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The role of self-regulated learning on science and design knowledge gains in engineering projects

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ABSTRACT
Research on self-regulated learning (SRL) in engineering design is growing. While SRL is an effective way of learning, however, not all learners can regulate themselves successfully. There is a lack of research regarding how student characteristics, such as science knowledge and design knowledge, interact with SRL. Adapting the SRL theory in the field of engineering design, this study proposes a research model to examine the mediation and causal relationships among science knowledge, design knowledge, and SRL activities (i.e. observation, formulation, reformulation, analysis, evaluation). Partial least squares modeling was utilized to examine how the science and design knowledge of 108 ninth-grade participants interacted with their SRL activities in the process of performing an engineering task. Results reveal that prior science and design knowledge positively predict SRL activities. They also show that reformulation and analysis are the two SRL activities that can lead to an improvement in post science and design knowledge, but excessive observation can hinder post design knowledge. These results have important implications for the construction of learning environments to support SRL based on students' prior knowledge levels.

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Design knowledge; engineering design; self-regulated learning; science knowledge; path modeling

Introduction

Increasing exposure to engineering design in K-12 education can benefit students by providing opportunities for them to solve real-life problems and apply classroom knowledge (Chiu et al., 2013). Solving engineering problems requires students to integrate relevant domain knowledge, such as science, mathematics, and design knowledge, to propose innovative and feasible solutions in authentic contexts (National Research Council, 2009). Science knowledge and design knowledge are particularly important in computer-supported engineering design, where computation tools compensate for lack of mathematics knowledge. For example, a task of designing an energy-efficient house with solar panels, students utilize their science knowledge about solar energy and basic design knowledge about house construction. Thus, students' particular science and design knowledge acts as the precedents for success in engineering design activities.

Besides prior science and design knowledge, engineering design activities involve iterative exploration and refinement of design products through observing, modeling, modifying, analyzing, and evaluating a project (Crismond & Adams, 2012). To sustain initiative, effort, and persistence in these iterative processes, students also need to have self-regulated learning (SRL) skills. These

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skills are "self-generated thoughts, feelings, and behaviors that are planned and cyclically adjusted to attain learning goals" (Zimmerman, 1990). When students self-regulate themselves in the learning process, they play an active role in adjusting their cognition and behaviors to their ever-changing learning environments. High self-regulated learners have high levels of metacognitive awareness, apply complex strategies based on the learning situation, and engage in iterative modification of learning by integrating self-feedback and external feedback (Chen & Bembenutty, 2018; Zimmerman, 2013). In contrast, low self-regulated learners are reactive. They may not be fully aware of their own metacognition, get immersed in a simple or single strategy, and avoid further efforts in completing the learning process. High SRL skills enhance students' ability to engage in complex learning topics (Winne & Azevedo, 2014).

Research documents the significance of domain knowledge (i.e. science knowledge and design knowledge) and SRL, as well as the relationship between them (Mosborg et al., 2005; Song et al., 2016; Taub et al., 2014). Students who have poor domain knowledge may have limited capacity to process information, and thus limited their ability to use a variety of SRL processes (Moos & Azevedo, 2008). However, even though researchers agree that domain knowledge and self-regulation are essential variables explaining learning processes, few studies have investigated their combined effects. The current study seeks to build a model to understand how domain knowledge interact with SRL in complex engineering design activities.

We first discuss the SRL model in the context of engineering design, followed by a research model that proposes the relationships between domain knowledge and SRL. We then describe how we examine these relationships and what we find. Finally, we discussed how the findings align with the literature and contribute to engineering design in a computer-based learning environment.

Theoretical framework and research model

A systemic review of engineering education reveals how urgent it is to reform the teaching and learning of engineering activities by incorporating theoretically sound frameworks (Karabulut-Ilgu et al., 2018). SRL theory originates from the social cognitive paradigm and emphasizes the reciprocal learner-environment interaction (Dinsmore et al., 2008). It illustrates how individual characteristics interact with their learning environments to consequently influence learning outcomes. Specially, SRL theory reveals the influencing mechanism between individual characteristics, SRL cognitive factors, and learning outcomes. In the engineering design environments where technology supports and tracks students' learning processes, SRL cognitive factors are the cognitive actions students perform to solve the task. Individual characteristics refer to students' prior domain knowledge and are contextualized as science knowledge and design knowledge in this study. Learning outcomes are students' domain knowledge after completing the engineering design task.

Zimmerman (1990, 2013) initiated SRL and described three macro-level phases of SRL: *forethought, performance, and self-reflection*. Learners prepare to learn at the *forethought phase*, use self-control and self-monitor at the *performance phase*, and optimize personal reactions to learning outcomes at the *self-reflection* phase. To operate SRL factors in the complex processes of engineering design, we developed a domain-specific model of SRL in engineering design by referencing the existing model of SRL in a basic science field (Lajoie et al., 2015). As displayed in Figure 1, learners regulate themselves through five cognitive processes: *observation*, *formulation*, *reformulation*, *analysis*, and *evaluation*. Specifically, learners make *observation*s to understand the task in the forethought phase. The performance phase is the phase when learners pursue the design task by *formulation* (i.e. start the design from scratch), *reformulation* (i.e. change and modify the project to align with the intentions at the outset), and *analysis* (i.e. check the functionality of the design). Finally, learners *evaluate* if their current design matches the intended design in the self-reflection phase. All five cognitive processes are iterative and cyclical. This comprehensive SRL model in the domain of engineering design connects and balances the generality and domain-specificity of SRL processes, which is of

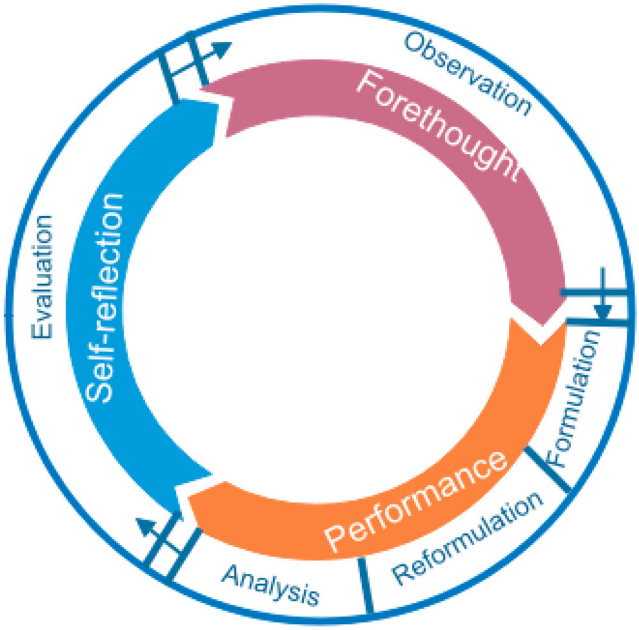

Figure 1. SRL processes in engineering design.

great importance in illustrating how students self-regulate their learning. These five factors are acting as a connecting role to interplay with prior domain knowledge and learning outcomes.

Following the assumption of SRL theory, a path model (see Figure 2) was proposed to show how individuals engaged in SRL and how SRL influenced learning outcomes in engineering design activities. As displayed in Figure 2, prior science knowledge, prior design knowledge, observation,

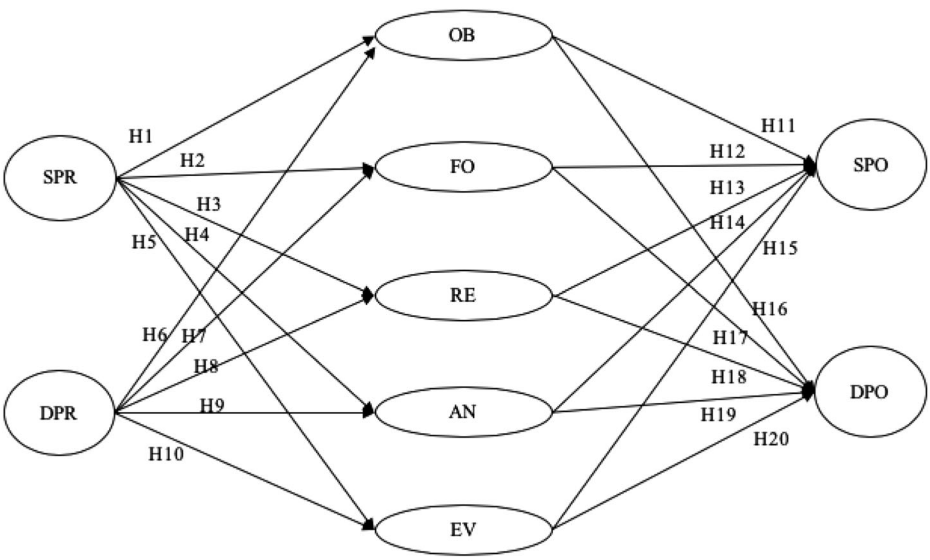

Figure 2. Hypothesized research models: H1 to H20 are the research hypotheses.

Note. SPR: Prior Science Knowledge; DPR: Prior Design Knowledge; OB: Observation; FO: Formulation; RE: Reformulation; AN: Analysis; EV: Evaluation; SPO: Post Science Knowledge; DPO: Post Design Knowledge.

formulation, reformulation, analysis, and evaluation are exogenous and/ or mediation variables. Post science knowledge and post design knowledge are endogenous variables. This model not only directly shows the significant relationships between these constructs (i.e. prior domain knowledge, SRL cognitive factors, and learning outcomes) but also informs the possible mediating effects of SRL. The research hypotheses are displayed along with the path model in Figure 2 and will be explained in detail in the following section.

Prior domain knowledge

Prior domain knowledge is the domain-specific declarative and procedural knowledge that learners bring to a learning experience (Dochy et al., 1999). Prior domain knowledge plays a primary role in learning processes and learning achievements through interacting with self-regulation (Hou, 2013; Song et al., 2016). Learners with higher prior domain knowledge are more likely to connect the new information with their existing knowledge schema when facing a complex task. They spend more time engaging in SRL processes and using more strategies, especially cognitive and metacognitive strategies (Taub et al., 2014). When no relevant prior knowledge is stored, learners may search for a solution randomly without any specific schema (Kalyuga, 2007). In engineering design, students need to activate their prior interdisciplinary knowledge to complete a design task successfully. Specifically, science knowledge and design knowledge are the key prior domain knowledge that could maximize the effects of SRL processes.

Researchers have found prior science knowledge can promote SRL through establishing a better understanding of science-related tasks. Without sufficient science knowledge, students cannot engage in SRL processes in a meaningful way. Moos and Azevedo (2008) examined the relationship between prior science knowledge and SRL processes when students learn the circulatory system with hypermedia. They found students' prior science knowledge was positively related to their planning and monitoring SRL process, a finding validated by Greene et al. (2010) in a study using the same learning task. In a long-term self-regulation study, Eilam and Reiter (2014) analyzed students' change of science knowledge and SRL in a Biology course. They found that positive SRL changes are associated with students' prior science knowledge. Therefore, prior science knowledge is supposed to influence SRL processes directly. We propose the following hypothesis:

H1: Prior science knowledge is positively related to the SRL process of observation.

H2: Prior science knowledge is positively related to the SRL process of formulation.

H3: Prior science knowledge is positively related to the SRL process of reformulation.

H4: Prior science knowledge is positively related to the SRL process of analysis.

H5: Prior science knowledge is positively related to the SRL process of evaluation.

In addition to prior science knowledge, prior design knowledge can also be a significant indicator of SRL processes. In the science of design, design knowledge refers to a collection of visions, proposals, and tools that designers use to stimulate, develop, and implement design ideas (Manzini, 2009). Design knowledge can be stored, retrieved, applied, and reused in different design projects and tasks, indicating that design knowledge is explicit, transferable, and accumulative (Baxter et al., 2007). Design knowledge allows learners to complete a design project thinking about what they are doing and what they will do reflectively. It is expected to significantly influence design processes by helping students reflect and monitor their design projects (Kitamura et al., 2004). All of these attributes of design knowledge reveal the conceptual connections between design knowledge and SRL even though no empirical studies have examined these relationships. Therefore, in conjunction with science knowledge, prior design knowledge is expected to influence SRL processes directly. Accordingly, we propose the following hypotheses:

H6: Prior design knowledge is positively related to the SRL process of observation.

H7: Prior design knowledge is positively related to the SRL process of formulation.

H8: Prior design knowledge is positively related to the SRL process of reformulation.

H9: Prior design knowledge is positively related to the SRL process of analysis.

H10: Prior design knowledge is positively related to the SRL process of evaluation.

SRL cognitive factors

As discussed before, observation, formulation, reformulation, analysis, and evaluation are the five cognitive processes that students may engage in engineering design. These five SRL cognitive processes map the forethought, performance, and self-reflection stages of SRL. Prior studies have shown that SRL processes or strategies can significantly influence learning outcomes, including learning capacity, reading comprehension, clinical performance, and grades (Bernacki et al., 2012; Chen & Huang, 2014; Papamitsiou & Economides, 2019; Sun & Rueda, 2012). SRL processes and strategies also influence learning outcomes where complex science topics are involved. For example, Kalyuga (2007) found students who obtained prompts on using SRL strategies had a more sophisticated understanding of the science content. Instead of simply gaining a collection of science facts, these students improved significantly in learning outcomes, including both content knowledge and the nature of science that they could use in the next round of the task. In a similar vein, it seems that SRL cognitive processes will influence post science knowledge and post design knowledge after students complete engineering design tasks. Therefore, we expect positive relationships between SRL processes and learning outcomes and propose the following hypotheses:

H11: The SRL process of observation is positively related to post science knowledge.

H12: The SRL process of formulation is positively related to post science knowledge.

H13: The SRL process of reformulation is positively related to post science knowledge.

H14: The SRL process of analysis is positively related to post science knowledge.

H15: The SRL process of evaluation is positively related to post science knowledge.

H16: The SRL process of observation is positively related to post design knowledge.

H17: The SRL process of formulation is positively related to post design knowledge.

H18: The SRL process of reformulation is positively related to post design knowledge.

H19: The SRL process of analysis is positively related to post design knowledge.

H20: The SRL process of evaluation is positively related to post design knowledge.

Methods

Research context

This study uses a quantitative design using data gathered from a larger study conducted on Energy 3D, a simulated environment where students can complete home-design projects applying their science and design knowledge (Xie et al., 2018). Energy3D is an open-source software that provides middle and high school students a 3D environment to solve worldwide issues, such as building a house that is environmentally friendly to save energy (http://energy.concord.org/energy3d/). The tools in Energy 3D allow students to design, construct, analyze, and evaluate buildings in real time to modify their design towards the optimal solution.

The participants were 111 ninth-grade students from a suburban high school in the northeastern United States. Three students' data were missing and 108 students are remaining. All the students enrolled in one of five physical science honors classes taught by a teacher who had over 17 years' experience teaching physical sciences and five years' experience mentoring engineering design projects. The age of these students ranged from 14 to 15. Among them, 53 (48.6%) were boys.

The design task consisted of designing a colonial-style zero-energy house that solar panels that would generate enough electricity to offset the consumption of energy throughout a whole year. The living space must come to 120–160 square feet, with ceilings 8–10 feet high, and the cost for materials must not exceed $50,000. Figure 3 shows an example of a student design from different directions. Students completed the task at class meetings on two consecutive days, spending 50 min on the first day and 80 min on the second on their design. Science knowledge and design knowledge of students were tested before and after the design activity using the same measures.

Measures

Science knowledge

Science knowledge was measured in the pre-test and post-test using 18 questions about green building science (Chao et al., 2017). These questions were selected from green building science textbooks (Hens, 2011; Montoya, 2010). Reflecting the focus of the engineering design task, these questions covered four types of domain knowledge, namely sun path and insolation, spatial and geometric, and heat transfer and representations. A panel of green building science experts, high school science teachers, engineering design professors, and learning scientists reviewed each question to ensure the validity of the test. Students answered each question by making a choice among design alternatives of given situations and giving corresponding explanations. Their science knowledge is the sum of their score on each multiple-choice question and its corresponding explanation. Three researchers independently assigned scores for 20% of all the explanations following a 5-level rubric. In this rubric, based on the accuracy and scientific relevancy, all the arguments in the explanations were classified into normative (correct and relevant), alternative (incorrect but relevant, correct but irrelevant), and irrelevant (incorrect and irrelevant). A score ranging from 0 to 4 was then assigned to each explanation based on the number of normative, alternative, and irrelevant arguments. For example, if the explanation contained more than three normative arguments without any alternative ideas, the researcher assigned 4 points. The researcher gave 0 points if students left the question blank or provided explanations with only irrelevant arguments. The inter-rater reliability (ranging from 0.94 to 1) and internal consistency of both pre-test (Cronbach's alpha = 0.82) and post-test (Cronbach's alpha = 0.83) has been established for the measure of science knowledge. More details can be found in our previous work (Chao et al., 2017).

Figure 3. An example of student design (North and East direction on the left; South and West direction on the right).

Design knowledge

Design knowledge was assessed by an instrument developed from analyzing experts' perception of the engineering design process (Mosborg et al., 2005). Participants were asked to select the five most important design activities to accomplish a high-quality design from a list of 20 terms. This list consists of a broad range of terms in design processes models (e.g. evaluating, brainstorming, understanding the problem), general design activities (e.g. sketching, communicating, iterating), and philosophies of design (e.g. using creativity, making trade-offs). Based on the perception of experts in prior research (Mosborg et al., 2005) and the current learning context and importance of SRL, we determined the six most important design activities as analyzing data, evaluating, planning, reflecting, setting goals, and understanding the problem. Students received one point for the number of these six they chose. Design knowledge is the accumulated score of all the most important items students choose.

SRL cognitive factors

Instead of using self-report measures, we used log files to identify the SRL cognitive factors as in our previous studies (Li et al., 2020; Xing et al., 2019; Zheng et al., 2020). The SRL cognitive factors are the five cognitive processes that students may engage in to achieve a final design solution. Specifically, observation, formulation, reformulation, analysis, and evaluation were classified from actions recorded in the log files of Energy3D (see details in Table 1). For example, observation is represented by actions students may take to help them understand the learning environment and task requirement, such as show heliodon, animate sun, and show shadow.

Analysis

PLS modeling was performed to examine the relationship between science knowledge, design knowledge, and SRL processes. PLS is a multivariate statistical modeling technique that integrates multiple regression, path analysis, principal component analysis, and multiple discriminant analysis without the assumption of normality (Chin et al., 2003; Fornell & Bookstein, 1982; Goggins & Xing, 2016). It is particularly suited to this study because of the small sample size and frequency data from log files. By defining exogenous variables and endogenous variables, PLS can analyze the causal order between variables (Xing, 2019) and measure direct, indirect, and mediation effects. In this study, PLS was used to examine how the prior science and design knowledge can affect students' post knowledge in both areas via SRL. Table 2 shows the descriptive statistics of all the variables that will be used for PLS modeling.

Results

The path model results are presented in Figure 4 and Table 3. Figure 2 is a graphical presentation of all direct effects with path coefficients and significance level. Table 2 lists all the hypotheses, path coefficients, z-values, and decisions.

Table 1. Coding scheme of SRL processes.

SRL processes	Definition	Example Actions
Observation	understand the learning environment and task requirement	Show heliodon, Animate sun, Show shadow …
Formulation	construct the project by including components	Add window, Add solar panel Add roof …
Reformulation	change and modify the project to align with the intended design	Edit window, Edit solar panel Edit external factors …
Analysis	derive functional information from the structure	Energy annual analysis, Solar energy analysis, Compute energy …
Evaluation	compare the current structure and function with the intended design to assess if the design solution is acceptable	Making notes

Table 2. Descriptive statistics for the measures.

	Mean	Median	SD
Observation	0.35	0.26	0.26
Formulation	0.27	0.22	0.19
Reformulation	0.26	0.18	0.21
Analysis	0.19	0.12	0.19
Evaluation	0.26	0.21	0.25
Science prior	0.49	0.46	0.21
Design prior	0.50	0.50	0.18
Science post	0.58	0.57	0.20
Design post	0.47	0.50	0.23

Structural models: direct effects

As shown in Figure 4 and Table 3, most of the hypotheses are supported. H1-H5 posit that prior science knowledge impacts the SRL processes. Table 3 shows that H1- H4 are supported. Particularly, prior science knowledge has an effect on observation (ß = 0.36, $p < 0.01$), formulation (ß = 0.20, $p < 0.05$), reformulation (ß = 0.27, $p < 0.01$), analysis (ß = 0.29, $p < 0.01$), meaning that students with higher prior knowledge would be more engaged in these four SRL processes. Surprisingly, H5 is not supported: prior science knowledge does not significantly influence SRL evaluation. With regard to the effect of prior science knowledge on SRL, H6, H8, H9, and H10 are confirmed, while H7 is not confirmed. That is, prior design knowledge significantly influences the observation (ß = 0.30, $p < 0.05$), reformulation (ß = 0.28, $p < 0.05$), analysis (ß = 0.22, $p < 0.05$), and evaluation (ß = 0.38, $p < 0.05$) processes, but not formulation. Students with higher prior design knowledge do not necessarily perform a lot of actions that add components to their design. In contrast, they may be more cautious with every step and more specific as to what they need for a better design.

With respect to the effects of SRL on post science knowledge and post design knowledge (H11 to H20), not all hypotheses are supported. Specifically, reformulation positively affects post science and design knowledge (H13 and H18), indicating that students who are engaged in changing and modifying their projects (i.e. reformulation) are more likely to show an increase in science knowledge (ß = 0.27, $p < 0.01$) and design knowledge (ß = 0.27, $p < 0.01$). Moreover, the positive effect of analysis on

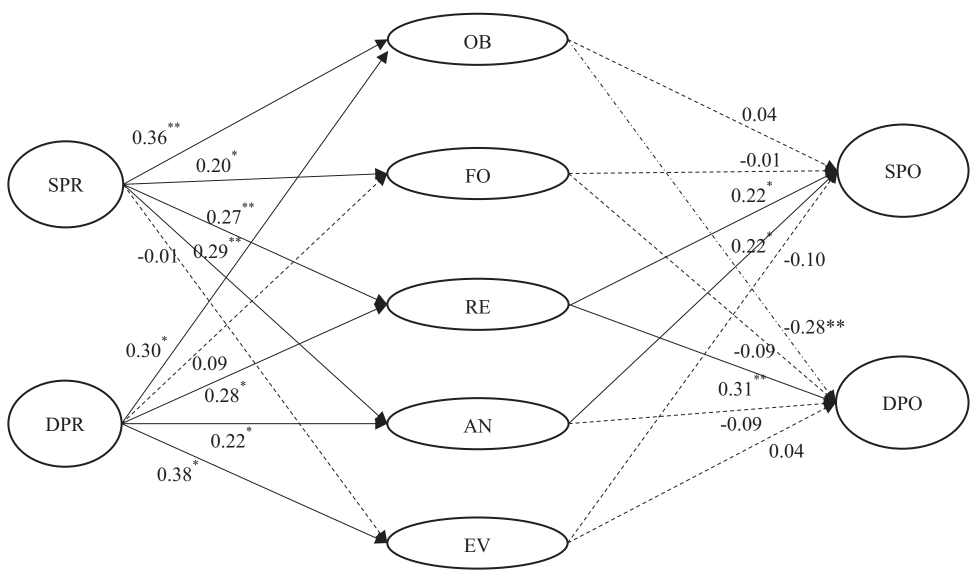

Figure 4. Path analysis results. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. "—" supported, "—" not supported, "--·-" oppositely supported.

Table 3. Hypotheses testing results.

Hypothesis	Path	Path coefficient (ß)	*z*-value	Decision
H1	SPR → OB	0.36**	2.95	Supported
H2	SPR → FO	0.20*	2.21	Supported
H3	SPR → RE	0.27**	2.62	Supported
H4	SPR → AN	0.29**	3.25	Supported
H5	SPR → EV	−0.01	−0.04	Not supported
H6	DPR → OB	0.30*	2.04	Supported
H7	DPR → FO	0.09	0.80	Not supported
H8	DPR → RE	0.28*	2.24	Supported
H9	DPR → AN	0.22*	2.06	Supported
H10	DPR → EV	0.38*	2.55	Supported
H11	OB → SPO	0.04	0.48	Not supported
H12	FO → SPO	−0.01	−0.05	Not supported
H13	RE → SPO	0.22*	2.33	Supported
H14	AN→ SPO	0.22*	2.01	Supported
H15	EV → SPO	−0.10	−1.22	Not supported
H16	OB → DPO	−0.28**	−2.87	Not supported
H17	FO → DPO	−0.09	−0.66	Not supported
H18	RE → DPO	0.31**	2.63	Supported
H19	AN→ DPO	−0.09	−0.66	Not supported
H20	EV → DPO	0.04	0.36	Not supported

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

post science knowledge (ß = 0.22, $p < 0.05$) is also supported (H14). The results do not confirm the remaining hypothesis (H11, H12, H15, H16, H17, H19, and H20). In fact, observation has a negative effect on post design knowledge (ß = −0.28, $p < 0.01$): students who spend a lot of effort on understanding the environment and task (i.e. observation) actually show less post science knowledge.

Structural models: mediating effects

We further examined the mediating effects in this structural model, focusing on how and to what extent SRL mediates the impact of the prior domain knowledge on the post domain knowledge. Following the three-step method established by Baron and Kenny (1986), we identified some significant mediation effects (see Table 4). As indicated in Table 4, prior design knowledge has a significant effect on both reformulation (ß = 0.30, $p < 0.05$) and analysis (ß = 0.24, $p < 0.05$). The link between prior design knowledge and post science knowledge is also significant (ß = 0.24, $p < 0.05$). But the link between prior science and post science knowledge is not significant when reformulation or analysis is added into the model. Therefore, both reformulation and analysis fully mediate the relationship between prior science knowledge and post science knowledge. Furthermore, reformulation and analysis partially mediate the relationship between prior science knowledge and post science knowledge because the relationship between prior science knowledge and post science knowledge is still significant when reformulation or analysis is added (ß = 0.20, $p < 0.05$; ß = 0.21, $p < 0.05$). Furthermore, we find the model does not support some mediating effects. Although the direct link between prior

Table 4. Mediating effect tests' results.

					IV + M → DV		
IV	M	DV	IV → M	IV → DV	IV	M	Mediating effect
SPR	OB	DPO	0.37**	0.03	0.09	−0.16	Not supported
SPR	RE	SPO	0.28**	0.57***	0.51***	0.20*	Partially mediated
SPR	RE	DPO	0.28**	0.03	0.05	−0.07	Not supported
SPR	AN	SPO	0.30**	0.57***	0.51***	0.21*	Partially mediated
DPR	RE	SPO	0.30*	0.24*	0.15	0.31**	Fully mediated
DPR	RE	DPO	0.30*	0.21	0.25	−0.11	Not supported
DPR	AN	SPO	0.24*	0.24*	0.15	0.37**	Fully mediated

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

science knowledge and observation is significant, the link between prior science knowledge and post design knowledge is not. Thus, observation does not mediate the influence of prior science knowledge on post design knowledge. Similarly, reformulation does not mediate the influence of prior science knowledge on post design knowledge, and it does not mediate the effects of prior design knowledge on post design knowledge.

Discussion

The findings on the significant effects of prior domain knowledge on SRL not only reconfirm and remain consistent with prior studies, but also provide new empirical evidence on the benefits of science knowledge and design knowledge. Students with higher prior science knowledge tend to be more engaged in SRL, especially observation, formulation, reformulation, and analysis. This finding supports Moos and Azevedo's (2008) study, which found students with higher prior science knowledge used significantly more planning and monitoring but fewer superficial strategies (e.g. note-taking, summarizing). Students with higher prior science would use their prior knowledge to engage in *knowledge verification*, particularly verifying the discrepancy between what they learn and their existing knowledge (Moos & Azevedo, 2008). Thus, students repetitively observed in order to make plans and monitored their design projects through processes of formulation, reformulation, and analysis. Nevertheless, low prior science knowledge students used their working memory on processing information in knowledge acquisition and therefore had less capacity for self-regulatory processes (Winne, 2001). Contrary to expectations, our path model did not show a relationship between prior science knowledge and evaluation. One possible explanation is that the frequency with which students evaluate their design is more related to their design knowledge, which drives students towards the intended design with efficiency and effectiveness.

As our aforementioned assumption predicted, design knowledge was significantly related to evaluation, as well as observation, reformulation, and analysis. Consistent with the conclusion that students with less prior knowledge used less varied strategies (Murphy & Alexander, 2002), we found less design knowledge lessened students' effort in SRL. Surprisingly, we did not find a significant relationship between design knowledge and formulation, which means that students with higher design knowledge were not necessarily more engaged in designing the house (Mosborg et al., 2005). Given high prior knowledge, they were more specific on what their design would include, spending more time on analyzing and modifying their design. In sum, both prior science knowledge and design knowledge are critical for SRL in engineering design tasks even though they may play a slightly different role in the SRL processes. This supports the call for ensuring students' cross-domain knowledge achieves a certain standard before assigning a complex engineering design project in instructional design.

Not all SRL processes are beneficial for the increase in learning outcomes. Reformulation and analysis are especially critical SRL processes, given their significant effects on post domain knowledge. This is particularly true when both reformulation and analysis were identified as full mediators and partial mediators in the relationship between prior domain knowledge and post domain knowledge. Reformulation and analysis reflect students' high level of thinking in modifying their design and monitoring their learning process. It is important to better scaffold these two processes in computer-based environments to maximize their learning outcomes. For example, prompts telling students how to use a specific reformulation and analysis tool should be added, referring to specific science or design knowledge. This may increase students' initiative to use these tools towards better learning.

Conclusion

The current study expands upon prior research by examining the interactions between science knowledge, design knowledge, and SRL processes in the context of engineering design. This study contributes to the advancement of SRL by theoretically making SRL factors explicit for detailed examination. Specifically, observation, formulation, reformulation, analysis, and evaluation are the key SRL factors that we have externalized following the complex engineering design process. Furthermore, based on this theoretical development, our work demonstrates its methodological strengths by employing data with multiple modalities. This study built a quantitative path model by relying on the combination of self-report measures and behavioral data in computer-based learning environments. This model suggests the significance of SRL as a mediator in engineering design, magnifying the positive effects of prior science knowledge and design knowledge. Our findings further emphasize the importance of fostering SRL adaptively in instructional design and learning environments design.

Although results were consistent with the current literature, the sample size and specific research context limits the generalizability of this study. It would be interesting to replicate this study with a larger sample size. Furthermore, the current study does not include many individual factors (e.g. motivation, personal traits) that might drive the findings. Future studies should include additional variables to better examine how SRL functions in engineering design. Finally, as the significant effects of reformulation and analysis are identified in this current study, an extended study examining the patterns of reformulation and analysis will provide more information about how to better facilitate these SRL processes in engineering design.

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Disclosure statement

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Statements on open data and ethics

The data will be available by individual application directly to the author.

The research was approved by the Ethics Committee of the (omitted for anonymous review).

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References

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Baxter, D., Gao, J., Case, K., Harding, J., Young, B., Cochrane, S., & Dani, S. (2007). An engineering design knowledge reuse methodology using process modelling. *Research in Engineering Design*, *18*(1), 37–48. https://doi.org/10.1007/s00163-007-0028-8

Bernacki, M. L., Byrnes, J. P., & Cromley, J. G. (2012). The effects of achievement goals and self-regulated learning behaviors on reading comprehension in technology-enhanced learning environments. *Contemporary Educational Psychology*, *37*(2), 148–161. https://doi.org/10.1016/j.cedpsych.2011.12.001

Chao, J., Xie, C., Nourian, S., Chen, G., Bailey, S., Goldstein, M. H., Purzer, S., Adams, R. S., & Tutwiler, M. S. (2017). Bridging the design–science gap with tools: Science learning and design behaviors in a simulated environment for engineering design. *Journal of Research in Science Teaching*, *54*(8), 1049–1096. https://doi.org/10.1002/tea.21398

Chen, P. P., & Bembenutty, H. (2018). Calibration of performance and academic delay of gratification: Individual and group differences in self-regulation of learning. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* (pp. 407–420). Routledge.

Chen, C.-M., & Huang, S.-H. (2014). Web-based reading annotation system with an attention-based self-regulated learning mechanism for promoting reading performance. *British Journal of Educational Technology*, *45*(5), 959–980. https://doi.org/10.1111/bjet.12119

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research*, *14*(2), 189–217. https://doi.org/10.1287/isre.14.2.189.16018

Chiu, J. L., Malcolm, P. T., Hecht, D., DeJaegher, C. J., Pan, E. A., Bradley, M., & Burghardt, M. D. (2013). WISEngineering: Supporting precollege engineering design and mathematical understanding. *Computers & Education*, *67*, 142–155. https://doi.org/10.1016/j.compedu.2013.03.009

Crismond, D. P., & Adams, R. S. (2012). The informed design teaching and learning matrix. *Journal of Engineering Education*, *101*(4), 738–797. https://doi.org/10.1002/j.2168-9830.2012.tb01127.x

Dinsmore, D. L., Alexander, P. A., & Loughlin, S. M. (2008). Focusing the conceptual lens on metacognition, self-regulation, and self-regulated learning. *Educational Psychology Review*, *20*(4), 391–409. https://doi.org/10.1007/s10648-008-9083-6

Dochy, F., Segers, M., & Buehl, M. M. (1999). The relation between assessment practices and outcomes of studies: The case of research on prior knowledge. *Review of Educational Research*, *69*(2), 145–186. https://doi.org/10.3102/00346543069002145

Eilam, B., & Reiter, S. (2014). Long-Term self-regulation of biology learning using standard junior high school science curriculum: LONG-TERM SELF-REGULATED BIOLOGY CURRICULUM. *Science Education*, *98*(4), 705–737. https://doi.org/10.1002/sce.21124

Fornell, C., & Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, *19*(4), 440–452. https://doi.org/10.1177/002224378201900406

Goggins, S., & Xing, W. (2016). Building models explaining student participation behavior in asynchronous online discussion. *Computers & Education*, *94*, 241–251. https://doi.org/10.1016/j.compedu.2015.11.002

Greene, J. A., Costa, L.-J., Robertson, J., Pan, Y., & Deekens, V. M. (2010). Exploring relations among college students' prior knowledge, implicit theories of intelligence, and self-regulated learning in a hypermedia environment. *Computers & Education*, *55*(3), 1027–1043. https://doi.org/10.1016/j.compedu.2010.04.013

Hens, H. (2011). *Applied building physics*. Ernst & Sohn.

Hou, H.-T. (2013). Analyzing the behavioral differences between students of different genders, prior knowledge and learning performance with an educational MMORPG: A longitudinal case study in an elementary school. *British Journal of Educational Technology*, *44*(3), E85–E89. https://doi.org/10.1111/j.1467-8535.2012.01367.x

Kalyuga, S. (2007). Expertise reversal effect and Its implications for learner-tailored instruction. *Educational Psychology Review*, *19*(4), 509–539. https://doi.org/10.1007/s10648-007-9054-3

Karabulut-Ilgu, A., Cherrez, N. J., & Jahren, C. T. (2018). A systematic review of research on the flipped learning method in engineering education. *British Journal of Educational Technology*, *49*(3), 398–411. https://doi.org/10.1111/bjet.12548

Kitamura, Y., Kashiwase, M., Fuse, M., & Mizoguchi, R. (2004). Deployment of an ontological framework of functional design knowledge. *Advanced Engineering Informatics*, *18*(2), 115–127. https://doi.org/10.1016/j.aei.2004.09.002

Lajoie, S. P., Poitras, E. G., Doleck, T., & Jarrell, A. (2015). Modeling metacognitive activities in medical problem-solving with BioWorld. In A. Peña-Ayala (Ed.), *Metacognition: Fundaments, applications, and trends: A profile of the current state-of-the-art* (pp. 323–343). Springer.

Li, S., Chen, G., Xing, W., Zheng, J., & Xie, C. (2020). Longitudinal clustering of students' self-regulated learning behaviors in engineering design. *Computers & Education*, *153*, 103899. https://doi.org/10.1016/j.compedu.2020.103899

Manzini, E. (2009). New design knowledge. *Design Studies*, *30*(1), 4–12. https://doi.org/10.1016/j.destud.2008.10.001

Montoya, M. (2010). *Green building fundamentals: A practical guide to understanding and applying fundamental sustainable construction practices and the LEED green building rating system*. Prentice Hall.

Moos, D. C., & Azevedo, R. (2008). Self-regulated learning with hypermedia: The role of prior domain knowledge. *Contemporary Educational Psychology*, *33*(2), 270–298. https://doi.org/10.1016/j.cedpsych.2007.03.001

Mosborg, S., Adams, R., Turns, J., Atman, C., Kim, R., & Cardella, M. (2005). *Conceptions of the engineering design process: An expert study of advanced practicing professionals*. 27.

Murphy, P. K., & Alexander, P. A. (2002). What counts? The predictive powers of subject-matter knowledge, Strategic processing, and interest in domain-specific performance. *The Journal of Experimental Education*, *70*(3), 197–214. https://doi.org/10.1080/00220970209599506

National Research Council. (2009). *Engineering in K-12 education: Understanding the status and improving the prospects*. National Academies Press.

Papamitsiou, Z., & Economides, A. A. (2019). Exploring autonomous learning capacity from a self-regulated learning perspective using learning analytics. *British Journal of Educational Technology*, *50*(6), 3138–3155. https://doi.org/10.1111/bjet.12747

Song, H. S., Kalet, A. L., & Plass, J. L. (2016). Interplay of prior knowledge, self-regulation and motivation in complex multimedia learning environments. *Journal of Computer Assisted Learning*, *32*(1), 31–50. https://doi.org/10.1111/jcal.12117

Sun, J. C.-Y., & Rueda, R. (2012). Situational interest, computer self-efficacy and self-regulation: Their impact on student engagement in distance education. *British Journal of Educational Technology*, *43*(2), 191–204. https://doi.org/10.1111/j.1467-8535.2010.01157.x

Taub, M., Azevedo, R., Bouchet, F., & Khosravifar, B. (2014). Can the use of cognitive and metacognitive self-regulated learning strategies be predicted by learners' levels of prior knowledge in hypermedia-learning environments? *Computers in Human Behavior*, *39*, 356–367. https://doi.org/10.1016/j.chb.2014.07.018

Winne, P. H. (2001). Self-regulated learning viewed from models of information processing. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives* (pp. 153–189). Lawrence Erlbaum Associates Publishers.

Winne, P. H., & Azevedo, R. (2014). Metacognition. *The cambridge handbook of the learning sciences*, *2014, ISBN 978-1-107-62657-7, págs. 63-87*, 63–87. https://dialnet.unirioja.es/servlet/articulo?codigo=5193709

Xie, C., Schimpf, C., Chao, J., Nourian, S., & Massicotte, J. (2018). Learning and teaching engineering design through modeling and simulation on a CAD platform. *Computer Applications in Engineering Education*, *26*(4), 824–840. https://doi.org/10.1002/cae.21920

Xing, W. (2019). Large-scale path modeling of remixing to computational thinking. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2019.1573199

Xing, W., Pei, B., Li, S., Chen, G., & Xie, C. (2019). Using learning analytics to support students' engineering design: The angle of prediction. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2019.1680391

Zheng, J., Xing, W., Zhu, G., Chen, G., Zhao, H., & Xie, C. (2020). Profiling self-regulation behaviors in STEM learning of engineering design. *Computers & Education*, *143*, 103669. https://doi.org/10.1016/j.compedu.2019.103669

Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist*, *25*(1), 3–17. https://doi.org/10.1207/s15326985ep2501

Zimmerman, B. J. (2013). From cognitive modeling to self-regulation: A social cognitive career path. *Educational Psychologist*, *48*(3), 135–147. https://doi.org/10.1080/00461520.2013.794676