Reducing Student Resistance to Active Learning: Development and Validation of a Measure.

Objectives

The goal of the study presented here was to test the reliability and validity of faculty responses to the Strategies to Reduce Student Resistance (SRSR) a measure of Science, Engineering, and Mathematics university faculty use and motivation (self-efficacy and value) for using instructional strategies to reduce student resistance to active learning. The development of this measure will support research and interventions designed to support faculty implementation of active learning strategies.

The scale examined here was adapted from a student version, developed and tested as part of a national study on student resistance to active learning in engineering programs. This project reveled a set of faculty behaviors which supported students' positive response to active learning strategies (Authors, 2017). Although student perspectives on faculty behavior is important, we felt it was necessary to adapt the scale to measure faculty's perspectives on the strategies they use and their motivation to use those strategies as part of their use of active learning in their classroom.

Research Questions

RQ1. Do the items on the SRSR scale correspond to the theorized model of latent SRSR?

RQ1. Is there a relation between planning, explanation, and facilitations strategies that relate to participants' value, sense of self-efficacy, and intention to use strategies to reduce student resistance?

RQ2. Is there are relation between faculty's motivation for SRSR and their use of SRSR?

Theoretical Framework

Tremendous effort has been invested to develop and document the effectiveness of evidence-based teaching practices such as active learning (P), peer instruction (), and Peer-Led Team Learning (). The significant cumulative investment by NSF and others over the past few decades has successfully shown that these and similar teaching practices can, in fact, improve student learning, engagement, and interest in STEM (). Many of these teaching practices are especially effective for educating a diverse student body () and for increasing the retention rate of students in STEM programs. Research suggests that the perennial calls to increase the number, quality, and diversity of STEM graduates could, in fact, be substantially met if these evidence-based teaching practices were widely adopted in undergraduate STEM departments ().

The translation of educational research to actual classroom practice has been slow (). As a result, numerous editorials and reports call for "collective action" to translate STEM education research into improved learning for undergraduate students through rapid uptake of evidence-based teaching practices, including active learning (e.g., The primary challenge now is to increase the use of evidence-based teaching practices. Our research () has identified instructor-reported barriers to adoption of these practices, including concerns about: (a) the efficacy of the teaching practices; (b) the preparation time required to implement the teaching practices; (c) class time and the instructor's ability to cover the syllabus; and (d) student resistance.

While instructor concerns about the *efficacy* of active learning and other evidence-based teaching practices are a legitimate barrier, this efficacy has been exhaustively documented (e.g., (); thus, it requires little additional research. Similarly, instructor concerns about both preparation and class time have been addressed convincingly in the literature (). However, student resistance (which we define as any negative student behavioral response to a teaching practice – such as refusing to participate, distracting others, or giving low course evaluations – which would discourage an instructor from using that activity) has not been the subject of significant research. We therefore focus on student resistance as the most actionable barrier to the adoption of active learning.

The existing literature offers a variety of tips for instructors wishing to reduce student resistance to nontraditional teaching practices (e.g.). These suggestions, however, are based on experiences of individual instructors, not on a strong empirical and theoretical base. In our prior research, we began to address this issue by developing and validating an instrument to assess the type and level of student resistance to different teaching practices (Author, 2017). The development of these scales focused on students' perspectives of faculty behaviors which reduced their resistance to active learning. This initial work tentatively identified specific instructor strategies, categorized as *explanation and facilitation* strategies (see Table 1), which correlated with reduced levels of student resistance (Authors, 2017, 2018). That work is the first time the use of these strategies has been empirically linked to reducing student resistance to active learning in STEM classrooms. To expand our understanding of strategies faculty can use to reduce resistance, as self-report measure of faculties use of these strategies, and their motivation for using these strategies is needed.

To support faculty effective implementation of evidence based teaching practice, we need not only provide instruction in SRSR but to better understand faculty's motivation for implementing these strategies. Prior research (has examined adoption of evidence-based teaching practices using motivational frameworks such as Expectancy Value Theory. That theory (E) postulates that people are motivated to engage in activities at which they think they can be successful (self-efficacy) and that have value to them (value). The SRSR scale not only assess faculty reported use of SRSR but also their motivation for using them. We anticipate that faculty reported motivation will predict faculty use of these strategies.

Data Sources

We distributed surveys using an online digital platform to college faculty interested in STEM education through existing list serves, social media, and word-of-mouth in Winter 2019. Participants were offered entrance into a drawing for a $500 Amazon gift card. A total of 540 individuals returned the survey; of those 540, 69 did not complete most or all of the survey and were excluded. We then categorized participants as faculty in STEM fields or not; 87 were identified as primarily teaching in an outside field. The remaining sample for the present analysis included 384 participants.

We measured participants' intention to use planning, explanation, and facilitation SRSR and the motivational antecedents of value and self-efficacy for each SRSR subscale using several indicators. Use, value, and self-efficacy for planning were each measured using six indicators, explanation four indicators, and facilitation five indicators. We present correlations and descriptive statistics for all use of SRSR indicators in Table 2. The majority of indicators were censored-inflated. The most appropriate method to address this limitation in the data is to use a latent tobit model with robust maximum likelihood estimations using numeric integration (MLR-NI; Muthén & Muthén, 2019), incorporates information from the raw data in addition to the variance-covariance matrix of indicators. Although this method provides less bias estimates, it cannot establish traditional fit indices and instead requires the comparison of less-constrained models. In this study, we utilize a model with a single-indicator as a null-model. Additionally, we provide estimates using a latent tobit model using WLSMV estimation (Muthén & Muthén, 2019), which does provide absolute goodness-of-fit indices.

Given the complexity of our model and sample size, we opted to use higher-order subscale constructed using the average of participants' response to each individual strategy within SRSR domain to answer our second and third research questions; we present correlations and descriptive statistics for all subscale indicators in Table 3. Internal consistency for each subscale was good (α = .70-.89); however, several subscale were both censored and leptokurtic. To address this issue, data were analyzed using a latent tobit model using WLSMV estimation (Muthén & Muthén, 2019).

Methods

To test our first research questions, we conducted a confirmatory factor analysis (CFA; Kline, 2016) using the indicators associated with the use of planning, explanation, and facilitation strategies using a single-factor model as our null-model. To test our second research question, we conducted a CFA using the higher-order subscales for use, value, and self-efficacy for using planning, explanation, and facilitation strategies. We first fit a simple structure model in which each indictor loads onto a single factor and residual variance of all indicators were uncorrelated. We then allowed theoretically and empirically justifiable residual variances to covary. To answer our third research question, we used a structural regression (SR) model in which we regressed participants' intention to use SRSR onto the antecedent motivational factors of value and self-efficacy.

Results

To answer our first research question, we compared model fit for nested CFA models with a single-factor against the hypothesized three-factor model. We present the model fit indices and standardized parameter estimates in Table 4. We found that the three-factor model outperformed the single-factor model and achieved adequate fit (Hu & Bentler, 1999) using both WLSMV and MLR-NI approaches. We present the best-fitting CFA model in Figure 1.

To answer our second research question, we compared model fit for a series of nest CFA models. We present model fit indices and standardized parameter estimates of our CFAs in Table 5. Our initial simple structure CFA failed to achieve adequate fit (Hu & Bentler, 1999). We then allowed then allowed for the residual variance related to participants use, value, and self-efficacy for each SRSR to covary, significantly improving model fit. Finally, we allowed the use of planning and explanation strategies and the value of explanation strategies, value planning strategies, and value of facilitation strategies to covary. This model achieved close fit and was used as the basis for the SR model. We present the best-fitting CFA model in Figure 2.

To answer our third research question, we fit a SR model in which latent SRSR motivational factors were regressed onto participants' intention to use SRSR. We present standardized parameter estimates in Figure 1. After controlling for the residual covariances identified in our previous analysis, we found a strong relation between participants' self-efficacy and value of SRSR ($r = .58$, $p < .01$) and the influence of self-efficacy ($\beta = .38$, $p < .01$) and value ($\beta = .52$, $p < .01$) on the use of SRSR ($R^2 = .64$, $p < .01$).

Significance

In this study, we examined the construct validity of a scale measuring the use of SRSR. Additionally, we examined whether their existed higher-order SRSR factors relating to participants' overall self-efficacy, value, and use of SRSR. Finally, we examined the degree to which participants' intention to use SRSR related to antecedent motivational factors of value and self-efficacy.

We found that the hypothesized three-factor model outperformed our single-factor null-model. This result suggest that there are three theoretically and empirically distinct domains of SRSR including planning, explanation, and facilitation strategies. This finding corresponds to extant research conducted with students which similarly established these three domains (Authors, 2017).

We found that each subscale contributed statistically and theoretically meaningfully to a higher-order factor model, suggesting there is a relation between participants' intention to use and value and self-efficacy for using planning, explanation, and facilitation SRSR. Given the improvement to model fit we observed after allowing the residual variance within each subscale domain to covary (e.g. use, value, and self-efficacy for planning), suggesting there is a significant relation between use, value, and self-efficacy within each domain in addition to the overarching SRSR factor. This finding is constant with previous research in motivation theory that has long suggested that antecedent motivational factors are task specific (e.g. Wigfield & Eccles, 2000). We found a strong relation between explanation and planning within the use and value subscales. Indicating that the strategies for reducing resistance may translate from students' perception of faculty behavior to faculty behavior. Additionally, we found a strong relation between value of explanation and value of facilitation, the set of strategies we identified represent an underlying construct of "resistance reducing strategies".

Congruent with extant literature within motivational theory, we found that participants' intention to use SRSR was predicted by their value and self-efficacy for using SRSR. Individuals who felt efficacious in using SRSR and/or valued SRSR were significantly more likely to indicate their intention to use SRSR. We also found a significant relation between participants' value and self-efficacy for using SRSR. These findings point to a theory of faculty behavioral change. If we support faculty efficacy and value for using these strategies, faculty are more likely to engage in strategies to reduce resistance. Our presentation will address the possible uses of this scale for evaluation of faculty trainings, research on faculty motivation for engaging in active learning, and effective implementation of evidenced based teaching practice.

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Table 1. Strategies Reduce Student Resistance.

Explanation Strategies	Facilitation Strategies
Clearly explain the purpose of the activities Discuss how the activities relate to students' learning Clearly explain what students are expected to do for the activities	Solicit student feedback about the activities Encourage students to engage with the activities through instructor's demeanor Walk around the room to assist students with the activity

Table 2.
Moments and Product Moments for SRSR Use Indicators

	PU1	PU2	PU3	PU4	PU5	PU6	EU1	EU2	EU3	EU4	FU1	FU2	FU3	FU4	FU5
PU1	1.00														
PU2	.28	1.00													
PU3	.55	.29	1.00												
PU4	.45	.25	.41	1.00											
PU5	.33	.29	.46	.25	1.00										
PU6	.44	.26	.50	.40	.45	1.00									
EU1	.42	.19	.33	.39	.29	.32	1.00								
EU2	.28	.24	.36	.21	.39	.35	.43	1.00							
EU3	.30	.26	.39	.26	.45	.42	.31	.49	1.00						
EU4	.22	.17	.22	.32	.35	.26	.31	.39	.46	1.00					
FU1	.30	.20	.21	.19	.21	.23	.22	.19	.20	.13	1.00				
FU2	.42	.32	.45	.42	.33	.33	.32	.15	.28	.14	.27	1.00			
FU3	.36	.26	.24	.23	.31	.27	.34	.29	.29	.13	.45	.34	1.00		
FU4	.39	.22	.27	.30	.27	.32	.21	.17	.27	.19	.41	.34	.36	1.00	
FU5	.26	.17	.22	.23	.23	.29	.19	.12	.20	.13	.27	.24	.27	.20	1.00
Median	11	9	10	11	9	10	11	10	9	9	11	11	10	11	10
Mean	9.95	8.88	9.37	10.16	8.10	9.62	9.95	9.35	8.35	8.03	10.26	9.74	9.29	10.07	8.66
SD	1.57	2.30	2.00	1.52	2.65	1.89	1.45	2.08	2.67	2.93	1.63	1.93	2.20	1.68	2.82
Skewness	-2.47	-1.35	-1.60	-2.55	-0.87	-1.79	-1.71	-1.45	-1.07	-0.89	-2.92	-2.14	-1.54	-2.65	-1.18

Kurtosis	8.17	1.52	3.03	7.48	<0.01	3.57	3.01	1.78	0.44	-0.29	9.37	5.33	2.17	8.49	0.44

Notes. All parameters significant at $p < .05$.

Table 3.

Moments, Product Moments, and Cronbach's Alphas for SRSR Subscales

	PU	EU	FU	PV	EV	FV	PSE	ESE	FSE
PU	1.00								
EU	.60	1.00							
FU	.62	.45	1.00						
PV	.68	.42	.47	1.00					
EV	.41	.65	.36	.63	1.00				
FV	.48	.37	.68	.69	.59	1.00			
PSE	.64	.37	.55	.55	.32	.50	1.00		
ESE	.50	.47	.52	.43	.40	.43	.78	1.00	
FSE	.48	.29	.71	.47	.29	.60	.77	.73	1.00
No. Items	6	4	5	6	4	5	6	4	5
α	.78	.72	.70	.80	.76	.76	.89	.83	.80
Mean	9.40	9.01	9.62	8.81	8.37	8.83	8.75	8.92	8.88
SD	1.40	1.74	1.41	1.26	1.66	1.37	1.41	1.38	1.38
Skewdness	-1.71	-1.01	-1.94	-2.33	-1.27	-2.38	-2.02	-2.00	-2.29
Kurtosis	5.22	0.83	6.39	9.61	1.80	8.63	6.97	6.02	8.58

Notes. All correlations significant at $p < .01$. Kurtosis = excess kurtosis (proper kurtosis – 3). Skewedness > 2.00 and excess kurtosis > 4.00 suggest substantial non-normality of data (Kim, 2013). PU = Use of Planning Strategies, EU = Use of Explanation Strategies, FU = Use of Facilitation Strategies, PV = Value of Planning Strategies, EV = Value of Explanation Strategies, FV = Value of Facilitation Strategies, PSE = Self-efficacy for Use of Planning Strategies, ESE = Self-efficacy for Use of Explanation Strategies, FSE = Self-efficacy for Use of Explanation Strategies.

Table 4.
Fit Indices and Parameter Estimates for CFA of Use of SRSR Indicators

	WLSMV		MLR-NI	
Fit Indices	Single factor	Three factor	Single factor	Three factor
χ^2 (*df*)	321.57** (90)	207.14** (87)		
$\Delta\chi^2$ (Δdf)		114.43** (3)		
k	45	48	45	48
RMSEA (90% CI)	.08 (.07, .09)	.06 (.05, .07)		
CFI	.86	.93		
TLI	.84	.91		
AIC			19,089.62	18,990.91
ΔAIC				98.71
BIC			19,267.98	19,181.16
ΔBIC				86.82
Parameter Estimates				
Planning (PU)				
λPU1 (ε_{PU1})	.73 (.46)	.75 (.44)	.75 (.44)	.76 (.42)
λPU2 (ε_{PU2})	.48 (.77)	.49 (.76)	.48 (.77)	.49 (.76)
λPU3 (ε_{PU3})	.70 (.51)	.72 (.49)	.72 (.49)	.75 (.44)
λPU4 (ε_{PU4})	.70 (.51)	.71 (.49)	.73 (.46)	.73 (.47)
λPU5 (ε_{PU5})	.65 (.58)	.66 (.57)	.65 (.57)	.66 (.57)
λPU6 (ε_{PU6})	.71 (.50)	.72 (.48)	.71 (.49)	.73 (.47)
Explanation (EU)				
λEU1 (ε_{EU1})	.68 (.54)	.76 (.42)	.70 (.52)	.72 (.48)
λEU2 (ε_{EU2})	.64 (.60)	.73 (.47)	.66 (.56)	.78 (.40)
λEU3 (ε_{EU3})	.43 (.60)	.71 (.49)	.63 (.60)	.72 (.49)
λEU4 (ε_{EU4})	.48 (.77)	.55 (.70)	.50 (.75)	.60 (.64)
Facilitation (FU)				
λFU1 (ε_{FU1})	.60 (.64)	.68 (.54)	.64 (.59)	.75 (.44)
λFU2 (ε_{FU2})	.67 (.55)	.75 (.44)	.68 (.53)	.72 (.48)
λFU3 (ε_{FU3})	.61 (.63)	.68 (.53)	.62 (.62)	.70 (.51)
λFU4 (ε_{FU4})	.62 (.61)	.70 (.51)	.63 (.60)	.72 (.49)
λFU5 (ε_{FU5})	.44 (.81)	.49 (.77)	.43 (.82)	.46 (.79)
Correlations				
PU↔EU		.84		.84
PU↔FU		.85		.84
EU↔FU		.67		.67

Notes. All parameters significant at $p < .05$. λIndicator = factor loading of indicator on latent variable. $i_{indicator}$ = residual variance of indicator.

Table 5

Model Fit Indicies and Parameter Estimates for Nested CFA

Model fit	Simple Structure	Within domain covariance	Across domain covariance
$\chi^2(df)$	497.63 (24)	81.52 (15)	36.12 (12)
RMSEA (90% CI)	.23 (.21, .24)	.11 (.09, .13)	.07 (.05, .10)
CFI	.74	.96	.99
TLI	.61	.91	.96
Parameter estimates			
Use (U)			
λPU (ε_{PU})	.80 (.36)	.86 (.27)	.80 (.36)
λEU (ε_{EU})	.60 (.64)	.60 (.64)	.54 (.71)
λFU (ε_{FU})	.79 (.37)	.74 (.45)	.76 (.42)
Value (V)			
λPV (ε_{PV})	.85 (.28)	.89 (.20)	.84 (.29)
λEV (ε_{EV})	.65 (.58)	.65 (.58)	.53 (.72)
λFV (ε_{FV})	.87 (.24)	.83 (.31)	.82 (.33)
Self-efficacy (SE)			
λPSE (ε_{PSE})	.92 (.16)	.95 (.10)	.94 (.11)
λESE (ε_{ESE})	.82 (.32)	.88 (.24)	.87 (.25)
λFSE (ε_{FSE})	.89 (.20)	.82 (.34)	.83 (.31)
Correlations			
U↔V	.80	.66	.74
U↔SE	.75	.65	.68
V↔SE	.60	.54	.58
$\varepsilon_{PU}\leftrightarrow\varepsilon_{PV}$		.65	.49
$\varepsilon_{PU}\leftrightarrow\varepsilon_{PSE}$		.55	.52
$\varepsilon_{PV}\leftrightarrow\varepsilon_{PSE}$		.39	.31
$\varepsilon_{EU}\leftrightarrow\varepsilon_{EV}$		.59	.57
$\varepsilon_{EU}\leftrightarrow\varepsilon_{ESE}$		.22	.26
$\varepsilon_{EV}\leftrightarrow\varepsilon_{ESE}$		.11	.19
$\varepsilon_{FU}\leftrightarrow\varepsilon_{FV}$		.71	.57
$\varepsilon_{FU}\leftrightarrow\varepsilon_{FSE}$		.76	.72
$\varepsilon_{FV}\leftrightarrow\varepsilon_{FSE}$		.70	.63
$\varepsilon_{EU}\leftrightarrow\varepsilon_{PU}$			.35
$\varepsilon_{EV}\leftrightarrow\varepsilon_{PV}$			.39
$\varepsilon_{EV}\leftrightarrow\varepsilon_{FV}$			.28

Notes. All parameters significant at $p < .01$. λIndicator = factor loading of indicator on latent variable. $\varepsilon_{Indicator}$ = residual variance of indicator.

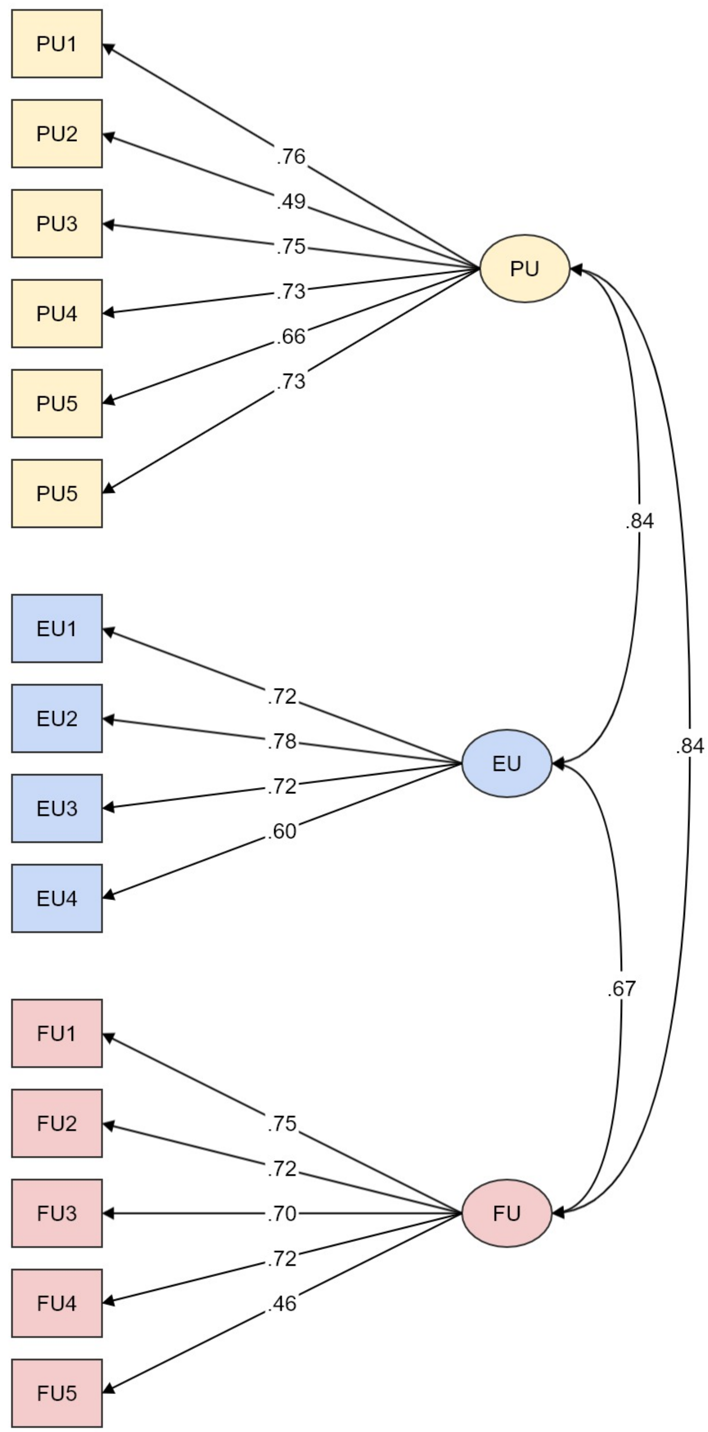

Figure 1. Latent path diagram for CFA of Use of SRSR by indicator. All parameters significant at $p < .01$.

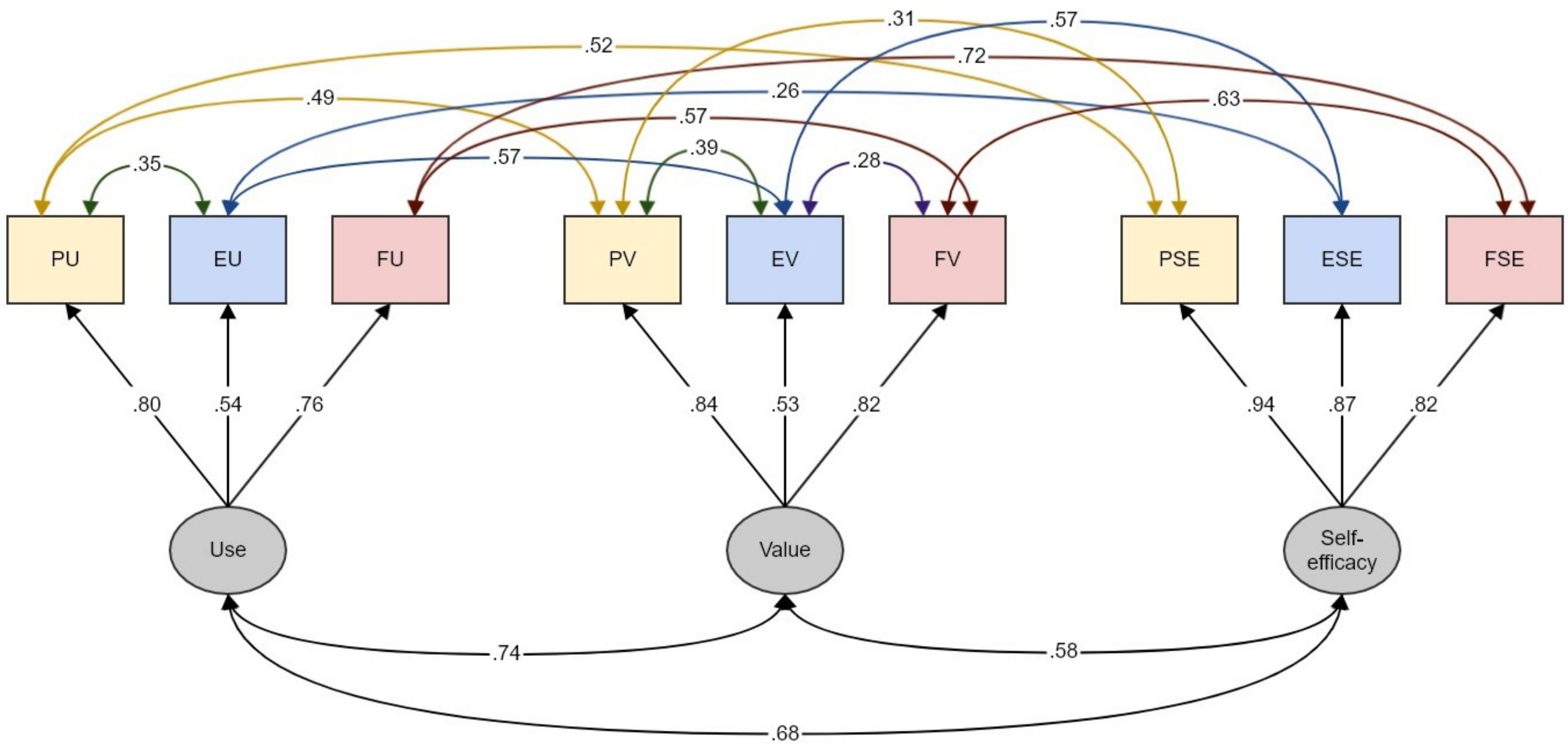

Figure 1. Latent path diagram for CFA of SRSR domain subscales on macro SRSR factors of use, value, and self-efficacy. Parameters are color coordinated for clarity; planning (yellow), explanation (blue), and facilitation (red). All parameters significant at $p < .01$.

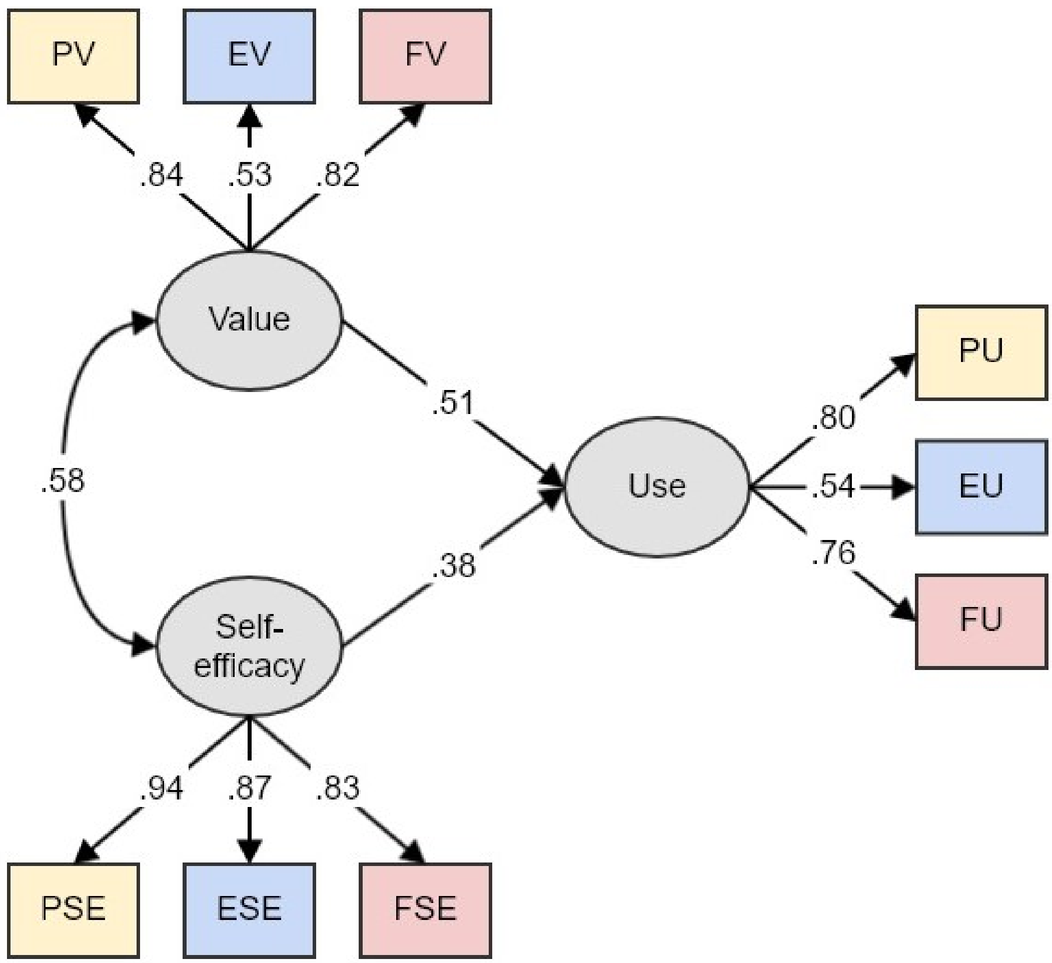

Figure 2. Latent path diagram for SR of use of SRSR on SRSR value and self-efficacy Residual variance and covariance omitted for clarity. All parameters significant at $p < .01$.