

# Task Interpretation, Cognitive, and Metacognitive Strategies of Higher and Lower Performers in an Engineering Design Project: An Exploratory Study of College Freshmen\*

OENARDI LAWANTO

Department of Engineering Education, Utah State University, Logan, UT 84322, USA. E-mail: olawanto@usu.edu

DEBORAH BUTLER

Department of Educational and Counseling Psychology, and Special Education, University of British Columbia, Vancouver, BC V6T 1Z4, CA. E-mail: deborah.butler@ubc.ca

SYLVIE CARTIER

Department of Psychopedagogy and Andragogy, University de Montreal, Montréal (Québec) H2V 2S9, CA.  
E-mail: sylvie.cartier@umontreal.ca

HARRY B. SANTOSO

Department of Engineering Education, Utah State University, Logan, UT 84322, USA. E-mail: harry.santoso@aggiemail.usu.edu

WADE GOODRIDGE

Department of Engineering Education, Utah State University, Logan, UT 84322, USA. E-mail: wade.goodridge@usu.edu

This paper examines the task interpretation and strategy use of higher- and lower-performing college freshmen while engaged in an engineering design project using a self-regulated learning (SRL) framework. Our goals were to consider how students' interpretation of task demands could be associated with their use of planning, cognitive, and monitoring/fix-up strategies, both as part of the design process and when managing their time, resources and teamwork. The main research question that guided the study was: In what ways did higher- vs. lower-performing students differ when engaged in an engineering design project? With regards to this question, we specifically explored how these two groups of students were similar or different in their: (1) task interpretation in relation to reported strategy use during the design process; and (2) task interpretation in relation to reported strategy use in project management. Seventy freshman engineering students enrolled in an introductory engineering design course at Utah State University were recruited for the study. From among that group, data from 20 higher- and 12 lower-performers were selected for analysis. Survey instruments and Web-based design journal entries were used to capture students' task interpretation, reported strategy use, including planning (PS), cognitive (CS), and monitoring/fix-up strategies (MF), and perceptions of important performance criteria (CR). Students' design performance was evaluated by the teacher. Descriptive and nonparametric statistics and graphical views were used to analyze student SRL profiles. Entries from students' design journals were coded using an SRL model and interpreted to triangulate and complement survey data to achieve deeper insight about SRL between the two groups. The findings suggested that both higher- and lower-performers were highly aware of important task requirements. However, higher-performing students had a greater awareness and reported greater use of monitoring and fix-up strategies associated with success in the design process. The higher-performing students also obtained higher scores on criteria for performance than lower-performing students, both in the design process and project management. Furthermore, journal writings revealed that higher performers were more thorough in identifying and describing design requirements and strategies for their projects than were the lower performers. This paper discusses the potential implication for design instruction in engineering college freshmen.

**Keywords:** cognitive strategies; college freshmen; engineering design; metacognition; self-regulated learning; task interpretation

## 1. Introduction

Self-regulated learning (SRL) is a significant predictor of academic performance. According to Zimmerman, self-regulated learning refers to students' "self-generated thoughts, feelings, and actions which are systematically oriented toward attainment of their goals" [1, p. ix]. SRL can be

defined essentially as a form of iterative, goal-directed activity that involves interpreting tasks, setting goals, selecting, adapting or even inventing strategies that are effective for achieving those goals, monitoring progress, and adjusting approaches as needed [2]. Effective SRL is invited by and particularly critical in complex or ill-structured tasks, such as engineering design [3–5]. Zimmerman argued

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that self-regulated learners are “metacognitively, motivationally, and behaviorally active participants in their own learning process” [6, p. 308].

Design is recognized as the critical element of engineering thinking [7]. While engaged in engineering design activities, students must identify demands, then plan, act, evaluate, and make necessary adjustments at multiple phases of the design process. These are processes associated with “metacognitive” control, or self-regulation, of cognitive activity. Moreover, Christiaans and Venselaar noted that applying metacognition leads to students’ ability to generate creative design solutions [8]. A student with good metacognitive knowledge, skills and awareness is better able to oversee his or her own learning process, plan and monitor ongoing cognitive activities, and compare cognitive outcomes with internal or external standards [9]. Finally, metacognition is not only essential in working through design processes (i.e., managing cognitive processes needed to work through a design task), but it is also heavily implicated in design project management, which requires building a good teamwork environment and managing resources (e.g., money, materials) and time.

Emerging evidence suggests, however, that students’ metacognitive skills may not be up to the level needed to navigate design activities successfully. For example, a recently completed STEM Talent Expansion Program (STEP) project, conducted in first-year engineering courses at Texas A&M University (TAMU), found gaps in students’ abilities to manage learning and problem solving [10]. Thus, the purpose of this exploratory study was to further advance understanding about how differences in metacognition might be related to higher- or lower-performance in engineering design activities. Building on emerging research, we focused specifically on how higher- and lower-achieving students differed in their interpretations of the requirements of design tasks and reported use of cognitive and self-regulating (i.e., metacognitive) strategies.

## 2. Relevant literatures

### 2.1 Metacognition in a self-regulated learning framework

Metacognition, which is defined as ‘thinking about thinking’ [11], plays a significant role in design performance. But, while metacognition in academic performance has been studied extensively, particularly in the areas of writing [12, 13], mathematics [14], and study strategies as a function of testing [15], few studies have comprehensively evaluated metacognition in the context of engineering design activities.

From cognitive perspective, metacognition has been associated with cognitive processes. The difference between cognition and metacognition is based upon functionality. While cognition concerns one’s ability to build knowledge, process information, acquire knowledge, and solve problems, metacognition concerns the ability to control the working of cognition to ensure that the goals have been achieved or the problem has been solved (e.g., [9]). Metacognitive activity usually precedes and follows cognitive activity.

Informed by the classical theories of metacognitive knowledge and experience introduced by Flavell [11], some researchers explain metacognition as encompassing two major components. For example, Baker [16] and Pintrich [17] divided metacognition into metacognitive knowledge and metacognitive control. Brown [18] explained that metacognition can be distinguished between knowledge about cognition and regulation. For example, students hold metacognitive knowledge about strategies that might be used for a particular task and the conditions under which the strategies might be useful. Metacognitive regulation is a process that learners use to adjust cognition through certain activities.

Researchers have maintained that the important issue in metacognition and SRL is to understand “the correspondence between metacognition and action. How do thoughts and feelings of learners guide their thinking, effort, and behavior?” [19, p. 21]. While many theoretical perspectives on metacognition and self-regulation have been offered (e.g., see [20–23]), for this research we chose to build from Butler and Cartier’s socio-constructivist model of self-regulation (see [24, 25]) because it allows for investigation into the interplay between metacognitive knowledge (e.g., students’ understandings about tasks and strategies, as mediating variables), and metacognitive skills, conceptualized as cycles of “self-regulation in action,” within the context of complex learning activity. This model involves eight central features that interact with each other to shape engagement in learning: *layers of context, what individuals bring, mediating variables, task interpretation, personal objectives, SRL processes, cognitive strategies, and performance criteria*. These features are combined into SRL phases that are a sequence of processes that capture students’ activities in completing an engineering design project.

In this study, we examined SRL episodes as that they were clustered into two dimensions of an engineering design project: as part of the design process (i.e., engaging in the work of engineering design) and project management (i.e., planning time, resources, teamwork). Following Butler and

Cartier's model, we considered that *layers of context* for engineering design and project management may include the learning environments such as school, classroom, teachers, instructional approaches, curricula, and learning activities. Recognizing the ways in which multiple interlocking contexts shape student engagement in learning is essential for understanding SRL.

The second feature involves *what individuals bring* to the context, including factors such as student strengths, challenges, interests, and preferences. Over time, students accumulate a learning history that shapes their development of knowledge and skills, self-perceptions, attitudes toward school, and concepts about academic work [14, 24, 25]. Third, students' SRL is shaped by *mediating variables, such as* knowledge, perceptions of competence and control over learning, and perceptions about the value of activities and tasks. These mediating variables also include emotions experienced before, during, and after completing a task. This study, while recognizing the importance of these components of the Butler and Cartier framework, did not focus our attention as centrally on these aspects as we have in prior research (e.g., see [26]).

The focus of attention in this study was on the fourth feature in this Butler and Cartier framework, namely *task interpretation*. Recognized as the heart of the SRL model, task interpretation shapes key dynamic and recursive self-regulating processes [20]. When confronted with academic work, students draw on information available in the environment, and on knowledge, concepts, and perceptions derived from prior learning experiences, to interpret the demands of a task [24, 25, 27] and identify important *criteria for judging performance*. Students' interpretation of task demands is a key determinant of the objectives set while learning, the strategies selected to achieve those objectives, and the criteria used to self-assess and evaluate outcomes [20, 24, 25]. Pintrich also emphasized the importance of goal setting that shapes learning activity as he defined self-regulation as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior. . ." [28, p. 453]. Thus, in this study, we were centrally concerned with how students' interpretations of tasks could be related to their selection of productive strategies for learning. We also recognized that students set *personal objectives*, such as achieving task expectations that will impact their direction for engaging or not engaging in learning. When a student effectively and consciously attempts to self regulate learning during a design task, task interpretation and personal objectives will continually reinforce each other, essentially activating a

greater depth of self-regulation and cognitive strategy employment.

Our theoretical framework suggests that, in light of their interpretations of task and personal objectives, students manage their engagement in academic work, including their selection of *cognitive strategies* for completing tasks, by using a variety of *self-regulating strategies*, including the planning, monitoring, and fix-up strategies focused on in this research. Ideally, students plan how to use available resources, select strategies to achieve task demands, self-monitor progress, and adjust goals, plans, or strategies based upon self-perceptions of progress or feedback and performance. These strategies are iterative and dynamic endeavors.

Self-regulated learning (SRL) is particularly necessary in the context of complex and ill-structured activity (i.e., problem solving), as is the case in an engineering design project. Previous studies revealed the essential role of SRL skills in mathematics and physics problem solving (e.g., [14, 29, 30]). Educators also fostered the use of the skills in the technology education field [31]. Although research suggested that exercising and using SRL skills can improve student learning, it is not yet clear how students use their understanding of task demand and cognitive and metacognitive strategies in an engineering design project. Thus, the focus of this paper is to explore differences in SRL for higher- and lower-performing students. More specifically, in the context of this research, we focused on how, for each group, the interpretation of task requirements in an engineering design project was reflected in their working plans and the reported use of planning, cognitive and monitoring/fix-up strategies and what they considered to be a good design performance.

## 2.2 Engineering design process and project management

Findings from previous studies suggested that metacognitive skills are essential in solving engineering design projects because of the nature and complexity of the design processes [3–5]. The ways in which students use strategies, observe what happens, and search for alternative solutions are examples of how metacognition is applied during these phases of the design process.

Engaging in an engineering design project is a structured and staged process. Dym and Little [32] contend that the design process consists of five phases: (1) defining the scope of the design problem, (2) creating a conceptual design, (3) creating a preliminary design, (4) creating a detailed design, and (5) documenting the design process. A similar model was proposed by Christiaans [33] and Cross

[34]. These design phases are considered high-level overall views of design processes. They involve a sequence of actions or design strategies, which are self-contained cognitive approaches and relate to the current state of the design process. For example, during a problem definition phase, students may need to analyze what their design problem entails. The problem may then be divided into several subsets, each of which may also need to be analyzed and evaluated. After clearly understanding the problem, they may be ready to propose a solution, analyze it, and decide whether to use it or find alternatives.

In this study, we focused on the first two of Dym and Little's [32] design phases: problem definition and conceptual design. These two phases were selected because students' success in understanding the objectives of the project and how they conceptually define and solve a design problem significantly impacts the remaining three design phases. Dym and Little [32] divided each of these phases into several sub-phases. The problem definition phase, for example, consists of four sub-phases: clarifying objectives, establishing metrics for objectives, identifying constraints, and revising a client's problem statement. Because students worked on their teacher's assigned design task as part of the course requirement, they were given no option to change or revise any part of it. As a result, we focused attention in this research on the first three sub-phases from the problem definition design phase. The second phase, conceptual design, involves six sub-phases: establishing functions, requirements, and means for functions, generating design alternatives, refining and applying metrics to design alternatives, and choosing a design solution. In sum, we investigated students' SRL as they engaged in the first two phases (and sub-phases) of engineering design processes as identified in the Dym and Little [32] model.

Metacognition and self-regulation may also be essential to the project management central in engineering design performance. Successful team design projects depend on the project management skills of each team member [35]. The Program Management Institute defines project management as "the application of knowledge, skills, tools, and techniques to project activities in order to meet or exceed stakeholder needs and expectations from a project" [36, p. 6]. While design processes involve attention to the technical requirements of a design project (e.g., What does the robot have to do? How do we design that?), project management in this study referred to managing the project as a whole (i.e., How much time do we have to solve this design problem? What resources do we need?).

Various studies have been conducted to evaluate

management of time, resources, and teamwork. For example, a study conducted by Bogus *et al.* suggested that a concurrent engineering approach can be applied to reduce time for completing a design project [37]. Lessard and Lessard outlined skills such as technical knowledge, creativity, people skills, planning ability, and management skills as an essential ingredient of an effective engineering team [38]. In this study, we also considered how SRL was implicated, not only in the design processes, but also in how the students managed the overall design project (i.e., time, resources, and teams).

### 3. The study

In this study, we employed two complementary methods to assess students' SRL: a questionnaire and student design journal entries. Butler and Cartier's SRL model [24, 25] was used to evaluate the dynamic and iterative interplay between self-regulating and cognitive strategies that occurred during design processes and managing the design project. The main research question that guided the study was: In what ways did higher- vs. lower-performing students differ when engaged in an engineering design project? With regards to this question, we specifically explored how these two groups of students were similar or different (1) in their task interpretation in relation to strategy use during the design process; and (2) in their task interpretation in relation to strategy use in project management.

#### 3.1 Participants

Participants were freshman engineering students in an introductory engineering graphics course at Utah State University (USU). Student participation was voluntary. Seventy students were recruited as participants, a subsample of which was selected to form groups of higher- and lower-performing students. Specifically, based on the students' project grades that reflected their design performance, it was found that the average ( $M$ ) was 84.1 (out of 100 maximum points) with a standard deviation ( $SD$ ) of 8.3 (i.e., a grade of B). Criteria included the demonstration of a successful robot design within the solid modeling software in addition to a clear solution evolution captured within journal entries. Evaluation of the design focused on feasible part development, part interaction and assembly functionality, and the final solution's adherence to specific design requirements. A 0.5  $SD$  was used to determine the cut-off values of the lower- and higher-performing student groups. Thus, those who earned less than or equal to  $(M - \frac{1}{2}SD)$  and more than or equal to  $(M + \frac{1}{2}SD)$  were considered lower- and higher-performing students, respectively. A similar approach of

using mean and standard deviation as criteria to define high and low performers has been used in other studies, such as a study on neuropsychological evaluation [39] and procurement mastery [40]. By employing 0.5 *SD*, we could differentiate between design performance distinctly enough and also have enough sample size for the two groups. The range of the actual scores for the lower-performing group was between 53.0 and 79.5 (i.e., grades of C+ or below), and for the higher-performing group was between 89.5 and 95.0 (i.e., grades of A– or above). Twelve (1 female and 11 males) and 20 (1 female and 19 males) students were in lower- and higher-performing groups, respectively. Female presence within the class used in this study is typically below 10%.

### 3.2 Context and design projects

The course in which participants were enrolled is required in the pre-professional mechanical engineering program at USU. In this course, the students use solid modeling software to develop and model a variety of objects. Lessons begin with simple extrusion and revolution exercises, continuing into the development of assembly parts, and finally focusing on relating multiple parts into complex assemblies. Emphasis is also given to document generation, dimensioning based on ANSI and ISO standards, and an introduction to Geometric Dimensioning and Tolerancing. The class then culminates with an introduction to finite element analysis upon both parts and assemblies.

The course delivered a curriculum that emphasized open-ended and ill-structured design projects as a capstone activity worth 20% of the students' course grade. Students began the semester learning how to use the software competently and then engaged in a design project requiring the development of a manufacturing robot within a solid modeling software package. Students were allotted 4 weeks to complete the design project and were required to track their design progress through weekly journal entries answering three primer questions about their design activity and progress. The main focus of the activity was towards the gripper and arm components of the robotic arm. The design of the gripper required versatility in its application around two distinct assembly line products without requiring a change in the gripper mechanism. Students were initially given a theoretical background or setting for the design requiring it to be implemented in an assembly line scenario.

Designs were mitigated by a provided set of constraints that were typical of those implemented in industry in which a design must accommodate a particular working environment or cost. Constraints included width and depth dimensions of

the robotic arm for both operating and resting scenarios, the type of actuators available for use (in the form of a supplied pneumatic actuator catalog), and general material parameters such as cross sections, types of materials, etc. from which the robotic arm should be created. The latter constraints forced student to ground their solutions upon feasible and realistic supplies and components. Students were encouraged to test and monitor the interaction of parts throughout their design process and verify the interaction of parts on the completed assembly, ensuring the solution's viability. Full motion was initiated through the application and simulation of modeled motors applied to appropriate locations on the robotic solution.

Solutions were assessed by the instructor based on adherence to design constraints, successful modeling of the robotic arm and journal entries of the design process exhibiting not only written entries but also *jpeg* images of the different stages of the design. Design constraints include: the gripper design accommodating two separate part geometries, the work envelope width and depth, the design being pneumatically actuated, the use of the proper fasteners, and the use of appropriate attachments. The *jpeg* images required with journal entries provided physical evidence that the work was actually completed. Journal entry dates and times were also automatically logged. Robotic arm demonstration was accomplished through an inspection of the solution by the instructor as well as a student demonstration and the recording of *avi* files demonstrating movement of the robotic arm. Journal entries comprised 22% of the design grade, while 78% was based on successfully meeting the design objectives. Students were given no training in self-regulating or cognitive strategies prior to the design activity.

### 3.3 Design journals

A first source of data collected for this project was students' journal entries. Journal entries were created as students engaged in the design project, and provided evidence, not only of the quality of the design outcomes, as judged by their instructor, but also of how students actually engaged in the design processes and project management. For purposes of this study, students' journal entries were examined for evidence of task interpretation and strategy use. Students wrote their journal entries on a weekly schedule and submitted them through the course's BlackBoard™ system, which allowed the instructor to verify the date of the weekly journal submissions.

### 3.4 Self-regulated learning survey: Engineering Design Questionnaires (EDQ)

In this study, we used the three subsections of the

**Table 1.** SRL features and examples in the context of defining the design project

Features	Examples of design process	Examples of project management
<u>Task Interpretation</u> When I am asked to work on a design task like the one I am about to solve, I am being asked to. . .	<ul style="list-style-type: none"> <li>• Get a good overview of the design objectives.</li> <li>• Comply with the design requirements or specifications.</li> </ul>	<ul style="list-style-type: none"> <li>• Manage the time available to me.</li> <li>• Seek the resources (e.g., materials, information, skills, knowledge of procedure, money) needed.</li> <li>• Work in a team effectively.</li> </ul>
<u>Planning Strategies</u> Before I begin to work on the design task, I. . .	<ul style="list-style-type: none"> <li>• List ways to identify design objectives.</li> <li>• Identify and understand the design requirements or specifications.</li> <li>•</li> </ul>	<ul style="list-style-type: none"> <li>• Plan my time to complete my design work.</li> <li>• Plan what resources (e.g., materials, tools, information, skills, knowledge of procedure, money) I need.</li> <li>• Figure out how my team will tackle or engage this project.</li> </ul>
<u>Cognitive Strategies</u> When working on this kind of design task, I am. . .	<ul style="list-style-type: none"> <li>• Reading the design description (or brief).</li> <li>• Specifying values for features (or attributes) of the designed object.</li> <li>•</li> </ul>	<ul style="list-style-type: none"> <li>• Considering how long each part of the design activity will take.</li> <li>• Searching, selecting, and using working materials/tools I need.</li> <li>• Brainstorming with my teammates to clarify and generate ideas as well as to develop solutions.</li> </ul>
<u>Monitoring/Fix-Up Strategies</u> During my work on my design task, I. . .	<ul style="list-style-type: none"> <li>• Look back at the design description (or brief).</li> <li>• Verifying whether I considered the design requirements or specifications.</li> </ul>	<ul style="list-style-type: none"> <li>• Thinking about how much time is left and what I still have to do.</li> <li>• Asking myself if I have found, selected, and used the materials/tools effectively.</li> <li>• Asking myself if I have actively participated in this group's activity (e.g., meetings, discussion, or brainstorming).</li> </ul>
<u>Criteria for Performance</u> At the end of this design task, I know that I have done a good job when I was able to. . .	<ul style="list-style-type: none"> <li>• Evaluate whether a good understanding of the design objectives was achieved.</li> <li>• Comply with the design requirements or specifications.</li> <li>•</li> </ul>	<ul style="list-style-type: none"> <li>• Finished my design task on time.</li> <li>• Have found and used the resources (e.g., materials, information, skills, knowledge of procedure, money) available well.</li> <li>• Play my role and complete my tasks in a team effectively.</li> </ul>

Engineering Design Questionnaire (EDQ) to collect data on how students thought about themselves and their engagement in engineering design activities, at the early, middle, and final stage of the project, respectively. This questionnaire was adapted from Butler and Cartier's Inquiry Learning Questionnaire (ILQ) and based on their theoretical model [24, 25].

Each subsection of the EDQ is designed to capture the main features of the Butler and Cartier SRL model (see Table 1 for a sample of the survey items): the first subsection assesses students' task interpretation and reported use of planning strategies; the second subsection captures students' reported use of cognitive strategies as well as monitoring/fix-up strategies; the third subsection captures students' understanding of the criteria of good design process and outcomes. Measurement scales of EDQ items ranged from 1 to 4 (i.e., 1 = almost never, 2 = sometimes, 3 = often, and 4 = almost always). Some EDQ items were negatively worded and the ratings were reversed before an individual's

score was computed. If an item had to be reversed, a person who chose 4 for that item now received a score of 1.

The EDQ was developed, pilot-tested, and used in previous research [4, 41] to capture the relationships among the main features (i.e., task interpretation, strategies, and criteria) of the SRL model for secondary and postsecondary students engaged in the design project. An exploratory factor analysis was conducted to identify the internal reliability of EDQ constructs. Table 2 shows that dimensions targeted in this study had very high Cronbach's Alpha scores.

### 3.5 Data collection procedure and analysis

Data from the EDQ were collected through Qualtrics<sup>TM</sup>, an online survey media, three times throughout the project time: at the early (i.e., first day of the project), middle (i.e., at the end of the third week), and final stages (i.e., the last day of the fourth week). Students' design journal entries were regularly collected online during the 4-week time

**Table 2.** Internal reliability scores of EDQ constructs

General category	Dimensions	No. of items	Cronbach's alpha
Task understanding Self-regulating strategies	Task Interpretation ( <i>TI</i> )	9	0.80
	Planning Strategies ( <i>PS</i> )	9	0.77
	Monitoring/Fix-up Strategies ( <i>MF</i> )	20	0.91
Cognitive Strategies	Cognitive Strategies ( <i>CS</i> )	25	0.91
	Criteria for Performance ( <i>CR</i> )	9	0.88

period of the project. Anytime that the students worked on their design project (i.e., during class time or outside of class), they were asked to write and submit a journal entry using a discussion forum in BlackBoard™ system. Students were required to write and submit at least one entry per week.

To analyze data from the EDQ, mean scores were calculated for task interpretation (*TI*), reported use of planning (*PS*), cognitive (*CS*), and monitoring/fix-up (*MF*) strategies, and perceptions of performance criteria (*CR*): (1) for design processes (for each of the two first phases in Dym and Little's [32] model and associated sub-phases, as described earlier), and (2) for project management (overall, and for time, resources and teamwork, separately). Given the small sample size and exploratory nature of the project, nonparametric statistics (i.e., Mann–Whitney U and Wilcoxon tests) were used to test differences. Further, because we anticipated higher mean scores for higher-performing students, we relaxed cut-offs for judging statistical significance to one-tailed values.

Qualitative data collected from students' design journals were first categorized according to the SRL features and coded using Dym and Little's [32] prescriptive model. Inter-rater reliability to evaluate the degree of agreement among two research assistants in segmenting, coding, and counting SRL features of students' journal entries was conducted. Specifically for the segmentation process, one journal entry written by the student to answer one journal prompt could be identified as one segment or more than one segment. A segment can be defined as a journal entry statement that represents an SRL component in a design sub-phase. Inter-rater reliability was at acceptable levels both for segmenting (90% agreement) and coding (94% agreement). Any disagreements between raters were reconciled before calculating their frequencies.

## 4. Findings

To answer our main research question involving identifying the differences in SRL profiles of higher- and lower-performing students, we focus on the relationship between task interpretation and strategy use. Here the findings are organized into two

sections: design process and project management. The design process section includes a report on SRL during problem definition and conceptual design. The project management section reports on SRL in time, resource, and team management.

### 4.1 Task interpretation and strategy use in the design process

In this section we report findings on the levels and quality of task interpretation (*TI*), reported use of planning (*PS*), cognitive (*CS*), and monitoring/fix-up (*MF*) strategies, and perceptions of performance criteria (*CR*) for higher- and lower-performing students as they engaged in the first two of Dym and Little's [32] design phases (and associated sub-phases). Drawing on findings from both the EDQ and design journals, we first compared the level and quality of each SRL feature across the two groups of students (e.g., *TI* for higher- vs. lower-performing students). Next, in order to trace how SRL features were connected within SRL episodes, we examined relationships among SRL features for each group of students (e.g., how levels of task interpretation could be related to use of planning, cognitive, or monitoring/fix-up strategies).

#### 4.1.1 Comparing the level and quality of SRL features across the groups of students

First, Table 3 presents the mean scores from EDQ for both groups on each SRL feature, combined across the first two phases of the design process. The statistical reliability of the comparisons between groups found by conducting Mann–Whitney tests (one-tailed) has been provided. Taken together, mean comparisons and reliability tests on the EDQ suggested that both higher- and lower-performing students did a good job in interpreting the task (*TI*) that they would expect to encounter during the design process (means of 3.52 and 3.48, respectively). Each group also reported similar levels of planning (means of 3.18 and 3.19, respectively). Higher-performing students appeared to be more likely to report using cognitive strategies than their lower-performing peers (means of 3.00 and 2.79, respectively), but this difference was not statistically reliable. Statistically-reliable group differences were found in monitoring/fix-up strategies (*MF*) and

**Table 3.** Comparison of mean SRL scores for higher- and lower-performing students (design process)

SRL feature	Higher-performing students <i>M</i> ( <i>SD</i> )	Lower-performing students <i>M</i> ( <i>SD</i> )
Task Interpretation ( <i>TI</i> )	3.52 (0.36)	3.48 (0.42)
Planning Strategies ( <i>PS</i> )	3.18 (0.45)	3.19 (0.36)
Cognitive Strategies ( <i>CS</i> )	3.00 (0.46)	2.79 (0.25)
Monitoring/Fix-up Strategies ( <i>MF</i> ) <sup>a</sup>	3.18 (0.45)	2.92 (0.30)
Criteria for Performance ( <i>CR</i> ) <sup>a</sup>	3.40 (0.45)	2.94 (0.59)

Note: <sup>a</sup> Significant at 0.05 level (one-tailed).

interpreting important performance criteria (*CR*), where higher-performing students' ratings were significantly higher than were those of lower-performing students (*MF*: means of 3.18 and 2.92, respectively) and (*CR*: means of 3.40 and 2.94, respectively). Significant differences ( $p < 0.05$ ) were found in *MF*, particularly during design metrics and design requirement sub-phases and in *CR* during design metrics, design constraints, design requirements, design means, design alternative, and design selection sub-phases.

While differences between higher- and lower-performing students were not consistently pronounced in the EDQ findings, analysis of journal writings across the two design phases revealed important differences in the level and quality of task interpretation and reported strategy use between the two groups of students. For example, journal writings showed important differences between higher- and lower-performing students in terms of number of entries ( $\chi^2 = 45.881$ ,  $df = 1$ ,  $p < 0.001$ ) and words per entry ( $\chi^2 = 56.720$ ,  $df = 1$ ,  $p < 0.001$ ) in which SRL processes were implicated (see Table 4). This suggests that the level of SRL for higher-performing students outpaced that of their lower-performing peers.

For example, overall higher-performing students mentioned SRL-related features more often in journals than did their lower-performing peers (i.e., 22.25 vs. 5.84 total segments per student, respectively). Detailed information about number of segments per student can be found in Table 5. We found from Chi-square tests that the difference in the total number of segments per student between both groups was significant ( $\chi^2 = 33.640$ ,  $df = 1$ ,  $p = 0.000$ ). Furthermore, analysis of journal entries found that higher-performing students provided a greater number of deep, thorough, and explicit journal entry segments than did lower-performing students (see Table 5). Chi-square tests indicated that there was a significance difference between groups in the number of deep, thorough, and explicit

journal segments ( $\chi^2 = 10.889$ ,  $df = 1$ ,  $p = 0.001$ ) for the design process.

For example, while both groups may have been able to recognize the key demands of design tasks, as represented in EDQ *TI* data, consistent with superior EDQ *CR* scores (reflecting a nuanced understanding of important performance criteria), journals of higher-performing students suggested that they engaged in a more thorough analysis of task demands. Consider, for example, the excerpts below that were drawn from the writing samples on *TI* of higher- and lower-performing students:

As I currently understand it, the design task is to create the arm so that it will rotate at least 90 degrees. The gripper also needs to be able to pick up and move a golf ball or pencil. Both of these parts of the robot must be able to attach to the slider on the provided part. (*Task Interpretation of higher-performing student—Design Objectives*)

My current understanding is that we are supposed to use the skills we've learned in solid edge, and apply them to creating a robotic arm. (*Task Interpretation of lower-performing student—Design Objectives*)

In this class, the explicit comments were considered to have depth when students were able to illustrate an understanding of the specific criterion required in a design or describe "how" they were accomplishing the tasks. Similarly, design journals revealed richer descriptions of cognitive strategies for higher-performing students as compared to those of lower-performing peers. The excerpts also display clear differences in how students worked on their design. While the higher-performing student showed rationales or reasons why an action was taken, the lower-performing students only reported a sequence of tasks needed for completion. Examples of this case are as follows:

I will get rid of the extra holes in the arm. And instead of milling out a slot in the side, I'll just punch straight through the arm segments. This just provides for a greater range of motion for the cylinders. After the cylinders are in place, I can add linear motion to move

**Table 4.** Number of entries and words between higher- and lower-performing students

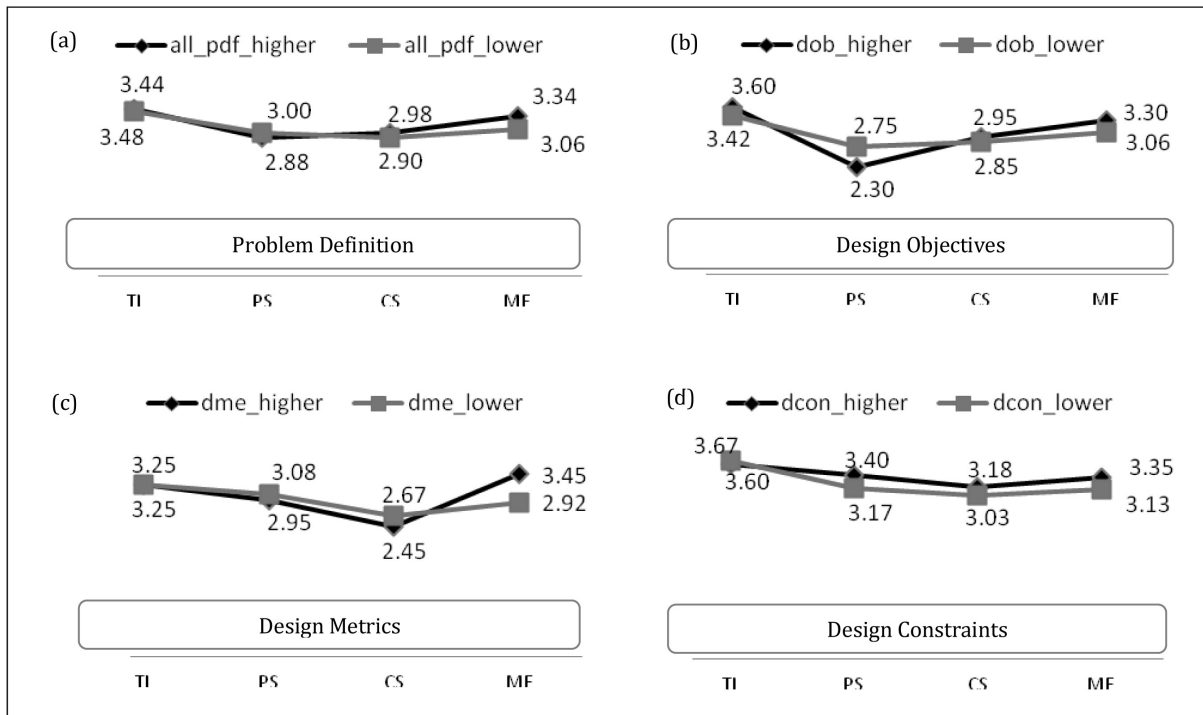
Groups of students	Total entries	No. entries/student	No. entries/week	No. words/entry
Higher performers	112	5.60	1.40	309.03
Lower performers	31	2.58	0.65	148.19

**Table 5.** Comparison of journal segment quality across groups (design process)

Groups Quality of journal report segment	Higher-performing students ( $\Sigma$ segments/student)	Lower-performing students ( $\Sigma$ segments/student)
Deep, thorough, explicit <sup>a</sup>	329/20 = 16.45 (73.93 %)	23/12 = 1.92 (32.86 %)
Narrow, less thorough, non-explicit	116/20 = 5.8 (26.07 %)	47/12 = 3.92 (67.14 %)
Total segments/student	(329 + 116) / 20 = 22.25	(23 + 47) / 12 = 5.84

Note: <sup>a</sup>  $p < 0.01$ .





**Fig. 1.** Problem definition across SRL features between higher- and lower-performing students: (a) all problem definition sub-phases; (b) design objectives; (c) design metrics; and (d) design constraints.

the arm. (*Cognitive Strategies of higher-performing student—Design Means*)

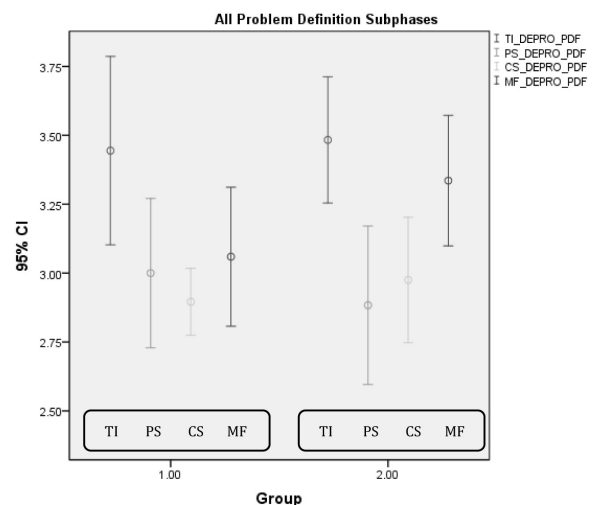
I'm going to start on the gripper, then on to the attachment base to the Jake's part of the robot. Then the valve. And lastly the fasteners. (*Cognitive Strategies of lower-performing student—Design Means*)

4.1.2 Relationships among SRL features for higher- and lower- performing students

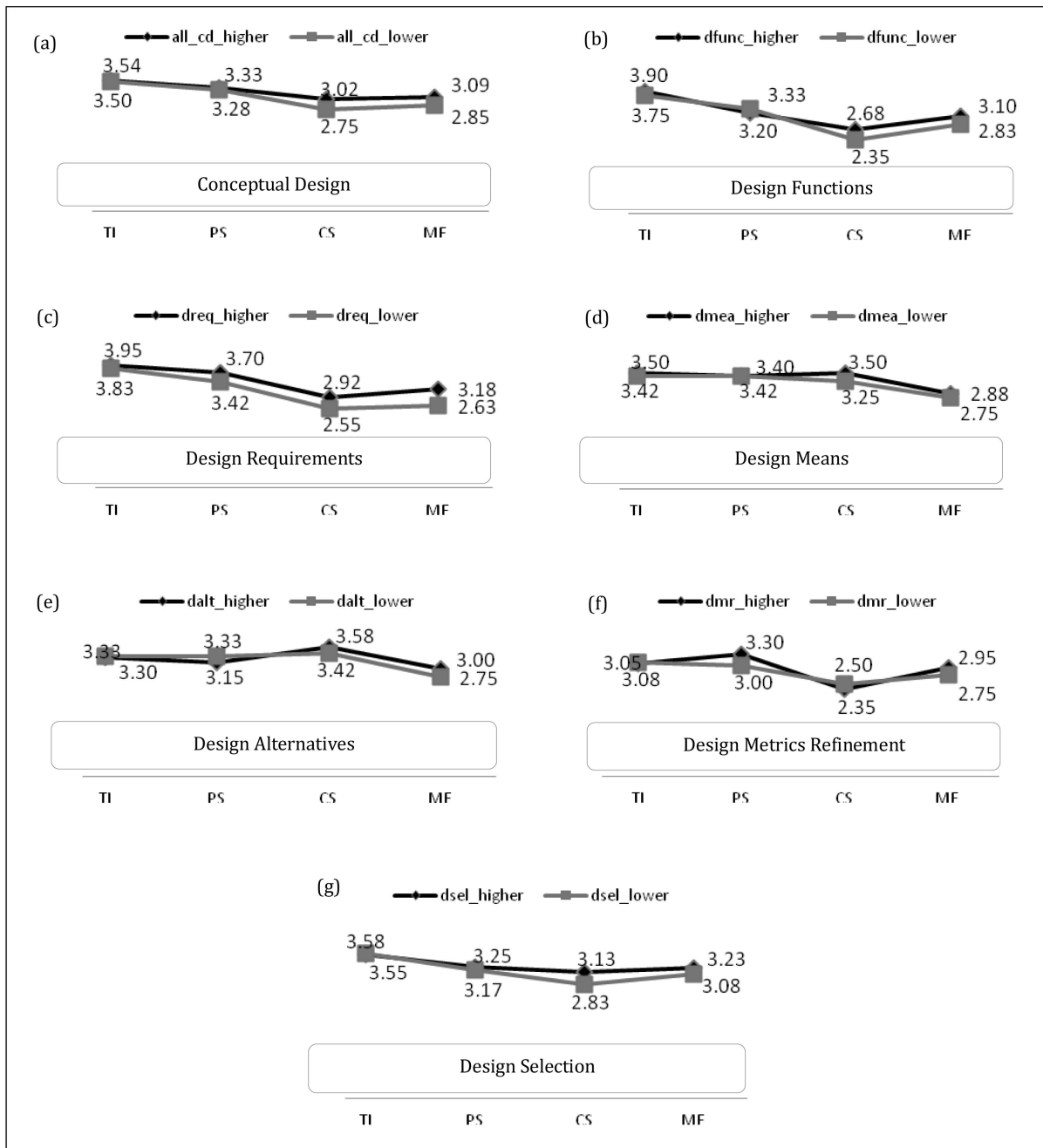
In addition to examining differences in the level and quality of higher- and lower- performing students' engagement in SRL, we turned our attention to how SRL features (i.e., *TI, PS, CS, MF*) were related as design processes unfolded (from the beginning to the middle to the end of the activity). To that end, Figs 1 and 3 present the mean scores on each SRL feature for both groups of students. Figure 1 presents data from the first of Dym and Little's design phases (problem definition), overall (panel (a)), and for each of the four sub-phases (panels (b)–(d)). Figure 2 presents data from the second of Dym and Little's design phases (conceptual design), overall (panel (a)), and for each of the six associated sub-phases (panels (b)–(g)), as identified earlier.

Consistent with the group comparison data presented above, patterns apparent in these panels also show little difference of mean values in levels of *TI* between groups based on EDQ data (e.g., in panel (a) in both figures levels of *TI* are essentially equivalent for both groups of students). However

these panels elaborate a more general conclusion, illustrating that *TI* similarities were apparent across the phases and sub-phases studied. Furthermore, and also consistent with the insignificant effect for group reported earlier, reported levels of planning were usually similar. Although no significant difference was found, the trend of SRL strategy patterns were suggestive that higher-performing students reported more planning in two sub-phases in con-



**Fig. 2.** Means and 95% Confidence Intervals of problem definition between lower- (Group 1,  $n = 12$ ) and higher-performing students (Group 2,  $n = 20$ ).

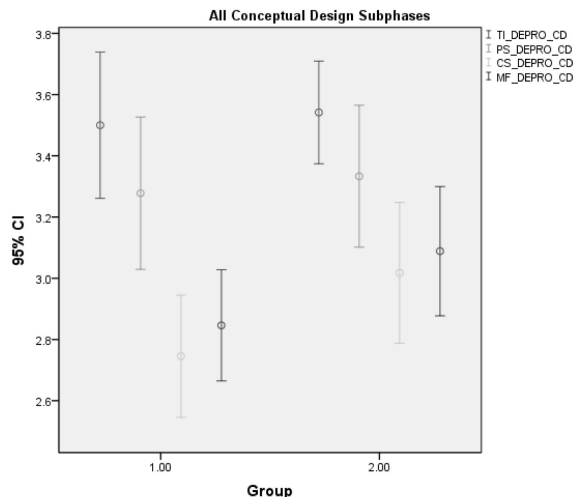


**Fig. 3.** Conceptual design across SRL features between higher- and lower-performing students: (a) all conceptual design sub-phases; (b) design functions; (c) design requirements; (d) design means; (e) design alternatives; (f) design metrics refinement; and (g) design selection.

ceptual design (Fig. 3, panels (c) and (f)). On the other hand, our findings were suggestive that lower-performing students reported more planning during one sub-phase in problem definition (defining design objectives; see Fig. 1, panel (b)). The statistically reliable overall finding of group differences in monitoring/fix-up strategies likely emerged from an apparent general trend for higher-performing students to have slightly higher scores in reported use of monitoring/fix-up strategies across design phases and sub-phases.

In addition, Fig. 2 shows that confidence intervals overlap of monitoring/fix-up strategies between the two groups is relatively narrow compared with task interpretation and other strategy use. These findings suggest that mean difference between both groups was relatively high for monitoring/fix-up strategies.

Furthermore, Fig. 4 shows that the confidence intervals overlap of cognitive and monitoring/fix-up strategies between the two groups are relatively narrow compared with task interpretation and planning strategies. These findings suggest that



**Fig. 4.** Means and 95% Confidence Intervals of all conceptual design sub-phases between lower- (Group 1,  $n = 12$ ) and higher-performing students (Group 2,  $n = 20$ ).

mean differences between both groups were relatively high on cognitive and monitoring/fix-up strategies.

From the EDQ, the findings suggest that, on average, students in both groups scored higher on task interpretation than their reported use of strategies in the design process. Students were aware of the need to identify what they were required to do, but reported less frequent use of strategies for planning, completing design tasks (i.e., use of cognitive strategies), and monitoring progress/fixing-up problems. A series of Wilcoxon tests was conducted to evaluate whether these gaps between SRL features were significant. The results indicated significant differences between *TI* and *PS* ( $Z = -2.909$ ,  $p < 0.01$ ), *TI* and *CS* ( $Z = -3.509$ ,  $p < 0.05$ ), and between *TI* and *MF* ( $Z = -2.296$ ,  $p < 0.05$ ) for higher performers. Similar to these findings, significant differences were also found for lower-performing students between *TI* and *PS* ( $Z = -2.051$ ,  $p < 0.01$ ), *TI* and *CS* ( $Z = -2.140$ ,  $p < 0.05$ ), and *TI* and *MF* ( $Z = -2.756$ ,  $p < 0.01$ ).

A point of interest revealed by these figures, based on EDQ data, is a general trend across groups to be relatively strong on task interpretation, but relatively weaker on reporting use of planning, and cognitive or monitoring/fix-up strategies to achieve goals. In this regard data from design journals reported slightly different patterns. Analysis of journal entries suggested that both higher- and lower-performing students focused more on monitoring and fix-up strategies than they did on understanding task demands or the use of other types of strategies. Higher performers described monitoring and fixing-up (155 segments) more often than task interpretation (114 segments), or use of planning (89 segments) or cognitive (87 segments) strategies.

Similarly, lower-performing students' focus on monitoring/fix-up strategies (33 segments) outstripped their focus on task interpretation (20 segments), or reported use of planning (10 segments) or cognitive strategies (7 segments). Here we found that task interpretation was described least frequently among SRL features.

In sum, while there were clear differences revealed through the journals in the level and quality of SRL between the two groups (e.g., with higher-achieving students reporting greater levels of SRL), it appeared that patterns across SRL features were very similar for the two groups. EDQ data showed *TI* higher than reported use of cognitive or self-regulating strategies. But journal entries revealed a greater focus on *MF*.

Significant differences between monitoring/fix-up strategies and task interpretation, and between monitoring/fix-up and associated use of planning and cognitive strategies were apparent in journal entries for both groups of students. Chi-squared tests indicated significant differences between *MF* and *TI* ( $\chi^2 = 6.249$ ,  $df = 1$ ,  $p < 0.01$ ), *MF* and *PS* ( $\chi^2 = 17.852$ ,  $df = 1$ ,  $p < 0.001$ ), and between *MF* and *CS* ( $\chi^2 = 19.107$ ,  $df = 1$ ,  $p < 0.001$ ) for higher performers. Similar to these findings, significant differences were also found for lower-performing students between *MF* and *TI* ( $\chi^2 = 3.189$ ,  $df = 1$ ,  $p < 0.05$ ), *MF* and *PS* ( $\chi^2 = 12.302$ ,  $df = 1$ ,  $p < 0.001$ ), and between *MF* and *CS* ( $\chi^2 = 16.900$ ,  $df = 1$ ,  $p < 0.001$ ).

#### 4.2 Task interpretation and strategy use while managing a design project

Similar to our evaluation of task interpretation and strategy use in the context of the first two phases of the design process, we also evaluated these features during project management in two ways. First, comparisons of the level and quality of SRL features were made between the two groups of students. Second, an analysis of relationships among SRL was conducted to determine if potential gaps existed between task interpretation and strategy use for either or both of the groups.

##### 4.2.1 Comparing the level and quality of SRL features across the groups of students

As was the case when considering EDQ data for students' participation in the design process, findings again suggested similar levels of task interpretation between higher and lower performers when focused on project management (means of 3.66 and 3.60, respectively). Although not statistically reliable (based on a Mann-Whitney U tests on ranks; see Table 6), trends in the data suggested that higher-performing students reported higher levels of planning (means of 3.36 and 3.17, respectively), implementing plans by selecting appropriate cogni-

**Table 6.** Comparison of mean SRL scores for higher- and lower-performing students (project management)

SRL feature	Higher-performing students <i>M (SD)</i>	Lower-performing students <i>M (SD)</i>
Task Interpretation ( <i>TI</i> )	3.66 (0.38)	3.60 (0.41)
Planning Strategies ( <i>PS</i> )	3.36 (0.47)	3.17 (0.47)
Cognitive Strategies ( <i>CS</i> )	3.12 (0.47)	2.96 (0.35)
Monitoring/Fix-up Strategies ( <i>MF</i> )	2.72 (0.43)	2.57 (0.20)
Criteria for Performance ( <i>CR</i> ) <sup>a</sup>	3.66 (0.35)	3.25 (0.50)

Note: <sup>a</sup> Significant at 0.01 level (one-tailed).

tive strategies to accomplish tasks (means of 3.12 and 2.96, respectively), and use of monitoring/fix-up strategies (means of 2.72 and 2.57, respectively). As we found when considering design processes, a statistically-reliable difference was found between groups on their recognition of important performance criteria ( $Z = -2.40, p = 0.008$ ), particularly for team management ( $p < 0.01$ ).

Further analyses of students' task interpretation and strategy use while managing the design project were conducted based on journal entries for three specific management tasks: time, resources, and teamwork. These analyses revealed that higher-performing students mentioned SRL-related features more often in journals than did their lower-performing peers (i.e., 12.90 vs. 3.58 total segments per student, respectively). A Chi-square test showed that the difference between the total number of segments per student in which SRL features were mentioned between groups was significant ( $\chi^2 = 4.765, df = 1, p = 0.014$ ). Detailed information about number of segments per student can be found in Table 7. Furthermore, on average, higher-performing students also provided better quality journal segments more frequently than did their lower-performing peers. Chi-square tests indicated that there was a significant difference between groups in the number of deep, thorough, and explicit journal segments ( $\chi^2 = 6.400, df = 1, p = 0.005$ ) for project management.

As examples of differences in the quality of strategy use (depth, thoroughness, explicitness) in journal entries, consider the following four descriptions of planning (*PS*) and cognitive strategies (*CS*) drawn from the writing samples of higher- and lower-performing students:

The project is due a week from today, so I need to either finish designing the cylinder on my own or find one that

works. Tasha is going to continue to design the gripper. We need to come up with a working robot by about Wednesday. (*Planning Strategies of higher-performing student—Time*)

We plan to do a lot on the project next week. I am going to draw up the air cylinders. We are going to attach them to the arm. (*Planning Strategies of lower-performing student—Time*)

Kris and I have a good game plan going and we think it will go fairly smoothly. He has my part files and he can use them to develop the pneumatic cylinders and attach them to the arm mechanism in the assembly file that I included with them. It contains the complete arm assembly sans the base. (*Cognitive Strategies of higher-performing student—Teamwork*)

Divide up work. Meet with teammate. Start designing Air cylinders and refining overall design. (*Cognitive Strategies of lower-performing student—Teamwork*)

The excerpts reveal that the higher-performing student reported clear and specific time schedule awareness for the execution of their plan. In contrast, the lower-performing student had a vague schedule for their potential progress. The excerpts also reveal how the higher-performing student specifically mentioned the way they work with their peers. Task assignments were explicitly written for each team member. On the other hand, the lower-performing student only reported a very general task assignment.

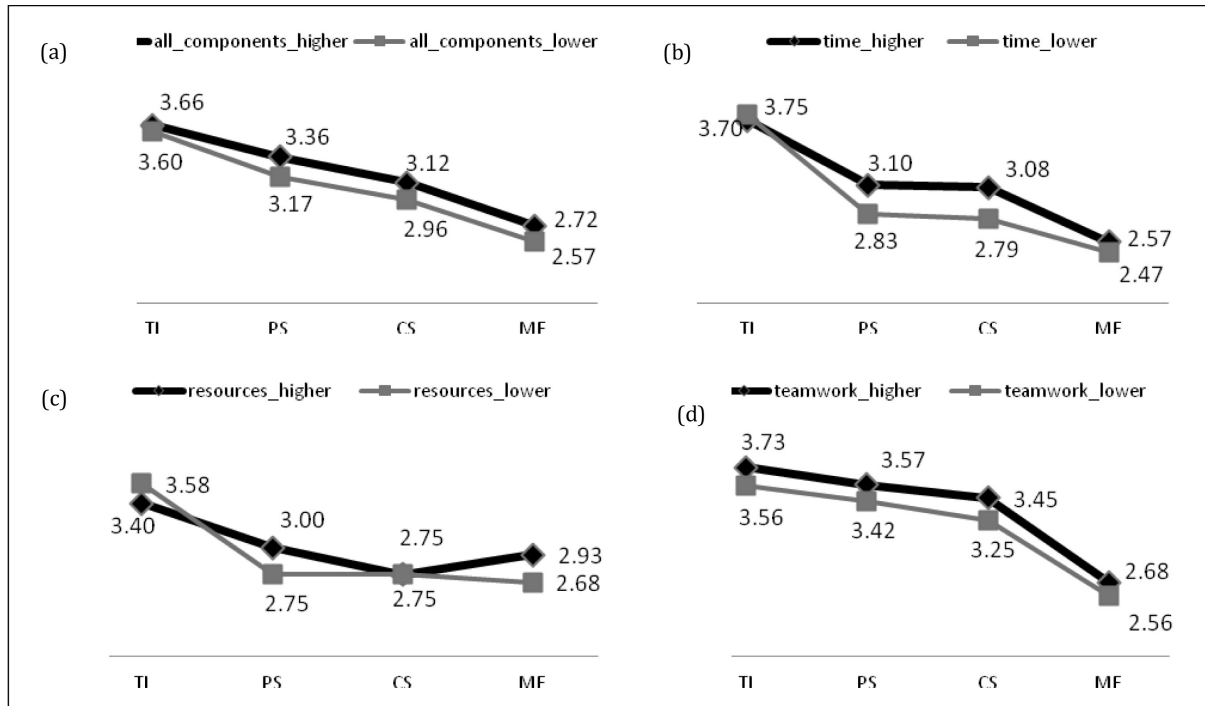
#### 4.2.2 Relationships among SRL features for higher- and lower-performing students

Findings from the EDQ (see Fig. 5) again suggested very similar levels of task interpretation on time-, resources-, and teamwork-management for both groups of students (see panel (a)–(d)). While there is some variability, overall there appeared to be little difference in the trends across SRL features between the two groups (see Fig. 5). For both groups, EDQ

**Table 7.** Comparison of journal segment quality across groups (project management)

Groups Quality of journal segments	Higher-performing students ( $\Sigma$ segments/student)	Lower-performing students ( $\Sigma$ segments/student)
Deep, thorough, explicit <sup>a</sup>	181/20 = 9.05 (70.16 %)	10/12 = 0.83 (23.26 %)
Narrow, less thorough, not explicit	77/20 = 3.85 (29.84 %)	33/12 = 2.75 (76.74 %)
Total segments/student	(118 + 77) / 20 = 12.90	(10 + 33) / 12 = 3.58

Note: <sup>a</sup>  $p < 0.01$ .



**Fig. 5.** Project management components across SRL features between higher- and lower-performing students: (a) all components, (b) time, (c) resources, and (d) teamwork.

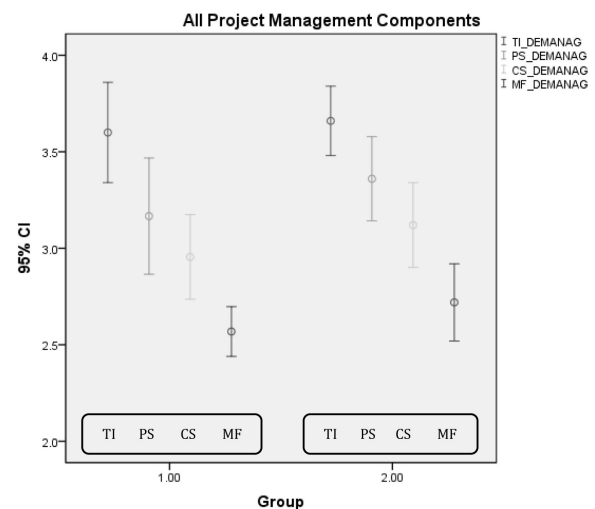
data revealed strong task interpretation, and relatively lower reported use of planning, cognitive and monitoring/fix-up strategies.

A series of Wilcoxon tests was conducted to evaluate whether these gaps between SRL features were significant. The results indicated significant differences between *TI* and *PS* ( $Z = -2.175, p < 0.05$ ), *TI* and *CS* ( $Z = -3.603, p < 0.01$ ), and *TI* and *MF* ( $Z = -3.921, p < 0.01$ ) for higher performers. Similar to these findings, significant differences were found for lower performers between *TI* and *PS* ( $Z = -2.442, p < 0.01$ ), *TI* and *CS* ( $Z = -2.864, p < 0.01$ ), and *TI* and *MF* ( $Z = -3.061, p < 0.01$ ).

Figure 6 shows that the confidence intervals overlap of task interpretation between the two groups is the widest compared with strategy use. These findings suggest that both higher- and lower-performing groups had similar levels of awareness regarding the understanding of the tasks required for project management.

When comparing patterns of SRL reflected in journal entries across the two groups while managing the design process, we found certain similarities. In contrast to the EDQ data, where reports of monitoring/fix-up strategies were lowest (see Fig. 5), analysis of journal entries suggested that both higher- and lower-performing students focused more on monitoring and fix-up strategies than they did on understanding task demands or the use of other types of strategies. Higher performers described monitoring and fix-up strategies (99 seg-

ments) more often than issues related to task interpretation (32 segments), or use of planning (64 segments) and cognitive (63 segments) strategies. Similarly, the focus of lower-performing students on monitoring and fix-up strategies (19 segments) outstripped their mention of task interpretation (3 segments), and use of planning (13 segments) and cognitive strategies (8 segments). Thus, these findings suggest that, while students were aware of important task demands (as revealed in the EDQ data), when engaged in project management (e.g.,



**Fig. 6.** Means and 95% Confident Intervals of project management components between lower- (Group 1;  $n = 12$ ) and higher-performing students (Group 2;  $n = 20$ ).

managing use of time, resources, and teamwork), students invested the most time on monitoring how things were going and debugging problems. Here we also found that task interpretation was described least frequently among SRL features.

Significant differences between monitoring/fix-up strategies and task interpretation, and between monitoring/fix-up and associated use of planning and cognitive strategies were apparent in journal entries for both groups of students. Chi-squared tests indicated significant differences between *MF* and *TI* ( $\chi^2 = 34.267$ ,  $df = 1$ ,  $p < 0.001$ ), *MF* and *PS* ( $\chi^2 = 7.515$ ,  $df = 1$ ,  $p < 0.01$ ), and between *MF* and *CS* ( $\chi^2 = 8$ ,  $df = 1$ ,  $p < 0.01$ ) for higher performers. Similar to these findings, significant differences were also found for lower-performing students between *MF* and *TI* ( $\chi^2 = 11.636$ ,  $df = 1$ ,  $p < 0.001$ ) and between *MF* and *CS* ( $\chi^2 = 4.481$ ,  $df = 1$ ,  $p < 0.05$ ).

## 5. Discussion

Despite a strong push to emphasize design in engineering education, research has found students, particularly engineering college freshmen, to be less skillful in managing learning strategies [10]. Furthermore, in a previous study, we found that college freshmen were not effective in selecting planning strategies while engaging in a similar design project [4]. This deficiency has the potential to hinder students' successful engagement with a design problem.

Thus, the research reported here contributes to a growing body of evidence suggesting that college freshmen might benefit from support to better engage metacognitive processes while engaged in engineering design projects. Findings here add to the research by uncovering particular areas where higher- and lower-performing students differed in the qualities of their metacognitive engagement (e.g., in their reported use of monitoring/fix-up strategies; in the depth, thoroughness and explicitness of their strategy descriptions). Our findings may complement results of another study [42] regarding design processes in engineering freshmen. Atman and colleagues suggested that, in general, college freshmen lack of information gathering, project realization, considering alternative solutions, total design time and transitions between design activities. The findings of the current study provide a picture of the design processes taking a slightly different point of view: by identifying task interpretation, cognitive, and metacognitive strategies of the two contrast groups of college freshmen. Engineering educators may benefit from this study by identifying the strengths and weaknesses of the two groups in order to improve the freshmen's strategies in conducting design activities.

Our findings from questionnaire data revealed that both higher- and lower-performing students emphasized task interpretation above strategy use in both the design process and project management when carrying out the design task. On the other hand, data from design journals revealed that both groups focused more on monitoring and fix-up than on other strategies (planning, cognitive) and on understanding the task requirements during the design process and project management. This phenomenon may be as a result of the students feeling that they already understood the task requirements and did not need to write down what they thought whenever they had new ideas regarding task interpretation. Moreover, the mere act of writing in design journals during design activities could influence the students. They may think more about the work, and what has and has not been done, both items being clearly related to monitoring/fix-up strategies,

With regard to project management, the higher achievers outperformed their lower-performing peers on criteria of performance, particularly in team management. The implications of these findings suggested that it may: (1) be important to encourage students to monitor their working throughout the design project and reflect on their performance; (2) be helpful to design a teamwork environment that can increase interactions among students in a team and increase the quality of how the interactions are managed; and (3) be useful to compare students' criteria for performance with the criteria from the instructor' perspective.

While based on a small sample, the findings from this exploratory study, which associates qualitative differences in task interpretation, cognitive, and metacognitive strategies with the level of students' performance during engineering design projects, suggest that it may be valuable to support: (1) the students' rich interpretation of task requirements and identification of important performance criteria; (2) the students' development and use of planning and cognitive strategies for achieving task requirements, and (3) the students' monitoring and reflecting on performance throughout the design process and during project management.

Although students with poor metacognition may benefit from training, promoting students to develop self-regulating strategies may not be an easy task. Innovative instruction for engineering design projects in terms of support from teachers and peers might be beneficial. Specifically, teachers and teaching assistants may be able to help students interpret tasks into working plans (e.g., evaluate if they have an executable plan). It may also be beneficial for students to compare criteria that they identify for effective performance with criteria

from the instructor's perspective. Previous studies in non-design contexts have revealed that journal writing enhances students' performance [43], helps students to think deeply and communicate their ideas during the learning of math [44], and provides cognitive and affective benefits [45]. Careful monitoring of students' journal writing can be conducted by student peers in a team, teaching assistants, and even by the instructor. Another potentially supportive option is to increase interactions among students in teams and increase the quality of how the interactions are managed.

Inasmuch as this study was exploratory in nature, the researchers must address four issues to improve future work in this area. *First*, in further research, we clearly need additional methods to assess real-time strategy use, as a complement to the two forms of "self-report" evidence gathered here. In future research we will learn from both successes and challenges and refine both of these data collection methods. For example, we will continue to assess students' interpretation of the EDQ items to ensure that they are interpreting the meaning of the task reliably, as situated in engineering design activities. *Second*, increasing the sample size is essential to improve the generalizability of the findings. Involving several departments or colleges may be necessary to elicit more diverse contexts in understanding students' SRL. *Third*, future study is needed to compare design processes commonly practiced by college engineering freshmen and students in grades 9–12 and also between college engineering freshmen and seniors. Freshmen may be insufficiently exposed and trained in the use of the rigid prescriptive design model as suggested by Dym and Little [32]. Previous studies conducted by Atman and colleagues revealed that there were differences in terms of problem solving strategies applied by freshmen and senior engineering college students [46, 47]. *Finally*, research findings that suggest female students may employ greater SRL strategies [48, 49] should be further investigated in the context of solving ill-structured activity that is common in engineering design. As the focus of this study was primarily to evaluate students' reported use of SRL skills in design activity, understanding the actual design process practiced by male and female college engineering freshmen will help us target specific SRL strategies relevant to these students.

## 6. Conclusions

The main goal of this study was to explore whether differences in task interpretation, cognitive, and metacognitive strategies might be associated with higher- and lower-academic achievement while students are engaged in an engineering design activity.

Here our findings revealed some important group differences. First, while EDQ data revealed relatively strong task interpretation for both groups, other data suggested that higher-performing students had a richer understanding of task requirements: journal entries revealed qualitatively richer descriptions of task demands. Thus, one important group difference, associated with task performance, was a rich understanding of task requirements. Second, there also appeared to be important group differences in reported strategy use. EDQ data revealed significantly higher reported use of *MF* strategies during the design process. Higher-performing students were more thorough in identifying and describing self-regulating and cognitive (design) strategies for their projects as evidenced by the content of journal writing. Taken together, these findings suggest that higher-performing students reflected on and managed their engagement in design processes during design and solution development.

A second important goal of this study was to observe relationships between task interpretation and reported strategy use for both groups of students. With the data collection occurring throughout the activities timeline thus linking it to performance, it was possible to associate participants' task interpretation with their reported and recorded use of strategies (in the EDQ and journals, respectively). Findings from EDQ indicated that during design, college freshmen emphasized task interpretation over developing plans, selecting strategic actions to implement the plans, and monitoring SRL features to solve the design task. Gaps between students' task interpretation and selection of strategies were present in both design process and project management for both higher- and lower-performing students. Interestingly, design journals revealed that, while they were well aware of task requirements, during project management, both groups focused more on monitoring and fix-up than using other strategies (planning, cognitive) to achieve their goals. This latter finding suggests how project management, as a key part of the engineering design process overall, focuses students attention explicitly on monitoring how work is proceeding, and making adjustments accordingly.

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**Oenardi Lawanto** is an assistant professor in the Department of Engineering Education at Utah State University, USA. He received his B.S.E.E. from Iowa State University, his M.S.E.E. from the University of Dayton, and his Ph.D. from the University of Illinois at Urbana-Champaign. Before coming to Utah State, Dr. Lawanto taught and held several administrative positions at one large private university in Indonesia. In his years of teaching experiences in the area of electrical engineering, he has gained new perspectives on teaching and learning. He has developed and delivered numerous workshops on student-centered learning and online-learning-related topics during his service in Indonesia. Dr. Lawanto's research interests include cognition, learning, and instruction, and online learning.

**Deborah Butler** is a professor at the Department of Educational and Counselling Psychology, and Special Education at the University of British Columbia (UBC), Canada. She received her BA from the University of California, San Diego, her MA from UBC, and her Ph.D. in educational psychology from Simon Fraser University in British Columbia, Canada. She joined UBC's Faculty of Education in 1994. Her scholarly interests include metacognition and self-regulated learning, strategic performance in complex activities, research methods in education, professional education, collaboration and co-regulation in teachers' professional learning, collaborative professional development models, and learning disabilities in adolescence and adulthood.

**Sylvie C. Cartier** is a professor at the Département de psychopédagogie et andragogie at the Faculté des sciences de l'éducation at the Université de Montréal, Canada. She received her BA and her M.ED from the Université de Sherbrooke, and her Ph.D. in educational psychology from the Université de Montréal in Québec, Canada. She joined the Université de Montréal's Faculty des Sciences de l'Éducation in 1998. Her research interests and publications are on self-regulated learning and learning difficulties in complex activities, classroom practices, collaboration and co-regulation in teachers' and pedagogical consultants' professional learning and collaborative professional development models.

**Harry B. Santoso** is a faculty member at Faculty of Computer Science, University of Indonesia. He received his B.S. and M.S. from Universitas Indonesia (UI) in Computer Science. Before pursuing his Ph.D. program majoring Engineering Education at the Department of Engineering Education, Utah State University, he taught some courses at UI (e.g., computer-assisted instruction and multimedia technique). He has been an administrator of the e-Learning system for several years in his department and university. He is also a member of E-School for Indonesia (Esfindo) research group, which has main objective of promoting a wide-access Internet-based e-Infrastructure for K-12 education. His research interest includes learning personalization, cognition and metacognition, multimedia content, e-Learning standardization, and distance learning.

**Wade Goodridge** is a Principal Lecturer in the Department of Engineering Education at Utah State University and instructs Solid Modeling, CAD, Introductory Electronics, Surveying, and Introductory Engineering courses at the Brigham City Regional Campus as well as the Logan campus of Utah State University. Wade has been teaching at the Utah State college of Engineering for over 11 years. He holds dual B.S. degrees in Industrial Technology Education and Civil Engineering from Utah State University, as well as an M.S. and Ph.D. in Civil Engineering from Utah State University. His research interests include metacognitive processes and strategies involved in engineering design using Solid Modeling, manipulative implementation into mechanics instructional methods, learning style impacts upon hybrid synchronous broadcast engineering education, and team teaching in broadcast environments.