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Development of Self-Efficacy and Mindset Scales for Advanced Manufacturing and Data Sciences

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Introduction and Literature Review

The purpose of this paper is to describe the development of a set of scales intended to measure self-efficacy and growth/fixed mindset relating to advanced manufacturing and data sciences (AMDS). The scales were developed as part of a larger National Science Foundation (NSF) funded project with the goal of creating a set of online courses and modules about AMDS. These courses and modules are intended to be completed by a variety of learners, including community-college students, 4-year university students, industry professionals, and informal learners who are looking to advance their skills. The scales will ultimately be used as measures to gauge the impact of the instructional activities being created as part of the NSF project. This paper will describe how the scales were developed and provide information on preliminary psychometric properties and validity evidence. We anticipate that individuals interested in how to assess the impact of advanced manufacturing courses or educational initiatives will be interested in this paper.

Manufacturing technology is rapidly evolving across many different industrial markets. The need to improve both affordability and performance has driven growth in advanced techniques like additive manufacturing. Further growth is expected as agile business practices such as just-in-time manufacturing and mass customization take hold.

Referred to as "The Internet of Things" or "Industry 4.0", factory sensors and visual data-dashboards are being rapidly installed on various shopfloors that aim to prevent errors and optimize production (Dai, et al., 2020). These new concepts are disruptive and difficult to implement with legacy manufacturing techniques. Companies must adapt to these new practices to remain competitive and expand their markets.

The area of data sciences in advanced manufacturing is especially important for industry professionals and engineering graduates given that access to big data sets is becoming more and more prevalent in the engineering workplace. In manufacturing, work has changed to rely less on discrete and isolated fabrication steps, and to rely more on the expansive amounts of data from the digitally connected thread available through the manufacturing flow. During the manufacturing process, many input variables indicating process conditions can be collected into a log file which can then be used to streamline the process and to examine the relationship between process conditions and products created. While this data has much potential for exploration and improving the production process, analyzing the data can be incredibly complex due to the size of the data set and the sheer number of variables.

Both advanced manufacturing and data science knowledge and expertise are now requirements for manufacturing sectors. With this growing field, it is necessary to align the development of undergraduate and graduate curriculum to support the advancing field of manufacturing. The instruments developed for this proposal will support the field of advanced manufacturing and data science in academic institutions as there are only a handful of degree programs integrating these concepts into curriculum, leading to a gap of knowledge in the current work force.

The project discussed here focuses on the creation of scales measuring mindset and self-efficacy for the domain of AMDS. Much of the literature around mindset stems from the work of Carol Dweck and her instrumental book *Mindset: The New Psychology of Success (2006).* According to Dweck, the set of beliefs that one has about themselves can be very powerful influences on behavior. A growth mindset indicates one's beliefs that ability or intelligence can be strengthened through training or practice. In contrast, a fixed mindset indicates beliefs that one's ability or intelligence is unchangeable and static, regardless of the experiences one has. While Dweck primarily focused on beliefs around intelligence, she did acknowledge that one's beliefs may vary when considering different domains. For example, one may have a different set of beliefs regarding their athletic abilities as compared to their beliefs regarding artistic abilities. While there may be some influence of one's mindset towards their own general abilities or intelligence, the varying beliefs for different domains points to the need for domain-specific instruments. Some researchers have started to explore the creation of domain-specific instruments measuring mindset, such as Karwowski (2014) who developed a scale about fixed versus growth mindset relating to creativity.

This need for domain-specific instruments also is needed for self-efficacy scales. Self-efficacy refers to one's confidence in being able to complete a specific task or skill. While one may have self-efficacy about one's general abilities, their self-efficacy likely differs across different types of domains. For a more detailed discussion of the need for domain-specific measures of growth mindset, see Zappe, Cutler, Spiegel, and Jordan (2022).

Context of this study

In 2019, the authors of this paper received a grant from NSF to study and develop online modules for pathways of learning in AMDS. The goal of this project is to create online modules to help increase AMDS knowledge and skills among industry professionals and college students. Specifically, these modules are intended to be used by four different learner groups: industry professionals who work in advanced manufacturing, 4-year university students, 2-year community college students, and informal learners who want to improve their skills or increase knowledge.

Online modules are being developed according to the Engineering Learning Framework (Spiegel, 2016), which uses cognitive principles and learning theory to make instructional design decisions. As the framework states, "Engineering Learning is an intentional design process that positions students to cognitively engage with content and data using professional tools, while interacting and collaborating with peers to develop their content expertise, skills, and professional practices. The end goal is to create the richest opportunities for students to become innovative STEM leaders." In addition to learning about AMDS principles, learners will complete a module on fixed/growth mindset, which describes what mindset is and asks the learners to reflect on their experiences and when they may have felt they had a growth or a fixed mindset.

Beyond the goals of module development around AMDS, this grant also includes an engineering education research component. Specifically, the engineering education research project aims to look at the relationship between different demographic and psychological characteristics of the learner and how these are impacted by the educational context. Figure 1 displays the relationships that are of interest to the overarching study. In addition, the five research questions being explored appear below:

RQ1: How do psychological characteristics of learners, including mindset, self-efficacy, and metacognition affect performance in the online course modules?

RQ2: How do the learners' demographic characteristics, such as gender, prior knowledge, and educational background affect performance?

RQ3: What is the interaction among the psychological characteristics and demographic characteristics of learners that affect performance?

RQ4: How do the psychological characteristics and their inter-relationships (mindset, self-efficacy, and metacognition) differ across the four learning settings?

RQ5: How do the learners' demographic and psychological characteristics affect their preferences and navigation patterns (i.e., preferences for specific types of assignments and course behaviors) with the various course design elements (i.e., less challenging versus more challenging assignments, reflection activities)?

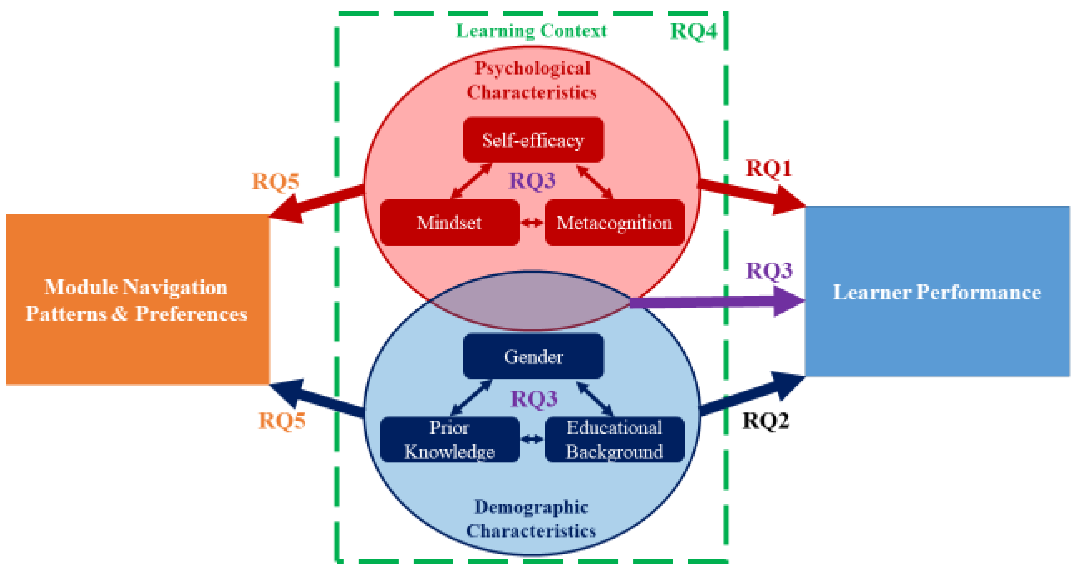

Figure 1: Illustration of research questions and the relationship of learners' characteristics to performance and navigation patterns and preferences

The proposed research design for this study included already-developed instruments with sufficient validity evidence as well as the development of new instruments. The instruments that needed to be created included scales measuring learners' self-efficacy for AMDS and whether they have a growth or fixed mindset relating to AMDS. This paper focuses on the development for these two instruments. Additional information about the overall project is available in Zappe et al. (July 2021).

Identification of AMDS skills: Interviews with industry

The first step of the overall project was to identify key AMDS knowledge, skills, and attitudes that industry is currently seeking that would serve as the content for the modules and courses. We conducted 23 interviews with employees in varying role groups across six industry partner companies which focused on AMDS. The interviews focused on current workforce efforts, current challenges the company is facing, what type of training and professional development the company provides, and how the company thinks about data and datasets. The interviews were recorded, transcribed, and coded to identify data that would help the project team build relevant modules.

From the interviews, 16 codes were identified: basic math, business acumen, communication, continued learning, data science, engineering design, management (working with people), manufacturing process, materials knowledge, practical knowledge and experience (hands-on experience), problem solving skills, programming coding skills, project management, teamwork, technology tools, and work ethic.

Scale Development

The interview codes were used to guide the development of the items for two separate scales. For each scale, the research team worked together to map the items to the skills identified from the interviews with the AMDS industry members. An initial draft was created by the project evaluators. Feedback was then received from the other members of the project team, including other educational experts and engineering faculty with expertise in AMDS. Two scales were created, which are described below; individual items on the scales are available in Appendices A and B.

AMDS Self-Efficacy Scale. First, a 21-item scale was created that is intended to measure learners' self-efficacy for a set of skills relating to advanced manufacturing – or how confident learners feel in their knowledge and abilities related to advanced manufacturing. An 11-point scale was used, following the recommendations by Bandura (2006), with a score of 0 indicating "Not at all Confident" and a score of 10 indicating "Extremely Confident." The directions on the scale stated, "On a scale of 0 to 10, rate your level of confidence in your ability to do the following." Each individual received a Self-Efficacy Scale score by summing the coded item values.

AMDS Mindset Scale (General and Personal). A scale intended to measure whether learners have a fixed or growth mindset for advanced manufacturing was also created. This scale had two subscales. First, the General Mindset Subscale is intended to measure an individual's generalized measuring general beliefs about whether AMDS skills were innate or could be developed with practice and training. Directions on the General Scale stated the following: "People differ in their knowledge and ability to do different tasks. For the following domains, rate how much you feel each is innate to the person (related to their intelligence or personality) versus how much you feel each can be learned through practice or training." To be similar to the Self-Efficacy Scale, an 11-point scale was used with 0 indicating, "Innate" and 10 indicating "Learned."

Second, the Personal Mindset Subscale, is intended to measure one's beliefs if they personally feel that they themselves could develop the skills with practice and training. The directions for this subscale stated, “For each of the following domains, rate how much you feel YOU personally can learn each of these based on practice and training.” Once again, an 11-point scale was used with 0 indicating, “I will not be able to learn this no matter how much practice” and 10 indicating, “I can become an expert at this if I practice a lot.”

Each individual received two separate subscale scores (a General score and a Personal score) by adding the coded item values.

The two separate subscales were designed to differentiate one’s generalized beliefs about certain characteristics in others and one’s personal beliefs about themselves. Previous research has explored perceptions of students with respect to an instructor’s mindset about students (Muenks et al., 2020), as well as research about faculty mindset about their students (Canning et al., 2019). This previous research highlighted that someone may hold different mindsets not only for different domains but for different groups of people. Therefore, having one scale measure participants’ broader perceptions of a characteristic as they perceive it in others and another scale to measure their mindset with respect to themselves can further explore how mindset may present differently in different contexts.

Additionally, having a growth mindset has been linked to overcoming stereotype threat (Spencer, Logel, & Davies, 2016; Yeager & Dweck, 2012). Stereotype threat impacts students from traditionally marginalized groups that are stereotyped as poor performers in certain domains (Steele, 1997; Steele 1999). By measuring both a participant’s broader mindset beliefs about others as well as personal mindset beliefs, the researchers wanted to explore the potential to see elements that could indicate stereotype threat or impact self-efficacy; for example, having a growth mindset for others, but a fixed mindset for yourself.

Pilot Study Methodology

The scales were administered to students at multiple institutions including a 2-year community college and a 4-year university located in the western United States. Instructors of courses in advanced manufacturing, computer science, math, and mechanical engineering asked students in their courses if they would be willing to participate in the study. Interested students received a link to a Qualtrics survey online. Students did not receive any incentive for participating in the study. The survey contained multiple scales, some of which related to the other aspects of the overall study being explored. A total of 136 students completed the scales.

Reliability and Classical Item Analysis

Table 2 provides the reliability coefficients (Cronbach’s Alpha) for each of the scales. The reliability coefficients for all scales were quite high.

Table 2: Reliability coefficients for each scale

Scale	Cronbach’s Alpha
AMDS Self-Efficacy Scale	0.919
AMDS Mindset (General)	0.876
AMDS Mindset (Personal)	0.933

A classical item analysis was conducted with the intention of flagging any item which does not seem to contribute to the reliability of the scale. Using a classical item analysis, most items were found to function statistically as intended, with the reliability if item removed being reduced. In a classical item analysis, we primarily look at the alpha if item deleted. If the item is considered to be functioning well statistically, it should not increase the reliability of the scale if it is removed. Therefore, any item that is flagged as having an "alpha if item removed" as greater than or equal to the scale reliability would be flagged as potentially problematic. Appendices A and B contain the items with the results of the classical item analysis.

AMDS Self-Efficacy: The classical item analysis for this scale indicated that most items were functioning as intended, with two exceptions: items 17 and 18. Item 17 stated, "Apply advanced math (calculus or linear algebra) to solve problems." Item 18 stated, "Explain the role and value of math to others." These two items are not contributing to the reliability of the study and are flagged as being potentially problematic.

AMDS Mindset (General): One item was identified as potentially being problematic, which is item 2: "Interpreting engineering designs (in CAD or on paper)." This item had an increased alpha if item removed.

AMDS Mindset (Personal): No items were flagged in the classical item analysis as being potentially problematic.

Preliminary Validity Evidence

To collect preliminary validity evidence, factor analyses were run on each individual scale/subscale, which was used to determine the internal structure of the instrument data. For each scale, we hypothesized that there would be just one factor. The factor analyses were conducted using principal axis factoring as the extraction method and varimax rotation with Kaiser normalization.

AMDS Self-Efficacy Scale: The 21-item scale indicated that there are 5 possible factors with eigenvalues greater than 1. However, examining the scree plot (see Figure 2) suggests that there are 2 large, primary factors. Almost all of the items load into the one major factor. There are 6 items that load more strongly on a second factor; these items include the following:

- Write/use simple code or programming
- Write/use code to solve specific problems
- Write/use advanced coding functions to optimize problem solving
- Use math to solve everyday problems
- Apply advanced math (calculus or linear algebra) to solve problems
- Explain the role and value of math to others

Based on the results, we consider Factor 1 to be AMDS Tools/Procedures and Factor 2 to be Problem Solving. Based on the classical item analysis, we plan to rerun the analysis by removing those items that are potentially problematic.

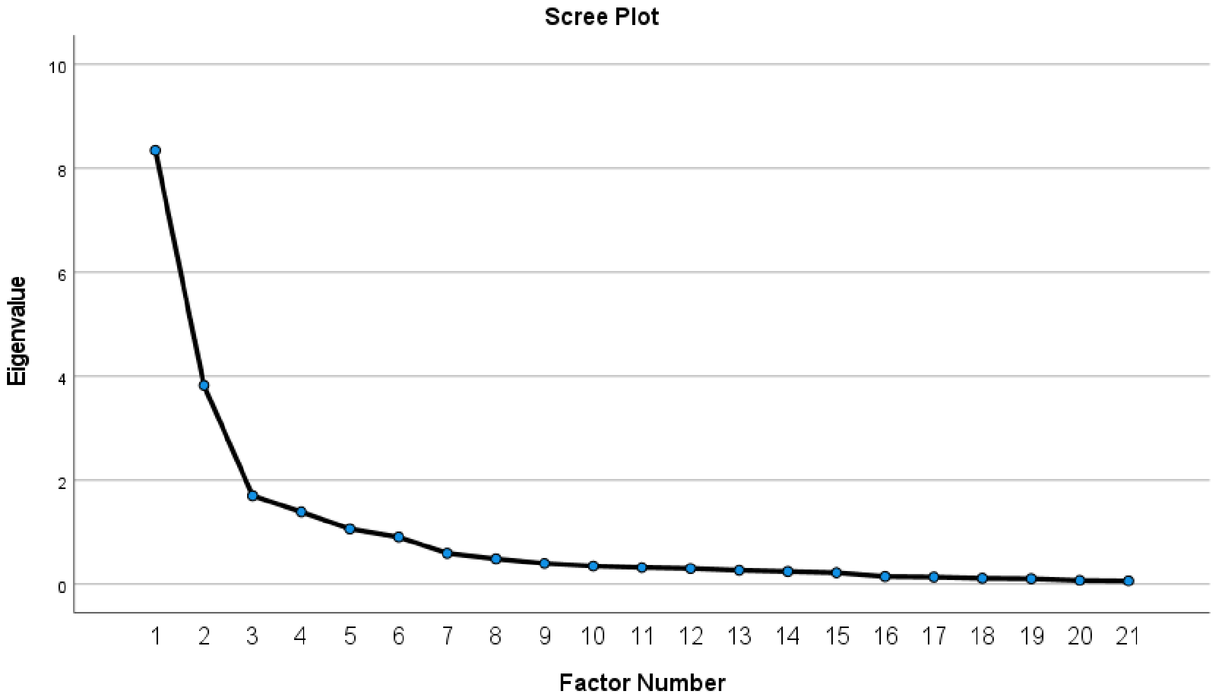

Figure 2: Scree plot for AMDS Self-Efficacy Scale

AMDS Mindset Scale (General): The data indicated three potential factors for this scale with eigenvalues greater than 1. The scree plot, displayed in Figure 3, also suggests either 2 or 3 factors. The general themes that are indicated by the three factors include 1) Technology and Data (5 items), 2) Project Management and Communication (6 items), and 3) Online and Pathways (2 items). Our plan is to reanalyze this data with the items flagged in the classical item analysis to determine which combination of items yields the clearest factor structure.

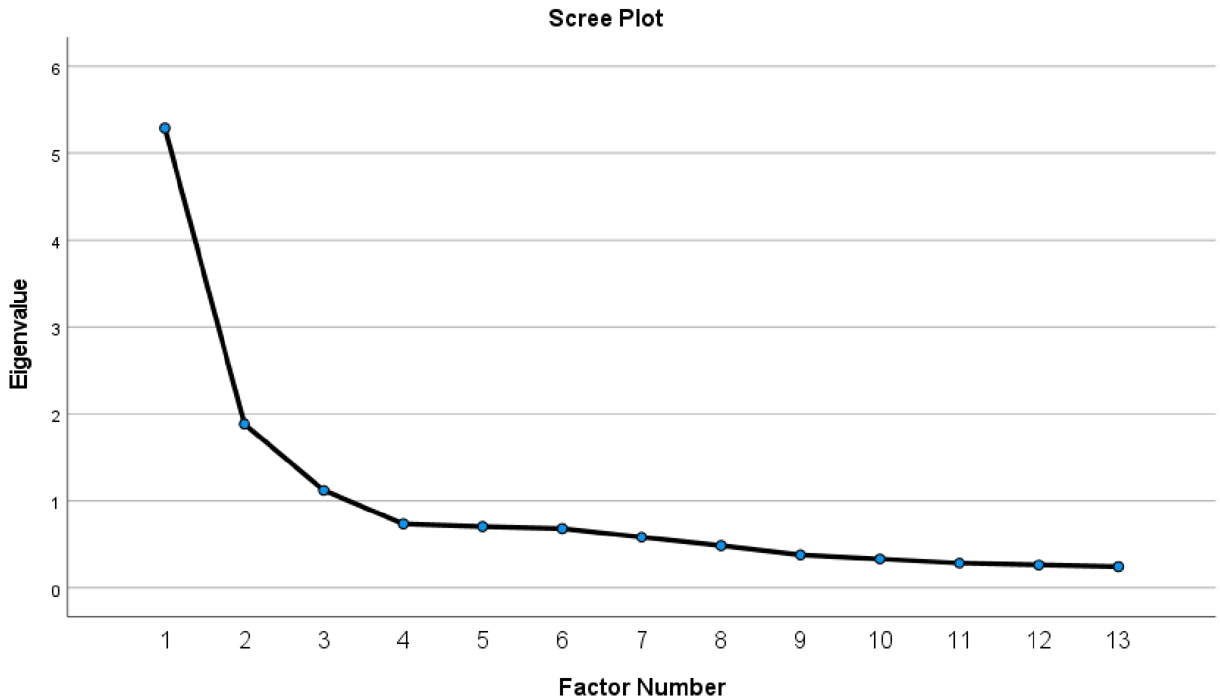

Figure 3: Scree plot for AMDS Mindset - General Scale

AMDS Mindset Scale (Personal): The factor analysis yielded two factors with eigenvalues greater than 1, which is also supported by the scree plot (See Figure 4). The items loaded very similarly as they did on the general scale, except with only 2 factors, which we labeled 1) Technology and Data and 2) Project Management and Communication. These two factors included all of the same items that had loaded on each factor as in the general scale with two exceptions. The final two items (Being successful in an online course and Making decisions about future career pathways) loaded onto the first factor with the Technology and Data items, rather than as a separate factor.

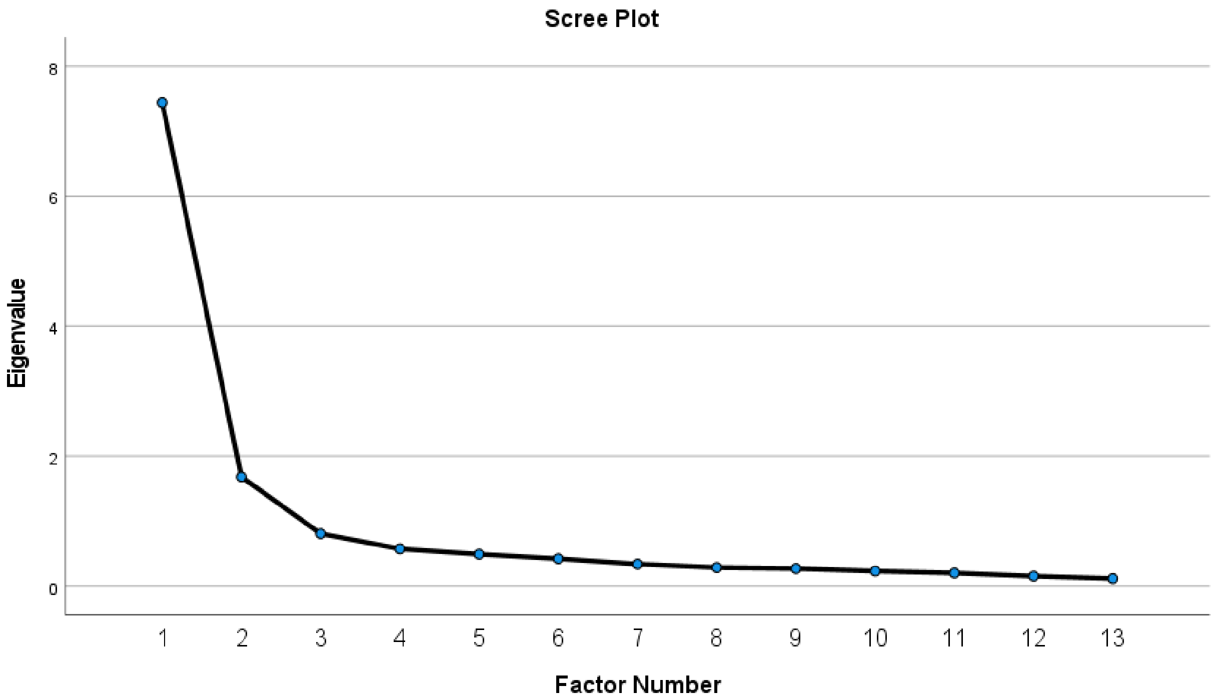

Figure 4: Scree plot for AMDS Mindset - Personal Scale

Discussion and Next Steps

This study represents our first steps in the development of instruments to measure learners' self-efficacy and mindset relating to advanced manufacturing. These instruments will be helpful to others who are planning or already have programs in advanced manufacturing and are curious about studying their impact.

One limitation of the study is that the sample size is still somewhat small for instrument development. We have continued to collect additional data and are planning to rerun analyses and continue the collection of validity evidence following the most recent *Standards for Educational and Psychological Testing* (AERA, APA, & NCME, 2014). Included in our plans is to gather data from expert judgment and to potentially collect learner think-alouds on the data. Once data collection is completed, we hope to publish the revised and final version of the scale in an archival journal. The plan moving forward is to re-run the analysis with the problematic items removed and settle on a final version of the instrument that has the cleanest factor structure and support from expert judgment.

For more information about this project or to use the instruments, please contact the authors.

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References:

American Educational Research Association, American Psychological Association and the National Council on Measurement (2014). *Standards for Educational and Psychological Testing*. Lanham, MD: American Educational Research Association.

Bandura, A. (2006). Guide for constructing self-efficacy scales. In Urdan, T. & Pajares, F (Eds.) *Self-Efficacy Beliefs of Adolescents.* Information Age Publishing 307-337.

Canning, E., Muenks, K., Green, D. & Murphy, M. (2019). STEM faculty who believe ability is fixed have larger racial achievement gaps and inspire less student motivation in their classes. *Science Advances*. 5. eaau4734. 10.1126/sciadv.aau4734.

Dai, H., Wang, H., Xu, G., Wan, J., & Imran, M. (2020). Big data analytics for manufacturing internet of things: Opportunities, challenges and enabling technologies. *Enterprise Information Systems, 14(*9-10): 1279-1303.

Dweck, C. S. (2006). *Mindset: The New Psychology of Success.* New York. Random House.

Karwowski, M. (2014). Creative mindsets: Measurements, correlates, consequences. Psychology of Aesthetics, *Creativity and the Arts*. 8(1): 62-70.

Muenks, K., Canning, E.A., LaCose, J., Green, D.J., Zirkel, S., Garcia, J.S., & Murphy, M. (2020). Does my professor think my ability can change? Students' perceptions of their STEM professors' mindset beliefs predict their psychological vulnerability, engagement, and performance in class. *Journal of Experimental Psychology: General, 149*(11): 2119-2144.

Spencer, S. J., Logel, C., & Davies, P. G. (2016). Stereotype threat. Annual Review of Psychology, 67, 415-437.

Spiegel, S. (2016). Engineering Learning. Retrieved 5/15/2022 from https://trefnycenter.mines.edu/pedagogy-resources/engineered-learning.

Steele, C. M. (1997). A threat in the air: How stereotypes shape the intellectual identities and performance of women and African-Americans. American Psychologist, 52, 613-629.

Steele, C. M. (1999, August). Thin ice: "Stereotype threat" and black college students. The Atlantic Monthly, 284(2), 44-47, 50-54.

Yeager, D.S. & Dweck, C.S. (2012). Mindsets that promote resilience: When students believe that personal characteristics can be developed. *Educational Psychologist, 47*(4): 302-314.

Zappe, S.E., Cutler, S. C., Spiegel, S., Jordan, D., & Vasquez, A. (2021). Work-in-Progress: Investigation of the psychological and demographic characteristics that impact performance in online modules and courses. *Proceedings of the Annual Conference of the American Society for Engineering Education*. Virtual conference.

Zappe, S. E., Cutler, S. C., Spiegel, S., & Jordan, D. (January 2022). The Need for Domain-Specific Measures regarding Mindset: Preliminary analysis of the Engineering Mindset Scale. *Proceedings of the annual Hawaii International Conference on Education*. Kona, HI.

Appendix A: Item statistics and alpha if item removed for AMDS Self-Efficacy Scale

To use the scales in this paper, we request that you please contact the authors, as the versions included here are subject to revision.

No.	Item	Mean	Standard Deviation	Alpha if Item Removed
1	Use technology effectively when needed (For example: computers and smart phones)	9.20	1.16	0.918
2	Use general software tools effectively when needed (For example: Microsoft Office or similar word processing, presentation slide software, or web browsers)	9.13	1.29	0.918
3	Use engineering/discipline specific software tools effectively when needed (For example, Solidworks or similar CAD software, MatLab, CAM, PLC, Minitab)	6.84	2.61	0.911
4	Read and interpret engineering designs (in CAD or on paper)	6.99	2.62	0.912
5	Draft or edit engineering designs (in CAD or on paper)	6.20	2.89	0.912
6	Explain how engineering designs impact the manufacturing process	6.59	2.70	0.912
7	Use data to make decisions	8.15	1.59	0.915
8	Analyze data appropriately to answer specific questions	7.87	1.70	0.914
9	Interpret data analysis results appropriately	7.74	1.69	0.915
10	Describe a manufacturing process to someone unfamiliar with manufacturing	6.26	2.98	0.911
11	Explain the different steps and decisions required to design an effective manufacturing process	5.84	2.74	0.910
12	Explain how different steps in the manufacturing process impact the end results	6.33	2.70	0.911
13	Write/use simple code or programming	8.00	2.58	0.918
14	Write/use code to solve specific problems	7.19	2.63	0.918
15	Write/use advanced coding functions to optimize problem solving	6.44	2.65	0.917
16	Use math to solve everyday problems	8.71	1.53	0.918
17	Apply advanced math (calculus or linear algebra) to solve problems	7.85	1.86	**0.920***
18	Explain the role and value of math to others	8.45	1.57	**0.919***
19	Create a budget for a project	6.99	2.18	0.916
20	Explain the supply chain for a specific product	6.25	2.64	0.912
21	Estimate the costs associated with a production process	6.32	2.22	0.914

*indicates item flagged for having alpha if item removed greater than or equal to coefficient alpha.

Appendix B: Item statistics and alpha if item removed for AMDS Mindset Scale

To use the scales in this paper, we request that you please contact the authors, as the versions included here are subject to revision,

		General Subscale			Personal Subscale		
No.	**Item**	**Mean**	**Standard Deviation**	**Alpha if Item Removed**	**Mean**	**Standard Deviation**	**Alpha if Item Removed**
1	Using technology tools	8.18	1.94	0.869	9.39	1.15	0.931
2	Interpreting engineering designs (in CAD or on paper)	8.10	1.94	**0.879***	9.19	1.24	0.930
3	Using data science effectively	7.91	1.90	0.868	9.07	1.30	0.929
4	Programming or coding	7.93	2.05	0.871	9.02	1.42	0.931
5	Using mathematics	7.51	2.12	0.866	9.01	1.54	0.931
6	Making business decisions	6.53	2.40	0.863	8.30	1.98	0.924
7	Managing people or a project	5.24	2.38	0.866	8.04	2.15	0.926
8	Solving problems as they arise	6.01	2.52	0.858	8.45	2.03	0.924
9	Communicating effectively	5.82	2.52	0.865	8.39	1.97	0.927
10	Time management	6.46	2.46	0.868	8.25	2.21	0.925
11	Working independently to understand new information	6.37	2.46	0.864	8.44	1.99	0.925
12	Being successful in an online course	6.74	2.56	0.868	8.45	2.28	0.928
13	Making decisions about future career pathways	6.88	2.26	0.867	8.33	1.98	0.927

*indicates item flagged for having alpha if item removed greater than or equal to coefficient alpha.