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Metacognition in an Engineering Design Project*

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This quantitative study investigated the relationship between cognitive self-appraisal (CSA) and cognitive self-management (CSM), and the level of problem difficulty for electrical-computer engineering, mechanical engineering, and computer science students working on their senior design projects. The study also evaluated metacognitive differences among the three groups. The study involved 168 engineering students working on 60 different design projects and 3 engineering professors who advised the students and evaluated the level of difficulty of the projects. Two Likert-scale survey instruments were used: Engineering Design Project Inventory (EDPI) for assessing students' CSA and CSM, and Rubric for Rating Students' Design Project (RRSDP) for evaluating the level of difficulty of the design projects. Statistical tests revealed (a) the existence of a significant relationship between students' cognitive self-appraisal and self-management, (b) the absence of a significant relationship between students' metacognition and level of project difficulty, and (c) the absence of significant metacognitive differences among the three groups of engineering students.

Keywords: metacognition; engineering design; cognitive self-appraisal; cognitive self-management

1. Introduction

Researchers have uncovered a close relationship between attributional beliefs, strategic learning, and achievement [1–3]. Although this relationship contributes positively to educational practices, knowledge of how those attributional beliefs, strategic learning, and achievement are related in ill-structured, problem-solving activities is still limited. Few studies provide in-depth information on the mental interaction between students' reflections about their knowledge states and abilities and the actual action that may take place during problem-solving activities. Furthermore, many studies involve working on hypothetical problems that do not reflect the authentic learning contexts that students may encounter in classroom activities. Hypothetical problems are generally simple, and clear instructions lead directly to solutions.

Because metacognition involves a cognitive dimension of evaluating one's knowledge and abilities [4], the context of the problem may influence the manner in which students apply their metacognitive abilities. Students' capability and confidence to solve a particular problem, and their subjective perception of the task value may correlate with the actual planning, monitoring, and regulating during a problem-solving activity. Paris and Winograd [4] referred to students' personal judgment about their ability to meet a cognitive goal as 'cognitive self-appraisal' and their abilities to plan, evaluate, and make necessary adjustment and revision during their work as 'cognitive self-management.' This personal judgment may correlate to students' perception about the nature of the tasks (e.g., the task difficulty). Because metacognitive ability is believed to play a crucial role in problem solving, especially when dealing with an ill-structured problem [5], any study focused on school-related problems will significantly benefit educational practices. Moreover, such studies will not only enhance our understanding about the mental interaction between students' personal reflections about their knowledge states and abilities and the actual executed action, but also lead to development of a practical theory that can serve as an instructive model of conditions leading to successful cognition and learning.

Due to the fact that design processes differ within engineering fields, (e.g., hardware- versus software-oriented designs), it is appropriate to speculate that students utilize different cognitive self-appraisal and self-management across the two design activities. Therefore, it was also the intent of this study to investigate if cognitive self-appraisal and self-management differ across different engineering disciplines. The results of this study will inform educators whether there is a rationale to provide different metacognitive intervention among engineering fields (e.g., electrical-computer engineering, mechanical engineering, and computer science). The following research questions guided this study:

1. What is the relationship between cognitive self-appraisal and self-management of the three groups of engineering students while engaged in a design project?
2. What is the relationship between a student's cognitive self-appraisal and self-management

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and the level of difficulty of the design problem of the three groups of engineering students?

3. How do the three groups of engineering students differ in cognitive self-appraisal and self-management while engaged in a design project?

2. Background on metacognition and engineering design

Although researchers offer varying definitions and models, metacognition remains a 'fuzzy' concept because researchers classify any cognition that might have relevance to knowledge and thinking as *metacognition* [4]. While Marzano et al. [6] simplified the definition of metacognition by explaining it as a state of awareness of our thinking, Cuasay [7] defined it as a process by which the brain organizes and monitors its cognitive resources. As specific tasks are performed, individuals use this awareness to control what they are doing. Looking at previous definitions, it is clear that metacognition is a fundamental tool that enables learners to control their own cognition. As a result, they tend to learn better [8, 9].

Researchers also classify the features or components of metacognition differently. Flavell [10] defined the phenomena of metacognitive knowledge as consisting of factors of person, task, and strategies. Paris and Winograd [4] offered a more comprehensive view in which metacognition is observed through two essential features of metacognition: *cognitive self-appraisal* and *cognitive self-management*. Furthermore, the knowledge about cognitive states and abilities is shareable among people [4] and influenced greatly by the social aspects of the situation [9]. These aspects include the affective and motivational characteristics of thinking. As with other knowledge, metacognitive understanding develops with age and experience [11] and progresses through insights that, in turn, lead to awareness or a conscious understanding of self as agent [12]. All of these theories have led us to a belief that metacognition plays an important role in learning at all educational levels and for any knowledge domain (e.g., language, mathematics, technology, and engineering) to do all kinds of cognitive activities (e.g., reading, troubleshooting, case-study, engineering design).

This study adopted Paris and Winograd's [4] view of two essential features of metacognition: cognitive self-appraisal and cognitive self-management. The reason for using this particular framework was twofold. First, compared to Pintrich's [13] idea of metacognitive knowledge and control, Marzano's et al. [6] knowledge and control of self and process, and Flavell's [10] classification of person, task, and strategy, the Paris and Winograd [4] framework articulated a distinct boundary between self-appraisal and self-management. Also, all of the essential components of metacognition offered by Pintrich [13], Flavell [10], et al., are included in Paris and Winograd's [4] cognitive self-appraisal and self-cognition. Second, this model places the learner at the center of the metacognition issue. While Flavell [10] defined the factor of person to be any cognitive processors, learners, or other individuals, Paris and Winograd [4] placed more focus on the learners themselves. Inasmuch as this study addresses individual student's metacognition, it is appropriate to adopt such a framework.

2.1 Cognitive self-appraisal

Self-appraisal in learning refers to learners' personal judgment about their ability to meet a cognitive goal. When electrical-computer engineering students are asked to design an 8-bit digital counter, they may immediately wonder if they have enough knowledge (i.e., declarative, procedural, and conditional knowledge) to respond to such a task. Self-appraisal includes 'judgments about one's personal cognitive abilities, task factors that influence cognitive difficulty or cognitive strategies that may facilitate or impede performance' [4, p. 17].

Self-appraisal includes a motivational aspect. Students' motivational components, such as intrinsic goal orientation, self-efficacy, task value, and learning beliefs play an important role in self-directed learning. In this study, the self-appraisal aspect was identified as students' self-confidence and self-efficacy to solve a particular problem, and how students valued the problem to be solved. Students' self-confidence refers to performance expectation and relates specifically to task performance. Self-efficacy includes judgments about the ability to accomplish a task as well as confidence in the skills needed to perform that task. Task value refers to students' perceptions of the design project in terms of interest, importance, and utility. These three motivational factors indicate personal reflections about knowledge states and abilities, and these self-judgments are deemed to be the forerunners of actions [4]. If students judge themselves as having little knowledge and expectation for success in solving a problem, and place minimal value on the problems they are about to solve, they will likely expend little effort to work on the problem.

2.2 Cognitive self-management

Self-management skill, often termed executive control of behavior [14], refers to the ability to plan before handling a task and making revisions during the work. Three skills are commonly used to indicate the presence of students' self-management: the ability to plan, regulate, and evaluate learning. Planning involves activities such as setting goals, analyzing tasks, and selecting strategies to achieve specific goals. Regulating refers to the fine-tuning and continuous adjustment of cognitive activities. Evaluating refers to assessing the current knowledge state of learners and tracking learners' attention as they learn, self-test, and question. Evaluating occurs continuously, before, during, and after a task. Cognitive self-management has direct implications for students' performance and subsequent instruction [4]. This study examined how students executed those three metacognitive self-regulatory tasks while engaged in engineering design activities.

2.3 Engineering design

Design is at the core of engineering practices [15] and has been recognized as a complex activity that requires knowledge beyond what is stated in the design problem. Jonassen [16] maintained that design problems are among the most ill-structured that are encountered in practice. When working on a design project, students generally bring with them a cultural medium, which may occur within and outside the design domain. While the internal factors of this behavior closely relate to the design and instruction provided by the instructor, the external factors include aspects that are a mixture of personal experiences and common cultural values. An anthropologist, Pierre Bourdieu [17], speculated that the culture medium affects the design process. He held that everyday activities influence the way someone approaches a design task. Therefore, '. . . learning and doing is more than a cognitive activity. Ways of knowing and doing are unique to each group, and can be called its specific culture' [18, p. 60].

To complete engineering design tasks successfully, students are challenged to rely on self-appraisal and self-management skills. Proficiency in exercising metacognitive abilities is one of the factors that distinguishes novices from experts [8], and is pedagogically valuable for students [19]. Experts monitor their own problem-solving activities as they observe their solution process and the outcomes of their performance [20].

An ethnographical study conducted by Strickfaden et al. [18] supported Bourdieu's [17] speculation. In the study, Strickfaden et al. [18] investigated the *references* that are considered to be the inroad to understanding the culture medium of a group of industrial design students. References are shared communication in the design environment that includes speech and visual representations (e.g., sketches and images from magazines or books). The study found that approximately 50% of all references come from inside the design; the other half comes from outside. References from outside either have a tangible relationship to the artifact being created or are more intangible, more distant from the task at hand.

Regardless of one's metacognition in design activities, numerous researchers believe that the nature of the design task and the cultural medium [17] of the students may influence the strategy used in solving design problems. Bourdieu defines culture medium as the behavior gained in various social interactions. As this culture medium influences the way someone pursues the design process [18], it may be justifiable to speculate that the culture medium influences how engineering students utilize their metacognitive ability. The culture medium of engineering students may very well be influenced by the nature of the design task. For example, there is a distinct difference between hardware- and software-oriented design activities. Software design problems are somewhat better structured than hardware design problems [21, 22]. Design tasks that are more hardware-oriented, such as mechanical or electrical-computer engineering-related designs, may involve evaluation of a manufacturing process, development of a new product or production process, schematic drawing, component selections, testing of product characteristics, analyzing of material behavior, simulation of in-field product performance, or optimization of system performance. Unlike hardware design, computer software design is constrained by language and systems, and, therefore, there is no single generalizable top-down model that will work for all task decomposition processes [22, 23]). Those tasks require designers to create various assumptions and working strategies, and generally follow a prescribed staging [24].

3. Method

3.1 Study participants and context of the design activities

This quantitative study involved 60 project teams comprised of 168 engineering students in Senior Design classes at a large U.S. Midwestern university in the fall semester, 2007. Among the 168 study participants, 48 were electrical-computer engineering students working on 22 projects, 66 were mechanical engineering students working on 23 projects, and 54 were computer science students working on 15 projects. Three professors participated in the study: one professor for each Senior Design class. Students were required to work in teams, and each team solved one design problem of their choice. The study also involved the course coordinator, who evaluated the proposed design projects to ensure that they met the requirements stated in the course syllabus.

The objective of the Senior Design course was to help senior engineering students transition into industry through self-chosen team projects that required them to emulate the day-to-day life of an actual engineering design environment. Students were expected to solve typical commercial or industrial problems by implementing design stages they had learned from their experience and past courses. They were expected to gain a variety of benefits from their ill-structured problem-solving experience that required them to synthesize and apply the knowledge gained through their engineering courses. They were to work within certain constrains (e.g., time, budget) and to present their progress and results through communication with clients and their professors.

All of the study participants engaged in intensive engineering design activities throughout the semester. Although it was required for students to work in a team, three ECE students received permission from their professor to work alone for their projects. There were no Senior Design projects completed by a single student in CS and ME. The advising professors of the three Senior Design courses agreed that all of the student projects were ill-structured problems with various levels of task difficulty. The advising professors evaluated the level of difficulty of design problems based upon Jonassen's [25] criteria of ill-structuredness, complexity, and dynamicity.

The students worked on a variety of design projects such as designing products that might satisfy individuals as their end-users, designing manufacturing systems/machineries used in industry, designing and building various instruments using a conventional micro controller chip, developing an electric circuit using silicon nitride membranes, and database migration, building security, and emergency response of a building using a 3-D virtual reality tool.

3.2 Instrumentation

Two survey instruments were used in this study: Engineering Design Project Inventory (EDPI) and Rubric for Rating Students' Design Project (RRSDP). Due to the lack of availability of instruments designed to evaluate students' CSA and CSM in an engineering design context, modification of two existing instruments was needed. The existing instruments included Problem Solving Inventory (PSI) developed by Heppner [26] and the Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich et al. [27]. The modification of the instrument was made by rewording words associated with problem solving in an engineering design activity. The purpose of the rewording process was to help the participants focus on problem solving in the design task as the context of each statement in the EDPI. The EDPI is a 34-item self-reporting instrument designed to assess a student's self-appraisal and self-management of cognition while solving relatively large ill-structured problems. Students rate themselves on a 7-point Likert scale from *not at all true of me* to *very true of me*. Eighteen items of EDPI were adopted from the problem-solving confidence scales of PSI and the task-value, self-efficacy, and metacognitive self-regulation scales of the MSLQ. Sixteen additional items were developed by the researchers (see the Appendix to read examples of EDPI items). The internal reliability coefficient of MSLQ motivation and learning strategies scales varied between 0.52 and 0.93; the internal reliability coefficient of PSI was 0.85. Items were modified by rewording them in such a way that they enabled students to focus on a particular problem. Three doctoral students who were knowledgeable in cognitive self-appraisal and cognitive self-management constructs read and suggested improvements in the EDPI instruments. The EDPI was pilot-tested in various engineering courses similar to the Senior Design course. The internal reliability coefficient of the EDPI self-appraisal scales varied between 0.839 and 0.870; self-management scales varied between 0.553 and 0.733.

The EDPI consisted of 19 items that assessed students' self-appraisal of cognition and 15 items that assessed self-management of cognition. The self-appraisal items assessed student self-confidence (SC), self-efficacy (SE), and task value (TV). The self-confidence scale was defined as self-assurance when engaged in problem-solving activities [26], while the self-efficacy scale assessed students' ability to perform. The task value scale is associated with students' evaluation of how they think of the task. As for students' self-management of cognition, three parts of activities, such as planning (P), monitoring (M), and regulating (R) processes were evaluated. The planning process included activities such as goal setting and task analysis. The monitoring process included activities such as tracking a students' attention as they work on the problem, self-testing, and questioning. Lastly, the regulating process included the fine-tuning and continuous adjustment of students' cognitive activities. Students were expected to complete the EDPI within 15 minutes' time.

The Rubric for Rating Students' Design Project (RRSDP) was used to evaluate the level of difficulty of students' design projects (LDDP). The RRSDP consisted of six indicators involving three variable attributes of problems [25]): ill-structuredness, complexity, and dynamicity. Ill-structured problems often possess aspects that are unknown [28], as well as multiple solutions or solution methods [29]. Complexity is determined by the number of issues, functions, or variables involved in the problem, the degree of connectivity among those variables, and the stability among the properties over time [30]. The advising professors rated their students' LDDP on a 4-point Likert scale from *few* or *low* or *unlikely* (a score of 1) to *many* or *high* or *likely* (a score of 4).

The EDPI and LDDP instruments were analyzed for content and face validity. Three doctoral students with knowledge in cognitive self-appraisal and self-management read and made suggestions for improving the EDPI. Two engineering professors also read and made suggestions to improve the LDDP instrument. Both instruments were approved by the researchers' Institutional Research Board.

3.3 Data collection procedures and analysis

Participation in the study was voluntary. Due to the sensitive nature of the data collected, no other identification was included in either survey instrument except for the last four digits of a student's university identification number (UIN).

Because the survey instruments assess students' perception, which reflects their metacognitive experience, they must be completed soon after experiences with self-appraising and self-managing occur. The study participants were invited to complete the EDPI at the final stage of the project. At the same time, the advising professors were requested to rate the level of difficulty of each project by completing the RRSDP.

The Hierarchical Linear Model (HLM) was used to evaluate the relationship between variables (research questions 1 and 2). Two-tailed Pearson Correlations between each subscale of students' self-appraisal of cognition and overall self-appraisal and self-management, as well as the two metacognitive features and level of design project difficulty were calculated using the standardized mean. Hierarchical linear regression [31] was conducted to investigate the relative importance of the contribution of each subscale of students' CSM. One-way Analysis of Variance (ANOVA) and Multivariate Analysis of Variance (MANOVA) tests were used to determine whether metacognitive differences existed among ECE, ME, and CS students (research question 3). The total score on the EDPI was used as a measure of overall metacognition.

4. Results

4.1 Relationship between CSA and CSM

In this investigation, the relationship between students' CSA and CSM was evaluated at two levels: (1) CSA and CSM of each student regardless of academic field, and (2) CSA and CSM of each group of students.

4.1.1 CSA and CSM of each student

A two-tailed Pearson correlation analysis indicated a significant correlation between CSA and CSM, $r\ (168) = 0.69$, $p < 0.01$. A curve-fit graph that shows the observed and linear curves of the correlation of these two variables is presented in Fig. 1a. This finding suggests that students' CSA was significantly correlated with CSM.

4.1.2 CSA and CSM of each group of students

Three bivariate correlation tests were conducted to evaluate the relationship between CSA and CSM among ECE, ME, and CS students. From the six correlation analyses, it was found that: (1) CSA was significantly correlated with CSM among ECE students, $r\ (48) = 0.74$, $p < 0.01$, (2) CSA was significantly correlated with CSM among ME students, $r\ (66) = 0.65$, $p < 0.01$, (3) CSA was significantly correlated with CSM among CS students, $r\ (54) = 0.72$, $p < 0.01$. Three curve-fit graphs that show the observed and linear curves of the correlations of the CSA and CSM for the ECE, ME, and CS students are presented in Fig. 1b-d. From these series of two-tailed Pearson correlation tests, it was concluded that there was a significant relationship between CSA and CSM for the three groups during their engagement in the design project. A strong indication of a significant relationship between CSA and CSM was found when the correlation test was conducted for all 168 students. It is worth noting that a scatter-plot graph of CSA and CSM indicates that these three groups of students were homogeneous as each of these groups was not distinctly clustered together, but rather they were mixed with one another.

4.1.3 Relative Importance of SE, SC, and TV towards CSM

A simple regression test was conducted to determine the relative importance of the contribution of each subscale of students' CSA (i.e., self-confidence, self-efficacy, task value) towards CSM. The results of the analysis revealed that task value ($\beta = 0.28$, $p = 0.00$) and self-confidence ($\beta = 0.28$, $p = 0.00$) were both highly significant predictors of the self-management score, followed by self-efficacy ($\beta = 0.26$, $p = 0.02$). It is obvious from this simple regression test that, although task-value and self-confidence were ranked first as a significant predictor of students' CSM, the differences among these regression coefficients were quite small. The three subscales of self-appraisal constituted about 46 percent of overall students' self-management.

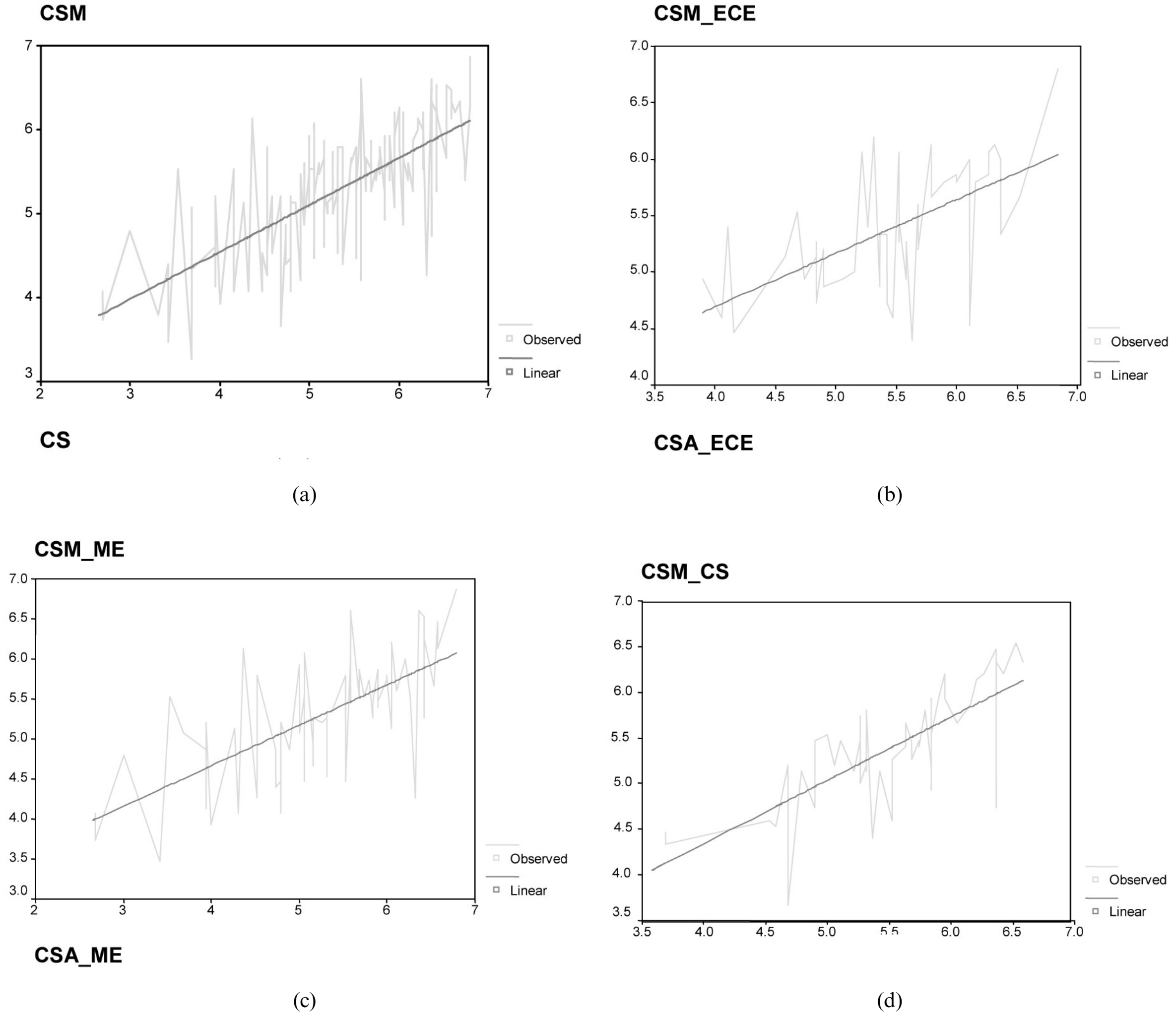

Fig. 1. Correlation between CSA and CSM of all students (1a), CSA and CSM of electrical-computer engineering students (1b), CSA and CSM of mechanical engineering students (1c), and CSA and CSM of computer science students (1d).

4.2 Relationship between metacognition and LDDP

The possible existence of a significant relationship between metacognition and the level of difficulty of the design projects (LDDP) was evaluated through a series of correlation tests conducted at three levels. First, a series of correlation tests was conducted to evaluate a possible significant relationship between students' overall metacognition (i.e., META) and the level of difficulty. The total score on the EDPI was used as a measure of overall metacognition. Second, a series of correlation tests was conducted to evaluate possible significant relationships between students' CSA and CSM and the level of difficulty for each group of students. Through a frequency count, it was found that the difficulty of the students' design projects was normally distributed (M = 16.07, SD = 3.20). A wide range of design difficulty was indicated among the projects.

4.2.1 Correlation between students' overall metacognition (META) and LDDP

A two-tailed Pearson correlation test was conducted, and no significant relationship was found between students' overall metacognition and the LDDP, r (168) = –0.02, $p > 0.05$.

4.2.2 Correlation between groups' metacognition and LDDP

Three Pearson correlation tests were conducted to evaluate the relationship between the group's metacognition and the LDDP. No significant relationship was found between each group's metacognition and the LDDP for ECE, ME, and CS students (Table 1).

4.2.3 Correlation between two metacognitive features and LDDP

Six Pearson correlation tests were conducted to evaluate the relationship between CSA and the LDDP, and between CSM and the LDDP. There was no significant relationship found between the two metacognitive features and the LDDP of ECE, ME, and CS students (Tables 2 and 3). This finding suggests that there was no significant relationship between CSA and LDDP at two levels of investigation: among the three groups of engineering students, and across metacognitive features.

4.3 Metacognitive differences among different groups of engineering students

Three one-way ANOVA tests were conducted to determine whether metacognitive differences existed among ECE, ME, and CS students during their engagement in a design project. The tests were conducted to evaluate (a) overall metacognition of each group of students, and (b) cognitive self-appraisal and cognitive self-management of each group of students. There were no significant differences in overall metacognition level among the three groups of students (see Table 4).

To confirm the ANOVA test results, a multivariate analysis of variance (MANOVA) test was conducted. MANOVA is an extension of the ANOVA test that evaluates two or more dependent variables simultaneously. From the multivariate tests, both the intercept and the factor effect (i.e., among three groups of students) were significant, Wilks' Lambda (F = 3784.68, $p < 0.05$) and (F = 2.955, p = < 0.05), respectively. From the result, it may be concluded that each effect is significant. However, when looking at the Tests of Between-Subjects Effects, the results of the Corrected Model and Between-Subject Factors were the same as the ANOVA results. Thus, the earlier finding was confirmed (i.e., that the three groups of students exhibited no significant differences in CSA and CSM while engaged in the design project).

Table 1. Correlation between LDDP and for Each Group

IDP		Test components	
ECE	LDDP	Pearson Correlation	–0.091
		Sig (2-tailed)	0.536
		N	48
ME	LDDP	Pearson Correlation	–0.084
		Sig (2-tailed)	0.504
		N	66
CS	LDDP	Pearson Correlation	0.018
		Sig (2-tailed)	0.895
		N	54

Table 2. Correlation between LDDP and CSA for Each Group

IDP		Test components	CSA
ECE	LDDP	Pearson Correlation	–0.051
		Sig (2-tailed)	0.730
		N	48
ME	LDDP	Pearson Correlation	–0.133
		Sig (2-tailed)	0.288
		N	66
CS	LDDP	Pearson Correlation	0.065
		Sig (2-tailed)	0.638
		N	54

Table 3. Correlation between LDDP and CSM for Each Group

IDP		Test components	CSM
ECE	LDDP	Pearson Correlation	–0.140
		Sig (2-tailed)	0.343
		N	48
ME	LDDP	Pearson Correlation	0.015
		Sig (2-tailed)	0.906
		N	66
CS	LDDP	Pearson Correlation	–0.047
		Sig (2-tailed)	0.738
		N	54

5. Discussions

5.1 Cognitive self-appraisal and cognitive self-management are closely related

A significant relationship was found between cognitive self-appraisal (CSA) and cognitive self-management (CSM) among ECE, ME, and CS students. This finding confirms the relationship between students' developmental attribution beliefs and strategic knowledge as found in previous studies [1, 3, 9, 32]. Paris and Winograd [4] concluded that two essential features of metacognition (i.e., self-appraisal and self-management of cognition) capture the information processing of declarative and procedural knowledge. While self-appraisal includes personal reflection about one's knowledge and abilities, self-management refers to how self-appraisal is put into action. Chan and Moore [1] maintained that students who were taught cognitive and metacognitive strategies and who attributed success or failure to personal effort and the effective use of those strategies can break the cycle of entrenched helplessness and its negative effects on learning and academic achievement. Another study conducted by Chambres et al. [9] found that even a fictitious position of expertise promotes metacognition and student effectiveness. For instance, students randomly said to be experts in English performed better than those said to be nonexperts.

The significant relationship between students' CSA and CSM that was found in this study does not imply a causal relationship. Rather, the findings indicated that the two metacognitive features are interdependent. Specifically, the findings showed that when students feel that they have the adequate knowledge, ability, and interest to solve design

Table 4. One-Way ANOVA Test on CSA and CSM for Each Group

Test Components		**Sum of Squares**	***df***	**Mean Square**	***F***	***Sig.***
Between groups		1.959	2	0.980	1.403	0.249
Within groups		84.949	165	0.515	1.933	0.148
Total		86.908	167	1.403	0.695	0.500
CSA	Between groups	2.806	2	0.726		
	Within groups	119.777	165	0.606		
	Total	122.583	167	0.474		
CSM	Between groups	1.212	2			
	Within groups	78.214	165			
	Total	79.426	167			

problems, they are more likely to be motivated to engage in the problem successfully through adequate planning, monitoring, and making necessary adjustments in their thinking. Similar findings by Chan and Moore [1] and Chambres's et al. [9] indicated the need to enhance students' self-appraisal to produce better cognitive self-management while engaging in an engineering design project.

5.2 Students' metacognitive abilities do not relate to the level of difficulty of the design project.

Results found that there was no significant relationship between students' metacognition and the level of difficulty of the design project (LDDP). The absence of any significant relationship between the two variables is inconclusive. It may be due to two influencing sources: factors internal to the students and an outside agent's determination of problem difficulty. Internal factors may involve students' lack of experience in predicting the complexity of their design projects, overconfidence, and trial-and-error working tactics. Because of these factors, students may not anticipate the unexpected during the project. The determination of problem difficulty by the professors may also be an influencing source of the absence of significant relationship between students' metacognition and LDDP. Students' metacognition and the level of problem difficulty were evaluated by two different groups of individuals who may perceive the level of difficulty differently. Consequently, the results of the correlation tests conducted may not show the true relationship between students' metacognition and LDDP.

5.3 Electrical-computer, mechanical, and computer science students do not employ different metacognitive skills while engaged in their design project.

Results of one-way ANOVA and MANOVA tests showed that ECE, ME, and CS students did not exhibit significant differences in CSA and CSM while engaged in the design project. There are three possible reasons for the absence of significant metacognitive differences among the three groups: First, the finding is an important new contribution to studies about the role of 'culture medium' in design education. The term 'culture medium' indicates the notion of the cultural information that individuals and groups hold as part of their make-up [18]. It may exist in any individual or group, and it includes facets of an individual's behavior gained through various social situations and interactions. The absence of any significant difference in employing metacognition among the groups may be due to metacognitive skill that the engineering students commonly possess.

Nevertheless, the culture medium might exist among individual and groups of students, but may not significantly impact their metacognitive ability. It would be interesting to investigate whether engineering and nonengineering students differ in their metacognition. Second, the level of self-appraisal and self-management regarding working on a design project might be similar across the senior students. The students who participated in the senior courses were in their senior year and, therefore, a homogenous metacognitive level may have existed among them. As their learning experience became more enriched, their metacognition likely improved.

Clearly, metacognitive ability is learnable [33] and develops with age and experience [11]. Third, a high percentage of undergraduate engineering students transferred within the College of Engineering during the first 2 years of their academic pursuit, a fact that might contribute to the insignificant metacognitive change among the three groups of students. As students change majors during their undergraduate study, students enrolled in the College of Engineering become a single homogeneous community with similar metacognitive skills. Thus, this may lead to metacognitive indifference among electrical-computer engineering, mechanical engineering, and computer science students.

The primary limitations of this study involve the homogeneity issue and the relatively small number of student participants in this study. Researchers may want to conduct a similar study that involves a larger number of engineering study participants from several colleges and universities. In addition, inviting students to evaluate the level of difficulty of their own design project may need to be considered so that the level of metacognition and difficulty of the problem are both based on students' perceptions. A similar study that involves problems with various levels of difficulty in other fields of engineering and sciences may also need to be considered to improve the generalizability of the findings. Another possible limitation is, as there are many other kinds of ill-structured problems beyond those investigated in this study, the results may not be relevant to all ill-structured problems in all sciences or all engineering disciplines.

6. Conclusions

The following conclusions summarize the answers of three research questions of the current study. The first conclusion is: A significant relationship exists between cognitive self-appraisal (CSA) and cognitive self-management (CSM) of ECE, ME, and CS students while engaged in the design project. In this study, a significant relationship was found between CSA and CSM in the three groups of engineering students at the final stage of their engagement in senior design projects. Students with a low CSA had a low CSM, and vice-versa. In other words, students' awareness of knowledge states and abilities impacted the way they planned, monitored, and made necessary adjustments. Although self-efficacy, self-confidence, and task value contribute less than 50 percent of overall students' self-management, it is strongly suspected that these three self-appraisal factors may have played an essential role in shaping students' self-management. Therefore, students should allocate time to discussing their design tasks with their teammates or instructors, especially at the early stage of the project. Issues that may relate to students' self-appraisal and self-management may be discussed to smooth the process of the later design stages.

The second conclusion is about the relationship between a student's CSA and CSM and the level of difficulty of the design problem (LDDP) of the three groups of engineering students. Statistical results revealed no significant relationship between students' metacognition and the LDDP. The researchers first evaluated the relationship of the two variables by looking at all students as a single group. No correlation was found between overall students' metacognition and LDDP. In addition, no significant relationships were found between students' CSA and the LDDP, nor between students' CSM and LDDP scores. Similar results were also found when correlation tests were conducted for each individual group of student samples.

The third conclusion is: No significant difference existed in CSA and CSM among ECE, ME, and CS students while engaged in the design project. Despite the belief of numerous researchers that design solutions do not occur in a vacuum and that each individual brings a 'culture medium' to the activity, this study found no evidence of metacognitive difference employed by the three groups of engineering students. The absence of significant differences of metacognition among ECE, ME, and CS students may indicate the possibility of an identical level of metacognitive skill by all of the senior students. Although this finding did not automatically suggest the presence of metacognitive differences across students at different academic levels (i.e., freshman, sophomore, junior, or senior), it is fair to speculate that a student's learning experience increases as his or her academic level advances.

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APPENDIX

Examples of Engineering Design Project Inventory (EDPI) Items

#	**STATEMENTS** **Please think of own your design problem while reading these statements**	**YOUR RESPONSES** **1 = not at all true of me** **7 = very true of me**
1.	I will be able to think up creative and effective solutions to this design problem.	1 2 3 4 5 6 7
2.	Before I approach this design problem, I will carefully examine the complexity of the problem.	1 2 3 4 5 6 7
3.	I will have the ability to solve this design problem even though no solution may be immediately apparent.	1 2 3 4 5 6 7
4.	I will think of related knowledge that could help me to solve this problem.	1 2 3 4 5 6 7
5.	I will have the relevant knowledge and problem-solving skills needed to solve this design problem.	1 2 3 4 5 6 7
6.	While solving this problem, I may often miss important details because I am thinking of other irrelevant things.	1 2 3 4 5 6 7
7.	It will be important for me to learn much from this design problem.	1 2 3 4 5 6 7
8.	I will ask myself questions to ensure that I understand the context of this problem and have the required knowledge to solve it.	1 2 3 4 5 6 7
9.	In the future, I will be happy with the decisions I make in this design problem.	1 2 3 4 5 6 7
10.	When I become confused while working on this problem, I will go back and try to resolve my confusion.	1 2 3 4 5 6 7

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