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Learning by Doing: Educators' Perspective on an Illustrative Tool for AI-Generated Scaffolding for Students in Conceptualizing Design Science Research Studies

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ABSTRACT

Design science research (DSR) is taught in university courses and used by students for their final theses. For successfully learning DSR, it is important to learn to apply it to real-world problems. However, students not only need to learn the new DSR paradigm (meta-level) but also need to develop an understanding of the problem domain (content-level). In this paper, we focus on content-level support (CLS), proposing an illustrative tool to aid students when learning to develop a conceptual design with DSR (e.g., for a prototype). Following the DSR paradigm, we deductively identify students' issues and use the scaffolding approach to develop design requirements (DRs) and design principles (DPs). To offer AI-generated scaffolding, we use the generative language model (GLM) "GPT-3." We evaluate our illustrative design through 13 expert interviews. Our results show that providing students with CLS is perceived to be helpful, but the interaction with the student needs to be designed carefully to circumvent unintended usage patterns. We contribute DPs and an illustrative instantiation thereof toward a DSR tool support ecosystem. More broadly, we contribute to the understanding of how humans can be supported by AI to solve problems, an important challenge in human-AI collaboration research.

Keywords: Problem solving, Artificial intelligence, Scaffolding, Design science research (DSR), Generative language models, GPT-3

1. INTRODUCTION

Design science research (DSR) is taught to students in university courses (Hevner, 2021; Winter & vom Brocke, 2021), used as an educational approach to solve domain-specific problems (Thuan & Antunes, 2022), and used by students for their final thesis (Knauss, 2021). To effectively learn DSR, besides learning the theory, students need to *experience* DSR by applying it to real-world problems (Goldkuhl et al., 2017; Winter & vom Brocke, 2021), confronting them with both *meta-level* knowledge regarding the DSR paradigm and *content-level* knowledge regarding the problem domain (Figure 1). Learning a new paradigm while navigating a new problem domain can be challenging.

An approach from educational theory to support students in challenging learning situations is *scaffolding* (Wood et al.,

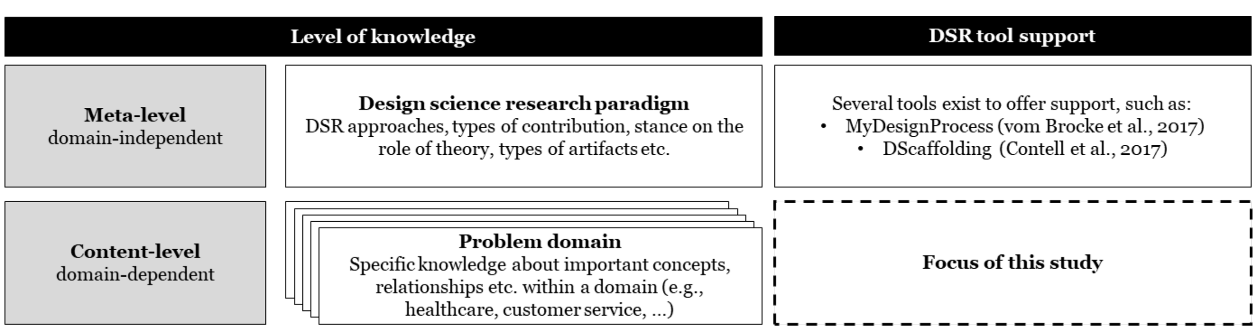

Figure 1. Focus of This Study with Respect to Levels of Knowledge

1976). Scaffolding aims to offer support such as learning materials or cues to enable students to solve problems they otherwise could not solve. Tool-based scaffolding was proposed to address several learning challenges (Law et al., 2020). Existing tools for DSR support (e.g., Contell et al., 2017; Gau et al., 2022; Morana et al., 2018a; vom Brocke et al., 2017) focus on problem-independent *meta-level* support, e.g., a canvas for organizing study contents or links to reading material. Offering content-level support (CLS), however, might be particularly helpful to novices, as they might lack the required prior knowledge to grasp the problem and develop appropriate solutions. CLS could include suggestions concerning problem or solution aspects (e.g., underlying issues, design principles (DPs)). However, preparing them for all topics a student might choose may not seem feasible.

With artificial intelligence (AI), however, we argue that CLS might be possible. In this article, we explore how it can help students apply DSR, more specifically, in the aspect of developing a conceptual design. We answer the research question: *How can we use AI-generated, content-level scaffolding to support students in developing their conceptual design with DSR?*

To answer this question, we develop an illustrative prototype following DSR. It provides scaffolding to address issues of students when solving problems, offering content-level suggestions through a generative language model (GLM). We evaluate our illustrative prototype through 13 expert interviews. Overall, interviewees liked the idea of CLS to aid students, highlighting the opportunity of receiving new ideas to challenge and improve the developed concept. We discuss required research on undesired behavior when using such generative AI. We evaluate the AI suggestion quality in a different, quantitative study (see Memmert et al., 2023), therefore it is out of scope for this paper.

With DPs and a situated instantiation, we contribute evaluated design knowledge towards a DSR tool support ecosystem as suggested by Morana et al. (2018b) and to the understanding of AI-based scaffolding opportunities in higher education, a trend suggested by Doo et al. (2020). More broadly, due to our deductive approach, we contribute towards a better understanding of how humans and AI systems can collaborate to solve problems, an important challenge for human-AI collaboration research (Dellermann et al., 2019). For this paper, we mostly follow the publication scheme for DSR papers by Gregor and Hevner (2013).

2. BACKGROUND

We explain *scaffolding* as conceptual and GLMs as technical foundation, with GLMs enabling the dynamically generated, context-specific scaffolding. We then relate our proposed tool to existing DSR support tools.

2.1 Scaffolding

Scaffolding is the "process that enables a child or novice to solve a problem, carry out a task or achieve a goal which would be beyond [their] unassisted efforts" (Wood et al., 1976, p. 90). This not only allows novices to successfully complete a task by concentrating on the aspects they can handle but also enables them to build "task competence […] at a pace that would far outstrip [their] unassisted efforts" (Wood et al., 1976, p. 90). Given our goal to support students in *learning to solve a problem* using DSR, supporting both *problem-solving* and *learning* through scaffolding seems appropriate. Wood et al. (1976, p. 98) explain several scaffolding functions such as fostering the learner's interest, maintaining their focus and motivation, reducing the task's "degrees of freedom," "marking [the task's] critical features" to challenge the learner, and, demonstration, which "may involve completion or even explication of a solution already partially executed by the tutee [themselves]." Kim and Hannafin (2011) identified different purposes such as procedural- (operational aspects), conceptual- (knowledge gaps), and strategic scaffolds (alternative approaches), which we refer to during design and discussion.

Scaffolding was discussed in real-life, "authentic learning tasks," as, given the "complexity of those tasks, learning may be hampered by the limited processing capacity of the human mind" (van Merrienboer et al., 2003, p. 5). As DSR is used to solve such complex, real-life problems (Hevner et al., 2010), scaffolding might thus be particularly suited. We, therefore, employ scaffolding for developing requirements of and principles for our solution. Seeking to explore the helpfulness of AI-generated scaffolding, we focus on offering (instead of fading) support.

2.2 Generative Language Model (GLM)

GLMs are a specific type of AI trained to predict an input text's (likely) continuation, producing a corresponding output. Figure 2 shows three examples of responses of the GLM "GPT-3" (Brown et al., 2020) to our inputs. Importantly, the model does not need training (data) with these inputs in mind.

As students might select any topic for their DSR study, building a repository of training data in advance (e.g., all possible issues or design requirements (DRs) for any potential topic) might not be feasible. Because of its flexibility to accept arbitrary input and produce corresponding output across domains without requiring problem-specific training data, and its capability to inspire humans (Lee et al., 2022; Memmert & Bittner, 2022) and "accurately reflect important aspects of human conceptual knowledge" (Hansen & Hebart, 2022, p. 6), we selected GLMs for realizing AI-generated scaffolding. However, GLMs can cause challenges. For example, the outputs might lack truthfulness (Lin et al., 2022) while seeming plausible, or worse performance when insufficient contextual information is provided (Floridi & Chiriatti, 2020) or when inexperienced users interact with such systems (Jiang et al., 2022). We reference these challenges during design.

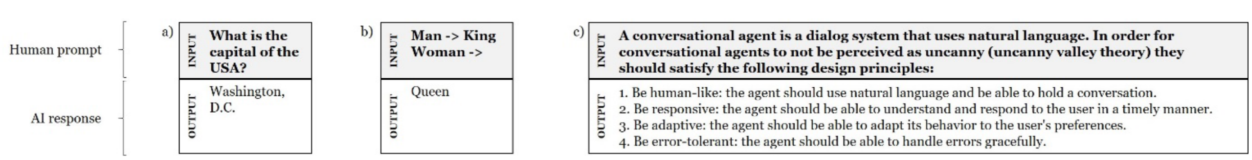

Figure 2. Authors' Exemplary Input Prompts and Outputs Generated by GPT-3

2.3 DSR Tool Support

DSR tool support was discussed within the IS community (e.g., at DESRIST 2017) and requirements were gathered accompanied by a call for a DSR tool support ecosystem (Morana et al., 2018b). A backward and forward search on this call and a search for "Design science tool," "Design science research tool," or "DSR tool" surfaced articles proposing design knowledge and tools such as "DScaffolding" (Contell et al., 2017), a mind-mapping-based tool targeted at novices to support learning DSR while conducting a study, or "MyDesignProcess.com" (Morana et al., 2018a; vom Brocke et al., 2017), a canvas-based tool to collaboratively plan, work on, document, and communicate DSR studies. Extending the latter, even a conversational agent was proposed to reduce the documentation effort (Gau et al., 2022).

The tools mentioned above focus on supporting the generic, problem-independent meta-level, not on content-level (Figure 1). Assuming one develops a study concept for "*facilitating an organization's innovation process*," meta-level support might include, e.g., listing the three most common DSR approaches (problem-independent). Conversely, CLS could include suggestions for potential issues, e.g., "*ideas of stakeholders often lack the required level of detail to be helpful*" (problem-dependent). In this study, we seek to offer the latter, complementing and thereby expanding existing DSR tool support, striving towards an ecosystem (Morana et al., 2018b).

3. METHOD

We follow the DSR approach by Kuechler and Vaishnavi (2012) to develop an illustrative prototype to aid novices in learning to apply DSR (Figure 3). To create *awareness for the problem*, we conceptualize DSR as a problem-solving approach. Consequently, we can deductively use the more general problem-solving literature to identify issues arising when humans, particularly novices, solve problems. Based on these issues, we develop literature-guided *suggestions*. More specifically, we derive DRs and formulate DPs (following Meth et al., 2015) based on scaffolding literature, leveraging learner-focused frameworks for "scaffolding complex learning" and scaffolding "ill-structured problem solving" (Law et al., 2020; Reiser, 2004). We *develop* an illustrative prototype based on a GLM, as GLMs can create context-dependent text enabling AI-generated scaffolding.

Our evaluation aimed to understand whether our design was assumed to be helpful to novices for developing concepts. We performed semi-structured expert interviews along an interview guideline (Meuser & Nagel, 2009), covering aspects like the overarching structure and CLS (see the Appendix). After we explained the functionality and planned interaction along prototype visualizations, interviewees reflected on their experience with novices and how such a tool might be beneficial. On the transcripts, we performed a qualitative content analysis using "Content Structuring/Theme Analysis," a mixed procedure using both deductive and inductive coding (Mayring, 2015). While not evaluated formally, during the interviews, the experts mentioned most of the issues we had identified from literature and used for tool development.

With regard to the DSR evaluation framework of Venable et al. (2016), our evaluation can be considered between ex-ante and ex-post. A conceptual prototype with an illustrative design for the user interface and the approach for producing AI suggestions (suggestion quality evaluated in a different study (Memmert et al., 2023)) was already developed, but the system is not yet technically implemented; for example, generating AI suggestions during the study required manual population of the template strings. It can be considered formative as we seek to "produce empirically based interpretations that provide a basis for successful action in improving the characteristics or performance of the evaluand" (Venable et al., 2016, p. 78), particularly given the idea's novelty and the unclear impact within a learning situation. We chose an artificial evaluation asking experts about the tool's potential impact, as experts are experienced with novices' challenges in general and might provide more fruitful feedback than students who might have only conducted one (partial) DSR study.

4. GLM-BASED DSR SUPPORT TOOL

To learn DSR effectively, students need to solve a problem practically (Goldkuhl et al., 2017; Winter & vom Brocke, 2021). We highlight issues that might arise and offer suggestions to support the concept development aspect of a DSR project.

4.1 Awareness of the Problem

DSR is an approach to solving complex, ill-structured problems (Hevner et al., 2010; vom Brocke et al., 2020). Solving such problems can be difficult for novices (Fischer et al., 2012) and

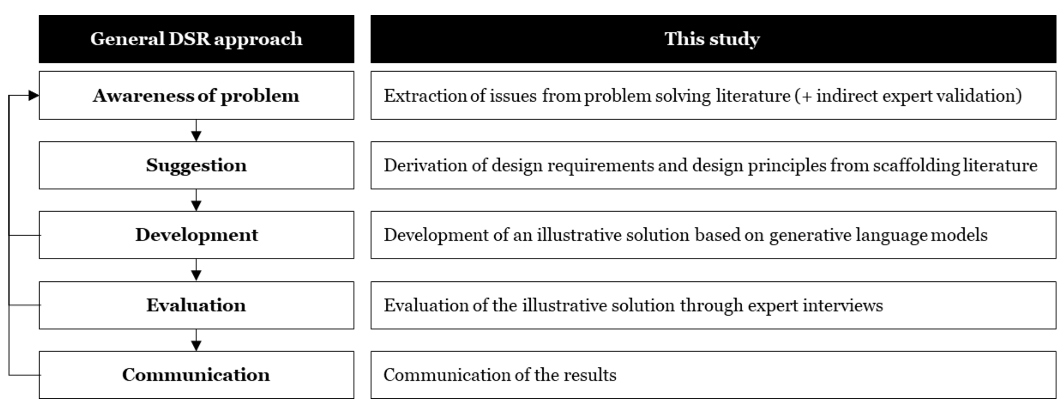

Figure 3. Our DSR Approach Based on Kuechler and Vaishnavi (2012)

even more challenging while learning a new paradigm (i.e., DSR). Several issues may arise.

A **lack of prior domain knowledge (I1)** can make it difficult to identify the relevant concepts to organize the path from problem to solution space (Fischer et al., 2012). An insufficient discovery of important issues, requirements, principles, or theories can result in an incomplete DSR concept. Due to the lack of prior domain knowledge and the problem's open-endedness, students might require additional information. Typically, teachers prepare material upfront so students can focus on learning instead of gathering information. Students are appreciative if they can select a DSR study topic themselves (Thuan & Antunes, 2022) and are encouraged to do so to increase engagement (Winter & vom Brocke, 2021). Due to this flexibility, however, it might not be feasible to prepare *CLS* upfront for every topic a student might select due to time constraints or because teachers might not have expert knowledge. Thus, there is a **lack of content-level support (I2)**.

Consequently, students must gather information themselves in addition to developing the concept, resulting in frequent **task switching (I3)**. When students have to switch between the task and searching for additional information, the *split-attention effect* (Sweller & Candler, 1992) can occur, which can be cognitively demanding and affect the learning process, especially "if the subject matter is complex" (Grévisse et al., 2019, p. 3). Additionally, students might **not be very effective in searching relevant information (I4)** because, as novices, they might not know for which information to search or lack the required search terms (Grévisse et al., 2019). The search might also be ineffective, as students might **lack methodological training (I5)** in the information-gathering methodologies employed in DSR such as literature search (Karlsson et al., 2012). Due to their lack of prior knowledge, students might find it challenging to navigate the domain, choosing an **inappropriate level of abstraction (I6)** for their analysis. They might focus on salient aspects or superficial details while neglecting other more important features (Law et al., 2020; Reiser, 2004). Lastly, while writing a final thesis or taking a university DSR course, students might face a **lack of time (I7)** to complete an entire study with literature analysis and empirical data gathering. This is a potential constraint highlighted by Cater-Steel et al. (2019) even for Ph.D. students given that "a significant DSR program typically encompasses many researchers over several years" (Gregor & Hevner, 2013, p. 339).

After the tool development, during the expert interview sessions for the tool evaluation, the general problem of increased complexity for learners due to learning both a new paradigm and domain was mentioned. While not systematically evaluated, the experts mentioned all but one (I3) of the issues. We assume I3 was not mentioned due to its operative nature. The split-attention-effect, however, is well documented in cognitive load literature (Sweller & Candler, 1992). Experts highlighted that issues vary across students and can partially be addressed through the supervisor.

4.2 Suggestion

Based on the identified, literature-guided issues and the scaffolding approach, we derive DRs for the solution and formulate DPs to address them (Figure 4).

Students lacking prior domain knowledge and are only just learning DSR might find it challenging to organize their thoughts on the right level of abstraction (I1, I6). A common means is to provide a guiding structure like a process or template to highlight the key elements (Law et al., 2020). This might be considered a *hard* scaffold, which refers to "static supports that can be anticipated and planned in advance based on typical student difficulties with a task" (Saye & Brush, 2002, p. 81). For ill-structured problems, this might aid students, preventing an oversimplified problem and solution

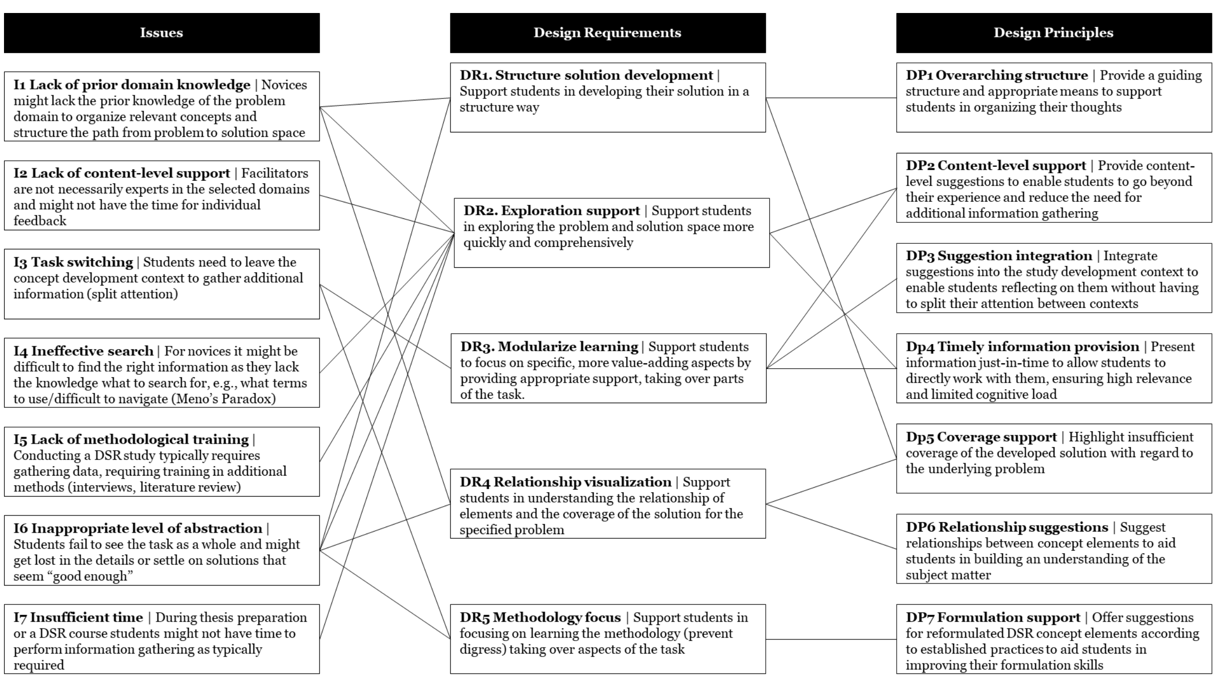

Figure 4. DSR Study Concept

representation (Law et al., 2020). Therefore, the tool should support students in **structured solution development (DR1)**. Thus, we propose:

DP1: Overarching structure. The tool should provide a guiding structure and appropriate means to support students in organizing their thoughts.

To develop sound solutions, the problem and solution space – reflected in our canvas through pre-defined DSR-specific concept elements – need to be explored appropriately, which might be difficult for students (I1, I4, I6, I7). *Conceptual scaffolds* can support students in identifying knowledge gaps, and *strategic scaffolds* in considering alternative perspectives on their "preliminary or tentative solutions" (Kim & Hannafin, 2011, p. 408), preventing adopting "oversimplified misconceptions" (Kim & Hannafin, 2011, p. 412). Typically, hints, prompts, or strategic tips can be provided by teachers to challenge students and aid them moving forward (Kim & Hannafin, 2011; Reiser, 2004; van Merrienboer et al., 2003). These might be considered soft scaffolds, as they are "dynamic and situational" (Saye & Brush, 2002, p. 82). Instructors might not always be able to provide problem-specific support, however, given the wide range of potential topics and limited resources (I2). Therefore, students should receive **exploration support (DR2)**. Additionally, to prevent students from having to switch between developing the concept and gathering additional information (I3), students should be supported to focus on specific aspects of the task through **modularizing learning (DR3)**. This "reduction in degrees of freedom" (Wood et al., 1976, p. 98) by taking over aspects of the overall task should help maintain focus. We therefore propose:

DP2: Content-level support. The tool should provide content-level suggestions to enable students to go beyond their experience and reduce the need for additional information gathering.

Content-level suggestions are additional information to be considered, which might increase cognitive load. To reduce cognitive load, AI-generated scaffolds are integrated directly into the tool, as otherwise, the split-attention effect (Sweller & Candler, 1992) might occur. We therefore propose:

DP3: Suggestion integration. The tool should integrate suggestions into the study development context to enable students reflecting on them without having to split their attention between contexts.

As additional information could potentially increase cognitive load, van Merrienboer et al. (2003, p. 9) recommend presenting information of lower complexity "precisely when learners need it during their work on the learning tasks," as the risk of cognitive overload is smaller. We therefore propose:

DP4: Timely information provision. The tool should present information just-in-time to allow students to directly work with it, ensuring high relevance and limited cognitive load.

Due to their potential lack of domain knowledge and incorrect level of abstraction, students might struggle to appropriately structure the path from problem to solution space, e.g., focusing only on certain aspects of the problem or solution (I6). Appropriate scaffolding, however, should enable students to think about "disciplinary relations" (Quintana et al., 2004, p. 347). Therefore, students should be supported in appropriately covering the solution for the specified problem through **relationship visualization (DR4)**. We therefore propose:

DP5: Coverage support. The tool should highlight insufficient coverage of the developed solution regarding the underlying problem.

Whereas experts can organize knowledge effectively within mental schemas, understanding the relationships between concepts can be difficult for novices (Fischer et al., 2012). Conceptual scaffolding can help "students consider tasks from different angles through the reorganization and connection of evidence" (Kim et al., 2018, p. 402). To increase transparency in solution development, relationship visualization should actively support students in linking conceptual elements by making suggestions for potential links, challenging them to further explore and structure the problem and solution space. We therefore propose:

DP6: Relationship suggestions. The tool should suggest relationships between concept elements to aid students in building an understanding of the subject matter.

A common scaffolding technique is offering *worked examples* (van Merrienboer et al., 2003) or expert modeling (Kim et al., 2018), where an instructor performs the task correctly for demonstration. To support the students in learning DSR standards, such as correctly formulating DRs or DPs, meta-level support might link to reference literature. Building on this idea, students should be supported in *applying* established ways of phrasing concept elements to maintain **methodological focus (DR5)** and prevent digressing. Thus, we propose:

DP7: Formulation support. The tool should offer suggestions for (re-)phrasing DSR concept elements according to established practices to aid students in improving their formulation skills.

4.3 Development

To implement the DPs, we have developed an illustrative design (Figure 5). The overarching structure (DP1) is manifested through concept elements (issues, DRs, DPs) in a template-like manner (hard scaffold). Concept elements can be linked to show the path from problem to solution space. The idea of problem and solution space was discussed in DSR literature (Thuan et al., 2019; vom Brocke et al., 2020), and so was creating relationships between problem and solution space elements (Venable, 2006). Our visualization is adapted from published DSR studies (e.g., Gnewuch et al., 2017; Meth et al., 2015). For comprehensiveness, we added elements typically included in the studies' manuscript (situation, general problem, artifact class). Besides providing humans with a quick overview, these capture the contextual information enabling the tool's core proposition: content-level support (DP2).

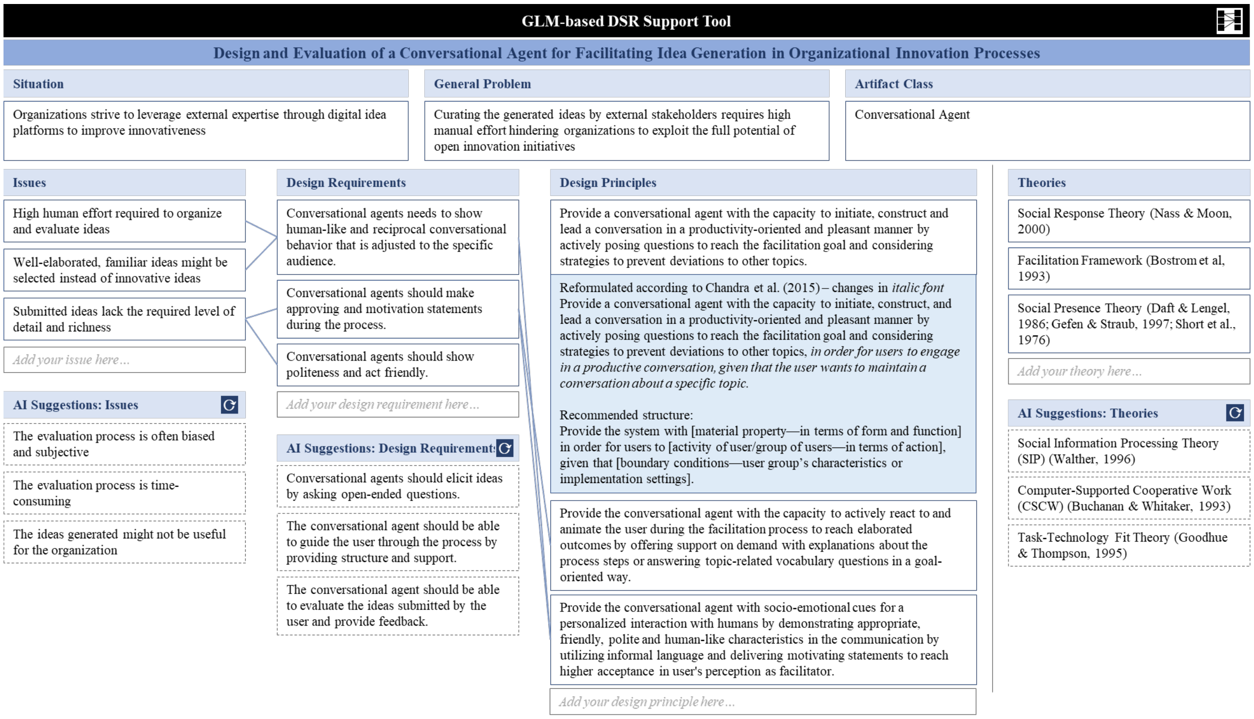

Figure 5. Illustrative Design of Our GLM-Based DSR Support Tool (Staged with Exemplary Contents Cited or Paraphrased from Poser et al., 2022)

Content-level support (DP2) is realized through context-specific suggestions. Unlike the pre-defined overarching structure (DP1, hard scaffold), these are generated dynamically during concept development, based on the current concepts' contents (soft/dynamic scaffold). To achieve such functionality, we employ a GLM. Learners, however, might not be familiar with GLMs, which can lead to worse output quality (Jiang et al., 2022). Thus, we do not let learners interact with the GLM directly but automate the request in the backend. The information the human entered in the tool's upper part is plugged into pre-defined templates and provided to the GLM, which generates suggestions displayed in the bottom part to be reviewed (and potentially integrated into the concept) by the human (see Figure 6). As insufficient contextual information might reduce the GLMs performance (Floridi & Chiriatti, 2020), we use the study setting information captured in DSR-specific concept elements of our canvas (situation, general problem) as additional input when generating suggestions. All suggestions for all concept elements in Figure 5 are AI-

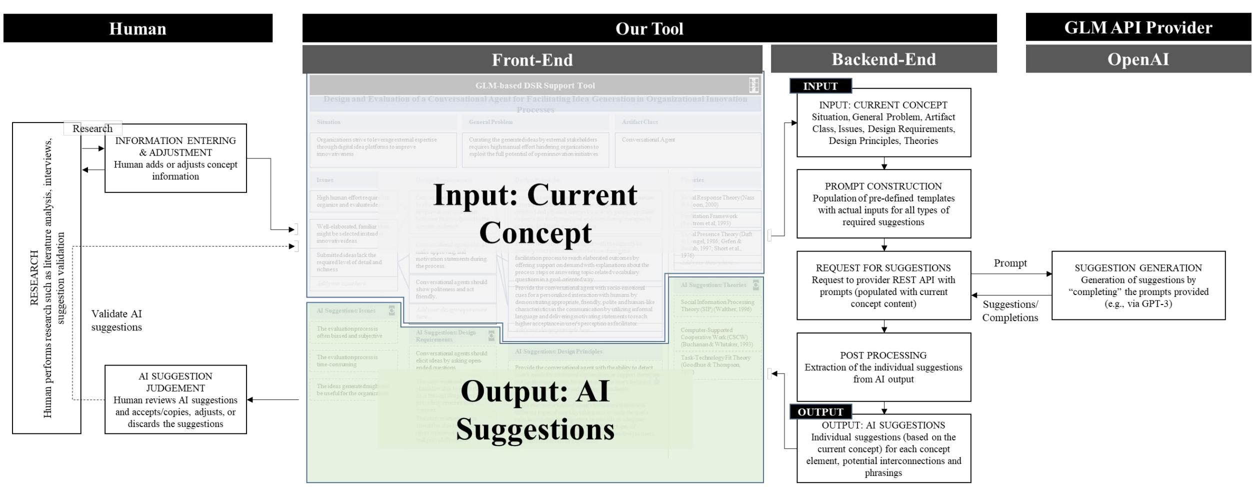

Figure 6. Schematic Flow of Information: Current Concept State (Upper Part) Is Filled into Pre-Defined Templates Resulting in *Prompts* Fed to the GLM (Provider API) to Generate Suggestions, and Cleaned Suggestions Are Reviewed by the Student

generated with this approach. For this study, the process was performed manually.

Modularization (DP3) is achieved by integrating AI support directly into the tool as condensed, itemized suggestions, displayed directly below the current concept. Reducing the need to leave the tool to search for additional information, students can thereby include the suggestions directly into the concept as they wish (copy, adjust, or ignore). We offer timely suggestions (DP4) by allowing the student to refresh the suggestions themselves, i.e., just-in-time when ready to review them. The tool offers coverage support by highlighting concept elements without connections (DP5). While the student connects the concept elements to build a coherent concept, the tool suggests potential links (DP6) based on the concept elements' texts (CLS), challenging the student to reflect. Lastly, the tool provides formulation support (DP7) for concept elements. The student can click on concept elements to see suggestions for re-phrasing them following established practices. Receiving the re-phrasing task, the original human input, and the target structure (e.g., DP structure (Chandra et al., 2015)), the GLM generates the suggestions (see Figure 7).

To effectively use the tool, students need an introduction to DSR, developing concepts using interlinked concept elements, and the tool's functionality. This includes highlighting the GLM's limitations, particularly the risk of plausible-sounding but incorrect information (Lin et al., 2022) and the necessity to treat them as hypotheses to be reflected on. For concept development, the student adds content (e.g., situation, general problem, issues) onto the empty canvas based on their initial research (e.g., literature analysis, data gathering). This serves as input for the GLM, which generates suggestions, challenging the student to develop the concept further. Adding new content, the student iteratively improves the concept, requesting suggestions when desired.

While the evaluation of suggestions was out of scope for this study (part of a different, quantitative study), we staged the tool with exemplary contents from a published DSR study to help the experts understand the tool idea during the interviews. However, the tool is not adjusted to this specific study. We intentionally did not formulate design features given the high uncertainty of the utility of this novel, AI-based scaffolding approach but instead chose an illustrative design to gather feedback.

5. EVALUATION

Seeking to determine whether the design is assumed to be helpful to novices, we conducted 13 interviews with Ph.D. students, postdocs, and professors (see Table 1) working at eight universities across four countries. All interviewees are experienced in using DSR and working with novices supervising students' theses or teaching DSR courses. Quotes from interviews held in German were translated by the authors.

Overall, the tool was perceived positively. Interviewees highlighted its potential to both support students in improving the DSR concept's quality and to better learn the DSR paradigm. Interviewees, though, raised concerns regarding potential undesirable usage patterns. We discuss the results along the DPs, in alignment with the thought process during the interviews, with a focus on the first two DPs.

Having an **overarching structure (DP1)** was perceived positively – "these are actually exactly the things that are important" (E9) – by many interviewees (e.g., E2, E3, E9), particularly to support novices (e.g., E2, E5, E9). It was seen as "guidance" or "process" offering "good structure" (E3, E9) that could increase the concept development speed (E4), encourage "justifying" design decisions (E12), and encourage starting with issues instead of the "typical pattern" of "solution first" (E5). The large amount of DSR literature can overwhelm novices (E7). A tool could offer "better support" than sending exemplary DSR studies to students (E4), explicating the relevant questions to be answered (E9) or fields to be filled (E11). Being confronted with learning both about the problem domain and the paradigm can be overwhelming (E7). The tool could allow students to focus on the actual problem first while being led through the process, and only once a sufficient understanding is reached, use specific methods to dive deeper into the topic (E7). A fixed structure might be more helpful for novices (e.g., E1, E2, E11), with one expert stating the structure to be "super helpful, especially for beginners, because I think it makes it easier for them to get started" (E2), as with more experience situation-appropriate adaptions are made (E5).

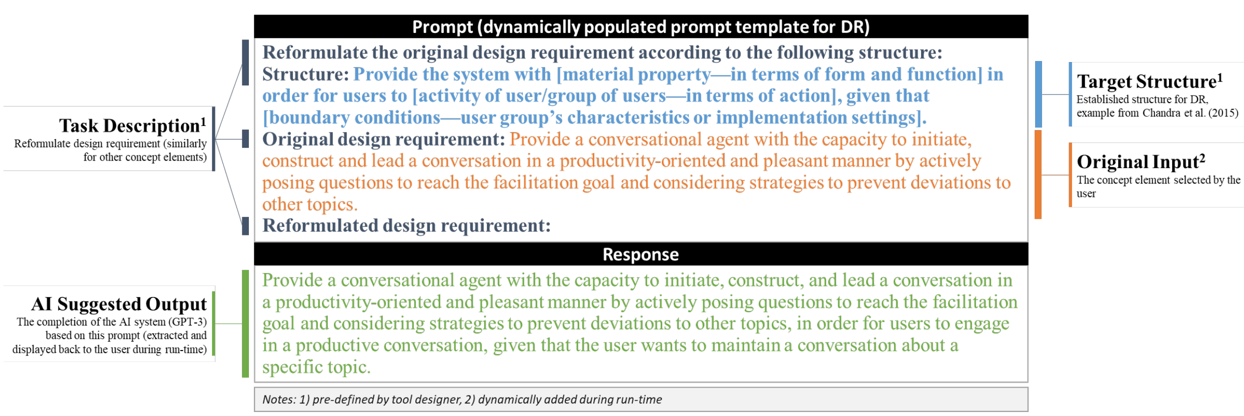

Figure 7. Automatically Assembled Prompt with a Pre-Defined Task Description and Target Structure, and Dynamically Added Student Input, Producing AI Output

#	Position	DSR Experience			Gender	Interview length [mins]
		Used in own publications	Supervised students	Taught DS(R) courses		
E1	PhD candidate	X	X		M	~41
E2	PhD candidate	X	X		M	~55
E3	PhD candidate	X	X		M	~51
E4	PhD candidate	X	X		F	~39
E5	Postdoc	X		X	M	~44
E6	PhD candidate	X	X		F	~43
E7	PhD candidate	X	X		M	~32
E8	Professor	X		X	M	~36
E9	Professor	X	X		M	~28
E10	PhD candidate	X	X		M	~45
E11	Postdoc	X	X		M	~37
E12	Professor	X		X	M	~53
E13	Postdoc	X	X		F	~50

Table 1. Interviewee Details

Many interviewees discussed the aspect of an overarching structure along our specific structure. Some interviewees recognized the flow from issues to DPs as familiar and helpful (e.g., E4, E8, E10) or as "essential part of DSR" (E2). However, several interviewees stressed that this exemplifies only one DSR approach and that there are other ways of conducting DSR and codifying design knowledge (e.g., E4, E11, E12). Our more *practical* approach is perceived to be in contrast to more theory-driven approaches, e.g., by Gregor (2006) (E12). Some critique was more fundamental, with one interviewee mentioning an unclear connection to current conversations around DSR (E12). Interviewees made several suggestions, including additional elements such as *stakeholders*, *environment*, or *organizational setting,* and *design features*, *design decisions*, or *design implementation* for better problem and solution space exploration, respectively (e.g., E1, E6, E13).

Some interviewees explained that students sometimes lack required domain knowledge (I1; E2, E3) as topics are innovative and at most partially mentioned in teaching (E3). Supervisors usually provide suggestions also on content-level, e.g., constructs, literature, or keywords for literature search (e.g., E7, E9, E10). Thus, most interviewees liked having complementary **content-level support (DP2)**, e.g., stating "I find this enrichment of content exciting, and it is certainly helpful" (E2) or "the interesting thing in my opinion is that you have these suggestions, so ideas that are qualitative, as brainstorming ideas or as idea givers, which I find very exciting" (E9). They saw AI suggestions as a source of inspiration, creative impulses, or new ideas (E1, E2, E4), expanding the concept but requiring validation (E2). Interviewees explained that some students lack methodological training (E4) for conducting interviews or literature search (I5; E1). Combined with insufficient domain knowledge, this can lead to ineffective literature search (I4; E2). Interviewees proposed suggestions could be "thought-provoking" (E10) or "pointers" (E2, E9) – "I think it's very good as a pointer in the sense of 'this could be relevant'" (E9) – for a more targeted, explorative literature search or data gathering (e.g., E2, E6). Suggestions could thus potentially speed up the search (I7; E2) or even change the way of working towards "rapid prototyping" (E13).

Suggestions were seen as opportunities to engage in reflection (E2) on ideas and to prevent students from "marrying their first idea" (I6; E5). Particularly when students work alone, the tool could act as a "sounding board" (E5), encouraging an iterative approach, with humans adding their initial ideas, receiving suggestions, conducting additional analysis, and refining their concept (E10). One expert summarized this thought as follows: "It also somehow fits in with DSR, because it has something iterative about it, maybe you only have 2 or 3 issues at first and maybe you have the first design requirements and you may or may not already have design principles; and then you get new theories suggested, then you would somehow engage with the literature again and then you could continue to work with your tool and add to it again. Then you would have work steps with the tool and without the tool. I think that's quite cool" (E10). Supervisors sometimes do not have the time or topic knowledge (I2) to provide recommendations or feedback on a detailed level (E6), particularly when supervising a broad spectrum of topics beyond their core research (E6).

Interviewees saw potential for using the tool across knowledge levels, from novices (e.g., E1, E2) over Ph.D. students (e.g., E10) up to experienced DSR researchers (e.g., E1, E5), with varying usefulness assessments regarding concept elements, with one expert stating that if "you get feedback on [what you have written], then that is certainly also beneficial for getting better results. That doesn't have to be the case only for novices. I would also say that if I were to somehow muddle along on my own, I wouldn't mind being encouraged to not be satisfied with what I wrote the first time around, and that's how professional designers work too" (E5). Using such a tool, however, requires understanding the underlying concepts, like differences between concept elements (e.g., E5, E8). Additionally, working with the tool requires discipline. Most interviewees raised the concern of novices accepting suggestions without reflection (e.g., E8, E13) using a "trial-and-error" approach (E4), refreshing suggestions until finding something plausible and superficially searching for matching sources, essentially "retrofitting" their solution (E8), with one expert raising the point that "depending on how good the tool will be later on, the question is whether the students can just use it, enter an example and generate their theses in the end" (E6).

Interviewees recommended preventing such unintended usage through design, e.g., by experimenting with timing (E3; see DP4), adding a reflection phase (E6, E13), marking AI-generated concept elements (E3), or adding a conversational agent encouraging engagement via a "Socratic dialog" (E8). Unintended usage was by far the most frequently raised concern. Others included, e.g., students' potential inability to provide sensible input (E8) or students not learning to work creatively and independently (E6).

Some interviewees discussed that the **integration of the suggestions (DP3)** makes knowledge more accessible than, e.g., having papers recommended by the supervisor, which can be overwhelming (E7). Some interviewees liked the "business model canvas"-like (E9) integrated one-pager (E1) while others found it overwhelming, particularly for extensive studies (E1, E6) and suggested incrementally displaying the steps (E9) in a "user flow" (E6).

Regarding the **timely information provision (DP4)** – in line with comments on DP2 – interviewees explained that providing suggestions all at once could lead to uncritical copying (E4). One interviewee, therefore, suggested investigating information provision timing and introducing a phase-based approach (E3).

Coverage support (DP5) and **relationship suggestions (DP6)** were presented together during the demonstration as both concern concept element linking. Coverage support was perceived as helpful (e.g., E1, E4, E5), as it can act as a "trigger" to justify design decisions (E5) and thereby foster learning the DSR mindset (E1). Interviewees found relationship suggestions (DP6) helpful, particularly in a "narrowing down mode" (E11) with many concept elements, with one expert stating "sometimes you have so many design requirements that you do not have an overview of everything that fits together with the content of the design principles" (E10). Relationship suggestions were seen as help to identify argumentation gaps (I6) and triggers for reflection (E6), potentially sharpening arguments (E2, E6) and the overall concept (e.g., E2, E6, E7). A supervisor might not discuss on this micromanagement level (E5), but the tool could do so, improving understanding.

Lastly, concerning **formulation support (DP7),** interviewees explained that formulating concept elements such as DPs is difficult for students (e.g., E2, E3, E4); for example, sometimes DPs are too generic or specific (I6; E1). They explained that formulation suggestions for the student-entered content – additionally to the generic concept element structure – were beneficial (E7, E10) for understanding concepts like DRs or DPs, and thereby, DSR aspects (E11). One expert explained that even with formulation references and as an expert, one still sometimes "has difficulties formulating and squeezing it in [the structure]. That's why I think this feature alone is something that is very helpful" (E4). Some concerns mentioned previously were reflected here too (e.g., accepting unfit suggestions).

6. DISCUSSION

6.1 Meta-Level Support

Most interviewees agreed that an overarching structure ("DSR canvas") – in general – could be helpful, particularly for novices to understand the idea of DSR. Offering a structure is based on the concept of *hard scaffolding* (Law et al., 2020). It can be considered a procedural scaffold (Kim & Hannafin, 2011), reducing complexity and leaving the novice to focus on the concept development. There is dissent, however, about how such a DSR structure should look. Several experts commented positively, while others suggested additional elements or questioned the DP-based approach altogether. One interviewee explained that there are different "churches of DSR" (E12) and that developing a canvas is like opening a "can of worms" (E12). There are many views on DSR, and our tool adopts *one* view (adapted from several published DSR papers). We do *not* seek to make a methodological contribution to the DSR paradigm, i.e., we do not claim this structure to be a good or the best way to support novices. Given the community discussion, developing a DSR canvas is way beyond our paper's scope. We show, however, that most experts agree on the need for scaffolding until students reach a certain DSR proficiency, allowing the supervisor to "offer feedback at a higher level instead of technical aspects" (E5).

6.2 Content-Level Support

We use the canvas-like structure as a vehicle to offer content-level suggestions, which can be considered soft or dynamic scaffolding, a part of holistic scaffolding as proposed by Law et al. (2020). Inspired by generative AI supporting humans in open and creative domains (Memmert & Bittner, 2022), we leveraged GLM to assist humans in creatively addressing open-ended, ill-structured problems through DSR. The experts' positive feedback suggests that such support could be helpful, particularly because it can provide humans with inspiration and new ideas to extend and sharpen their concepts and with pointers to more effectively gather information, matching DSR's iterative nature. Such CLS could be considered conceptual scaffolding, helping students becoming aware of knowledge gaps through cues (Kim & Hannafin, 2011). In challenging the students (Wood et al., 1976) to explore new ideas by offering additional perspectives, it might also fulfill the *strategic scaffolding* purpose (Kim & Hannafin, 2011). Particularly for students who have nobody around to challenge their ideas, this might be helpful, reducing the chance of "marrying the first ideas" (E5). We use scaffolding modes like hints or expert modeling (e.g., rephrasing concept elements) known to be effective (Kim et al., 2018). Students must learn, however, to treat suggestions as – potentially false (Lin et al., 2022) – hypotheses requiring validation.

Besides the canvas (meta-level support), CLS might further reduce "the number of constituent acts required to reach solution" (Wood et al., 1976, p. 98), by offering conceptual elements as a basis for iteration (E10) as opposed to an empty sheet. As people might lose motivation when overwhelmed (Corbalan et al., 2008), reducing complexity might lead to students retaining an interest, fulfilling the *direction maintenance* scaffolding function (Wood et al., 1976). As motivation increases when students self-select to add scaffolding (Kim et al., 2018), we have students themselves request suggestions.

Based on the theoretical perspective, we assume the tool to be more helpful the more severe the issues are for a particular student. Even still, multiple experts explained that beyond novices, even experts could benefit from AI-based scaffolding. A certain understanding of DSR and the domain is required, though. Future research should investigate the relative importance of these issues and DSR proficiency.

The canvas reflects the problem and solution space through lists of concept elements, iteratively developed by the learner, supported by AI-generated suggestions for adjusting or extending each of the lists. Though experts expect benefits from CLS for both problem and solution space exploration – even suggesting broadening the scope – the effectiveness requires further investigation.

Having developed our tool deductively from the issues of novices solving problems, it might be adaptable to other creative problem-solving approaches, such as design thinking (proposed by interviewee). Our approach of generating dynamic scaffolding is flexible, requires no additional training data, and is adjustable to other structures (e.g., canvases). We thus believe such a GLM-based approach could be a fruitful avenue for research on AI-generated scaffolding for problem-solving.

The tool might take over the scaffolding function of *demonstrating solutions*, expecting the "learner will then 'imitate' it back in a more appropriate form" (Wood et al., 1976, p. 98). Several interviewees, however, raised concerns about undesired use patterns. Instead of using suggestions as inspiration to challenge their ideas, students might copy them without reflection. This, though, is not a concern specific to *generative* AI. In AI-assisted decision-making, the phenomenon of overreliance is well-known (e.g., Buçinca et al., 2021). Similarly, in the design area, the phenomenon of "design fixation" (Jansson & Smith, 1991) refers to the effect of humans being less creative when shown solution examples. As DSR is an approach for *designing* artifacts, and AI suggestions could constitute (partial) solution examples, design fixation might occur. Therefore, we propose to explore using AI-assisted decision-making and design fixation knowledge.

Our design follows Law et al. (2020) in providing holistic scaffolding combining hard (template) and soft, dynamic scaffolding (CLS). We emphasize CLS, as there already is structural, tool-based facilitation available, but suggest CLS should complement meta-level facilitation. The tool is not intended to replace teaching DSR but being used along a DSR course or during final thesis preparation, allowing the supervisor to focus on higher-level feedback.

6.3 Limitations

We did not derive the canvas design but adapted an existing approach, as developing a DSR canvas is beyond the scope of this paper, and, more importantly, the canvas is not our core proposition. On the contrary, our approach, though exemplified along this specific canvas, is flexible and should be tested with other (DSR) canvases. Additionally, for our prototype, we did not derive design features but used an illustrative design, as our goal was to get feedback on the general idea of AI-generated, content-level scaffolding. Our tool is not yet implemented technically and has not been tested with end-users. Our conceptual approach, however, including generating AI suggestions, can already be executed manually, serving as a foundation for the next iteration. According to scaffolding literature and experts interviewed, positive effects of using the tool can be expected. These effects, however, should be measured in an end-user study.

6.4 Contribution and Outlook

We showcase a flexible way of combining static and dynamic scaffolding with novel technology. We deductively developed DPs, instantiated them as an illustrative tool, and evaluated them through expert interviews. We thereby contribute design knowledge in the form of a situated implementation of the artifact (level 1) as well as one aspect toward a nascent design theory (level 2), according to Gregor and Hevner (2013). Through this new focus on content, we complement existing DPs for DSR tool support focusing on meta-level support (e.g., vom Brocke et al., 2017).

We show that AI-generated, content-level scaffolding might be a pathway to supporting students. For the next iteration, we suggest a naturalistic evaluation (Venable et al., 2016). We offer ideas for design improvements, particularly for the human-AI interaction. Going forward, integrating AI-generated, content-level scaffolding into DSR teaching should be explored. Regarding the challenge of human-AI collaboration for problem-solving (Dellermann et al., 2019), we propose investigating *generative* AI. We offer a structured approach to generating suggestions along an existing solution framework (i.e., canvas), potentially adaptable to other creative problem-solving approaches.

7. CONCLUSION

Students must experience DSR by applying it to real-world problems to learn DSR effectively. We propose an illustrative tool to support them, as navigating the new paradigm and a new domain can be difficult. Conceptualizing DSR as a problem-solving approach, we use scaffolding as a theoretical and GLM as a technical foundation. We show that complementing partially existent meta-level support with content-level support is perceived as helpful. Proposing design knowledge through DPs and an illustrative, situated instantiation, we directly contribute towards an ecosystem of DSR tool support, as suggested by Morana et al. (2018b) and show that, as suggested by Doo et al. (2020), AI-based scaffolding can be used in higher education. More broadly, due to our deductive approach, we contribute to the understanding of how humans can be supported by AI to creatively solve problems, which was described as a challenge for human-AI collaboration (Dellermann et al., 2019). We encourage our community to further explore generative AI like GPT-3 or ChatGPT for this challenge.

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APPENDIX

Interview Questions

Experience
- How did you come in contact with DSR novices?
    - Do your students use DSR in term papers or final theses?
    - Have you taught DS(R) courses?

Overarching Structure
- How does the overarching structure support students in developing an understanding for how to develop prototypes using DSR?
- Do you provide students with a structure?

Content-Level Support
- How can content-level suggestions for concept elements support students?
- Which changes do you expect with regards to the depth and breadth of development?
- How could the speed towards the first concept draft change?
- Do you support your students on content-level?

Suggestion Integration
- What is the impact of having the suggestions displayed directly in the tool?
- How does this influence the need to work with other tools?

Timely Information Provision
- How could the ways of working of students improve by having the suggestions displayed just below concept elements?

Coverage Support
- How can the tool support the development of adequate solutions?
- How can it support achieving a good coverage of the solution with respect to the problem?

Relationship Suggestions
- How can suggestions for relationships between concept elements support students?

Formulation Support
- How can theory-driven formulation support students?
- Is there an additional benefit for having AI suggestions additionally to the general structure of the concept element (design principle)?

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