Expanding and Refining a Decision-Making Competency Inventory for Undergraduate Engineering Students

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***Abstract*—This Full Research Paper discusses ongoing work to develop a survey instrument to reliably assess undergraduate engineering student self-regulated decision-making. This work focuses on a second round of item expansion and refinement to the Decision-Making Competency Inventory (DMCI) to develop items related to learning from past decisions. The refined instrument was distributed to first-year engineering students enrolled in a large, public, land-grant institution located in the southeastern United States in the Fall of 2018. Of the approximately 1,200 students in first-year engineering courses, 883 valid surveys were randomly split into two separate samples for exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA results indicated a viable four-factor solution, which was explored with the CFA. The CFA results also indicated a four-factor model was appropriate. Improving this instrument will help researchers document and understand students' decision-making skills and how they relate to observed decisions like initial choice of major or change of major. A decision-making instrument will also be valuable in evaluating the effectiveness of interventions to help students build their decision-making competency and make adaptive choices.**

Keywords—Decision-making, first year engineering, major choice, exploratory factor analysis, confirmatory factor analysis

I. Introduction

Students make decisions daily that have direct and indirect consequences on their life. Small decisions like what to eat, or where to study have limited long-term impact; however other decisions like what major to declare, what experience to choose, or whether or not to remain at their institution can have dramatic effects on their future. To help students make self-regulated decisions, it is important to understand and document their current decision-making abilities.

Self-regulation is an important tool for students and has been identified as a differentiating factor between students' abilities to overcome individual learning differences, which were previously described as intelligence or diligence limitations. Self-regulation, compared to these previous descriptions, also allows for students to build and use strategies to overcome their individual learning differences [1]. Zimmerman has also concluded that "superior academic functioning" has been closely connected with the use of self-regulation strategies [2].

Previous work in the literature about self-regulation of decision-making has identified skills necessary for decision-making success both in engineering and science as well as in life more generally [3]. These skills – selection, optimization, and compensation – are all discussed in the context of goal seeking; students must select an appropriate goal, optimize their chances of meeting that goal while using appropriate strategies, and compensating when the goal proves unattainable by adjusting or reselecting the goal. In a cross-sectional sample, Hynes et al. found that the use of the selection, optimization, and compensation skills were directly and positively correlated with higher GPAs for both student groups, engineering and liberal arts.

These examples lead us to conclude that exercising self-regulation helps students more easily find academic success by making better decisions relative to their coursework and course goals.

II. Self-Regulated Decision-Making

For this work, we are using Byrnes' model of decision making [4] as our theoretical framework because it draws on self-regulation. Byrnes' Self-Regulated Model of Decision

Making (SRMDM) is so named because it argues that "self-regulated decision making involves making choices that increase the chances that adaptive goals will be attained" [4].

Byrnes' model focuses on entire phases of decision making instead of single facets within the phases. This model also describes adaptive decision-makers as "thorough, efficient, and effective" in evaluating options to meet goals and overcome natural shortcomings [4]. These components allow Byrnes' model to have greater predictive power for a larger ranger of decisions as well as the ability to explain variance in the responses.

The SRMDM consists of three phases and one component. The first phase is the *Generation Phase*. As the name suggests, this is the phase where options are generated. Decision-makers enter this phase when they have a goal in mind, but options are not immediately apparent. Next is the *Evaluation Phase*. It is here that the options formed in the generation phase are assessed or evaluated. It is common for a decision-maker to iterate between the generation and evaluation phases. For example, if the evaluation phase reveals that none of the options generated are feasible, the decision-maker needs to create new options and then evaluate those.

Once decisions have been made, they are implemented and reflected upon in the *Learning Phase*. This reflection is intended to evaluate the decision-maker's success or failure at meeting their goals. Knowledge gained in this process can then be used in future decisions. Lastly, all phases of the decision-making process can be affected by *Moderating Factors*, which can hinder a person's ability to attain goals or learn from their mistakes. Byrnes categorizes these factors as limitations, biases, and tendencies. Examples of moderating factors include memory capacity, inadequate knowledge, and emotionality.

The Decision-Making Competency Inventory (DMCI) is a 20-item single scale that was intended to measure self-regulated decision-making. It was designed by Miller and Byrnes [5]–[7] and items were developed around metacognitive, motivational, and behavioral subscales; however, these subscales were not supported by exploratory factor analysis. Additionally, factor loadings were observed to be heavily influenced by question wording. Miller and Byrnes suggested that the instrument be used as a single scale instead.

As mentioned in a previous paper documenting our first attempt to revise the DMCI [8], our goal is to revise this existing instrument to create useful subscales that map to the SRMDM. Our first revision produced three factors: Generation and Evaluation, Impulsivity or Lack of Process, and Reflection. Although we did find that these factors mapped much more closely to the components of the SRMDM than the original DMCI, our new inventory lacked key components related to learning such as adjusting behaviors. The goal of this study is to continue our instrument refinement and continue to build robust and meaningful subscales relating to the SRMDM.

III. METHODS

A. Instrument

All 20 items of the original DMCI were included in their original form. This ensured that the DMCI could be calculated at any time even if the revisions did not improve the instrument. Based on the results discussed in our previous work, we made wording adjustments to several of the added items. Some items were split, and others were re-worded prior to distribution.

Four new items were developed with the intention of documenting learning. In our previous work, the factors began to align with specific phases of Byrnes's SRMDM, some more strongly than others. The weakest factor, Reflection, aligned the most with learning. These four new items were added to the instrument to build that factor into a Learning factor. The items were constructed after a thorough review of the SRMDM and the language that is used to describe the learning phase in the model.

B. Distribution & Sample

In the Fall of 2018, the revised instrument was distributed to first-year students at a large, land-grant institution in the southeastern United States. Students were offered extra credit for completing the survey via Google Forms. The survey was available for the first ten days of class. Out of the approximately 1200 students enrolled in first-year engineering classes, 1004 students responded to the survey and indicated they were 18 years old or over.

From this survey data, 67% reported they are male, 31% reported they are female, less than 1% reported they were female to male transgender, and less than 1% did not want to disclose their gender. Relative to the population demographics, women are slightly overrepresented in this sample. Just over 79% of the participants identified as Caucasian or White, 6% identified as Hispanic, 5% as African American or Black, 5% as Asian, 4% as two or more races, the remaining 1% included individuals who identified as American Indian or Alaskan Native, Middle Eastern, or preferred not to disclose their race. Relative to the population, White and Asian participants are slightly overrepresented while Black, Asian, and two or more races are slightly underrepresented.

C. Data Cleaning

Before analysis, the data was cleaned to improve the reliability and validity of the analysis. All data analysis was conducted using R statistical software [9]. Participants who did not answer one or more relevant questions were removed from the sample, which left 929 responses. Skewness ranged from -0.937 to 0.697 and kurtosis ranged from -0.737 to 1.144, well within the normality assumptions (skew ± 2 and kurtosis ± 7) [10]. Forty-six outliers were identified and removed using Mahalanobis distance ($\chi^2 = 67.985$, df = 36, p = 0.001) leaving 883 valid responses to be used for exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) [11], [12].

Data was intentionally allocated to an EFA or CFA data set to ensure that it was used in the most effective way. To be effective in data allocation, the minimum sample size was determined for both EFA and CFA and remaining participants were split evenly between the two groups. For the EFA, the standard practice of allocating a minimum of 10 participants per item was used (n = 360), which is sufficient for the number of items in our scale [13]. For the CFA, a sample size minimum was calculated based on EFA model quality measures as defined by Gagné and Hancock [14]. The minimum sample size

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for the CFA was determined to be 503, using quality estimates from previous data of a similar population. The remaining 20 responses were evenly split between the two groups. Responses were only used for one of the two analyses and randomly assigned to either the EFA or CFA data set (n = 370 and 513, respectively).

IV. Exploratory Factor Analysis Results

An EFA was conducted using principal component extraction of the correlation matrix. An oblique factor rotation (direct oblimin) allowed the factors to correlate. Prior to factor analysis, the correlation matrix for all the items was checked for multicollinearity. Correlations between items ranged between -0.272 and 0.603 and were well below the suggested threshold of 0.9 [15]. However, the determinate of the correlation matrix was 9.986E-7, below the desired threshold of 1E-5 to reduce singularity issues [15]. Items were reviewed for potential problems by two of the authors. The two authors agreed that Q21, Q76, and Q78 should be removed from subsequent analyses because these three items were worded ambiguously and should be dropped. 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") was removed because its sentence structure was long and convoluted, while Q76 ("When I have a big decision to make I usually believe that I will make a good decision") and Q78 ("When I have a big decision to make, I am usually confident that things will turn out OK once I make the decision") were removed because they asked about confidence rather than decision-making skills. Removing these three items increased the determinate to 3.738E-6. Four additional items (Q25, Q81, Q98, and Q100) were removed based on communalities below 0.2 [16] and are listed below.

Q25: I try not to make important decisions when I am feeling stressed.
Q81: When I have a big decision to make I make it and then pay attention to how it turns out.
Q98: I try not to let my emotions influence my decisions.
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.

The determinate of the correlation matrix without these seven items was 1.084E-5, just above the threshold value.

Analysis of the remaining items yielded five eigenvalues greater than 1.0 that explained 53% of the variance. Parallel analysis indicated that three factors would be a viable solution. Upon visual inspection of the scree plot, three, four, or five factors could be sufficient for the model and therefore were explored. The three- and five- factor models did not provide solutions that were theoretically reasonable. In the three-factor solution, all the positively worded items loaded onto a factor, all the negatively worded items loaded onto a separate factor, and the third factor consisted of only items that were cross-loading onto the other two factors. The four and five factor solutions were relatively similar except two items loaded onto their own factor in the five-factor solution. As the five-factor solution did not provide more meaningful factors than the four-factor solution, the four-factor solution was explored in more detail.

Q93 ("I often reflect on my decision after implementing it and seeing the outcome") did not load onto any of the four factors above the cutoff level of 0.32 which indicates that there is a less than 10% overlap in variance [17]. The model was re-run without this item and reviewed again. When reviewing one of the factors, Q94 ("I often reflect on *how* I made my decision after implementing and seeing the outcome") loaded with items that related to pre-decision data gathering (i.e. "I try to think of all the possible outcomes", "I gather the information I need", etc.). This reflection item did not theoretically align with the other items on the factor and therefore was removed from analysis. According to Osborne, using theory to drive EFA models is the best approach: "the over-arching value has to be [the] theoretical framework and an easily interpretable factor structure. Absent this, which we use to make sense of the data, none of the technical details seem important" [18, p. 43]. With Q93 and Q94 removed, another item, Q104 ("When I am faced with a familiar problem, I rely on my past experiences to determine which actions I need to take next") did not load above the 0.32 cutoff and was subsequently removed from analysis. The last item removed was Q8 ("When I have a big decision to make, I usually seek out advice from people whom I know to be knowledgeable") due to low loading values. Although the loading value was above 0.32, there was a noticeable jump in loadings between 0.32 and 0.4 so 0.4 was used as the final cutoff. Using a gap between loading values instead of a standard cutoff value is an accepted practice in EFA and is encouraged when appropriate for the data [17].

The final EFA model with 25 items is described in Table I. The final model from the EFA results consisted of four factors that have been labeled (1) information gathering, (2) avoidance, (3) learning, and (4) impulsivity. Reliability of each factor was calculated using Cronbach's alpha and is noted in the table. Three of the four factors have a Cronbach's alpha above 0.8. Although Cronbach's alpha is smaller than ideal for Factor 4, it is still an acceptable value for scale development [19], [20]. In addition, the Cronbach's alpha estimate of internal consistency "reflects both the number of items and their average correlation" [19, p. 251]. Thus, lengthening a scale (increasing number of items) will typically increase its alpha. The alpha observed for Factor 4 may be at least partially a function of too few items (4 vs 5 to 7 for other factors). The factor with the highest alpha is also the one with the most items. The model outlined below, along with an *a priori* model were examined via confirmatory factor analysis and is described in the next section.

TABLE I: ITEMS AND FACTOR LOADINGS FOR THE FOUR FACTOR SOLUTION.

Item	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1[a]: Learning (Cronbach's alpha = 0.8609)				
Q24A+: When choosing an approach to solving a dilemma, I take into account what I'm good at.	0.74	-	-	-
Q24B+: When choosing an approach to overcoming an obstacle, I take into account what I struggle with.	0.69	-	-	-
Q103*: When I know why I failed at a task, I am confident in my ability to change my behavior to perform better the next time I'm faced with the same task.	0.67	-	-	-
Q23: When I am given an important assignment, I think about strategies I could use to complete it.	0.63	-	-	-
Q96: Once I know my goal, I consider strategies I have used in the past to meet similar goals.	0.58	-	-	-
Q102*: When my decisions result in unfavorable outcomes, I change my behavior when faced with a similar situation.	0.51	-	-	-
Q3: When I have a big decision to make, I think about similar past decisions I made and what happened.	0.50	-	-	-
Q101*: When I have a big decision to make, I consider the consequences of my past similar decisions before I determine how I should move forward.	0.50	-	-	-
Factor 2: Avoidance (Cronbach's alpha = 0.8104)				
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). (-)	-	0.73	-	-
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. (-)	-	0.64	-	-
Q77: When I have a big decision to make, I just go with a decision that all my friends are going with. (-)	-	0.63	-	-
Q20: Whenever I have to make the same big decision, I tend to make the same mistakes. (-)	-	0.54	-	-
Q80: When I have a big decision to make, I usually follow the advice of anyone who gives it to me. (-)	-	0.50	-	-
Q97: I am often distracted from my most important goals by other less important goals.(-)	-	0.48	-	-
Q10: When I have a big decision to make, I tend to forget important things when making the decision. (-)	-	0.48	-	-
Q75: When I have a big decision to make, I just choose what seems OK at the moment. (-)	-	0.46	-	-
Factor 3: Information Gathering (Cronbach's alpha = 0.8159)				
Q4: When I have a big decision to make, I take time to review all of my options before deciding.	-	-	0.72	-
Q82: When I have a big decision to make, I try to think of all the possible options.	-	-	0.69	-
Q2: When I have a big decision to make, I take time to make sure that I am understanding things correctly.	-	-	0.59	-
Q7: When I have a big decision to make, I make sure that I get all the facts.	-	-	0.58	-
Q26+: When I have a big decision to make, I gather the information I need.	-	-	0.52	-
Q5: When I have a big decision to make, I consider possible consequences before making any decision.	-	-	0.46	-
Factor 4: Impulsivity (Cronbach's alpha = 0.6182)				
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. (-)	-	-	-	0.66
Q9: When I have a big decision to make, I tend to rush into making it. (-)	-	-	-	0.45
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. (-)	-	-	-	0.40

[a] Note: Item 24 originally was a single item that included "what I'm good at and what I struggle with" which was split into two items. Negatively worded items (-), new items (*), or reworded items (+) are indicated accordingly

V. CONFIRMATORY FACTOR ANALYSIS RESULTS

Confirmatory factor analysis was performed on two models using the remaining 513 responses. To evaluate each model, fit statistics including chi-square (χ^2), comparative fit index (CFI), root mean square error of approximation (RMSEA), and Akaike information criterion (AIC) were analyzed and used to compare models. A small chi-square statistic with a large p-value indicates a better fit of the model. A non-significant chi-square statistic is ideal, but difficult to achieve with a large sample [21]. CFI should be above 0.9 to indicate an acceptable fit and greater than 0.95 to indicate a good fit [22], RMSEA should be minimized and is considered acceptable below 0.06 [22], AIC should be compared between models with a smaller number indicating a better fit [12]. Modification indices were used to evaluate if a model could be refined to better reflect data behavior. An estimated reduction in chi-square value is reported for every modification, therefore a large modification index value would suggest the modification would result in a 'better' model. A drop of 3.84 in the chi-square test statistic would indicate a statistically significant drop at the $\alpha = 0.05$ level and one degree of freedom. However, these values should be interpreted with skepticism and should only be used if there is theoretical support. Each model was evaluated independently and then compared to the other.

A. A Priori Model

The *a priori* model was developed from data collected the year prior and is described in detail in another publication [8]. It contains three factors that partially align with Byrnes's SRMDM [4]. The first factor contains many of the generation and evaluation items. It makes sense that, because these two phases are strongly linked, it may be difficult to identify them as distinct factors. The second factor contains items that relate to a lack of self-regulation. They aligned mostly with the moderating factors that prevent a person from making a decision. The third factor relates primarily to the learning phase but focuses on the reflection part of learning. We understand that learning encompasses more than just reflection, but that phase could not be sufficiently measured with the items that were on the earlier version of the instrument. We added the four new items (Q101 – Q104) to the third factor which is where we hypothesized *a priori* they would fit. This model was a theoretical adaption of our original model. These additional items were written with the intention that the reflection factor would become a robust learning factor.

A priori Model:

Factor 1: Q2, Q3, Q4, Q5, Q7, Q26, Q82, Q83 (Generation and Evaluation)

Factor 2: Q1, Q9, Q10, Q20, Q22, Q75, Q77, Q80, Q97 (Impulsive, Lack of process)

Factor 3: Q23, Q93, Q94, Q96, Q98, Q101, Q102, Q103, Q104 (Reflection/Learning)

The fit measures for this model are reported in Table II. Fit measures for this model were acceptable across the board. Modification indices were also reviewed to determine if modifications would be helpful to building a better model. No modification provided sufficient reduction in the chi-squared value to warrant the added complexity.

B. *EFA Model*

The EFA model was developed as described in the previous section. This was the only model that had four factors and divided the items into interpretable factors. High scores on Factor 1 and 3 indicated well-developed self-regulation whereas Factor 2 and 4 can better differentiate negative behaviors related to decision-making.

The EFA model fit measures are reported in Table II and indicate a robust model. Modification indices were reviewed and no changes to the model were made as the reduction in chi-squared values did not warrant the additional complexity .

C. *Cross-Model Discussion*

Although the *a priori* model had sufficient fit measures, the EFA model had improvements in all the fit measures with the exception of the AIC. The AIC measures, however, are relatively similar to each other indicating a parsimonious fit for both models. The EFA model also produced easily interpretable factors that better isolate specific positive and negative decision-making behaviors, which may help in future work. Items for each factor for the EFA Model with regression coefficients are shown in Fig. 1

TABLE II. SUMMARY OF CFA FIT MEASURES FOR THE REFINED MODELS.

Model	**Fit Measures**			
	χ^2 (df, p-value)	***CFI (>0.9)***	***RMSEA (<0.06)***	***AIC (minimize)***
a priori Model	582.599 (249, p<0.001)	0.903	0.051	27994
EFA Model	538.870 (269, p<0.001)	0.931	0.044	28495

VI. RESULTS SUMMARY

The first factor, *Learning*, contains eight items. This factor focuses on reflecting on past decisions and the information gained from making those decisions. Contrasting with information gathering, *Learning* focuses on the knowledge development after the decision has been made. *Learning* not only includes reflection, but also includes changing behaviors and learning from previously unsuccessful decision-making strategies. This factor most closely aligns with the learning phase in Byrnes's SRMDM [4].

The second factor, *Avoidance*, contains eight items. This factor is primarily concerned with avoiding making decisions for oneself and allowing other people, like parents or friends, to make the decision. It contains many of the negatively-worded items, but centers around avoiding making a decision and includes many of the moderating factors discussed by Byrnes [4]. However, we do not know *why* a decision-maker would avoid or disengage by this measure and are not making a judgement. There are many valid reasons to avoid making a decision like anxiety or guilt that cannot be measured by this instrument.

The third factor, *Information Gathering*, contains six items that focus on collecting facts, assessing strategies, and evaluating options prior to making a decision. This factor seems to measure a decision-maker's choices and activities prior to a decision being made, identifying the processes a decision-maker will use to reach their decision. This factor is most closely connected with the generation and evaluation phases of Byrnes's Self-Regulation Model of Decision Making [4].

The final factor, *Impulsivity*, contains three items. This factor relates to rushing to make a decision and the consideration, or lack thereof, of the consequences of a decision. Accompanying *Avoidance*, this *Impulsivity* is most closely connected with the moderating factors in Byrnes's Self-Regulation Model of Decision Making [4]. It is important to note that this instrument cannot determine why a student would tend to make impulsive decisions; it can only evaluate whether a student reports a tendency to make impulsive decisions.

VII. DISCUSSION AND CONCLUSION

The results of the exploratory and confirmatory factor analyses contribute to the development of an instrument that can measure decision-making abilities of undergraduate engineering students. The four subscales successfully differentiate important aspects of the theoretical constructs within our framework. Factor 1 (Learning) and Factor 3 (Information Gathering) relate to the three phases of the SRMDM whereas Factor 2 (Avoidance) and Factor 4 (Impulsivity) relate to the moderating factors component of the model. Differentiating self-regulated decision-making behaviors between pre-decision behavior (Information Gathering) and post-decision behavior (Learning) can be helpful in future work. Isolating two negative but different behaviors can help identify unique groups of students who are struggling to make self-regulated decisions.

While the AIC measure for the *a priori* Model was slightly better than the EFA Model, the benefits of theoretical validity outweigh the moderate differences between fit measures. The EFA Model aligns more closely with the SRMDM because both *Information Gathering* and *Learning* map more directly onto the Generation, Evaluation, and Learning phases of the theory compared to the *a priori* Model. Additionally, the EFA Model allows for the separation of two negative attributes of decision making, *Avoidance* and *Impulsivity*, instead of just the one that was present in *a priori* Model.

Future work for this model could include an expansion of the *Impulsivity* factor. Currently, this factor only has three items which could be expanded by writing additional items with the intention that they will load onto *Impulsivity*. The new items would require an additional survey deployment and subsequent analysis to verify their loadings. The caveat of this potential expansion of the factor is if it will add predictive value to the instrument. Ideally, this expansion would also improve the Cronbach's alpha for the factor.

Having a reliable instrument to understand how students make big decisions will allow future research into many populations, including first-year engineering students. With the development of the four-factor model, we will be able to compare and contrast different aspects of decision-making. Future work will utilize and build on the final model of this instrument to explore relationships between self-regulated decision-making competency and real-world behaviors, especially relating to selection and changing of their academic major.

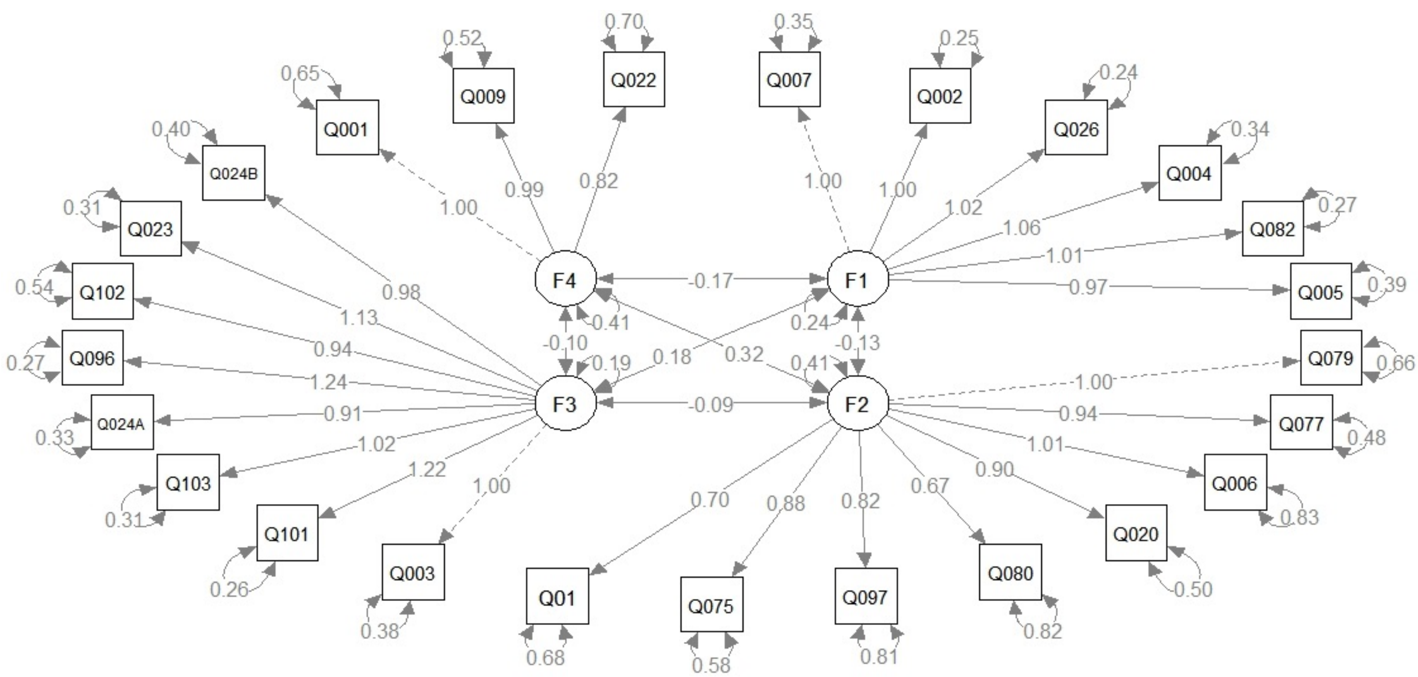

Fig. 1. Visual of Confirmatory Factor Analysis of Revised Model 3. The center circles indicate each factor with double-sided arrows between factors indicating correlation values between factors. Squares indicate each variable with single-sided arrows indicating regression coefficients. Dashed lines indicate the variable that was standardized for each factor. Rounded arrows indicate error values for each factor or variable.

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References

[1] B. J. Zimmerman, "Becoming a Self-Regulated Learner: An Overview," *Theory Pract.*, vol. 41, no. August, pp. 64–70, 2002.

[2] B. J. Zimmerman, "Self-Regulated Learning and Academic Achievement: An Overview," *Educ. Psychol.*, vol. 25, no. 1, pp. 3–17, 1990.

[3] M. M. Hynes, A. F. McKenna, C. B. Rogers, M. K. Mueller, X. Neumeyer, and R. M. Lerner, "The Role of Intentional Self-Regulation in Achievement in Engineering," in *ASEE Annual Conference & Exposition*, 2011.

[4] J. P. Byrnes, *The Nature and Development of Decision Making*. Mahwah, NJ: Lawrence Erlbaum Associates Inc., 1998.

[5] D. C. Miller and J. P. Byrnes, "To achieve or not to achieve: A self-regulation perspective on adolescents' academic decision making.," *J. Educ. Psychol.*, vol. 93, no. 4, pp. 677–685, 2001.

[6] D. C. Miller and J. P. Byrnes, "Adolescents' decision making in social situations: A self-regulation perspective," *J. Appl. Dev. Psychol.*, vol. 22, no. 3, pp. 237–256, 2001.

[7] J. P. Byrnes and D. C. Miller, "The relative importance of predictors of math and science achievement: An opportunity-propensity analysis," *Contemp. Educ. Psychol.*, vol. 32, no. 4, pp. 599–629, 2007.

[8] M. K. Orr, K. M. Ehlert, M. L. Rucks, and M. Desselles, "Towards the Development of a Revised Decision-Making Competency Instrument," in *Proceedings from ASEE 2018: American Society for Engineering Education Annual Conference & Exposition*, 2018.

[9] R Code Team, "R: A language and environment for statistical computing.," *R Foundation for Statistical Computing, Vienna, Austria.*, 2013. [Online]. Available: http://www.r-project.org/.

[10] P. J. Curran, S. G. West, and J. F. Finch, "The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis.," *Psychol. Methods*, vol. 1, no. 1, pp. 16–29, 1996.

[11] C. A. Mertler and R. A. Vannatta, "Pre-Analysis Data Screening," in *Advanced and Multivariate Statistical Methods: Practical Application and Interpretation*, 4th ed., Glendale, CA, 2009, pp. 25–66.

[12] B. G. Tabachnick and L. S. Fidell, *Using Multivariate Statistics*, 6th ed. Upper Saddle River, New Jersey: Pearson Education Inc., 2013.

[13] A. Rouquette and B. Falissard, "Sample size requirements for the internal validation of psychiatric scales," *Int. J. Methods Psychiatr. Res.*, vol. 20, no. 4, pp. 235–249, 2011.

[14] P. Gagne and G. R. Hancock, "Measurement Model Quality, Sample Size, and Solution Propriety in Confirmatory Factor Models," *Multivariate Behav. Res.*, vol. 41, no. 1, pp. 65–83, 2006.

[15] A. P. Field, *Discovering statistics using SPSS*. SAGE Publications, 2005.

[16] D. Child, *The Essentials of Factor Analysis*. 2006.

[17] B. G. Tabachnick, L. S. Fidell, and J. B. Ullman, *Using Multivariate Statistics*, 6th Editio. Pearson Education Inc., 2012.

[18] J. W. Osborne, *Best Practices in Exploratory Factor Analysis*. Scotts Valley, CA: CreateSpace Independent Publishing, 2014.

[19] J. C. Nunnally and I. H. Bernstein, *Psychometric Theory*, 3rd Editio. McGraw Hill, 1994.

[20] K. Sijtsma, "On the Use, the Misuse, and the Very Limited Usefulness of Cronbach," *Psychometrika*, pp. 107–120, 2009.

[21] J. J. Albright and H. M. Park, "Confirmatory Factor Analysis using Amos , LISREL , Mplus , SAS / STAT CALIS *," *Trust. Indiana Univ.*, vol. 4724, no. 812, p. 86, 2009.

[22] S. Bialosiewicz, K. Murphy, and T. Berry, "An Introduction to Measurement Invariance Testing : Resource Packet for Participants," in *American Evaluation Association*, 2013, pp. 1–37.