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Confirmatory factor analysis of the framing agency survey

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Validation of a Measure of Design Framing Agency

Abstract

In this research paper, we investigate the structure and validity of survey data related to students' framing agency. In order to promote increased opportunities for students to engage in and learn to frame design problems that are innovative and empathetic, there is a need for instruments that can provide information about student progress and the quality of learning experiences. This is a complex problem because, compared to problem solving, design problem framing is less studied and harder to predict due to the higher levels of student agency involved. To address this issue, we developed a survey to measure framing agency, which is defined as opportunities to frame and reframe design problems and learn in the process. This study extends past research which focused on the construct of framing agency and developing an instrument to measure it following best practices in survey design, including using exploratory factor analysis of pilot data, which recovered six factors related to shared and individual consequentiality, problem structure and constrainedness, and learning. However, as a pilot, the sample limited generalizability; the current study addresses this limitation. We used a national cohort that included multiple engineering disciplines (biomedical, mechanical, chemical, electrical, computer, aerospace), types of formal design projects (e.g., first-year, design-spine, senior capstone) and institution types, including private religious; Hispanic-serving; public land-grant; and research flagship institutions (N=449). We report sample characteristics and used confirmatory factor analysis (CFA) to provide validity evidence, reporting the chi-square and standardized root mean square residual as estimates of fit. We report Cronbach's alpha as a measure of internal consistency.

We found that overall, the CFA aligned with the prior exploratory results, in this case, recovering four factors, measured on a seven-point scale: shared consequentiality (the extent to which the student identifies that their understanding of the problem changed as result of a teammate's decision, $M = 6.15$; $SD = 1.13$); learning as consequentiality (the extent to which the student identifies learning as the result of decisions, $M = 5.88$; $SD = 0.98$); constrainedness (the extent to which the student reports the ability to make decisions despite design constraints, $M = 4.95$; $SD = 1.49$); and shared tentativeness (the extent to which the student identifies uncertainty about the problem and solution, $M = 4.02$; $SD = 1.76$). This suggests the survey can provide valid data for instructional decisions and further research into how students learn to frame engineering design problems and what role framing plays in their professional formation.

Introduction and Research Purpose

Developing the ability to design solutions to problems is key for engineering students learning to be professionals [1]. Many design experiences happen in the first-year and senior year courses, though increasingly they are being incorporated into courses along the entire program [2]–[4]. Instructors must make many decisions when developing design challenges, not all of which are clear. For instance, in senior capstone design, faculty commonly contend with ABET requirements, ethics, project management, appropriate scope, appropriate technical content, and team dynamics [5]–[7]. With all of these challenges, it is not surprising that design education does not always result in students learning to direct design practices, especially related to design problem framing and innovation [5].

In order to promote increased opportunities for students to engage in and learn to frame design problems and solve them in ways that are innovative and empathetic, there is a need for instruments that can provide information about student experiences related to design learning experiences. This is a complex problem because, compared to problem solving, design problem framing is less studied and harder to measure [8]. To address this issue, we developed a survey to measure framing agency, which is defined as opportunities to frame and reframe design problems in ways that are consequential, and to learn in the process [9], [10]. Past work suggests such a survey can, despite the comparative limited progress on measuring of problem framing, provide efficient and meaningful information about student perceptions of their roles as designers in relation to specific design learning experiences [11], [12]. In the current study, we aimed to investigate the validity of data from such a measure for making instructional decisions or contributing to research progress on problem framing. Using a national cohort of students in engineering design courses, we answer the following research question:

- Do the items in the Framing Agency Survey align to subconstructs of shared and individual consequentiality, problem structure and constrainedness, and learning?

Theoretical Framework

We ground the survey constructs in an understanding of the role that framing agency plays in the design process and established constructs that provide insight into agency. We consider the ways that agency can be individual or shared between designers and others, how designers remain open to many ways to frame and solve problems, how they make decisions because of and despite constraints, how consequential those decisions are, and how they learn in this process.

Shared Framing Agency

Designers have agency, in that they are empowered to make decisions related not only to the designed solution, but about the problem itself [13]. Framing agency is agency related to the focus or frame of the decisions about how to define and bound the problem [14]. Framing agency can be shared in several ways. Designers might consider the input of stakeholders, collaborators, or even material constraints. This takes multiple forms, including disagreeing, collaborating, and considering other viewpoints [15]. For instance, designers may come together with differing ideas about design solutions and discuss together the implications of each design until they either choose one of those solutions or develop a new solution that considers the different perspectives.

Shared agency can be impacted by power dynamics, such as the relationship between student and instructor. Because they have experienced low agency in other classes [16], students commonly expect to have low agency design learning experiences. This can shape how they engage in a design project, contributing to the overall challenges instructors face in supporting students to develop professional engineering practices.

Constrainedness

Constraint is endemic to engineering design problems [17]. Design problems are not fully constrained, but constraints arise from the sociotechnical context [18]. Overly constrained design problems that limit the designer's ability to make decisions would therefore reduce their agency

[19]. On the other hand, unconstrained design projects are not authentic, as context provides inherent constrains, and provokes greater creativity [20].

We borrow a term—opportunity structure—from sociology to characterize the possible decision space and the consequentiality of those decisions [21] in order to provide an understanding of the possible frames that designers might take up. However, in the context of learning, student perceptions of their ability to make decisions impact their understanding of the constrainedness of the problem [22]. This means that studying students' perceptions of constraints is a vital part of understanding how newcomer designers contend with the opportunity structure of design problems.

Tentativeness

Because design problems are ill-structured [23]—meaning that they have many possible solutions and paths towards those solutions—the design problem and solution co-evolve [24]. Designers thus remain tentative in their design work [25]. Navigating the dynamic relationship between problem and solution [24], they may explore many possible solutions and solution paths [26]. Thus, they remain tentative in their assessment of the problem and report less certainty in their solutions before committing to a particular design solution. In this way, designers exercise their framing agency as they evaluate the implications of various framings and solutions for stakeholders and systems.

Consequentiality and Learning

Humans may make many decisions, but our experience tells us that not all decisions as consequential. In the context of designing, we consider the ways in which a decision might be consequential—to the framing or reframing of the problem, and to the designer's learning about the problem. Framing problems supports sense of ownership over the problem itself [27]. The problem definition process, including bounding the problem, involves deliberate choices made by the designer based on their own goals and perspectives, making those choices not only consequential to the solution, but to the problem itself [25]. The process of gathering information to understand or address the problem makes those decisions consequential to learning as well [28]. In this way, designers also choose what to learn at the same time that they decide how to frame and then solve the problem.

Methods

Prior studies report on the development of the Framing Agency Survey[11], [12], including initial qualitative studies to characterize framing agency as a distinct construct, as well as typical survey development procedures, such as literature review to ground the subconstructs in theory, expert evaluation of items, pilot testing and quality assurance, and exploratory factor analysis of data collected in multiple settings.

Although commonly heard, no survey or test may be determined to be "valid"; rather validity is a contextualized argument about whether the data from an instrument provide valid information for a particular usage[29]. Thus, when stakes are higher, such as in the case of using data to make decisions that can negatively impact a person's growth or progress, the requirement for a validity argument should be correspondingly high [29]. Our survey is likely to be used in future research to investigate questions about the role that framing agency plays in the professional formation of engineers; in addition, it could also be used to inform minor changes to curricula. While not as stringent as high stakes measures, the requirements for a validity argument necessitate more evidence than prior studies provide.

The current study therefore extends past work by conducting confirmatory factor analysis with a larger, national cohort to contribute to validity work.

Instrument

The survey consisted of 19 questions on seven-point Likert scales. Based on the results of the EFA [11], they fall into six sub-constructs: Individual Consequentiality, Shared Consequentiality, Learning as Consequentiality, Constrainedness, and Shared Tentativeness. The items in each factor are found in table 1.

Table 1: Established latent factors and items in each factor

Latent Factor	*Item*	*Item Label*
Individual Consequentiality: ($\alpha = 0.85$) The extent to which an individual reports that the problem changed, or their understanding changed as a result of decisions made individually meaning that the decisions were consequential.	How responsible or not responsible have you felt: [for making decisions personally?]	A1
	How responsible or not responsible have you felt: [for coming up with your own ways to make progress on the design project?]	A2
	How responsible or not responsible have you felt: [for the outcomes of the design project?]	A3
	Considering the decision you described, how important or unimportant was: [the decision?]	A4
	Considering the decision you described, how important or unimportant was: [the impact of that decision on your design process?]	A5
Shared Consequentiality: ($\alpha = 0.77$) The extent to which an individual reports that the problem changed, or their understanding changed as a result of decisions made by the team, meaning that the decisions were consequential.	Considering the decision you described, how important or unimportant was: [the decision?]	B1
	Considering the decision you described, how important or unimportant was: [the impact of that decision on your design process?]	B2

Latent Factor	*Item*	*Item Label*
Learning as Consequentiality: (α = 0.78) The extent to which an individual reports that their understanding changed because of decisions made individually or by the team, meaning that the decisions were consequential	How much or little have you learned as a result of: [decisions about the design problem you personally made?]	C1
	How much or little have you learned as a result of: [decisions about the design problem a teammate made?]	C2
Constrainedness: (α = 0.79) The extent to which an individual reports having opportunity to make decisions about the problem despite having design requirements or constraints.	Considering these constraints, how free or restricted: [have you felt when making decisions yourself?]	D1
	Considering these constraints, how free or restricted: [have your teammates seemed when making decisions?]	D2
	How free or limiting does the design problem seem to be?	D3
Shared Tentativeness: (α = 0.81) The extent to which an individual reports team certainty about the design problem and solution.	How certain or uncertain do you feel that: [your design project has a single right solution?]*	E1
	How certain or uncertain do you feel that: [you have to solve the problem as given to you?]*	E2
	How certain or uncertain do you feel that: [you have to just develop what was asked of you?]*	E3
	How certain or uncertain do you feel that: [you know the optimal solution?]	E4
Individual Tentativeness: (α = 0.56) The extent to which an individual reports individual certainty about the design problem and solution.	How certain or uncertain do you feel that: [you understand the design problem?]	X1
	Considering your design project, did you have many or few: [opportunities to make decisions as a team related you your design project?]	X2

* Reversed item

We ultimately removed the individual tentativeness factor for having a Cronbach alpha lower than the generally acceptable value of 0.6 used in education literature [30], and so it does not appear in subsequent analysis.

We dummy-coded all responses to have the most negative response translating into a 1 and the most positive into a 7 (with the exception of the three negatively coded items). We had a percent missing information of 10.6% (N=41) and so choose to employ listwise deletion [31], [32] for any observation missing any item across all five factors.

Data Collection and Analysis

We collected data over the course of two semesters in design-focused courses at four universities (including Hispanic-serving, public land grant, small private, and research flagship institutions) across the United States (N=23, N= 77, N=11, and N=271). Design courses included first-year, design-spine, and senior capstone set in biomedical, mechanical, chemical, electrical, computer and aerospace engineering programs. Students completed the survey in their courses for nominal points at the end or near-end of their design work. Instructors agreed to include the survey to jointly contribute to research and to gain information about how their design courses supported framing agency.

We used CFA, an extension of structural equation modeling that is theory-driven, in that it tests conjectured relationships between and among variables [33]. In the results, we report both the preliminary tests and CFA results.

Results

We began by calculating descriptive statistics for each item (Table 2). While the items show non-normal distribution, we assume that the responses are not ordinal and should be treated as continuous. However, the maximal likelihood estimator is robust to skewness less than two and kurtosis less than seven [34], suggesting that our results will be robust despite the non-normality.

Table 2: Descriptive statistics by item

Item	n	Mean	SD	Skew	Kurtosis
A1	378	5.87	1	-1.63	4.88
A2	377	5.98	1	-1.79	6.01
A3	378	6.04	0.97	-1.71	5.47
A4	365	6.07	0.96	-1.26	2.82
A5	363	6.07	1.03	-1.43	3.24
B1	362	6.13	1.14	-2.14	5.98
B2	359	6.18	1.13	-2.04	5.32
C1	373	5.92	0.88	-1.32	4.89
C2	373	5.84	1.07	-2.01	6.63
D1	371	4.89	1.51	-0.57	-0.6
D2	369	4.92	1.47	-0.6	-0.55
D3	373	5.03	1.5	-0.63	-0.41
E1	375	4.9	1.76	-0.41	-0.89
E2	374	3.46	1.6	0.48	-0.43
E3	375	3.77	1.66	0.25	-0.81

We initially conducted a model containing the five factors and all planned items. However one item (E4) had inadmissible negative variance [35], and so we removed it and respecified the model.

We examined goodness of fit indices, comparing a one-factor model to the theoretically-derived five-factor model. The fit indices are found in table 3. A significant $\chi2$ indicates that a test statistic larger than the one found would be found if we reject the model. However, the $\chi2$ test is inflated by non-normal data [36]. Due to our highly skewed data, we would expect a high $\chi2$ and thus a significant result. For this reason, we consider other goodness of fit indices.

Table 3: Goodness of fit indices comparing a one-factor and a five-factor model

Fit Index	One-Factor Model	Five-Factor Model
$\chi2$	695.15	248.65
P-Value ($\chi2$)	<0.001	<0.001
RMSEA	0.235	0.08
P-Value (RMSEA) <= 0.05	0	0.054
SRMR	0.112	0.055
TLI	0.461	0.91
CFI	0.581	0.92
df	35	67

We calculated an RMSEA of 0.08, indicating a reasonable fit, and we failed to reject the 90% confidence interval indicating that our model is a close fit to the data [37]. Our model has an SRMR value of 0.055, indicating adequate fit to the data [38]. CFI and TLI values are greater than 0.9 but less than 0.95, indicating reasonable fit to the data [38]. Table 4 shows the individual factor loadings across all the items to consider the impacts of each.

Table 4: Individual factor loadings across items, all factors significant to $p < 0.001$

	Standard Estimate	Standard Error	z-value	R^2
Individual		0.32	0.24	0.057
Consequentiality	0.66	0.52	3.98	0.436
	0.68	0.52	4.00	0.464
	0.77	0.57	4.05	0.59
	0.73	0.59	4.03	0.526
Shared		1.02	0.88	0.782
Consequentiality	0.94	0.07	14.29	0.889

Learning as		0.81	0.91	0.829
Consequentiality	0.75	0.08	12.95	0.569
Constrainedness		0.87	0.49	0.239
	0.67	0.17	7.47	0.451
	0.85	0.24	6.67	0.716
Shared Tentativeness		1.40	0.93	0.867
	0.97	0.04	24.26	0.938
	0.78	0.05	12.92	0.361

We used the reference indicator method of determining factor loadings [39] and consider specifically the loadings with all variables standardized [40]. All items are significant and have standardized parameter estimates about 0.5, which is usually considered the rule of thumb for convergent validity [41].

There are some correlations between factors (Table 5), particularly between the consequentiality factors, which is not entirely unexpected.

Table 5: Correlation between factors

		Standard Coefficient	Standard Error	Z Value	P Value
Individual Consequentiality					
	Shared Consequentiality	0.43	0.046	5.567	<0.001
	Learning as Consequentiality	0.68	0.04	7.40	<0.001
	Shared Tentativeness	0.07	0.03	1.01	0.31
	Constrainedness	0.16	0.05	2.56	0.01
Shared Consequentiality					
	Learning as Consequentiality	0.50	0.06	7.04	<0.001
	Shared Tentativeness	0.04	0.07	0.59	0.56
	Constrainedness	0.12	0.08	2.01	0.04
Learning as Consequentiality					
	Shared Tentativeness	0.11	0.05	1.58	0.11
	Constrainedness	0.16	0.07	2.68	0.01
Shared Tentativeness					
	Constrainedness	-0.08	0.08	-1.31	0.19

Based on the results of this analysis we built a model of the relationships between factors and items, and between factors, which are presented in Figure 1.

We considered the potential modification indices that would result in a significant change in the $\chi2$ of the model. However, the ones that would result in the largest decrease in the $\chi2$ are not theoretically sound and primarily consisted of suggested freely estimated parameters that crossed between factors.

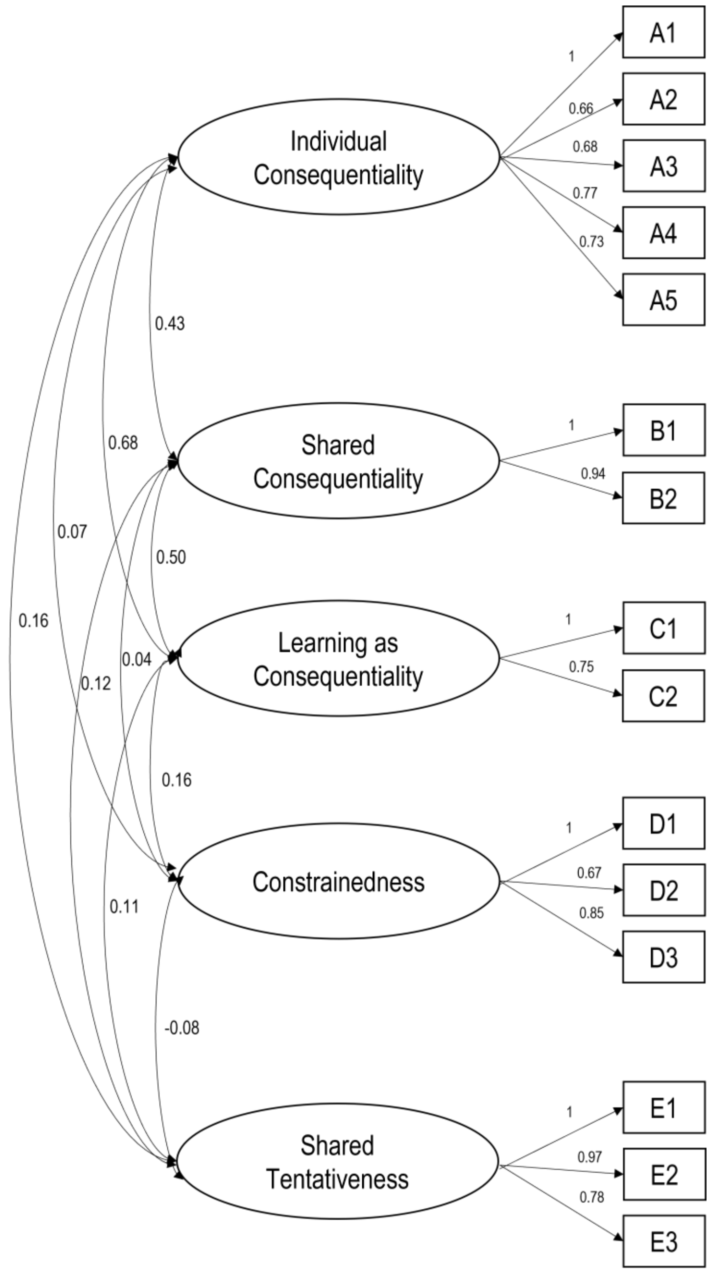

Figure 1: Model found in factor analysis

Thus, the CFA recovered four factors, measured on a seven-point scale:

- ***Shared consequentiality***. The extent to which the student identifies that their understanding of the problem changed as result of a teammate's decision, $M = 6.15$; $SD = 1.13$;
- ***Learning as consequentiality***. The extent to which the student identifies learning as the result of decisions, $M = 5.88$; $SD = 0.98$;

- ***Constrainedness***. The extent to which the student reports the ability to make decisions despite design constraints, $M = 4.95$; $SD = 1.49$; and
- ***Shared tentativeness***. The extent to which the student identifies uncertainty about the problem and solution, $M = 4.02$; $SD = 1.76$

Conclusions

Because the fit indices indicate a close fit to the data, we can conclude that the latent factors reasonably predict the items in the survey. This largely affirms the results of the previous EFA, indicating that the Framing Agency Survey provides data that are valid for uses like instructional refinement and further studies into the role that framing agency plays in the professional formation of engineers. However, such studies will require a larger dataset, as well as analysis examining the structure of the survey that includes measures of relevant constructs, such as engineering identity, engineering self-efficacy, and persistence intentions. Our ongoing research aims to develop full structural models that include demographic covariates to permit investigation of varied impacts on privileged and minoritized students.

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References

[1] C. B. Zoltowski, P. M. Buzzanell, A. O. Brightman, D. Torres, and S. M. Eddington, “Understanding the Professional Formation of Engineers through the Lens of Design Thinking: Unpacking theWicked Problem of Diversity and Inclusion,” *ASEE Annu. Conf. Expo. Proc.*, Jun. 2017, Accessed: Dec. 06, 2022. [Online]. Available: https://par.nsf.gov/biblio/10036285-understanding-professional-formation-engineers-through-lens-design-thinking-unpacking-thewicked-problem-diversity-inclusion

[2] B. Frank, D. Strong, R. Sellens, and L. Clapham, “Progress with the professional spine: A four-year engineering design and practice sequence,” *Australas. J. Eng. Educ.*, vol. 19, no. 1, pp. 63–74, Jan. 2013, doi: 10.7158/22054952.2013.11464079.

[3] Z. S. Roth, H. Zhuang, and A. Zilouchian, “Integrating design into the entire electrical engineering four-year experience,” presented at the 2019 ASEE Annual Conference & Exposition, Jun. 2019. Accessed: Feb. 12, 2023. [Online]. Available: https://peer.asee.org/integrating-design-into-the-entire-electrical-engineering-four-year-experience

[4] R. Khan and L. Romkey, “Scaffolding reflection across the design curriculum: Triangulating Student, Alumni, and Faculty Perspectives of the Role of Design within an Engineering Science Program,” presented at the 2022 ASEE Annual Conference & Exposition, Aug. 2022. Accessed: Feb. 12, 2023. [Online]. Available: https://strategy.asee.org/scaffolding-reflection-across-the-design-curriculum-triangulating-student-alumni-and-faculty-perspectives-of-the-role-of-design-within-an-engineering-science-program

[5] A. J. Dutson, R. H. Todd, S. P. Magleby, and C. D. Sorensen, “A Review of Literature on Teaching Engineering Design Through Project-Oriented Capstone Courses,” *J. Eng. Educ.*, vol. 86, no. 1, pp. 17–28, 2013, doi: 10.1002/j.2168-9830.1997.tb00260.x.
[6] R. H. Todd, C. D. Sorensen, and S. P. Magleby, “Designing a Senior Capstone Course to Satisfy Industrial Customers,” *J. Eng. Educ.*, vol. 82, no. 2, pp. 92–100, 1993, doi: 10.1002/j.2168-9830.1993.tb00082.x.
[7] C. L. Dym, A. M. Agogino, O. Eris, D. D. Frey, and L. J. Leifer, “Engineering Design Thinking, Teaching, and Learning,” *J. Eng. Educ.*, vol. 94, no. 1, pp. 103–120, 2005, doi: https://doi.org/10.1002/j.2168-9830.2005.tb00832.x.
[8] M. Dzbor and Z. Zdrahal, “Design as interactions of problem framing and problem solving,” in *ECAI 2002: 15th European Conference on Artificial Intelligence, July 21-26, 2002, Lyon France : Including Prestigious Applications of Intelligent Systems (PAIS 2002) : Proceedings*, European Coordinating Committee for Artificial Intelligence, Association française pour l’intelligence artificielle, 2002, pp. 210–214.
[9] J. P. Donaldson and B. K. Smith, “Design thinking, designerly ways of knowing, and engaged learning,” in *Learning, Design, and Technology*, M. J. Spector, B. B. Lockee, and M. D. Childress, Eds., Cham: Springer International Publishing, 2017, pp. 1–24. doi: 10.1007/978-3-319-17727-4_73-1.
[10] V. Svihla, J. Gomez, M. Watkins, and T. Peele-Eady, “Characterizing Framing Agency in Design Team Discourse,” in *2019 ASEE Annual Conference & Exposition Proceedings*, Tampa, Florida: ASEE Conferences, Jun. 2019, p. 32505. doi: 10.18260/1-2--32505.
[11] V. Svihla, A. Gallup, and S. “Pil” Kang, “Development and insights from the measure of framing agency,” in *2020 ASEE Virtual Annual Conference Content Access Proceedings*, Virtual On line: ASEE Conferences, Jun. 2020, p. 34442. doi: 10.18260/1-2--34442.
[12] V. Svihla and A. Gallup, “Do loss aversion and the ownership effect bias content validation procedures?,” *Pract. Assess. Res. Eval.*, vol. 26, no. 1, Mar. 2021, doi: https://doi.org/10.7275/34d8-qe13.
[13] R. Alsop, M. Bertelsen, and J. Holland, *Empowerment in Practice*. in Directions in Development - General. The World Bank, 2005. doi: 10.1596/978-0-8213-6450-5.
[14] M. J. Lehtonen, P. Yeow, and J. Chew, “Empowering change for future-making: Developing agency by framing wicked problems through design,” *Futures*, vol. 139, p. 102952, May 2022, doi: 10.1016/j.futures.2022.102952.
[15] E. S. Chang, J. Heckhausen, E. Greenberger, and C. Chen, “Shared Agency with Parents for Educational Goals: Ethnic Differences and Implications for College Adjustment,” *J. Youth Adolesc.*, vol. 39, no. 11, pp. 1293–1304, Nov. 2010, doi: 10.1007/s10964-009-9488-7.
[16] V. Svihla and R. Reeve, “Facilitating Problem Framing in Project-Based Learning,” *Interdiscip. J. Probl.-Based Learn.*, vol. 10, no. 2, Art. no. 2, Oct. 2016, doi: 10.7771/1541-5015.1603.
[17] M. M. Dabbeeru and A. Mukerjee, “Discovering implicit constraints in design,” *AI EDAM*, vol. 25, no. 1, pp. 57–75, Feb. 2011, doi: 10.1017/S0890060410000478.
[18] M. D. Gross, S. M. Ervin, J. A. Anderson, and A. Fleisher, “Constraints: Knowledge representation in design,” *Des. Stud.*, vol. 9, no. 3, pp. 133–143, Jul. 1988, doi: 10.1016/0142-694X(88)90042-7.
[19] L. L. Bogusch, J. Turns, and C. J. Atman, “Engineering design factors: how broadly do students define problems?,” in *30th Annual Frontiers in Education Conference. Building on*

A Century of Progress in Engineering Education. Conference Proceedings (IEEE Cat. No.00CH37135), Oct. 2000, p. S3A/7-S3A12 vol.2. doi: 10.1109/FIE.2000.896664.
[20] C. M. Burns and K. J. Vicente, "A participant-observer study of ergonomics in engineering design:: how constraints drive design process," *Appl. Ergon.*, vol. 31, no. 1, pp. 73–82, Jan. 2000, doi: 10.1016/S0003-6870(99)00017-4.
[21] D. Narayan and P. Petesch, "Agency, opportunity structure, and poverty escapes," *Mov. Poverty Cross-Discip. Perspect. Mobil.*, pp. 13–45, Jan. 2007.
[22] V. Svihla, S. Wettstein, J. Brown, E. Chi, and M. Wilson-Fetrow, "Consequential Agency in Chemical Engineering Laboratory Courses," presented at the 2022 ASEE Annual Conference & Exposition, Aug. 2022. Accessed: Dec. 13, 2022. [Online]. Available: https://peer.asee.org/consequential-agency-in-chemical-engineering-laboratory-courses
[23] D. H. Jonassen, "Toward a Design Theory of Problem Solving," *Educ. Technol. Res. Dev.*, vol. 48, no. 4, pp. 63–85, 2000, doi: https://doi.org/10.1007/BF02300500.
[24] K. Dorst and N. Cross, "Creativity in the design process: co-evolution of problem–solution," *Des. Stud.*, vol. 22, no. 5, pp. 425–437, Sep. 2001, doi: 10.1016/S0142-694X(01)00009-6.
[25] A. Morozov, D. Kilgore, and C. Atman, "Breadth In Design Problem Scoping: Using Insights From Experts To Investigate Student Processes," presented at the 2007 Annual Conference & Exposition, Jun. 2007, p. 12.321.1-12.321.24. Accessed: Dec. 13, 2022. [Online]. Available: https://peer.asee.org/breadth-in-design-problem-scoping-using-insights-from-experts-to-investigate-student-processes
[26] S. Schrader, W. M. Riggs, and R. P. Smith, "Choice over uncertainty and ambiguity in technical problem solving," *J. Eng. Technol. Manag.*, vol. 10, no. 1, pp. 73–99, Jun. 1993, doi: 10.1016/0923-4748(93)90059-R.
[27] D. A. Schön, *Educating the reflective practitioner: Toward a new design for teaching and learning in the professions*. in Educating the reflective practitioner: Toward a new design for teaching and learning in the professions. San Francisco, CA, US: Jossey-Bass, 1987, pp. xvii, 355.
[28] M. Zahedi, "Exploring framing within a team of industrial design students," *DRS Bienn. Conf. Ser.*, Jun. 2016, [Online]. Available: https://dl.designresearchsociety.org/drs-conference-papers/drs2016/researchpapers/118
[29] D. R. Eignor, "The standards for educational and psychological testing," in *APA handbook of testing and assessment in psychology, Vol. 1: Test theory and testing and assessment in industrial and organizational psychology*, in APA handbooks in psychology®. Washington, DC, US: American Psychological Association, 2013, pp. 245–250. doi: 10.1037/14047-013.
[30] K. S. Taber, "The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education," *Res. Sci. Educ.*, vol. 48, no. 6, pp. 1273–1296, Dec. 2018, doi: 10.1007/s11165-016-9602-2.
[31] D. McNeish, "Missing data methods for arbitrary missingness with small samples," *J. Appl. Stat.*, vol. 44, no. 1, pp. 24–39, Jan. 2017, doi: 10.1080/02664763.2016.1158246.
[32] K. Alper, "The effect of misssing data handling methods on goodness of fit indices in confirmatory factor analysis," *Educ. Res. Rev.*, vol. 9, no. 8, pp. 208–241, Apr. 2014, doi: 10.5897/ERR2014.1709.
[33] J. B. Schreiber, A. Nora, F. K. Stage, E. A. Barlow, and J. King, "Reporting structural equation modeling and confirmatory factor analysis results: A review," *J. Educ. Res.*, vol. 99, no. 6, pp. 323–338, Jul. 2006, doi: 10.3200/JOER.99.6.323-338.

[34] S. J. Finney and C. DiStefano, "Nonnormal and categorical data in structural equation modeling," in *Structural equation modeling: A second course, 2nd ed*, in Quantitative methods in education and the behavioral sciences: Issues, research, and teaching. Charlotte, NC, US: IAP Information Age Publishing, 2013, pp. 439–492.
[35] R. B. Kline, *Principles and practice of structural equation modeling, 2nd ed*. in Principles and practice of structural equation modeling, 2nd ed. New York, NY, US: Guilford Press, 2005, pp. xviii, 366.
[36] J. Benson and J. A. Fleishman, "The robustness of maximum likelihood and distribution-free estimators to non-normality in confirmatory factor analysis," *Qual. Quant.*, vol. 28, no. 2, pp. 117–136, May 1994, doi: 10.1007/BF01102757.
[37] E. E. Rigdon, "CFI versus RMSEA: A comparison of two fit indexes for structural equation modeling," *Struct. Equ. Model. Multidiscip. J.*, vol. 3, no. 4, pp. 369–379, Jan. 1996, doi: 10.1080/10705519609540052.
[38] L. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Struct. Equ. Model. Multidiscip. J.*, vol. 6, no. 1, pp. 1–55, Jan. 1999, doi: 10.1080/10705519909540118.
[39] D. A. Sass, "Testing Measurement Invariance and Comparing Latent Factor Means Within a Confirmatory Factor Analysis Framework," *J. Psychoeduc. Assess.*, vol. 29, no. 4, pp. 347–363, Aug. 2011, doi: 10.1177/0734282911406661.
[40] S. Pornprasertmanit, J. Lee, and K. J. Preacher, "Ignoring Clustering in Confirmatory Factor Analysis: Some Consequences for Model Fit and Standardized Parameter Estimates," *Multivar. Behav. Res.*, vol. 49, no. 6, pp. 518–543, Nov. 2014, doi: 10.1080/00273171.2014.933762.
[41] G. W. Cheung and C. Wang, "Current Approaches for Assessing Convergent and Discriminant Validity with SEM: Issues and Solutions," *Acad. Manag. Proc.*, vol. 2017, no. 1, p. 12706, Aug. 2017, doi: 10.5465/AMBPP.2017.12706abstract.