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Leveraging Machine-Executable Descriptive Knowledge in Design Science Research – The Case of Designing Socially-Adaptive Chatbots

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Abstract. In Design Science Research (DSR) it is important to build on descriptive (Ω) and prescriptive (Λ) state-of-the-art knowledge in order to provide a solid grounding. However, existing knowledge is typically made available via scientific publications. This leads to two challenges: first, scholars have to manually extract relevant knowledge pieces from the data-wise unstructured textual nature of scientific publications. Second, different research results can interact and exclude each other, which makes an aggregation, combination, and application of extracted knowledge pieces quite complex. In this paper, we present how we addressed both issues in a DSR project that focuses on the design of socially-adaptive chatbots. Therefore, we outline a two-step approach to transform phenomena and relationships described in the Ω-knowledge base in a machine-executable form using ontologies and a knowledge base. Following this new approach, we can design a system that is able to aggregate and combine existing Ω-knowledge in the field of chatbots. Hence, our work contributes to DSR methodology by suggesting a new approach for theory-guided DSR projects that facilitates the application and sharing of state-of-the-art Ω-knowledge.

Keywords: Design science research · Descriptive knowledge · Prescriptive knowledge · Ontology · Chatbot · Conversational agent

1 Introduction

Design Science Research (DSR) seeks to design, build, and evaluate socio-technical artifacts that extend the boundaries of existing knowledge in order to address unsolved problems in a new and innovative way or to solve known problems in a more effective manner [1–3]. The knowledge used to inform a DSR project can be divided into two broad areas: descriptive knowledge (Ω-knowledge) and prescriptive knowledge (Λ-knowledge) [1, 2, 4]. The first describes "the what knowledge about natural phenomena and the laws and regularities among phenomena" [2, p. 343]. Its primary purpose is to inform and justify the research question and the assumed relationships [2]. The second consists of the "how knowledge of human-built artifacts" [2, p. 343]. It includes artifacts and design theories that address a similar research problem from the

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past. Overall, both knowledge areas are important as “the success of a design research project is predicated on the research of the team in appropriately drawing knowledge from both Ω and Λ to ground and position the research” [2, p. 343].

Since access to existing prescriptive knowledge that can be (re-)used in the design of a new artifact is limited [1], DSR scholars often rely on Ω-knowledge and (kernel) theories in order to follow a theory-guided artifact construction [2]. However, as in any other research domain, it requires a lot of effort to aggregate and apply the existing Ω-knowledge, which restricts its application in DSR. One reason is the data-wised unstructured textual nature of scientific publications [5] (problem 1). Scientific knowledge communication largely depends on “text production, reading and interpretation” [6, p. 1] and follows a document-centered knowledge exchange [5]. Moreover, there is a lack of comparable identifiers for terminologies, definitions, and concepts among research areas [5]. This makes the extraction of relevant components more difficult and requires a lot of creativity and rigor [5, 7]. As a consequence, Ω-knowledge with a clear structure can be of great value but does not solve the Ω-knowledge application problem alone [5]. The aggregation, combination, and application of many phenomena and relationships described in the Ω-knowledge base can be very complex (problem 2) [5]. Many of the empirical results interact or exclude each other, which makes it quite difficult to choose the right pieces of knowledge for a foundation of the design. Therefore, approaches that leverage computing resources to aggregate and combine the existing knowledge base could support researchers in their DSR project. However, there is currently only very limited machine support, which makes access to scientific publications very difficult [5]. As a consequence, DSR researchers face the challenge that “the creation, reading and processing of scientific literature is currently tying up an extremely high cognitive capacity” [5, p. 2]. Thus, solutions should simplify the application, (re-)use, and sharing of existing Ω-knowledge in DSR. Hence, we articulate the following research question:

How to transform descriptive Ω-knowledge into a machine-executable representation in order to simplify knowledge access in design science research projects?

To answer this research question, we first present our DSR project in which we experienced both problems outlined above. In our DSR project we investigate the design of socially-adaptive chatbots and have identified large amounts of publications that deliver descriptive Ω-knowledge. However, this knowledge was not directly accessible (problem 1) and much of the empirical evidence interacted or excluded each other which made an application quite complex (problem 2). To address both problems in our DSR project, we followed a two-step approach to transform Ω-knowledge into machine-executable design knowledge. We instantiated a system that aggregates and combines existing Ω-knowledge. Hence, this paper contributes to DSR methodology by suggesting a new approach for a theory-guided design that facilitates the application and sharing of existing Ω-knowledge in DSR. From a more practical point of view, this enables building artifacts based on state-of-the-art and up-to-date Ω-knowledge.

2 Conceptual Foundations

2.1 Types of Knowledge in DSR

Knowledge in DSR projects can be distinguished into two broad areas, namely Ω-knowledge and Λ-knowledge [2]. Ω-knowledge comprises descriptive and explanatory knowledge and evolves from a behavioristic-oriented research approach [1]. It consists of the *"what-knowledge"* about natural, artificial, and human-related phenomena and their sense-making relationships [2]. It includes (kernel) theories that consist of *"any descriptive theory that informs artifact construction"* [2, p. 340] and therefore provides the theoretical basis for DSR projects (i.e., sometimes also referred to as justificatory knowledge [2]). The other knowledge area (i.e., Λ-knowledge) comprises applicable and prescriptive knowledge and evolves from a design-oriented research approach [1]. It consists of the *"how-to-knowledge"* about artifacts designed by humans such as constructs, models, methods, instantiations, and design theories [2]. Figure 1 provides a more detailed description of different types of Ω- and Λ-knowledge in DSR [2].

Descriptive Ω - knowledge		Prescriptive Λ - knowledge				
Phenomena	Sense-making	Constructs	Models	Methods	Instantiations	Design theory
Description of natural, artificial, and human-related phenomena.	Knowledge of the sense-making relationships among phenom-ena.	Vocabulary and symbols to define and understand problems & solutions.	Designed representation of problem and solution.	Algorithms, practices, and recipes for performing a task.	Physical realization that act on the natural world.	Abstract, coherent body of prescriptive knowledge that describes the principles of form and function.

Fig. 1. DSR knowledge base and definitions following Gregor and Hevner [2].

From a DSR knowledge consumption perspective, researchers draw valuable information from both knowledge areas [2, 4]. On the one side, Ω-knowledge informs and justifies the research question and assumed relationships and builds the foundation for an artifact [2, 4]. On the other side, Λ-knowledge provides existing artifacts and design theories that address a similar research problem from the past [2, 4].

From a DSR knowledge contribution perspective [4], contributions to Ω-knowledge increase the understanding of the world, whereas contributions to Λ-knowledge increase the understanding of technological innovations [1, 2]. In this context, two research streams evolved that either emphasized their contribution on design theories or on innovative artifacts [2]. However, various discussion in the past have led to the common understanding that both types of contributions are valuable and intertwined [2, 4].

2.2 Structures of Knowledge

Knowledge can be captured in structured (e.g., databases), semi-structured (e.g., XML), or unstructured (e.g., natural language) data [8]. A typical knowledge management problem is the difficulty to access and extract knowledge that is captured in unstructured text-based data such as in scientific publications [7]. Nevertheless, scientific knowledge communication depends on *"text production, reading and interpretation"* [6, p. 1] and therefore largely relies on document-centric information flows [5]. This leads to problems as the scientific output in the form of text-based articles has almost doubled in the last ten years [5]. As a result, *"scientists spend a large part of their time reviewing literature, presenting their own research in document form and [...] working independently on very similar research results"* [5, p. 2].

To address this problem, various initiatives aimed to augment the scientific knowledge communication process in order to simplify the access and extraction of existing knowledge. For example, in the IS domain there is an ongoing effort to provide concepts and tools in order to systematically capture constructs and their relationships [9, 10]. Some approaches leverage nomological networks that identify potential pathways for theory integration and development [9]. Therefore, researchers screen variables of functional and structural components from past quantitative research publications and identify shared variables. Then they connect these with each other in a nomological network in order to reduce theory fragmentation and to identify similar phenomena across disciplines [9]. Other approaches leverage tools to automatically identify construct identity in literature reviews and meta-analyses in order to recognize whether two constructs refer to the same real-world phenomenon [10]. These tools are a valuable extension to support experts as they leverage computing resources and natural language processing algorithms. Particularly in the DSR contexts, initiatives aim to develop tool support in order to help researcher and practitioners to structure, manage, and present the multi-faceted nature of DSR projects including the resulting design knowledge and artifacts [11, 12]. In the field of computer science, various communities (e.g., knowledge engineering, description logics, logic-based databases) investigated approaches for decades to structure and capture knowledge in a machine-executable form. In this context, ontologies are considered as an important enabler to establish a shared common understanding and to enable a (re-)use of knowledge [13]. Ontologies are conceptual models that provide a controlled vocabulary to describe a set of concepts and relations of a domain [8]. Based on the ontological conceptualization, a knowledge base is a repository that links classes in the ontology to individual instances [14]. Thus, such an approach enables a machine-executable expression of meanings and concepts that can be directly processed [15].

As a consequence, ontological approaches have been applied in various domains [13]. Efforts are made to use ontologies to accumulate scientific knowledge in medicine [14] or to store user characteristics in user models [16]. In addition, the Semantic Web Initiative [15] proposed standards to make existing knowledge on the Web more available. Therefore, various standards have been defined including the RDF data model, the RDF Schema (RDFS) and the Web Ontology Language (OWL), as well as the SPARQL Protocol And RDF Query Language (SPARQL) [8]. They enable the description of concepts, provide rich sets of operators, and further allow the use of a reasoner to check for mutually consistency and to recognize which concepts fit under which definitions [17]. In addition, various software packages exist that support various ontology languages and enable the editing of ontologies. One of the most famous open-source ontology software packages is Protégé developed at Stanford university [18]. It is used in various research projects such as clinical decision support systems, collaborative ontology development, and many others [18].

3 DSR Project: Designing Socially-Adaptive Chatbots

In our DSR project, we focus on designing chatbots. Chatbots are software-based systems that converse with humans via the use of text or speech based natural language [19]. They are assumed to solve the app overload, reduce costs, and enhance customer experience and are used in several contexts (e.g., customer service, energy feedback, collaboration systems) [19–22]. However, many chatbots failed as the interactions did not feel natural [23]. In this context, various studies revealed that humans react to chatbots in a similar way as humans usually react in interpersonal communication [24, 25]. To describe this phenomenon, Nass and colleagues have introduced the Computer are Social Actors (CASA) paradigm which states that human-computer interaction is fundamentally social and natural [24, 26]. Social behavior is always triggered whenever the computer exhibits sufficient cues that can be associated with the behavior or appearance of human beings (e.g., natural language, gender, response delay) [24, 27]. Therefore, scholars often refer to these cues as *social cues* [28]. As humans constantly adapt their social cues (e.g., adapt their formality of speech according to the conversation partner), chatbots could also adapt their social cues to the user, task, and context in order to make the interaction more natural and to increase user satisfaction.

To achieve this goal, we conduct a DSR project and suggest the development of socially-adaptive chatbots that adapt their social cues to an interaction. This is a promising approach as adaptive systems have shown to enhance user satisfaction [16] and performance [29] in other contexts. Therefore, we followed established DSR guidelines and reviewed existing knowledge about social cues by conducting a literature review [30]. In our literature review, we identified various relevant publications across domains (e.g., chatbots, dialog systems, embodied conversational agents). However, we identified only few publications that provide prescriptive Λ-knowledge for the design of socially adaptive chatbots. The vast majority of identified publications describes phenomena of social cues and/or explains the reason for these phenomena. Thus, a large body of research appears to be hidden in the textual nature of publications delivering Ω-knowledge.

To reveal and apply the existing Ω-knowledge, it is necessary to identify and extract relevant descriptions of phenomena and relationships from empirical results. However, it is not clear how the extracted Ω-knowledge should be represented and how it could subsequently be (re-)used in the design of socially-adaptive chatbots (problem 1). Furthermore, much of the revealed empirical findings interact and exclude each other. For example, Sah and Peng [31] showed that a user is more willing to disclose intimate information in a health context when a chatbot addresses the user directly and personally. However, others revealed that a direct address in a financial context can also have a negative effect on information disclosure [32]. Thus, both publications provide different recommendations to increase information disclosure depending on the context. This becomes even more complicated when we further account for different user variables such as demographics (e.g., age, gender), geography (e.g., country of origin), and usage behavior (e.g., sporadic users, experienced users) [33]. As a result, it is very complex to aggregate, combine, and apply the existing Ω-knowledge to investigate social cues of chatbots (problem 2). Thus, both problems limit researchers and designers to efficiently access and apply the existing body of knowledge in order to design socially-adaptive chatbots.

4 Leveraging Machine-Executable Ω-Knowledge for Designing Socially-Adaptive Chatbots

To address both problems introduced above, we present our approach to simplify access to existing Ω-knowledge in the design of socially-adaptive chatbots. Our approach leverages the use of machine-executable Ω-knowledge and is outlined below.

4.1 Step 1: Transform Ω-Knowledge into Prescriptive Design Rules

To address problem 1, we aimed to transform Ω-knowledge embedded in textual publications in a consistent and prescriptive format. One of the main vehicles to convey prescriptive design knowledge in the IS discipline are design principles and technological rules [34]. They are statements *"that prescribes what and how to build an artifact in order to achieve a predefined design goal"* [34, p. 4040]. Chandra et al. [34] propose to include three components in order to articulate purposeful prescriptive design knowledge: These include (1) the actions made possible through the artifact, (2) information about the properties making the action possible, and (3) boundary conditions for when it will work. With this, we could define prescriptive design rules that help designers to achieve a specific outcome in a specific situation (e.g., to achieve X and you believe you are in Y, then design the social cue like Z) [4]. Thus, in step 1, we suggested to transform existing Ω-knowledge into prescriptive social cue design rules.

To perform step 1, we reviewed each publication for (1) outcomes of a social cue design (e.g., positive attitude towards chatbot), (2) types of investigated social cue design characteristics (e.g., formal clothing), and (3) factors that influence the outcomes of a social cue design characteristic (e.g., user, task, context). With all three components, we were able to state a purposeful prescriptive social cue design rule. In case a publication described a direct cause-and-effect relationship without any uncertainty (e.g., do X to achieve Z), we defined an abstract boundary condition, e.g., based on the user types (e.g., user profession: *students*), study type (e.g., experimental task: *desert survival problem*), or the overall domain (e.g., context domain: *service domain*). To illustrate the overall process, Fig. 2 shows two examples that are explained below.

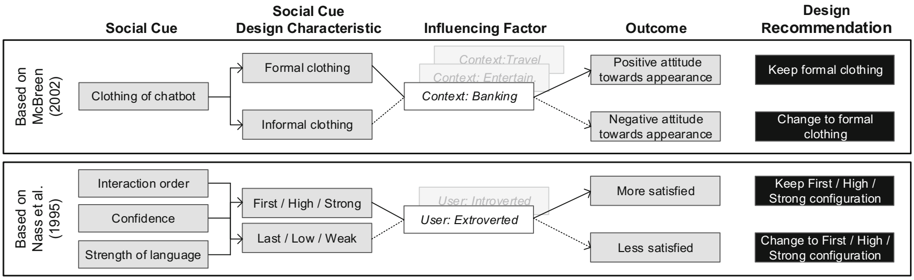

Fig. 2. Exemplary development of prescriptive social cue design rules.

In the first example, McBreen [35] showed that different clothing styles of a chatbot (i.e., formal, informal) lead to different outcomes (i.e., attitude towards chatbot) depending on the context of the interaction (i.e., banking, entertainment, travel). Thus, we derived the prescriptive social cue design rule that the clothing style of a chatbot should fit to the interaction context in order to maximize the user attitude towards the chatbot. In the second example, Nass et al. [36] showed that design characteristics of a specific set of social cues (i.e., interaction order, confidence level, strength of language) lead users to assume that the chatbot possesses a specific personality (i.e., extroverted, introverted). In addition, they showed that users are more satisfied when the chatbot's personality matches their own. Thus, we derived the rule that the design of the interaction order, confidence level, and strength of should match the personality of the user in order to maximize user satisfaction. Finally, we derived over 150 prescriptive social cue design.

In the next step, we faced the problem that a manual aggregation, combination, and application of the developed knowledge is highly complex (problem 2). Various prescriptive social cue design rules provide different design recommendations for different influencing factors. To showcase this, Table 1 displays the prescriptive social cue design rules for selecting the design characteristic of only one social cue, namely the chatbot's gender. The 18 derived social cue design rules illustrate that a manual design selection for only one social cue is already a challenging task.

Table 1. Prescriptive social cue design rules for selecting the gender of a chatbot.

Social cue design	Influencing factor	Outcome	Ref.
Gender: *male*	User Gender: *female* Chatbot role: *tutor bot*	Positive impact on user performance and effort	[37]
Gender: *female*	User Gender: *male* Chatbot role: *tutor bot*	Positive impact on user performance and effort	[37]
Gender: *male*	Platform: *website*	Less attribution of negative stereotypes	[38]
Gender: *female*	Chatbot role: *Q&A agent*	Positive impact on comfort, confidence and enjoyment	[39]

(*continued*)

Table 1. (*continued*)

Social cue design	Influencing factor	Outcome	Ref.
Gender: *male*	Chatbot role: *job interview*	Higher perceived power, trust, and expertise	[40]
Gender: *female*	Chatbot role: *job interview*	Higher perceived likeability	[40]
Gender: *female*	Chatbot role: *job interview* User Personality: *agreeable & trusting users*	Higher willingness to listen to chatbot persona	[41]
Gender: *male*	Chatbot role: *job interview* Personality: *extraverted & neurotic users*	User is less likely to inflate themselves	[41]
Gender: *female*	Frustration of user: *high due to errors*	Increases impact of affective excuses to reduce frustration	[42]
Gender: *male*	Chatbot role: *stereotypical male jobs*	Positive impact on satisfaction score	[43]
Gender: *female*	Chatbot role: *stereotypical female jobs*	Positive impact on satisfaction score	[43]
Gender: *male*	Chatbot role: *tutor bot*; Feedback type: *negative*	Positive impact on learning performance	[44]
Gender: *female*	Chatbot role: *tutor bot*; Feedback type: *positive*	Positive impact on learning performance	[44]
Gender: *female*	Context: *sales*; Product gender: *female*	Positive belief in the credibility of advice	[45]
Gender: *male*	Context: *sales*; Product gender: *male*	Positive belief in the credibility of advice	[45]
Gender: *female*	Conversation topic: *love and relationships*	Positive impact informative rating	[24]
Gender: *male*	Conversation topic: *technology*	Positive impact informative rating	[24]
Gender: *male*	Feedback type: *positive and negative evaluation*	Positive impact on competence and friendliness	[24]

4.2 Step 2: Make Prescriptive Design Rules Machine-Executable

To address problem 2, we aimed to increase application of the previously derived prescriptive social cue design rules. Therefore, we suggested to transform the design rules into a machine-executable representation. This enables researchers and designers to leverage computational resources to aggregate and combine existing knowledge. Therefore, we relied on ontological models and suggested to conceptualize the previously derived design rules in a prescriptive social cue design rule ontology and explicitly instantiate each rule in a knowledge base. Subsequently, we built a social cue configuration system that leverages computing resources and enables researchers and designers to apply and share the derived knowledge base.

To perform step 2, we first followed the ontology engineering process proposed by Ostrowski et al. [46] and conceptualized all design rules in a prescriptive social cue design rule ontology. We used Protégé to develop the ontology in order to check for consistencies among the classes and properties [17]. Therefore, we first defined the main classes of a social cue design rule (i.e., social cue design rule, social cue, influencing factor, outcome). Second, we defined subclasses for each identified social cue design (e.g., chatbot clothing, chatbot gender), influencing factor (e.g., user age, task complexity, context domain), and outcome (e.g., attitude towards the chatbot, user satisfaction). Next, we defined properties which describe attributes of instances of the classes and the relations to other instances [46] (i.e., a social cue design rule has social cue, has influencing factor, and has outcome). Finally, we conceptualized all relevant classes and relationships of a prescriptive social cue design rule. To increase readability, we simplified and aggregated the classes and properties and display a simplified ontology in Fig. 3.

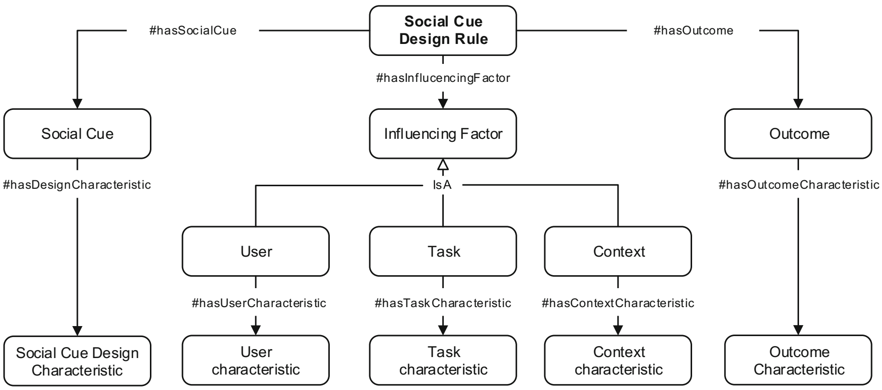

Fig. 3. Simplified prescriptive social cue design rule ontology.

In the next step, we developed a prescriptive social cue design rule knowledge base by creating several instances that capture individual empirical findings from the identified publications. Therefore, we reviewed each prescriptive social cue design rule and identified instances of each rule (e.g., clothing design characteristic: *formal*; context characteristic: *banking,* attitude towards the chatbot: *positive*). Next, we defined instances of the social cue design rule class, each of which holds specific properties concerning a particular rule (e.g., *rule 1* has clothing design characteristic *formal,* has context characteristic *banking,* and has a *positive* attitude towards the chatbot). After this, we were able to query the knowledge base in order to list all relevant prescriptive social cue design rules which fulfill a specific configuration condition (e.g., select *all* social cue design characteristics from the prescriptive social cue design rules where the context characteristic is *banking* and the attitude towards the chatbot is *positive*). The resulting output includes all social cue design characteristics that meet the query conditions (e.g., chatbot clothing should be *formal* according *to rule 1* and chatbot age should be *old* according to *rule 3*). However, the resulting design recommendations can contain conflicts as they might violate potential disjoint assumptions (e.g., *rule 2* proposes the chatbot gender to be *male* whereas *rule 5* proposes a *female* chatbot name). In such a case, researchers need to resolve the conflicts by reviewing both publications from which the design rules originated. Thus, it is important to provide researchers with relevant background information about the underlying reference of each design rule in order to review and resolve conflicts for a specific configuration. Finally, we built a prototypical chatbot social cue configuration system that enables user to access, configure, and query the developed design recommendations (see Fig. 4).

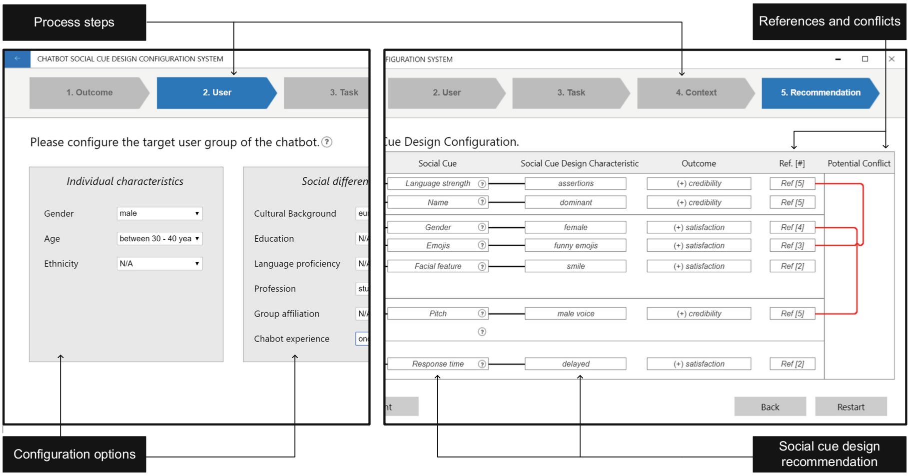

Fig. 4. Prototypical chatbot social cue configuration system. (Color figure online)

The chatbot social cue configuration system follows a four step configuration process: first, designers can configure the desired outcome of the chatbot social cue design (e.g., attitude towards chatbot: *positive*). In the next three steps, designers can configure assumed influencing factors (e.g., context: *banking*). Finally, the system queries the knowledge base and displays prescriptive social cue design recommendations (e.g., clothing of chatbot: *formal*). Potential design conflicts are highlighted with a red line and users can click on the reference buttons to review the corresponding reference. As a consequence, our chatbot social cue configuration system can simplify the access to relevant Ω-knowledge (problem 1) and helps to aggregate, combine, and resolve the complexity of existing Ω-knowledge (problem 2).

5 Discussion

Current state-of-the-art knowledge is typically captured in scientific publications that represent knowledge in natural language. Hence, researchers are faced with two problems: first, researchers need to deal with the data-wise unstructured textual nature of scientific publications (problem 1). Second, several knowledge pieces can influence or exclude each other which makes an aggregation and combination very complex (problem 2). Thus, both problems restrict the application and sharing of Ω-knowledge in DSR. To address both problems, we proposed a two-step approach to generate machine-executable design knowledge that simplifies access to relevant Ω-knowledge in DSR. We applied the two-step approach in our DSR project to publications that investigate the outcomes of social cues of chatbots. Therefore, we transformed descriptive Ω-knowledge about social cues of chatbots into prescriptive social cue design rules (step 1). Next, we built a prescriptive social cue design rules ontology and knowledge base in order to develop a prototypical chatbot social cue configuration system (step 2). This enables researchers and designers to easily query the existing knowledge base and reduces manual effort to aggregate and combine social cue design rules. A graphical interface that links the rules to the underlying references further decreases the time to resolve any conflicts.

To apply the proposed two-step approach, researchers need to elaborate its suitability beforehand, as it cannot be applied in every context and to every type of descriptive knowledge. Therefore, researchers need to assess whether they can identify the three components needed to articulate purposeful prescriptive design knowledge, i.e., (1) actions made possible through the artifact, (2) information about the properties making the action possible, and particularly (3) boundary conditions for when it will work [34]. To demonstrate that the two-step approach can also be applied in other contexts, we exemplary applied the two-step approach to three publications that contribute valuable knowledge for the design of adaptive systems in other domains (i.e., cross-cultural websites [16], PC games [47], education systems [48]). Therefore, we performed step 1 and reviewed the publications for the three relevant information in order to define purposeful prescriptive design rules [34] (see Fig. 5).

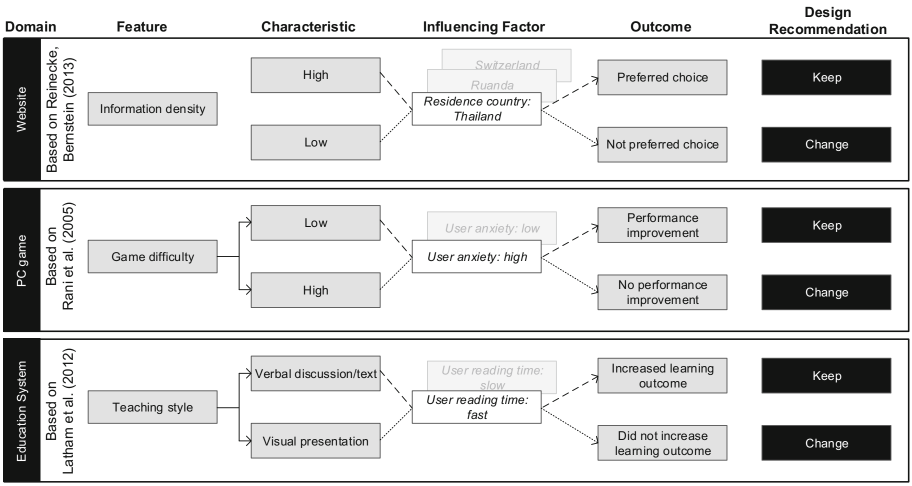

Fig. 5. Prescriptive design rules for other types of adaptive systems.

In the first example, Reinecke and Bernstein showed [16] that (1) user prefer different website designs (2) in terms of information density (3) depending on the user's cultural origin. After identifying the three information, we were able to derive a prescriptive design rule, i.e. adapt the information density of a website to the cultural origin of a user. In addition, Rani et al. [47] investigated in a computer game context how an adaptation of the game's difficulty to the user's anxiety level can improve performance. Moreover, Latham et al. [48] showed that the teaching style of an education system impacts learning outcomes depending on the user's reading time. Both findings can be transformed into prescriptive design rules for the design of games or education systems depending on an influencing factor (i.e., anxiety level, reading time).

After transforming the Ω-knowledge into prescriptive design rules, we can perform step 2 and make the derived design rules machine-executable. Therefore, we can conceptualize the identified classes (e.g., website design rule, website information density, cultural origin, outcome), define properties (e.g., has information density, has cultural origin, has outcome), and instantiate the knowledge base by reviewing each prescriptive design rule (e.g., website design rule *rule 1* has information density *high*, has cultural origin *Thailand*, and has the outcome *preferred choice*). Finally, a website configuration system could query this knowledge base in order to reveal the optimal design features of a website for specific users (e.g., select *all* design characteristics from the prescriptive design rules where the user origin is *Thailand* and the design matches the user's *preferred choice*). Finally, a website configuration system could display the optimal design characteristics (e.g., information density should be *high*), which enables researchers to efficiently access, query, and (re-)use existing Ω-knowledge for the design of websites.

Consequently, we showed that the proposed approach can also be applied to simplify access to knowledge of other adaptive systems. We argue that the transformation of descriptive Ω-knowledge into a machine-executable form can be of high value for almost any field, as it allows scholars to efficiently retrieve, apply, and share design-relevant Ω-knowledge. However, our proposed approach to transform descriptive Ω-knowledge into machine-executable design rules is not free of limitations. First, we did not evaluate the approach with researchers and practitioners to see whether they accept such an artifact as well as finally trust and use the artifact. Although we applied the proposed two-step approach to other publications, future research should investigate the application and adoption of the proposed two-step approach in a controlled experiment or focus group assessment. Second, the approach does not account for causality. It only aggregates empirical cause-and-effect relationships without questioning the underlying theoretical assumptions [49]. Thus, it does not *"identify the causal claims upon which proposed design principles or theories are founded"* [50, p. 8]. Therefore, future approaches should capture the underlying theoretical foundations. Third, the aggregation of empirical results leads to a loss of precision, which could lead to an incompatible comparison of two identical labels, e.g., the construct *perceived threat* could refer to different phenomena and instances in two different publications. Therefore, future approaches should conceptualize constructs on an item level. Fourth, the initial transformation of textual knowledge in an ontology model and knowledge base requires extensive preprocessing to structure such data in a machine-executable way [13]. Therefore, future research can address this problem by developing solutions to enhance knowledge collection. Finally, the proposed two-step approach can only be used to support the scientific design process. It is not intended to replace the manual knowledge extraction process, since the iterative process of research, going back and forth in small steps, is a mandatory prerequisite for innovation and creativity. However, a simplified access to the existing knowledge-base will support researchers and practitioners to efficiently leverage existing knowledge in their DSR project.

6 Conclusion

In this paper we present a two-step approach that makes existing Ω-knowledge more applicable in DSR projects. Therefore, we propose to transform descriptive Ω-knowledge into machine-executable representation. This enhances the application of existing Ω-knowledge and facilitates the (re-)use and sharing of already extracted knowledge pieces. In addition, we show that the two-step approach is not only limited to the specific context of socially-adaptive chatbots. Hence, researchers and designers can apply our approach to simplify knowledge access in their DSR projects. This facilitates a theory-guided artifact design process and supports building a more comprehensive body-of-knowledge in the field of IS and beyond.

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