Towards the Development of a Revised Decision-Making Competency Instrument

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Introduction

Students make decisions that affect their academic success every day, some relatively small (whether to study, what to study, how to study), and others larger (what major to choose, whether to persist in that major, whether to persist in college). In order to help students make adaptive, self-regulated decisions, rather than impulsive or maladaptive ones, we need a better understanding of the relationship between decision-making competency and real-world behaviors and outcomes. To advance this understanding, this research paper discusses the process of refining and expanding an existing instrument to measure decision-making competency.

Theoretical Framework

The Self-Regulation Model of Decision-Making (SRMDM), posits that that self-regulated decision-makers spend time in three phases: generation of options, evaluation of options, and learning from the results. Additionally, adaptive decision-makers are aware of moderating factors (such as stress or lack of information) and work to overcome them [1]. The model is illustrated in Figure 1 and described in more detail below.

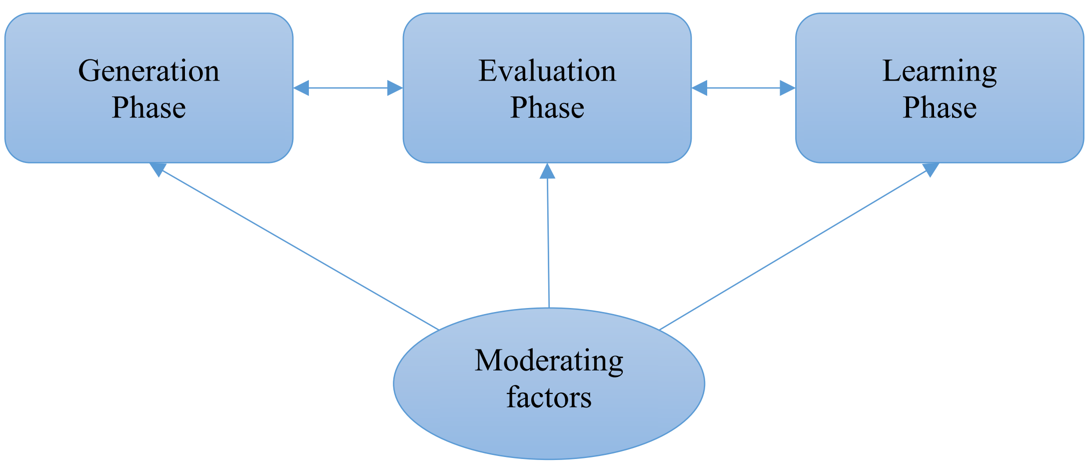

Figure 1. Byrnes' Self-Regulation Model of Decision-Making

Generation Phase
The generation phase consists of cue interpretation, goal setting, and strategy construction. This phase is only faced when an individual wants to accomplish something but is not presented with options. Thus, options must be generated by the individual.

Cue interpretation is the process by which someone analyzes internal or external cues by first detecting the cue, determining the nature of the cue, deciding whether to respond to the cue, and deciding how to respond if a response is needed. After one decides that a response is needed, they must begin goal-setting. In this phase, individuals will develop options that they feel will help to accomplish their goals. Once an option is chosen, a strategy must be constructed to accomplish the goal. If the problem is not entirely new, one might use the same strategy that was used in the past to complete a task. If the goal is not the same, but similar to a previous goal, analogical reasoning might be utilized. In analogical reasoning, analogies that compare past and present goals and strategies can be useful. If no past connections to the present issue can be made, an individual may use causal reasoning to accomplish a goal. Understanding the causes of a system or problem can give individuals insight into the root cause and normal operations. Another option for strategy construction is advice seeking. Advice seeking comes in a variety of different forms such as asking others for help, seeking information online, reading textbooks, etc. These strategies are not mutually exclusive. A decision-maker might use all of these techniques to construct a strategy.

Evaluation Phase
If a decision maker has options presented to them, they skip the generation phase and move directly into the evaluation phase, where possible responses are analyzed. The evaluation phase consists of the consideration of goals, evaluation strategies, and outcomes and their relationships to one another. When evaluating options, decision-makers vary in the factors they consider important and the weight they contribute to each of these factors. Therefore, the strategies used in and the outcomes of the evaluation phase can vary greatly from one person to the next and one decision to the next. An individual's values, self-perception, and emotions play a role in the evaluation process as well as factors such as power, morality, and efficiency of strategies [1]. During this phase, the goal is to develop an evaluation strategy that optimizes thoroughness, efficiency, and effectiveness.

Moderating Factors
Byrnes defines moderating factors as "factors that affect the likelihood and ease with which goals are attained." Moderating factors have also been described as the reasons why adults make poor decisions [1]. Memory limitations are a type of moderating factor that can affect the decision-maker's ability to process information, generate options, and evaluate options. Goals and effective strategies can easily be forgotten if they are not rehearsed on a continual basis. Biases are also moderating factors because they affect the decision-maker's perspective, causing them to consciously or subconsciously alter the context of different situations. For instance, hindsight bias causes people to be surer of an outcome after it has already occurred than if they were to predict the outcome in advance. The danger in this is that it gives the decision-maker a level of confidence in predicting future events that is incongruent with their actual ability to predict future events. Every decision maker, whether self-regulated or dysregulated, is faced with moderating factors. However self-regulated decision-makers have strategies in place to overcome these factors. Some strategies include creating to-do lists that organize and prioritize

tasks, recognizing biases and acknowledging that they might affect decision making, and regulating one's emotions.

Learning Phase
Self-regulated decision-makers enter the learning phase after a decision is made. In this phase, the strategies are implemented, and the consequences of the decision and the strategy used to make it are observed. The SRMDM assumes that successful decision-makers have accurate knowledge of contexts, strategies, and themselves. This knowledge is not innate, but it is acquired over time. These factors make self-regulated decision-makers more likely to learn from their previous decisions than dysregulated decision-makers.

Background and Motivation

The Decision-Making Competency Inventory (DMCI) developed by Miller and Byrnes has shown good internal consistency and convergent validity with select scales of the Learning and Study Strategies Inventory—High School Version (LASSI-HS) [2]. However, the current DMCI functions as a single-scale instrument. It was developed around metacognitive, motivational, and behavioral subscales, but these subscales were not supported by an exploratory factor analysis. Instead, they found four factors: Informed Awareness, Self-Appraisal, Autonomy, and Self-Confidence. Because the factor loadings were influenced by how the questions were worded, factor scores were not used in subsequent analysis.

The goal of this study is to expand and refine the DMCI in an attempt to achieve useful subscales that relate to the Self-Regulation Model of Decision-Making. Knowing more detail about student's decision-making competency and how it relates to their success could help us design better interventions to help students make adaptive choices.

Method

Scale Construction Procedure
We kept all 20 items of the original DMCI to ensure that it would be possible to calculate DMCI scores for future work if the revised instrument did not prove to be better. The items are shown in Table 1. Many started with the stem "When I have a big decision to make..." Prior to making additions to the DMCI, we categorized the existing items according to which aspect of the SRMDM they were most closely related to: generation phase, evaluation phase, learning phase, or moderating factors. These categorizations are also noted in Table 1. Negatively worded items (those on which a high score would indicate a lack of self-regulation) are followed by "(-)."

Table 1. Original Items. For Theoretical Construct, G=Generation Phase, E=Evaluation Phase, L=Learning Phase, M= Moderating Factors. Final factor assignments are also included. X indicates item was removed from analysis and was not included in the final factors.

No.	Original Item	Theoretical Construct	Final Factor
Q1	When I have a big decision to make... [I often make it without considering how likely it is that things will turn out OK.] (-)	E	2
Q2	When I have a big decision to make... [I take time to make sure that I am understanding things correctly.]	E	1
Q3	When I have a big decision to make... [I think about similar past decisions I made and what happened.]	L	1
Q4	When I have a big decision to make... [I take time to review all of my options before deciding.]	E	1
Q5	When I have a big decision to make... [I consider possible consequences before making any decision.]	E	1
Q6	When I have a big decision to make... [I usually hope that the problem goes away and that I don't have to make the decision.] (-)	G	2
Q7	When I have a big decision to make... [I make sure that I get all the facts.]	M	1
Q8	When I have a big decision to make... [I usually seek out advice from people whom I know to be knowledgeable.]	E	X
Q9	When I have a big decision to make... [I tend to rush into making it.] (-)	E	2
Q10	When I have a big decision to make... [I tend to forget important things when making the decision.] (-)	E	2
Q20	[Whenever I have to make the same big decision, I tend to make the same mistakes.] (-)	L	2
Q21	[When I have a big decision to make about doing something that requires my skill, I often make a bad decision because I either underestimate or overestimate how good I am at something.] (-)	L	X
Q22	[When I have a big decision to make about doing something that requires a certain skill, I often don't bother to think about how much skill I have.]	E	2
Q73*	When I have a big decision to make... [I tend to rush into making it.] (-)	E	X
Q74*	When I have a big decision to make... [I tend to forget important things when making the decision.] (-)	E	X
Q75	When I have a big decision to make... [I just choose what seems OK at the moment.] (-)	G	2
Q76	When I have a big decision to make... [I usually believe that I will make a good decision.]	L	X
Q77	When I have a big decision to make... [I just go with a decision that all my friends are going with.] (-)	G	2
Q78	When I have a big decision to make... [I am usually confident that things will turn out OK once I make the decision.]	L	X
Q79	When I have a big decision to make... [I like to let someone else make the decision for me (for example, my parents or a friend).] (-)	G	2
Q80	When I have a big decision to make... [I usually follow the advice of anyone who gives it to me.] (-)	G	2
Q81	When I have a big decision to make... [I make it and then pay attention to how it turns out.]	L	X

(-) = negatively worded
* = repeated item

Table 2 shows a tally of how many positively and negatively worded items address each construct in the original DMCI. Notably, there were no positively-worded items related to the generation phase of decision-making and only one item related to moderating factors. We attempted to balance the number of items for each construct and how many items of each construct were negatively worded by creating 16 additional items. The new items and their hypothesized constructs are shown in Table 3.

Table 2. Item counts for the original and expanded survey.

Theoretical Construct	Original Survey			Expanded Survey		
	Positively Worded	Negatively Worded	Total	Positively Worded	Negatively Worded	Total
Generation Phase	0	5	5	3	5	8
Evaluation Phase	4	4	8	6	5	11
Learning Phase	2	2	4	4	3	7
Moderating Factors	1	0	1	5	3	8

Table 3. Added Items. For Theoretical Construct, G=Generation Phase, E=Evaluation Phase, L=Learning Phase, M= Moderating Factors.

No.	Added Item	Theoretical Construct	Final Factor
Q23	[When I am given an important assignment, I think about strategies I could use to complete it.]	G	3
Q24	[When choosing an approach to a problem, I take into account what I'm good at and what I struggle with.]	E	X
Q25	[I try not to make important decisions when I am feeling stressed.]	M	X
Q26	[When I lack the knowledge to make a good decision, I ask for advice or search for the information I need.]	M	X
Q27	[When I lack the knowledge to make a good decision, I choose the option that seems the best.] (-)	M	X
Q28	[When I have a big decision to make with many options, I choose one aspect to focus on.] (-)	E	X
Q82	When I have a big decision to make... [I try to think of all the possible options.]	G	1
Q83	When I have a big decision to make... [I consider the pros and cons of each option.]	E	1
Q93	[I often reflect on my decision after implementing it and seeing the outcome.]	L	3
Q94	[I often reflect on my decision PROCESS after implementing it and seeing the outcome.]	L	3
Q95	[After I make a decision, I don't look back.] (-)	L	X
Q96	[Once I know my goal, I consider strategies I have used in the past to meet similar goals.]	G	3
Q97	[I am often distracted from my most important goals by other less important goals.]	M	2
Q98	[I try not to let my emotions influence my decisions]	M	3
Q99	[I do not let my emotions delay an important decision.] (-)	M	X
Q100	[When I have too many factors to keep track of in my head, I write them down so I can evaluate them and decide.]	M	X

(-) = negatively worded
*new item

Instrument
Two of the original items were repeated, resulting in a 38-item survey which was administered using Google forms. Items were grouped into 10 per section (8 in the last section), with the row order shuffled within each section. No responses were required. Response choices were on an anchored scale from 1=not at all like me to 5=very much like me.

Data Collection Procedure
In Fall 2017, students in first-year engineering courses at a large public university in the Southeast were offered extra credit for completing a survey that included the aforementioned items via Google forms. Out of approximately 1200 students, 737 completed the survey. According to institutional research, the first-year engineering population is 25% female, 75% male and 79% White, 8% Black, 4% Hispanic, 4% two or more races, and 3% Asian.

Pre-Analysis

Analysis was conducted in IBM SPSS Statistics 24. First, the two repeated questions were used to remove inconsistent records. Students who answered either repeated question more than one value apart were removed from the records leaving 664 valid records. The repeated questions (Q73 and Q74) were then removed from further analysis. Another 35 participants were missing one or more relevant responses. Skewness values ranged from -0.915 to 0.847 and kurtosis ranged from -0.986 to 0.878, both of which are in an acceptable range for normality assumptions [3]. Mahalanobis distance was used to identify and remove outliers (df=36, p=0.001, χ^2 = 67.98), leaving 606 valid responses [4], [5]. Three hundred responses were randomly selected for the exploratory factor analysis, and the remaining 306 were set aside for confirmatory factor analysis.

Exploratory Factor Analysis

Exploratory factor analysis was conducted in SPSS using the correlation matrix for principal axis extraction, similar to Olson [6]. An oblique factor rotation (direct oblimin) allowed the factors to correlate.

The correlation matrix for all decision-making items was checked for multicollinearity. Item correlations ranged from -.404 to 0.611, which is well within the suggested limit of 0.9 [7]. However, the determinant of the correlation matrix, which should be greater than 1E-5 to avoid singularity problems, was only 3.96E-7 [7].

The largest correlation was between two confidence items from the original instrument, Q76 and Q78. Because confidence was not what we were seeking to measure with this scale, these items were removed, which increased the determinant to 1.17E-6. Remaining items were examined for potential problems and four more were removed: Q27 had an obvious answer, Q28 was a strategy, but not a particularly good one, Q99 used a double negative, and Q21 was complex [8]. This brought the determinant up to 6.84E-6.

Three more items were cut due to low communalities. Items Q25, Q81, and Q100 had communalities less than 0.3 before extraction or less than 0.25 after extraction of four factors. Removing these brought the determinant to an acceptable level of 2.34E-5. Two more items were removed to refine the instrument: item Q95 was loading as a single-item factor and item Q24 did not load well on any factor.

For the remaining 24 items, four eigenvalues were greater than 1.0 and explained 54% of the variance. However, the fourth factor had only two items (Q6 and Q79) and Q26 did not load on any factor at our target level of 0.4. The scree plot suggested three factors may also be appropriate and Q26 did load acceptably on the three-factor solution.

We decided to evaluate three models using confirmatory factor analysis on the remaining half of the data. Model 1 is a four-factor model with 23 items (Q26 dropped). Model 2 is a three-factor model with 24 items. And Model 3 is a three-factor model with 22 items (Q6 and Q79 dropped rather than forced into three factors). All subscales had Cronbach's alpha values ranging between 0.748 and 0.877. The items on each factor, a short description, and Cronbach's alpha for each subscale are given below.

Model 1 (23 items):

- Factor 1: Q2, Q3, Q4, Q5, Q7, Q82, Q83 (Generation and Evaluation, alpha=0.868)
- Factor 2: Q1, Q9, Q10, Q20, Q22, Q75, Q77, Q80, Q97 (Impulsive, Lack of process, alpha=0.845)
- Factor 3: Q23, Q93, Q94, 96, Q98 (Reflective, alpha=0.748)
- Factor 4: Q6, Q79 (Avoidance, alpha not interpretable)

Model 2 (24 items):

- Factor 1: Q2, Q3, Q4, Q5, Q7, **Q26**, Q82, Q83 (Generation and Evaluation, alpha=0.877)
- Factor 2: Q1, **Q6**, Q9, Q10, Q20, Q22, Q75, Q77, **Q79**, Q80, Q97 (Impulsive, Lack of process, Avoidance, alpha=0.858)
- Factor 3: Q23, Q93, Q94, 96, Q98 (Reflective, alpha=0.748)

Model 3 (22 items):

- Factor 1: Q2, Q3, Q4, Q5, Q7, **Q26**, Q82, Q83 (Generation and Evaluation, alpha=0.877)
- Factor 2: Q1, Q9, Q10, Q20, Q22, Q75, Q77, Q80, Q97 (Impulsive, Lack of process, alpha=0.845)
- Factor 3: Q23, Q93, Q94, 96, Q98 (Reflective, alpha=0.748)

Confirmatory Factor Analysis

Each of the three models above was tested on the remaining half the data (n=306) using AMOS. A summary of fit statistics is shown in Table 4. The chi-square statistic is a measure of the difference between the predicted covariance matrix and the observed covariance matrix. Small values and larger p-values indicate better fit. Ideally, we would like a non-significant chi-square statistic, but that can be difficult to achieve with a large sample [9]. CFI should be greater than 0.9 for an acceptable fit, greater than 0.95 for a good fit [10]. RMSEA is considered good when less than 0.06 [10]. AIC and CAIC are criteria used to compare two or more models; smaller values indicate better fit and parsimony [4]. Model 3 was the best fit and parsimony by all indices, so it was chosen for further examination.

Table 4. Model Fit Indices

Model	Items	Chi-Square ($p>0.05$)	CFI (>0.9)	RMSEA (<0.06)	AIC (smaller is better)	CAIC (smaller is better)
1	23	**415.18** ($p <0.001$)	0.895	**0.053**	519	765
2	24	**515.23** ($p <0.001$)	0.864	**0.059**	617	858
3	22	**379.27** ($p <.001$)	**0.900**	**0.053**	473	695
Revised 3	21	**312.02** ($p < .001$)	**0.921**	**0.047**	**402**	**614**

Examination of the modification indices for Model 3 suggested that the fit of the model would be most improved by adding regression path from Q22 to Q26. Other large indices indicated a potential link between Q26 and Q23. As Q26 had a relatively low loading on a 7-item factor, we chose to eliminate Q26, rather than complicate the model with cross-factor linkages. All indices improved with the revision of Model 3 (Table 4). The regression coefficients are shown in Figure 2, and the items are detailed in Table 5.

Table 5. Final Factors

Factor 1 - Generation and Evaluation		
Q2	When I have a big decision to make... [I take time to make sure that I am understanding things correctly.]	E
Q3	When I have a big decision to make... [I think about similar past decisions I made and what happened.]	L
Q4	When I have a big decision to make... [I take time to review all of my options before deciding.]	E
Q5	When I have a big decision to make... [I consider possible consequences before making any decision.]	E
Q7	When I have a big decision to make... [I make sure that I get all the facts.]	M
Q82	* When I have a big decision to make... [I try to think of all the possible options.]	G
Q83	* When I have a big decision to make... [I consider the pros and cons of each option.]	E
Factor 2 - Impulsive, Lack of Process		
Q1	When I have a big decision to make... [I often make it without considering how likely it is that things will turn out OK.]	E
Q9	When I have a big decision to make... [I tend to rush into making it.]	E
Q10	When I have a big decision to make... [I tend to forget important things when making the decision.]	E
Q20	[Whenever I have to make the same big decision, I tend to make the same mistakes.]	L
Q22	[When I have a big decision to make about doing something that requires a certain skill, I often don't bother to think about how much skill I have.]	E
Q75	When I have a big decision to make... [I just choose what seems OK at the moment.]	G
Q77	When I have a big decision to make... [I just go with a decision that all my friends are going with.]	G
Q80	When I have a big decision to make... [I usually follow the advice of anyone who gives it to me.]	G
Q97	* [I am often distracted from my most important goals by other less important goals.]	M
Factor 3 - Reflection		
Q23	* [When I am given an important assignment, I think about strategies I could use to complete it.]	G
Q93	* [I often reflect on my decision after implementing it and seeing the outcome.]	L
Q94	* [I often reflect on my decision PROCESS after implementing it and seeing the outcome.]	L
Q96	* [Once I know my goal, I consider strategies I have used in the past to meet similar goals.]	G
Q98	* [I try not to let my emotions influence my decisions]	M

* = new item

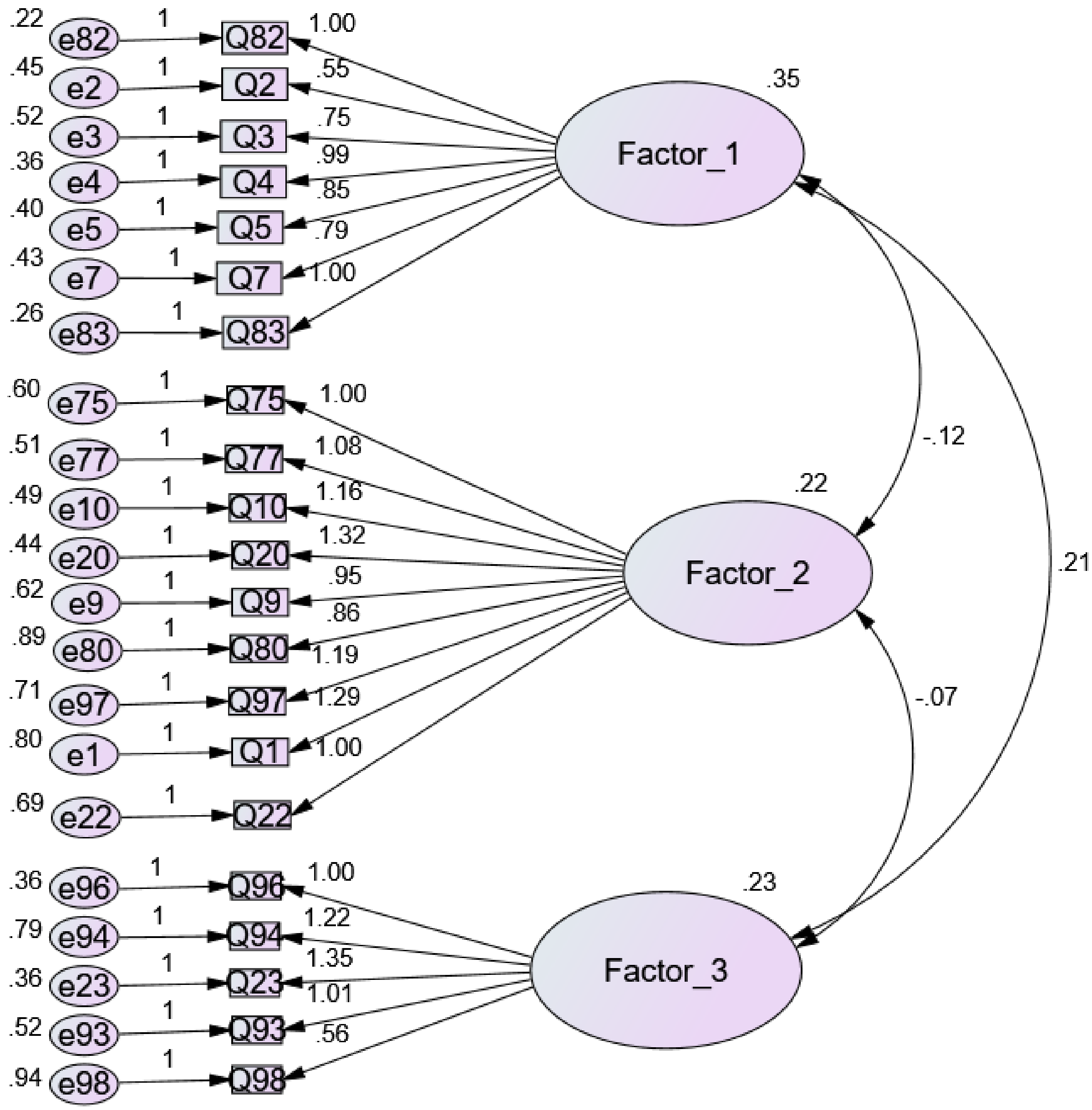

Figure 2. Confirmatory Factor Analysis of Revised Model 3

Results Summary

In summary, Factor 1 included seven items that related to the generation and evaluation phases of the decision-making process. It seems reasonable that these two constructs cannot be separated because to evaluate options, one must generate options and if one generates multiple options, at least some degree of evaluation must be employed. It is not surprising, therefore, that students who rated themselves highly on generation questions also rated themselves highly on evaluation questions and that these items loaded together into a single factor. Factor 2 items represent a lack of self-regulation in the decision-making process. It is expected that the Factor 2 score may correlate negatively with other measures of self-regulation. This will be investigated in future work. Additionally, the learning phase was somewhat represented by Factor 3 through reflection on past experiences. We acknowledge that learning encompasses more than reflection and suggest that future iterations should add items that address other aspects of learning. Another interesting point is that moderating factors items did not load together, and very few were kept. It is possible that it makes the most sense to think about moderating factors relative to the phase they affect.

Discussion and Conclusion

The results of our exploratory and confirmatory factor analysis provide support for building an instrument that evaluates decision-making abilities of post-secondary engineering students. The three subscales (Generation and Evaluation, Impulsiveness/Lack of Process, and Reflection) are related to much of the underlying theoretical constructs within our framework; however, more work must be done to refine the instrument and the dimensions it measures. One major drawback to the original survey instrument developed by the same authors who developed the SRMDM was that the items did not map well to the four parts of the model (Generation, Evaluation, Learning, and Moderating Factors). Miller & Byrnes [2] instead built items around metacognitive, motivational, and behavioral subscales with limited support from a subsequent EFA. By focusing on building an instrument centered around the underlying constructs of the theory and support from our EFA and CFA results presented here, we have improved the original survey instrument, enabling it to be a more representative measure of the theory to which it is related.

In future iterations, we will build on this instrument by refining the language used in the items and expanding the topics that the items cover. Specifically, we will be seeking feedback from individuals in our target population to participate in a think-aloud activity to help refine item language. We will begin this refinement by targeting specific items that had large response variation or complicated the model in the CFA. Additionally, we will focus on ways to build items that probe on the aspects of learning beyond reflection. We understand that self-regulated learning not only incorporates reflection, but also planning, monitoring, controlling, and adjusting behaviors [11]. As such, adding items to Factor 3 that represent these other aspects of learning could build a more comprehensive measurement in that dimension. Future work will also evaluate the convergent and predictive validity of the revised instrument and compare it to that of the original DMCI.

In this paper, we have presented an improved instrument to measure self-regulated decision-making in early post-secondary engineering students. Students who are more self-regulated in their decision-making will make adaptive decisions that are supported by their knowledge of their own skills, the context, and moderating factors. Utilizing this instrument can help practitioners provide more individualized support for their students when making important decisions such as declaring/changing majors or seeking research and/or industry experience. This work sits within the larger context of our research where we are seeking to connect self-regulated decision-making with student pathways to engineering degree completion [12]. The results of this study, along with our future work, will contribute to the creation of an interactive system for students that will support them in building and improving their self-regulated decision-making skills.

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