the reusability of the formulated design principles. This study prioritizes evaluating the utility of the formulated design principles that are effective in solving the problem. The evaluation activities in this study have been carried out using the built prototype, i.e., practitioners directly evaluated the prototype and indirectly evaluated the formulated design principles. This is because many of the implemented functionalities in the prototype are related to (in the early stage of design) or guided by (in the later stage of design) the formulated design principles. The interview questions, especially those related to evaluating the property functionality (i.e., a property affects utility), concern the formulated design principles. However, as stated by Iivari et al. (2021), to maintain the practical relevance of DSR, the reusability of the formulated design principles should be explicitly evaluated. They provide a five-criteria framework for lightly evaluating the reusability of design principles, accessibility, importance, novelty and insightfulness, actability and guidance, and effectiveness. Therefore, future research following Iivari et al.'s (2021) framework could be conducted to increase the reusability of the five formulated design principles.

The fourth future research opportunity concerns evaluating (and building) the tool so as to involve more human users in a single decision task. Practitioners from both organizations mentioned that having more human users use the tool in the same decision task would be interesting. The HC-HDSS prototype has been evaluated by two human users in one decision task. More human users would mean that more knowledge could be created and shared, i.e., the total amount and diversity of knowledge would increase. Meanwhile, it would also mean that the complexity of the digital tool would increase, as more functionalities may be needed to support the complexity engendered by more human users.

For example, triggered by practitioners' comments about involving more human users in a single decision task, the author shared the idea (in the same meeting) that if there were more than two human users, all of them could work as one group in the prototype. They could also work as a pair, as the two practitioners used the prototype in this study. In other words, more than one human pair would use the prototype. Then, functionalities for assessing the results from different human pairs should be implemented in the following steps of the prototype. In addition, when more human users use the tool in a single decision task, more ideas may be generated. The generated ideas could be compared within the same type (i.e., change technology, change management, and change behavior), as shown in Figure 9.2b, and then compared and decided on by human users across the types. This idea was shared and appreciated by the practitioners.

On the other hand, along with the increased complexity of the digital tool, functionalities related to utilizing machine capabilities and/or human–machine hybrids in decision-making may change. New design principles may emerge. Therefore, a future study could evaluate the current prototype but with more human users participating in the same decision task.

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APPENDICES

Appendix 1: The twelve statements for assessing monitoring and event management practice implemented in the prototype

1. We detect all changes of state (information, warning, exception/error).

2. We have decided which changes of state that have significance for the management of an IT service.

3. We compare the number of events with the number of incidents.

4. We monitor software licenses to ensure that licenses are valid.

5. We ensure that events are communicated to relevant function/department/people that need to be informed or take further control actions.

6. We monitor the number of incidents that occurred and the percentage of these that were triggered without a corresponding event.

7. We have rules for when events should trigger other processes (i.e., change mgmt, config mgmt).

8. We monitor the number and the percentage of events that required human intervention and whether this was performed.

9. All tickets are assigned a priority.

10. We provide the means to compare actual operating performance and behaviour against design standards and SLAs.

11. We provide a basis for service assurance, reporting and service improvement.

12. We monitor the number of events/alerts generated without actual degradation of service/ functionality (false positives – indication of the accuracy of the instrumentation parameters, important for CSI).

Appendix 2: The interview questions used in episode 2b (in BIE iteration two)

1. Can you describe the strengths of the tool?

2. Can you describe the weaknesses of the tool?

3. The tool tries to support the use of humans' capability (to use their intuition, experiences and skills). What do you think about it?

3.1. Different people have different experience and skills (like the two human participants in the example). This tool tries to support to make use of humans different experience and skills. What do you think about it?

3.2 This tool tries to support humans to express their experience and skills. What do you think about it?

3.3. The tool tries to support humans share their knowledge and learn from each other. What do you think about it?

3.4 if answer for question 3.3 is YES, do you think the tool support humans share or learn something that is difficult to be expressed out?)

4. The tool utilize machines' capability, do you think it is good enough? Or too much? Or too little?

5. Do you think machines' capability (e.g. giving statistic information) utilized in this tool compensate certain humans' weakness?

6. The tool support decision-making by a process (step 2 to 4). Do you think by this process, the tool support combine both humans' and machines' capability in a good way? Do you have other suggestions?

7. Are you satisfied with the type of decision made in this tool or do you have any suggestions of other decisions that could be made in a future version?

8. What do you think about the tool concerning easy of use?

Appendix 3: The interview questions used in episode 3 (in BIE iteration three)

1. Can you describe the strengths of the tool?

2. Can you describe the weaknesses of the tool?

3. The tool tries to utilize humans' strengths in decision-making. What do you think about it? (e.g., to use humans' expertise, experiences and intuition)

4. The tool tries to utilize humans' strengths to compensate machines' weaknesses. What do you think about it?

5. The tool tries to utilize machine's strengths in decision-making. What do you think about it? (e.g., Efficient and Effective; Reducing human biases)

6. The tool tries to utilize machines' strengths to compensate humans' weaknesses. What do you think about it?

7. The tool tries to utilize machines' strengths /capabilities to strengthen/ augment humans' capability. What do you think about it?

8. The tool tries to utilize humans' capability to strengthen machines' capabilities. What do you think about it?

9. What do you think the design is centered on humans?

10. The tool tries to combine humans and machines capabilities in a guided decision-making process. What do you think about it?

11. What do you think about the quality of the decision you made by using this tool? (E.g., satisfied? The decision is good enough?)

12. What do you think about the tool, e.g., the labels, statements formation, work flow etc., related to understandable?

13. What do you think about the tool concerning easy of use?

14. What do you think about the tool's relevance to your organization? E.g., statements for assessing the selected ITIL practice

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