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Student Preparedness for Artificial Intelligence-Driven Volatility, Uncertainty, Complexity, and Ambiguity (VUCA) Environments: Scale Development and Validation

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ABSTRACT: *Technology has permeated the workplace, which demands new skills from the labor force. This is characterized by constant transformations and is known as the VUCA (Volatility, Uncertainty, Complexity and Ambiguity) world, with artificial intelligence (AI) being a key driver. This study aimed to develop a comprehensive scale to measure students' preparedness to face AI-driven VUCA by integrating AI across the three dimensions of the 21st-century skill set as an attempt to fill the gap in the availability of such a tool. A quantitative research design was employed, with 626 students pursuing higher education sampled using a convenience sampling technique. The initial item pool consisted of 29 items drawn from an array of research articles. The content validity index, purification, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were* *carried out on three dimensions. The validated final scale has 25 items, with a high reliability score of 0.882.*

Keywords: Artificial intelligence, Career, Higher education, Scale development, VUCA

INTRODUCTION

Developed by the United States Military Academy in the early 1990s, the VUCA concept is used to comprehend the Volatility, Uncertainty, Complexity, and Ambiguity world that began after the end of the Cold War (Forsythe et al., 2018). The current era, in simple terms, is characterized by swift and erratic changes, which are referred to as the VUCA era, and it can be visualized in the context of the global economy and society more often. *Volatility* is a sign of elevated fluctuations, with the ability to quickly change circumstances (Brodnick & Gryskiewicz, 2018). *Uncertainty* is defined as the influence on decision-making, often created by technological breakthroughs (Cook, 2022). *Complexity,* on the other hand, refers to the growing complexity of associations and interactions resulting from technology, globalization, and the dynamics of an increasingly interconnected market. *Ambiguity* is the absence of clarity or clear understanding (Chen, 2024; Potsangbam, 2017; Priyanto, 2023; Sari et al., 2024).

The Workplace–VUCA–Higher Education Interconnection

Technology has permeated the workplace, and for the past 20 years, we have seen how computers, social media, and mobile technology have changed the nature of work (Kautish et al., 2022). Some occupations and professions are becoming obsolete because of groundbreaking innovations and new information and communication technologies (ICTs). A closer look revealed that a wide range of sectors and businesses are impacted, including manufacturing, financial, educational, and even medical (Cascio & Montealegre, 2016). Such large-scale drastic changes that are propelled by technological innovation and modernization are a classic feature of the VUCA environment (Rossouw & Goldman, 2023). Therefore, the use of ICTs and other technology-driven business models has increased the demand for highly qualified, creative, and innovative individuals while also dislodging middle-level skilled workers from repetitive, routine-oriented professions (Hodgson, 2016). In other words, as frontrunners, students must acquire supplementary skills that complement technologies while preserving their distinctive human qualities (Alsaadi et al., 2025; Zouhaier, 2023).

This is when the role of higher education comes in (Abdelzaher & Onumonu, 2024; Mielkov, 2020; Worley & Jules, 2020; Randolph, 2011). To equip students with the skills they need to successfully navigate the complexity of the modern labor world, higher education institutions (HEIs) have brought about significant changes in the structure of instructional activities and the teaching methods employed, since fostering innovative and creative mindsets in addition to imparting knowledge is essential for preparing learners for the VUCA-labor world (Besonia, 2024; Bühler et al., 2022; Bannister, et al., 2024; Minciu et al., 2025; Latha, 2020).

AI-Driven VUCA Workplace

The labor market continues to be altered because of the rapid advancement of new technologies such as artificial intelligence (AI), which is a key driver in creating VUCA environments (Duke, 2026; Ahmad, 2020). AI, simply stated, is the ability of a machine to mimic intelligent human behavior and carry out intelligence-related tasks. It is a general term for information systems that are triggered by biological processes and encompasses a range of abilities, such as computer vision, machine learning, deep learning, natural language processing (NLP) and machine reasoning (Aneja et al., 2018). By permanently changing the dynamic between humans and machines, the Fourth Industrial Revolution (4IR), which encompasses the development of technologies such as AI, has brought about a profound shift in economic history (Bajpai & Biberman, 2019). As a result, there has been a "structural shift in labor markets" (Autor, 2019), whereby regular manual jobs have been glaringly replaced by technology-driven functions in practically every industry. Considering this, relevant skills have become progressively more crucial for both firms and employees. Firms look to hire people with specialized skill sets, especially those related to AI (Ahmad, 2020; Fagun, 2025). According to Tanasciuc (2024), rather than merely replacing employment, AI is altering them by generating novel job descriptions and updated skill requirements. India is a major contributor to the global higher education ecosystem and one of the main source countries for international students. In this regard, assessing Indian students' fitness for AI-driven VUCA situations offers important insights into the preparedness of a significant portion of the future global workforce.

Framework for 21st Century Skills

Researchers outline a set of skills that help students succeed and thrive in the AI-driven VUCA workplace. All three agreed on a core framework, i.e., *the 4Cs—critical thinking, creativity, collaboration, and* communication—as fundamentally essential in technologically advanced environments. The importance of digital literacy, metacognitive skills, computational thinking, and emotional intelligence is further emphasized by Rodrigues et al. (2024), whereas Çelik et al. (2024) place greater emphasis on strong problem-solving abilities and ICT proficiency. By merging technical skills such as cloud computing, analytical reasoning with human-centric, and AI, with human qualities such as empathy, flexibility, initiative, originality, and first-principles thinking, Bühler et al. (2022) expand the scope, especially in engineering education.

In response to contemporary educational difficulties, the Partnership for 21st Century Skills (P21) created the Framework for 21st Century Learning in the early 2000s (Zhou, 2023). This framework identifies essential skills needed for thriving in the new workplace (Child & Shaw, 2016). It has garnered international attention, including in Confucian-heritage societies, where it largely resonates with traditional values while offering fresh perspectives on ethical creativity, social construal of self, and critical thinking as both cognitive and affective (Child & Shaw, 2016; Guo & Woulfin, 2016; Tan, 2019). Educational institutions around the world are prioritizing the development of these 21st century skills because they are thought to be essential for students to achieve future economic prosperity and success in global competition (Child & Shaw, 2016; Zhou, 2023). Duncan (2009) referred to 21st century skills as *"skills that increasingly demand creativity, perseverance, and problem solving combined with performing well as part of a team",* which outline three major skills with eleven sub-skills that are comprehensive-1. Learning and innovation skills (communication and collaboration, critical thinking and problem-solving, and creativity and innovation skills), 2. Digital literacy skills (information, media, and ICT literacy), and 3. Career and life skills (flexibility and adaptability, initiative and self-direction, social and cross-cultural, productivity and accountability, and leadership and responsibility skills) (Menggo et al., 2022; Erol, 2021; Van Laar et al., 2017, 2020; Tan et al., 2017; Trilling & Fadel, 2009; Vijver & Leung, 2021). This skill set covers a wide range of skills that are holistic and equip the future workforce for a VUCA world.

Students' Preparedness for VUCA Contexts

With a GDP of USD 5 trillion by 2025, India hopes to be among the top three economic superpowers by 2030 (Ratcheva & Leopold, 2018; Pinzone et al., 2017). As stated earlier, the global labor market would require new employability skill sets to increase productivity and competitiveness across industries (Singh & Sharma, 2019). The workforce of the future, however, appears to be woefully equipped to meet the demands of Industry 4.0. According to recent reports, half of the 310 million school graduates who will make up the future workforce will not have the necessary skills to spearhead the Fourth Industrial Revolution. The data for higher education graduates are not available, although they remain more relevant. This is due to the lack of a tool to measure it comprehensively. Therefore, this study aimed to develop and validate a comprehensive scale to measure students' preparedness for facing AI-driven VUCA by integrating VUCA aspects with AI across the three dimensions of the 21st century skill set.

LITERATURE REVIEW

Skills have taken precedence over subject-specific knowledge in the 21^{st} century. Specifically, academic work that is innovative and project-oriented, as well as job and life skills, has become increasingly important (Adesina, 2025; Katz et al., 2023; Voogt et al., 2013). In contrast to the industrial society, which developed an understanding of industrial production style in the past century, it can be argued that these skills are more strongly associated with the information society, which understands change and transformation in the direction of developments that take place in today's social, economic, and technological arenas (Piazer et al., 2025). Dede (2010) asserts that 21st-century skills encompass more than just knowledge and skills and that knowledge acquisition, comprehension, and performance are all components of 21st-century abilities. Stated differently, these skills are the outcomes of combining information and talent and are those that are required in the current century (Trisnawati et al., 2023; Griffin & Care, 2015).

Looking at some of the other recommended 21st century skill sets, the International Society for National Educational Technology Standards (IS-NETS) has stated a set of skills that students should possess (Education, 2000). Similarly, The Conference Board of Canada (2000), the American Association for School Librarians (AASL), Johnson (2009) and Hixson et al. (2012) state certain skill sets. However, partnership frameworks created for 21st century skills are comprehensive and cohesive and, if possessed, equip students to thrive in a rapidly changing, interconnected world.

Need for Scale Development—Research Gap

As far as the knowledge of the investigators here is understood, numerous scales exist on the topic covering 21st century skills, such as a scale for primary school students (Boyaci & Atalay, 2016), a scale focused on the science skills of eighth graders (Karakaş, 2015), a scale for secondary school students (Ongardwanich et al., 2015), a 21st century skills competence perception scale for preservice teachers (Aygün et al., 2016), a 21st century skills scale for in-service and preservice teachers (Jia et al., 2016), and even a multidimensional scale for adolescents and early adulthood students in the 15–25 age group (Cevik & Senturk, 2019). Nevertheless, there is an absence of an all-inclusive 21st century skills scale to measure how equipped College and University students are for the AI-driven VUCA workplace. Existing digital literacy measures fall short of capturing skills such as managing ambiguity, co-creating with AI systems, understanding AI-generated outputs, and making decisions in the face of uncertainty, which reflect the generative and autonomous nature of modern AI. As a result, a more future-focused and context-specific scale that measures students' readiness for AI-driven VUCA situations is needed.

The goal of this study is to develop and validate a 21st-century skills scale to measure student preparedness for AI-driven VUCA environments (MSP-AI-VUCA).

METHOD

The research model for this study is quantitative and grounded in a strong literature and a theoretical framework, with a scale development and validation approach. The study followed the guidelines for construct conceptualization and psychometric testing for development, exploratory and confirmatory factor analyses, and reliability testing (Hair et al., 2004); thus, a strong base for the scale was established.

Scale Development

Phase 1: Establishing the items for the initial version

Research articles were thoroughly searched in both domestic and foreign databases, and the items needed for each of the three dimensions under the 21st century skill set were developed. Numerous articles and measurements were employed, such as Çepni et al. (2024), Cevik & Senturk (2019), EL AOURI (2024), Minciu et al. (2025), Sari et al. (2024), Van Laar et al. (2017), Erol (2021), Tan et al. (2017), Trilling & Fadel (2009), Vijver & Leung (2021), and Dewi et al. (2025). The investigators integrated the four VUCA aspects driven by AI into three major dimensions of skill set-1. Learning and innovation skills (LIS): Communication and collaboration (3 items), critical thinking and problem-solving (3 items), and creativity and innovation skills (3 items); 2. Digital literacy skills (DLS): Information (3 items), Media (3 items), and ICT literacy (3 items); and 3. Career and life skills (CLS) - Flexibility and adaptability (2 items), Initiative and self-direction (3 items), Social and cross-cultural (2 items), Productivity and accountability (2 items), and Leadership and responsibility skills (2 items). All three dimensions of the scale were measured on a five-point Likert scale ranging from 1=strongly disagree to 5=strongly agree.

Phase 2: Expert opinion

Two English-language specialists were consulted after the draft was created, and the precision of the wording in all 29 items was verified. Furthermore, six expert subjects, i.e., professors from various universities, were selected to assess the scale's face and content validity. To have adequate control over chance agreement, at least five experts are advised for consent, although the number of experts for judgment is always discretionary (Zamanzadeh et al., 2015). The panel was asked to use a four-point Likert scale (1 = not relevant, 2 = somewhat relevant, 3 = quite relevant, 4 = highly relevant) to rate the items on question clarity, relevance, accuracy, and understandability.

Phase 3: CVI Calculation

The content validity index (CVI) method was used to assess the six experts' judgments of the scale's content validity using the item-level CVI (I-CVI) and scale-level CVI (S-CVI) methods (Zamanzadeh et al., 2015; Ayre & Scally, 2014). The CVI is defined as *"the degree to which an instrument has an appropriate sample of items for the construct being measured* (Polit & Beck, 2006)*"*, whereas the S-CVI is defined as *"the proportion of total items judged content valid"*, and the I-CVI is the "*percentage of agreement on the relevancy of each item",* which ranges from zero to one (Lynn, 1986). The ratio of the number of experts who have voiced a favorable opinion to the total number of experts for each item was subtracted by one to achieve this constant rate. Items whose values were less than 0.80 were deleted. On the whole, an S-CVI/average of 0.9 or above indicates excellent content validity, whereas I-CVI values of at least 0.83 from all six experts are acceptable (Lynn, 1986). Here, the S-CVI/average was 0.965, and the I-CVI of all 29 items was either 0.83 or 1; thus, these items were retained.

Sample Size and Demographics

The data were collected in online mode over the course of approximately 6 weeks (July and August, 2025) from a total of 650 students from colleges and universities in eight states across the country—Assam, Himachal Pradesh, Punjab, West Bengal, Odisha, Kashmir, Jharkhand and Bihar—using a convenience sampling technique. However, after data screening (checking for incomplete responses and response inconsistencies), 626 responses were retained for the final analysis. Furthermore, the sample we have gathered includes a large number of international students enrolled in different Indian colleges, making the developed scale applicable in any setting. It consisted of 35.1% males and 64.9% females between the age groups of 18–21 (58%), 22–25 (30.5%) and 26 and above (11.5%) from undergraduate and postgraduate degrees. Among those with higher education degrees, 59.5% pursued arts, 36.7% pursue science and 3.8% pursue commerce.

Data Analysis

The acquired data served as the basis for the validity and reliability study. Çakmak et al. (2014) stated that using data from various sample groups is the proper approach for performing exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Relative metrics, such as the number of items or factors, are used to estimate the sample size. Even though 200 individuals is an adequate sample size as an absolute requirement, Kline (1994) underlines that working with larger samples is more appropriate. In general, the sample size should ideally be five to ten times the number of items on the scale (Kline, 2023; Tavşancıl, 2010). With respect to factor analysis, Çokluk et al., (2010) a general rule has been established that a sample size of at least 300 is suitable. In this regard, it may be said that the study's sample size is large enough to carry out the required statistical analysis.

According to Worthington and Whittaker (2006), EFA and CFA should be performed with different samples. Thus, EFA was performed on the first half of the sample (n = 326) using SPSS v29. Before the EFA was performed, two preliminary tests, the Bartlett test of sphericity (BTS) and the Kaiser–Meyer–Olkin (KMO) test of sampling adequacy, were performed to determine whether the data were appropriate for factor analysis. Afterward, the factor structure generated by the EFA process was examined via CFA using AMOS v26 software on the second half of the sample (n=300). Using Cronbach's alpha to measure internal consistency, the final scale's statistical reliability was then assessed.

RESULTS

The corrected item–total correlation statistics were examined as part of the purification process on the 29-item scale, and those with less than or equal to 0.3 were considered insignificant. Those items are advised for deletion from the item list because they exhibit a small degree of common variance with the other items on the scale (DeVellis & Thorpe, 2021). Hence, three items, i.e., DLS17, CLS19 and CLS26, were deleted because they were insignificant contributors to the structure and failed to meet the minimum factor loading of 0.4 (Murphy et al., 2016). The remaining 26 items were incorporated into the subsequent tests.

Results of Exploratory Factor Analysis (EFA)

To ensure the validity of the EFA, it is imperative to ascertain whether the data gathered are suitable for the analysis (Conway & Huffcutt, 2003). Therefore, two tests were conducted to determine whether the data were appropriate.
1. Kaiser–Meyer–Olkin (KMO) Sampling Adequacy Measure: According to the literature, the analysis is terminated, and the procedure is restarted if the value calculated in terms of the sample size is less than 0.50. In parallel, according to Pallant (2005), the KMO value needs to be greater than 0.6. The value obtained here was 0.798, which is above the suggested threshold for factor analysis. It also reflects an acceptable level of shared variance among the items and reflects the extent to which interitem correlations are sufficiently compact. 2. Bartlett's Sphericity Test: A significant (χ^2 = 14464.741, df = 325, p < 0.001) result demonstrated that the correlation matrix is not an identity matrix and enables us to conduct factor analysis (Table 1).

Table 1: KMO and Bartlett's Test Results (*N*=626)

Kaiser–Meyer–Olkin Measure of Sampling Adequacy		0.798
Bartlett's Test of Sphericity	Approx. Chi-Square	14464.741
	df	325
	Sig.	.000

Total Variance

The percentage of total variance explained by each component should be examined to determine the number of variables that are both required and sufficient for EFA. Thus, a cumulative variance higher than 60% or an eigenvalue greater than 1 can be used to determine it. After the total variance explained by the construct was calculated, it was determined that each of the three components had eigenvalues greater than 1. Furthermore, 31.931% of the variation was explained by component 1, 25.184% by component 2, and 21.839% by component 3. This accounted for 78.953% of the total variance and was deemed satisfactory, as it exceeded 60%.

Rotated component matrix

In the next phase, the rotated component matrix was analyzed to extract the underlying factor structure, using principal component analysis (PCA) for extraction and Varimax with Kaiser normalization for rotation. The principles guiding this EFA analysis include the deletion of items with factor loadings less than 0.5 (Kaiser, 1960), items with similar loadings on two factors, and items that were misclassified on the basis of particular conceptual factors (Costello &

Osborne, 2019; Ferguson & Cox, 1993). As displayed in Table 2, strong factor loadings are observed across all three dimensions. The factor loading of the first subfactor (LIS) ranged from 0.842 to 0.991 and consisted of 9 items. The second subfactor (DLS) loading ranged from 0.787 to 0.879 and consisted of 8 items. The third subfactor (CLS) loading ranged from 0.754 to 0.906 and consisted of 9 items. Each construct has moderate to high interitem correlations, as reflected by the significant shared variance of the items. We noticed that all values were ≥ .30 and thus considered appropriate as per the benchmark (Hair et al., 2006, 2010). Additionally, no significant cross-loadings were found, suggesting that the variables have excellent discriminant validity. Therefore, all 26 items from the three dimensions were retained and added to the factor's underlying construct.

Table 2: Rotated component matrix (*N*=626)

Items		1	2	3
I can work effectively in teams and communicate complex ideas in AI-driven environments	LIS1	0.976		
I can speak to my teammates and explain clearly when AI gives uncertain results	LIS2	0.978		
I can adjust how I communicate and work with others when AI tools change unexpectedly	LIS3	0.974		
I can analyze complex problems and develop appropriate solutions in AI-driven scenarios	LIS4	0.842		
I can evaluate AI-generated information and make decisions in uncertain situations	LIS5	0.969		
I will reconsider my decisions when AI-generated results turn out unexpected or contradictory	LIS6	0.951		
I can come up with new ideas with the help of AI-generated guidance	LIS7	0.97		
In a fast-changing situation, I can think outside the box and develop new approaches when working with AI tools	LIS8	0.97		
I can make appropriate decisions when AI-tool provides complex information	LIS9	0.991		
I can access information efficiently and effectively in an AI-mediated portal	DLS10		0.858	
I can evaluate the information gained from AI-mediated portals even when many sources are involved	DLS11		0.828	
I can responsibly use the information from AI-mediated portals to make sound decisions in a fluctuating context	DLS12		0.803	
I can understand and analyze the purpose behind AI-empowered digital media	DLS13		0.877	
I can create my own media content even when AI mediated tools are complex to use	DLS14		0.875	
I am aware that media content changes quickly and it can influence individuals' beliefs and behaviors	DLS15		0.787	
Even in ambiguous spaces, I can choose the right platform to connect and share ideas	DLS16		0.879	
I can adjust quickly when digital platforms keep changing	DLS18		0.812	
I can adjust to new environments when AI systems become complex	CLS20			0.906

I take the first step to solve any problem when AI mediated system outcomes are unclear	CLS21	0.754
I can stay motivated and focused on my goals even when AI tools change suddenly	CLS22	0.892
I can explore new ways to improve myself using AI tools even if the process is complex	CLS23	0.895
I can easily work alongside others from different cultures while using AI driven tools that are difficult to maneuver	CLS24	0.798
I stay open-minded and listen carefully when team members from different cultures have different views even while working in a constantly evolving situation	CLS25	0.783
I will be dependable for my tasks even if things go wrong or AI tools fail	CLS27	0.879
I can guide others effectively if we face sudden changes or unclear instructions from AI-mediated tools.	CLS28	0.853
I will take responsibility for group tasks even if AI-mediated tools make the process complicated.	CLS29	0.877

Results of Confirmatory Factor Analysis (CFA)

The convergent validity of the construct following EFA is examined by CFA on the second half of the samples. The standardized loadings for each of the 26 items in the first CFA model ranged from 0.05 to 1.00. Owing to the low correlation (0.05) between the item and the construct, item CLS28 was eliminated, and the CFA was re-evaluated. This discrepancy can occur because EFA is exploratory and allows items to load more freely, whereas CFA imposes stricter constraints, in which each item is restricted to its hypothesized factor. Additionally, the dataset was randomly split into two independent subsamples for EFA and CFA to reduce capitalization on chance, which may lead to minor variations in item performance. The model's 25-item factor structure is shown in Figure 1. The loadings ranged from 0.56 to 1.00 and were thus all retained.

The three 25-item dimensions were examined for model fit indices. The df was 272; the similarity ratio of the chi-square statistic was calculated to be $P<0.01$; and the ratio of chi-square statistics to degrees of freedom was calculated as (X^2/df) 2.704 (i.e., between 1 and 3); thus, the model was good. The root mean square error of approximation was calculated as (RMSEA) 0.075 (i.e., >0.06) and thus is an acceptable fit; the root mean square residual (RMR) was calculated as 0.025 (<0.08) and thus is a perfect fit; the comparative fit index (CFI) was calculated as 0.936 (i.e., <0.95) and thus is a perfect fit; the goodness-of-fit index (GFI) was calculated as 0.844 (i.e., <0.9) and thus is an acceptable fit; and the adjusted goodness-of-fit index (AGFI) was 0.814 and is also an acceptable fit. Since all fit indices met the threshold values, the structural validity of the three-dimensional 25-item scale was accepted (Hu & Bentler, 1999; Kline, 2023; Tabachnick et al., 2013).

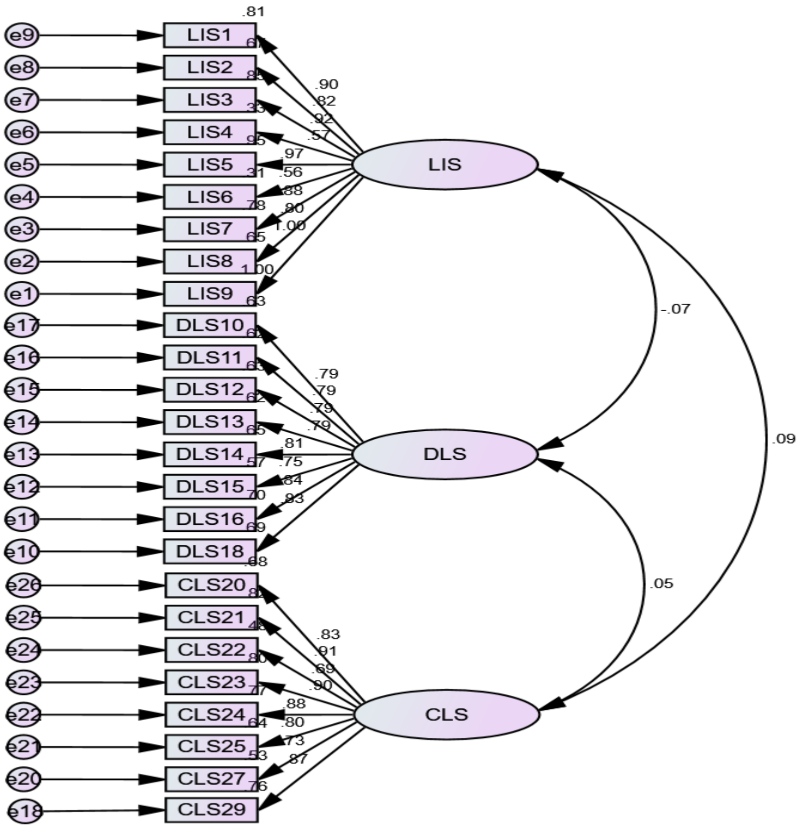

Figure 1: The Factor Structure of the Model with 25 Items for Scale Measuring Student Preparedness for the AI-VUCA World

Results of Reliability Analysis

The scale's reliability was assessed using the Cronbach's alpha internal consistency coefficient (Table 3). According to Bütüner (2008), a scale might be deemed reliable if its reliability coefficient is greater than 0.70. Here, for the entire scale, reliability analyses yielded a Cronbach's alpha coefficient of α =0.882. Furthermore, the analysis of each dimension-based Cronbach's alpha coefficient revealed that Factor 1 (LIS) had a Cronbach's alpha coefficient of α =0.953, Factor 2 (DIS) had α =0.933, and Factor 3 (CLS) had α =0.945. Therefore, the scale may be said to show good reliability and overall internal consistency. Hence, it is designed to measure what it was supposed to be, i.e., students' preparedness to face AI-driven VUCA workplaces.

Table 3: Reliability Quotients (*N*=626)

Dimensions	No. of Items	Cronbach's Alpha
Learning and innovation skills (LIS)	9	0.953
Digital literacy skills (DIS)	8	0.933
Career and life skills (CLS)	8	0.945
Overall	25	0.882

DISCUSSION

The MSP-AI-VUCA scale fills a significant void in the measurement of landscapes because of its three-dimensional structure and high overall reliability quotient. Current VUCA tools, such as Çepni et al.'s VUCA World Management Questionnaire, focus on organizational actors instead of students and completely ignore AI competencies. AI interaction competencies, including problem-solving, persuasion literacy and self-efficacy, are measured by AI literacy scales such as the Meta AI Literacy Scale (MAILS) by Carolus et al. (2023); however, this scale is not embedded in VUCA-specific settings of volatility and ambiguity. Furthermore, broader student-focused tools such as the Graduate Work Readiness Scale (Cabellero et al., 2021) and the Future Skills Readiness Scale (Alquarni, 2025) decrease AI-VUCA specificity. Like HE-eRQ, digital competency tools emphasize institutional e-readiness rather than student-level AI-driven VUCA preparedness (Goh & Blake, 2021). Thus, the MSP-AI-VUCA scale connects these previously disparate assessment traditions by combining AI competency and VUCA readiness factors into a single, psychometrically validated tool created especially for college and university students.

Educational Implications in the Indian Context

For Indian HEIs, in terms of the National Education Policy (NEP) 2020's emphasis on transdisciplinary learning, critical thinking, and technological integration, the MSP-AI-VUCA scale has important educational implications. As a result of the continuous transformation in the work landscape, there is a pressing need to update the training that students in the 21st century require and to supply the facilities and personnel necessary to meet the demands of education. To enable focused curriculum adjustments, educators might use dimension-level results to pinpoint gaps in VUCA resilience, adaptive thinking, or AI literacy. Such targeted interventions can enhance adaptability and digital competence among Indian learners. The tool also helps universities benchmark students' readiness across disciplines, which informs the creation of skill-development programs in line with initiatives such as Digital India and Skill India. This ultimately improves graduates' employability in a labor market that is becoming more unstable because of artificial intelligence. The conclusions of this study also have ramifications for global student mobility and international education. Being ready for AI-driven and volatile situations becomes a crucial skill as students increasingly move beyond national borders for work and education (Hadar et al., 2020). In addition, educational policymakers can use the results retrieved from the employment of the scale to design structured policies and programs. If properly implemented, these changes have the potential to improve living standards, work environments, and overall quality of life (Ras et al., 2017).

Theoretical Contributions

By operationalizing student preparedness as an integrated construct at the nexus of AI competency and VUCA readiness, the MSP-AI-VUCA scale improves theory in two areas traditionally considered distinct from each other. Its verified three-dimensional structure offers empirical proof that VUCA adaptability and AI-related skills are not separate but connected aspects of a single preparation construct. This calls into question the compartmentalized conceptions seen in the literature on VUCA management and AI literacy. By changing the unit of study from corporate actors and employees to higher education students, the scale also expands readiness theory into higher education, providing a theoretical framework for comprehending how students perceive and become ready for AI-mediated uncertainty, complexity, and rapid change.

Limitations

First, the study used self-reported data from the students, which is prone to response bias and social desirability. Second, cross-cultural generalizability to different national contexts may be limited because the sample was taken from Indian higher education institutions, although few international students were present. Third, the cross-sectional design makes it impossible to evaluate the three-dimensional structure's temporal stability and test-retest reliability. Fourth, scale material may need to be updated on a regular basis to remain contextually relevant because of the quickly developing nature of AI technology. Fifth, a formal pilot study was not carried out before the primary data collection, although the scale was established on the basis of a thorough review of the literature and expert validation. Sixth, on the basis of the same criteria, usual guidelines suggesting the creation of a wider initial item pool were not carried out. Therefore, to further improve and reinforce the MSP-AI-VUCA scale, future research is recommended to carry out longitudinal studies, collect mixed methods of data, carry out initial pilot studies, and incorporate a wider variety of demographics.

CONCLUSION

The present study aimed to develop and validate a tool to gauge students' preparedness for AI-driven VUCA environments using a sample of 626 college and university-going individuals across eight states in the country. This was intended to address the urgent need for an empirically grounded and validated instrument to gauge students' readiness in this rapidly transforming professional landscape. The analysis was carried out using IBM SPSS v29 for EFA and AMOS v26 for CFA, with the sample divided into two halves. Following item pooling for the three major dimensions documented under the 21st century skill set, the S-CVI/average was 0.965 for the initial 29 items as per the expert judgment. Nevertheless, 3 items were deleted (DLS17, CLS19 and CLS26) during the purification process, as they were insignificant contributors to the factor structure. EFA was then conducted for the remaining 26 items using principal component analysis and varimax with the Kaiser method after confirming sample size adequacy. Furthermore, all 26 items were retained, and in the subsequent step, the CFA led to the deletion of CLS28 because of low correlation; thus, it was reassessed with 25 items. Finally, the reliability testing results further indicated that the tool provides a robust measure of students' preparedness for the AI-driven VUCA environment.

Ethical Considerations

Consent was obtained from participants that their participation was voluntary, and the confidentiality and anonymity of the responses were ensured.

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