WIP: Assessing the Reliability of the AI Adoption and Motivation Survey Instrument in Engineering Education

Daniel Kane, Utah State University

Daniel Kane is a third-year Ph.D. student in the department of engineering education at Utah State University. His research interests include spatial ability, accessibility for students with disabilities, artificial intelligence in education, and enhancing electric vehicle charging system infrastructure. Daniel has contributed significantly to the development of the Tactile Mental Cutting Test (TMCT) which is a significant advancement in assessing spatial ability for blind and low-vision populations. His research has helped inform teaching methods and develop strategies for improving STEM education accessibility. Currently, he is studying how AI tools are utilized by students across USU's colleges to optimize their educational value. Daniel has also served as president of the ASEE student chapter at USU where he initiated outreach activities at local K-12 schools and promoted student engagement in research.

Michaela Harper, Utah State University

Michaela Harper is a doctoral student at Utah State University, pursuing a Ph.D. in Engineering Education. She holds a Bachelor's degree in Environmental Studies, focusing on STEM and non-traditional education approaches, and a Master's degree in Engineering Education, where she explored faculty perspectives on Generative Artificial Intelligence (GAI). Michaela's current research delves deeply into the effects of disruptive technologies on engineering education, driven by her passion for uncovering the foundational nature of phenomena and applying an exploratory and explanatory approach to her studies. Her work aims to illuminate how technological advancements reshape educational landscapes through student and faculty engagement.

Dr. Wade H Goodridge, Utah State University

Wade Goodridge is a tenured Associate Professor in the Department of Engineering Education at Utah State University. His research often has a focus on what drives us to learn, how we learn and how well we do it, and what can improve that learning. This work is often directed with a spatial thinking emphasis. Dr. Goodridge has investigated different learning modalities (fully online, hybrid, blended courses), cognitive and metacognitive learning processes (self-regulation, engineering problems solving, neural efficiency in engineering problem solving) learning motivators (engineering self-efficacy), and effective and personalized engineering education interventions (tactile engineering curriculum, physical teaching models, XR environments and AI informed systems of delivering and monitoring engineering learning). Dr. Goodridge has created a valid and reliable instrument to assess spatial ability in blind and low vision (BLV) learners thus opening new areas of research centered on tactile spatial ability. He has created tactile and visual learning tools and has offered professional development experiences on how to improve the education of tomorrows engineers.

Dr. Cassandra McCall, Utah State University

Dr. Cassandra McCall is an Assistant Professor in the Engineering Education Department at Utah State University (USU). Her research focuses on the intersections of disability, identity formation, and culture and uses anti-ableist approaches to enhance universal access for students with disabilities in STEM, particularly in engineering. At USU, she serves as the Co-Director of the Institute for Interdisciplinary Transition Services. In 2024, Dr. McCall received a National Science Foundation CAREER grant to identify systemic opportunities for increasing the participation of people with disabilities in engineering. Her award-winning publications have been recognized by leading engineering education research journals at both national and international levels. Dr. McCall has led several workshops promoting the inclusion of people with disabilities and other minoritized groups in STEM. She holds B.S. and M.S. degrees in civil engineering with a structural engineering emphasis.

Linda Davis Ahlstrom, Utah State University

Linda Ahlstrom PhD student currently studying Engineering Education at Utah State University. Interested in the Univerity to Industry interface and the use of AI tools in engineering. MS Electrical Engineering Cal State Long Beach. Worked in industry: Biomedical, Software Development and Aerospace.

Dr. Oenardi Lawanto, Utah State University

Dr. Oenardi Lawanto is a professor in the Department of Engineering Education at Utah State University, USA. He received his B.S.E.E. from Iowa State University, his M.S.E.E. from the University of Dayton, and his Ph.D. from the University of Illinois at Urbana-Champaign. Dr. Lawanto has a combination of expertise in engineering and education and has more than 30 and 14 years of experience teaching engineering and cognitive-related topics courses for his doctoral students, respectively. He also has extensive experience in working collaboratively with several universities in Asia, the World Bank Institute, and USAID to design and conduct workshops promoting active-learning and life-long learning that is sustainable and scalable. Dr. Lawanto's research interests include cognition, learning, and instruction, and online learning.

WIP: Assessing the Reliability of the AI Adoption and Motivation Survey Instrument in Engineering Education

Introduction

Recent advances in generative Artificial Intelligence (AI) have rapidly altered the landscape of higher education, prompting increased student use of AI tools for learning, problem solving, and career preparation. Prior work within this research program has shown that AI adoption among university students is widespread but uneven, varying by academic level, discipline, and perceived relevance to professional practice [1-2]. Engineering students, especially, demonstrate differential patterns of adoption, with students closer to workforce entry reporting higher levels of AI use than first-year students, suggesting that task value and perceived usefulness play an important role in adoption decisions [1], [3]. Cross-disciplinary analyses further indicate that AI use is shaped by disciplinary norms and task structure, consistent with technology acceptance research emphasizing perceived usefulness as a primary driver of adoption [1], [4].

While students frequently describe AI as useful for explanation, efficiency, and ideation, they also express concerns about trust, overreliance, and academic integrity, highlighting the need to examine adoption beyond simple measures of frequency of use [5-6]. These findings align with prior work showing that trust in technology and motivational factors such as goal orientation and task value influence students' willingness to adopt and reuse emerging tools [7-10]. In response, an AI adoption and motivation survey was developed to capture multiple dimensions of student engagement with AI, integrating constructs related to motivation, learning strategies, perceived usefulness, trust, and technology reuse intentions [3], [7], [10-11]. Because the survey adapts items from multiple validated instruments for use in a novel and rapidly evolving domain, establishing the internal consistency of its constructs is a necessary methodological step [12]. This work is framed within the context of Classical Test Theory (CTT), which conceptualizes an observed score as the combination of a true score and measurement error and evaluates instrument quality through psychometric properties such as internal consistency [13-14]. This framework is particularly suited to the present study, as it establishes foundational evidence of instrument quality before applying more complex measurement models, including factor analysis and item response theory [12], [14]. Consistent with Classical Test Theory, internal consistency was evaluated prior to any examination of latent structure. The purpose of this work-in-progress paper is therefore to examine the reliability of the survey when administered to engineering students at an Intermountain West, R1 institution.

Methods

The AI use survey was adapted from three parent instruments, following guidelines established for adopting and adapting existing scales [15], and following the methodology presented in similar instrument development publications in the field of engineering education. See for example, [16-20]. Parent instruments include the Motivated Strategies for Learning Questionnaire (MSLQ) [21], a healthcare student survey on AI perspectives [22], and the Reliance on Technology Questionnaire [23]. Specific items from each parent instrument were selected for use in the adapted survey to provide a more complete view into students' perspectives involving both AI and their role as students. Items from the MSLQ were adopted to provide insight into students' learning strategies (LS) and motivational factors (MF). Learning strategies are assessed on the MSLQ from constructs of critical thinking (CT) and help-seeking (HS). Motivational factors are measured from constructs of intrinsic goal orientation (ISO), extrinsic goal orientation (EGO), and task value (TV). The MSLQ has been validated and demonstrated adequate reliability in a general population [24] and with an engineering student population [25]. The healthcare student survey on AI perspectives (P) provides items that assess students' perspectives on AI and their understanding of its implications on their education [22]. The Reliance on Technology Questionnaire contributes items on technology reuse intentions, perceived usefulness, and trust which were adapted to measure reuse intentions of AI (RI), AI perceived usefulness (PU), and trust in AI (T). Details of parent instruments are shown in table 1. Adapted items were presented alongside demographic items within an online Qualtrics survey.

Table 1. Constructs measured in each parent instrument with their associated abbreviations and sample items.

Parent Instrument	Construct Name	Abbreviation	Sample Item
Motivated Strategies for Learning Questionnaire (MSLQ)	Intrinsic Goal Orientation	IGO	The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible
	Extrinsic Goal Orientation	EGO	
	Task Value	TV	
	Critical Thinking	CT	
	Help Seeking	HS	
	Motivational Factors (IGO + EGO + TV)	MF	
	Learning Strategies (CT + HS)	LS	
Healthcare student survey on AI perspectives (Teng et al.)	AI Perspectives	P	I feel hopeful about having AI available in my classes
Reliance on Technology Questionnaire	AI Reuse Intentions	RI	In my opinion, using the disruptive technology, such as Chat GPT, increased my problem solving effectiveness.
	AI Perceived Usefulness	PU	
	AI Trust	T	

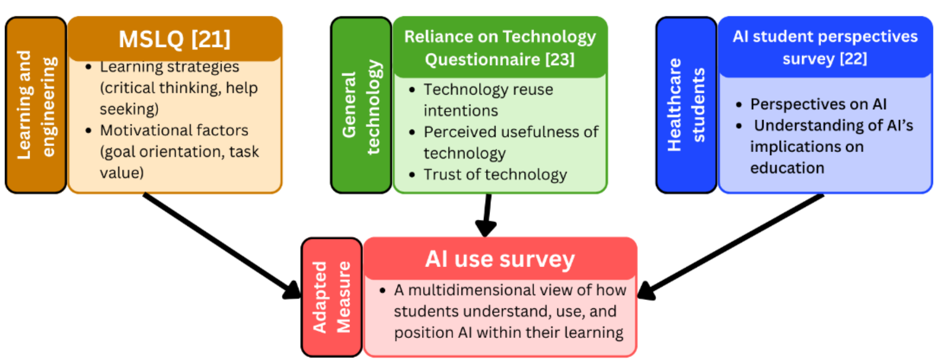

Figure 1. Construct integration framework for the adapted AI use survey.

Population

The survey was distributed online through a series of emails sent to the entire student body population of a large R1 western university. Participation in the survey was voluntary, and all participants were required to digitally sign an IRB-approved informed consent document before participating. As compensation, students were entered into a raffle for an online gift card. A total of 1,679 students responded to the survey. This paper specifically focuses on responses from students who indicated that their major is housed in the college of engineering. Before filtering out ineligible responses, there were a total of 238 responses from engineering students. After cleaning the data, responses from 140 students were included for analysis in the study. Demographic information regarding gender, race, and academic level are shown in figure 2.

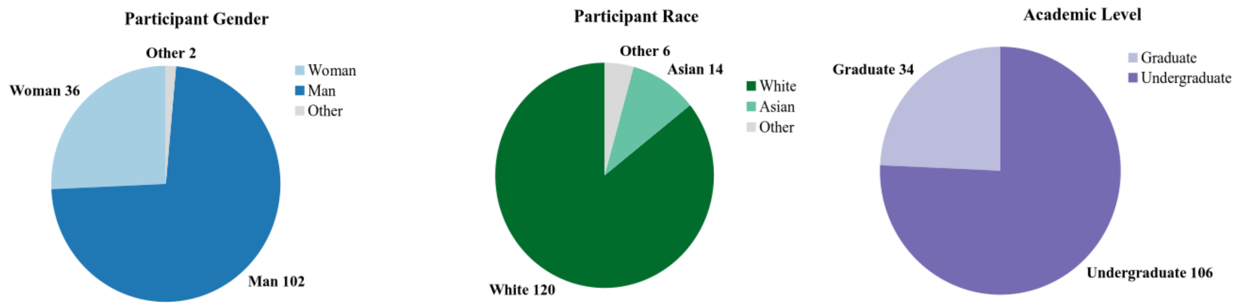

Figure 2. Participant demographics

Data analysis

Items adapted from the MSLQ and the Reliance on Technology Questionnaire were measured using a 7-point Likert scale, while items from the Teng et al. survey employed a 10-point Likert scale. All responses were converted to numerical values for analysis. Reliability analysis for this data includes a measure of internal consistency for each construct measured in the survey using McDonald's Omega and Cronbach's alpha. Cronbach's alpha has been used widely as a measurement of reliability in social science despite known limitations [26-27]. One alternative to Cronbach's alpha which has proven to be a more robust indicator of internal consistency when working with human subject data is McDonald's omega [28-29]. This analysis utilizes McDonalds omega in an effort to more accurately represent the internal consistency of this instrument while also reporting Cronbach's alpha values to be consistent with other reliability analysis publications. In accordance with many other studies on human subjects, for the purpose of this analysis, reliability coefficients greater than 0.7 are considered acceptable [30]. All reliability analysis for this study was conducted using Jamovi version 2.7 [31].

Limitations

While the sample size used in this analysis is of adequate size for a study on reliability, participants were selected from one college at a single institution. Future reliability studies could benefit from a more diverse sample of students. Results of this reliability analysis may not be completely generalizable to students at different institutions. There may also be selection bias associated with the sampling technique, with students who use AI and have a favorable view of AI integration being more likely to participate in the study. Furthermore, the use of McDonald's omega and Cronbach's alpha assumes unidimensionality within constructs which has not formally been established using factor analysis methods [32].

Results

Reliability coefficients for items adopted from the MSLQ were calculated for each of the five constructs originating from the MSLQ including IGO, EGO, TV, CT, and HS. Results of the reliability analysis for this portion of the survey are presented in Table 2. Omega coefficients for IGO, TV, and CT are considered acceptable for the purpose of this study. The construct in this portion of the study with the highest reliability is TV with an omega coefficient of 0.871. The lowest omega value was for HS.

Table 2. Reliability coefficients by construct for items adapted from the MSLQ.

	IGO	EGO	TV	CT	HS
N items	4	4	5	5	4
Mean	5.29	5.18	5.91	4.78	4.44
SD	0.87	1.02	0.872	1.07	1.07
Alpha	0.71	0.627	0.856	0.831	0.565
Omega	0.741	0.669	0.871	0.833	0.63

Constructs including IGO, EGO, TV, CT, and HS adopted from the MSLQ can be grouped into broader constructs of motivational factors (MF) and Learning Strategies (LS). Grouping these constructs into broader categories allows for a greater number of items in each group, allowing for a more robust reliability analysis. Results of a reliability analysis with the broader constructs of MF and LS are shown in Table 3. When viewed as broader constructs, omega values for each construct are adequate.

Table 3. Reliability coefficients for MF and LS.

	MF (IGO, EGO, TV)	LS (CT, HS)
N items	13	9
Mean	5.49	4.63
SD	0.616	0.786
Alpha	0.738	0.67
Omega	0.794	0.723

The portion of the instrument adopted from the Teng et al. survey was organized into one single section without clearly defined constructs of AI perception. Internal consistency of this subset of items was relatively low with an omega coefficient of 0.643. Results of the analysis are shown in Table 4.

Table 4. Reliability coefficients for items adapted from the Teng et al. survey.

	AI perspectives (P)
N items	7
Mean	7.29
SD	1.15
Alpha	0.537
Omega	0.643

Reliability for the Reliance on Technology Questionnaire was relatively high. Item groups for each of the constructs measured (RI, PU, and T) all demonstrated good reliability when used with the engineering student population. The value of McDonald's omega for the RI construct are notably the highest of all constructs assessed in this work with a value of 0.907. Details are shown in Table 5.

Table 5. Reliability coefficients for items adapted from the Reliance on Technology Questionnaire.

	RI	PU	T
N items	5	4	4
Mean	5.8	5.43	3.7
SD	1.14	1.37	1.25
Alpha	0.903	0.891	0.794
Omega	0.907	0.899	0.801

Discussion and Conclusions

Preliminary analysis of the survey indicates good overall reliability of the scale across all portions in measuring targeted constructs with an engineering student population. However, certain constructs measured in the survey demonstrate lower reliability, indicating a potential for future work to further define constructs or revise items.

Three of the five MSLQ constructs including IGO, TV, and CT had omega coefficients higher than 0.7, indicating that they reliably measure the constructs intended when used with an engineering student population. MSLQ constructs of EGO and HS had lower omega coefficients. These findings are in alignment with other studies which have found lower reliability coefficients for EGO and HS constructs [33]. However, as shown in Table 3, items adopted from the MSLQ may be the most useful when grouped into broader constructs of motivational factors and learning strategies. In this study, omega coefficients for MF and LS were both above 0.7, indicating adequate reliability. Based on these results, it is recommended to use the selected MSLQ items to measure the broader constructs of MF and LS in relation to students' use of AI.

The Teng et al. survey on AI perspectives demonstrated inadequate reliability with the engineering student population. This is likely due to the seven items in this portion of the survey measuring unrelated AI perspectives. The introductory publication of the Teng et al. survey included little information on the validity and reliability of the instrument [22]. Based on these results, it is recommended to use the items which are derived from the Teng et al. survey item-by-item to analyze AI perspectives rather than as a single construct of AI perspectives. Future work on establishing reliability and validity of this portion of the survey will include identifying latent constructs within the AI perspective items using exploratory and confirmatory factor analysis.

The Reliance on Technology Questionnaire showed the highest coefficients of reliability out of all the constructs measured in this work. Each of the constructs measured in the subset of items derived from the Reliance on Technology Questionnaire had an omega coefficient that was greater than 0.8 which indicates good reliability.

Results of this analysis position the survey as a reliable instrument for measuring constructs of motivational factors, learning strategies, reuse intentions, perceived usefulness of AI, and trust in AI within an engineering student population. Other items within the survey also have potential for providing insights into specific student perspectives on AI and could be the focus of future work to further identify relevant constructs related to students' AI perspectives.

Future Work

Future directions of research with the AI survey include further validating the survey through exploratory and confirmatory factor analysis. The current reliability analysis can also be strengthened through expanding the sample size and collecting data in populations with more diversity of gender, race, and other demographic variables which may influence the reliability of the instrument. Further work will also include comparing responses to the survey at the university level to responses from students at technical colleges who may approach the integration of AI into their coursework differently than university engineering students.

Acknowledgements

This material is based upon work supported by the National Science Foundation through Award No. 2346881. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

References

[1] L. D. Ahlstrom, O. Lawanto, C. J. McCall, M. Harper, W. H. Goodridge, and D. Kane, "Work-in-progress: Uncovering AI adoption trends among university engineering students for learning and career preparedness," presented at the 2025 ASEE Annual Conference & Exposition, ASEE PEER, Jun. 2025. doi: 10.18260/1-2--55921.

[2] D. Kane, W. H. Goodridge, L. D. Ahlstrom, O. Lawanto, M. Harper, and C. J. McCall, "WIP: understanding patterns of generative AI use: a study of student learning across university colleges," presented at the 2025 ASEE Annual Conference & Exposition, ASEE PEER, Jun. 2025. doi: 10.18260/1-2--55915.

[3] F. D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Q.*, vol. 13, no. 3, pp. 319–340, 1989, doi: 10.2307/249008.

[4] N. Saito, "Analysis of Trends in the Use of Generative AI for Learning by Attributes and Characteristics of University Students," presented at the –The Asian Conference on Education & International Development 2024, May 2024, pp. 1027–1037. doi: 10.22492/issn.2189-101X.2024.83.

[5] M. Harper, C. J. McCall, D. Kane, W. H. Goodridge, L. D. Ahlstrom, and O. Lawanto, "Work-in-progress: voices of the future: student insights on AI's role in shaping learning, integrity, and norms in higher education," presented at the 2025 ASEE Annual Conference & Exposition, ASEE PEER, Jun. 2025. doi: 10.18260/1-2--55922.

[6] J. Stübinger, "Beyond traditional boundaries: The impact of Generative Artificial Intelligence on higher education," in *The Human Side of Service Engineering*, AHFE Open Acces, 2024. doi: 10.54941/ahfe1005094.

[7] P. R. Pintrich, D. A. F. Smith, T. Garcia, and W. J. Mckeachie, "Reliability and Predictive Validity of the Motivated Strategies for Learning Questionnaire (Mslq)," *Educ. Psychol. Meas.*, vol. 53, no. 3, pp. 801–813, Sep. 1993, doi: 10.1177/0013164493053003024.

[8] A. Alkaabi, F. Jabeen, A. Dwivedi, and S. Jose, "Artificial intelligence adoption in the service industry: investigating the role of perceived usefulness and ease of use," *Int. J. Product. Perform. Manag.*, pp. 1–23, Dec. 2025, doi: 10.1108/IJPPM-06-2024-0369.

[9] P. R. Pintrich, "A Conceptual Framework for Assessing Motivation and Self-Regulated Learning in College Students," *Educ. Psychol. Rev.*, vol. 16, no. 4, pp. 385–407, Dec. 2004, doi: 10.1007/s10648-004-0006-x.

[10] F. G. K. Yilmaz, R. Yilmaz, and M. Ceylan, "Generative Artificial Intelligence Acceptance Scale: A Validity and Reliability Study," *Int. J. Human–Computer Interact.*, vol. 40, no. 24, pp. 8703–8715, Dec. 2024, doi: 10.1080/10447318.2023.2288730.

[11] M. Teng *et al.*, "Health care students' perspectives on artificial intelligence: countrywide survey in canada," *JMIR Med. Educ.*, vol. 8, no. 1:e33390, 2022, doi: 10.2196/33390.

[12] T. A. Brown, *Confirmatory Factor Analysis for Applied Research*. New York London: The Guilford Press, 2015.

[13] M. R. Novick, "The axioms and principal results of classical test theory," *J. Math. Psychol.*, vol. 3, no. 1, pp. 1–18, Feb. 1966, doi: 10.1016/0022-2496(66)90002-2.

[14] R. F. DeVellis and C. T. Thorpe, *Scale Development: Theory and Applications*. Applied Social Research Methods, 2021. Accessed: Jan. 21, 2026. [Online]. Available: https://www.amazon.com/Scale-Development-Applications-Applied-Research/dp/154437934X

[15] R. L. Johnson and G. B. Morgan, “Adopting or Adapting an Existing Scale,” in *Survey Scales*, New York, NY, USA: The Guilford Press, 2016, pp. 18–34.
[16] J. DeWaters, J. C. Moosbrugger, and P. Sharma, “Development and Application of a Questionnaire to Measure Student Attitudes Toward and Understanding of Engineering,” presented at the 2017 ASEE Annual Conference & Exposition, Jun. 2017. Accessed: Feb. 11, 2026. [Online]. Available: https://peer.asee.org/development-and-application-of-a-questionnaire-to-measure-student-attitudes-toward-and-understanding-of-engineering
[17] J. Dirisina and R. L. Shehab, “Classifying Survey Items related to Engineering Self-Concept for Application in First-Year Engineering,” presented at the 2024 ASEE Annual Conference & Exposition, Jun. 2024. Accessed: Feb. 11, 2026. [Online]. Available: https://peer.asee.org/classifying-survey-items-related-to-engineering-self-concept-for-application-in-first-year-engineering
[18] K. West, B. F. Carroll, J. Shin, and K. J. Crippen, “Towards a Survey Instrument for Use In Proactive Advising,” presented at the 2024 ASEE Annual Conference & Exposition, Jun. 2024. Accessed: Feb. 11, 2026. [Online]. Available: https://peer.asee.org/towards-a-survey-instrument-for-use-in-proactive-advising
[19] K. A. Davis, L. C. Arinze, S.- Berka, C. Cooper, and J. Tort, “BOARD # 351: Developing a Survey Exploring the Impact of Global Undergraduate Experiences on Engineers’ Career Pathways (RFE #2308607),” presented at the 2025 ASEE Annual Conference & Exposition, Jun. 2025. Accessed: Feb. 11, 2026. [Online]. Available: https://peer.asee.org/board-351-developing-a-survey-exploring-the-impact-of-global-undergraduate-experiences-on-engineers-career-pathways-rfe-2308607
[20] F. Zhang, B. M. Holloway, and E. Holloway, “Validity Evidence for the Sophomore Engineering Experiences Survey,” presented at the 2024 ASEE Annual Conference & Exposition, Jun. 2024. Accessed: Feb. 11, 2026. [Online]. Available: https://peer.asee.org/validity-evidence-for-the-sophomore-engineering-experiences-survey
[21] P. R. Pintrich and A. Others, “A Manual for the Use of the Motivated Strategies for Learning Questionnaire (MSLQ),” 1991. Accessed: Jan. 20, 2026. [Online]. Available: https://eric.ed.gov/?id=ED338122
[22] M. Teng *et al.*, “Health Care Students’ Perspectives on Artificial Intelligence: Countrywide Survey in Canada,” *JMIR Med. Educ.*, vol. 8, no. 1, p. e33390, Jan. 2022, doi: 10.2196/33390.
[23] S. Al-Natour, I. Benbasat, and R. T. Cenfetelli, “The Effects of Process and Outcome Similarity on Users’ Evaluations of Decision Aids,” *Decis. Sci.*, vol. 39, no. 2, pp. 175–211, 2008, doi: 10.1111/j.1540-5915.2008.00189.x.
[24] P. R. Pintrich, D. A. F. Smith, T. Garcia, and W. J. Mckeachie, “Reliability and Predictive Validity of the Motivated Strategies for Learning Questionnaire (Mslq),” *Educ. Psychol. Meas.*, vol. 53, no. 3, pp. 801–813, Sep. 1993, doi: 10.1177/0013164493053003024.
[25] W. Lee, J. F. Rhoads, E. J. Berger, and J. Deboer, “WIP: Validating a Motivated Strategy for Learning Questionnaire (MSLQ) in an Active, Blended, and Collaborative (ABC) Dynamics Learning Environment,” presented at the 2020 ASEE Virtual Annual Conference Content Access, Jun. 2020. Accessed: Jan. 20, 2026. [Online]. Available: https://peer.asee.org/wip-validating-a-motivated-strategy-for-learning-questionnaire-mslq-in-an-active-blended-and-collaborative-abc-dynamics-learning-environment

[26] Y. Yang and S. B. Green, “Coefficient Alpha: A Reliability Coefficient for the 21st Century?,” *J. Psychoeduc. Assess.*, vol. 29, no. 4, pp. 377–392, Aug. 2011, doi: 10.1177/0734282911406668.
[27] Y. F. Zakariya, “Cronbach’s alpha in mathematics education research: Its appropriateness, overuse, and alternatives in estimating scale reliability,” *Front. Psychol.*, vol. 13, p. 1074430, 2022, doi: 10.3389/fpsyg.2022.1074430.
[28] I. Trizano-Hermosilla and J. M. Alvarado, “Best Alternatives to Cronbach’s Alpha Reliability in Realistic Conditions: Congeneric and Asymmetrical Measurements,” *Front. Psychol.*, vol. 7, May 2016, doi: 10.3389/fpsyg.2016.00769.
[29] A. F. Hayes and J. J. Coutts, “Use Omega Rather than Cronbach’s Alpha for Estimating Reliability. But…,” *Commun. Methods Meas.*, vol. 14, no. 1, pp. 1–24, Jan. 2020, doi: 10.1080/19312458.2020.1718629.
[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, Art. no. 6, Dec. 2018, doi: 10.1007/s11165-016-9602-2.
[31] *Jamovi*. (2025). [Online]. Available: https://www.jamovi.org
[32] K. Sijtsma, “On the Use, the Misuse, and the Very Limited Usefulness of Cronbach’s Alpha,” *Psychometrika*, vol. 74, no. 1, pp. 107–120, Mar. 2009, doi: 10.1007/s11336-008-9101-0.
[33] R. Taylor, “Review of the Motivated Strategies for Learning Questionnaire (MSLQ) Using Reliability Generalization Techniques to Assess Scale Reliability,” May 2012, Accessed: Jan. 21, 2026. [Online]. Available: https://etd.auburn.edu/handle/10415/3114