A Comprehensive Psychometric Validation of Student Online Readiness

Hugh Kellam, Jin Liu and Tranell Gilmore
College of Education, University of Texas at Arlington, TX, USA

hugh.kellam@uta.edu (Corresponding Author)
jin.liu@uta.edu
tranell.gilmore@uta.edu

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Abstract: As online and hybrid education continue to expand, institutions require valid and equitable tools to identify students who may need additional support before beginning online coursework. Although numerous online readiness assessments have been developed, relatively few have undergone comprehensive psychometric validation, and most have not established measurement invariance across demographic groups, limiting confidence in subgroup comparisons and the use of readiness assessments for equity-informed decision-making. The purpose of this study was to provide a comprehensive psychometric validation of the Online Readiness and Student Success Assessment (ORSSA), a five-factor instrument designed to measure Learning Organization, Learning Preferences, Learning Skills, Technical Readiness Access, and Technical Readiness Skills among incoming online university students. Data were collected from 2,669 undergraduate students enrolled in online degree and certificate programs at a large public R1 university in the southern United States. Confirmatory factor analysis (CFA) using weighted least squares mean and variance adjusted (WLSMV) estimation was conducted to evaluate the proposed factor structure. Additional analyses examined model-based reliability (McDonald's omega), convergent and discriminant validity, measurement invariance across gender, ethnicity, and first-generation status, and Multiple Indicators Multiple Causes (MIMIC) modeling to investigate relationships between demographic characteristics and online readiness factors. Results supported the proposed five-factor model, which demonstrated superior fit relative to alternative models, strong standardized factor loadings, excellent model-based reliability, and satisfactory evidence of convergent and discriminant validity. Measurement invariance analyses demonstrated that the ORSSA functions equivalently across gender, ethnicity, and first-generation status, supporting meaningful and fair comparisons among demographic groups. MIMIC analyses further identified significant demographic differences across several readiness dimensions, particularly in Learning Organization, Learning Skills, and Technical Readiness, while also revealing higher online learning preferences among some historically underrepresented student groups. These findings establish the ORSSA as a psychometrically robust and equitable measure of online readiness that extends beyond traditional readiness assessments by integrating comprehensive validation procedures with demographic fairness testing. The instrument provides higher education institutions with actionable information that can be used during student onboarding to identify readiness strengths and potential barriers, enabling targeted interventions, personalized student support, and data-informed strategies to improve retention and success in online learning environments.

Keywords: Online readiness, Psychometric validation, Confirmatory factor analysis, Measurement invariance, MIMIC modeling, Student success

1. Introduction

Online readiness refers to the extent to which students possess the technological resources, technical competencies, self-regulatory skills, learning preferences, and personal characteristics necessary to successfully engage in online learning environments (Hung et al., 2010; Pillay, Irving and Tones, 2007; Reyes-Millán et al., 2023). As online and hybrid education continue to expand globally, online readiness has emerged as an important construct because it has been associated with student engagement, persistence, academic performance, satisfaction, and successful adaptation to virtual learning environments (Dray et al., 2011; Joosten and Cusatis, 2020; Martin, Stamper and Flowers, 2020). Assessing readiness enables institutions to identify potential barriers to student success before coursework begins and to implement targeted interventions that support equitable participation, retention, and achievement (Wladis and Samuels, 2016; Joosten and Cusatis, 2020). Over the past two decades, numerous instruments have been developed to measure online readiness, which typically assess combinations of self-directed learning, learner control, motivation, communication competencies, technology access, technology skills, self-efficacy, and study habits through self-report survey measures (Yu and Richardson, 2015; Zhong et al., 2023). Despite their contributions, important limitations remain. Many instruments rely primarily on exploratory validation approaches rather than quantitative psychometric methods such as confirmatory factor analysis, model-based reliability estimation, and structural equation modeling (Viladrich, Angulo-Brunet and Doval, 2017; Alanoglu, Karabatak and Yang, 2025).

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Furthermore, relatively few readiness instruments have established measurement invariance, or the degree to which an instrument measures the same construct in the same way across different groups, and this limits confidence in subgroup comparisons and raises questions about the fairness of interpreting readiness differences across diverse populations (Van de Schoot, Lugtig and Hox, 2015; Çimşir, Uzunboylu and Yavuz, 2024). Existing studies have also tended to examine demographic factors independently rather than simultaneously, making it difficult to understand the complex relationships between student characteristics and readiness dimensions (Martin, Stamper and Flowers, 2020). Finally, most readiness instruments focus on describing readiness levels rather than serving as equity-oriented diagnostic tools that inform targeted student support initiatives and institutional decision-making (Barber et al., 2021; Joosten and Cusatis, 2020). These limitations highlight the need for comprehensive readiness assessments that integrate contemporary psychometric validation methods, establish fairness across diverse student populations, and provide actionable information for improving student success in online learning environments (Putnick and Bornstein, 2016; Çimşir, Uzunboylu and Yavuz, 2024).

The Online Readiness and Student Success Assessment (ORSSA) was developed at a university in the southern United States to address these gaps by integrating comprehensive readiness dimensions with contemporary psychometric validation procedures, including measurement invariance testing and MIMIC modeling, thereby supporting both accurate assessment and equity-informed student support. The ORSSA survey is unique as a data collection tool due to its extensive ability for student demographic data collection and incorporation into a larger student success pathway. The previous paper on the ORSSA using the first 392 participants provided a preliminary validation of the survey scale and questions via principal component analysis. There was a good fit with 35 of the 41 survey questions having values in the component matrix over 0.6, which was excellent for a pilot survey. Overall, 37 questions loaded onto the five factors of learning organization, learning skills, technical readiness access, technical readiness skills, and learning preferences. These encouraging results prompted the more robust validation of the ORSSA structure undertaken in this study. However, the abovementioned gaps have not been addressed in the preliminary study. This study will go beyond this preliminary validation and provide a robust validation of the ORSSA by involving all incoming students who are enrolled in an online degree or certificate program at an R1 institution from January 2024 to May 2025. Multiple psychometric evidence was investigated, including factor structure, concurrent and discriminant validity, reliability, and measurement invariance. Finally, MIMIC modeling was conducted to gain a better understanding of how multiple demographic factors are associated with factors of ORSSA simultaneously. The study was guided by the following research questions:

RQ1: Does the ORSSA demonstrate an empirically supported factor structure consistent with its proposed theoretical framework?

RQ2: To what extent does the ORSSA exhibit adequate reliability, convergent and discriminant validity?

RQ3: Is measurement invariance of the ORSSA supported across gender, ethnicity, and first-generation status, and

RQ4: What relationships between demographic variables and the latent constructs are revealed through MIMIC modeling?

2. Literature Review

2.1 Existing Online Readiness Assessments

Online readiness assessments have evolved substantially alongside the growth of online learning in higher education. Early readiness instruments developed between 1999 and 2007 primarily focused on students' access to technology, basic computer skills, and general attitudes toward distance learning (Mattice and Dixon, 1999; Smith, Murphy and Mahoney, 2003; Watkins, Leigh and Triner, 2004). These early studies relied largely on descriptive statistics and exploratory factor analysis to identify readiness dimensions and establish preliminary evidence of reliability. As online learning became more widespread, readiness frameworks expanded to include self-directed learning, learner control, motivation, communication competencies, and technology self-efficacy, reflecting a growing recognition that success in online learning depends on both technological and academic factors (Dray et al., 2011; Yu and Richardson, 2015). More recent instruments have adopted increasingly sophisticated psychometric approaches, including confirmatory factor analysis, structural equation modeling, convergent and discriminant validity testing, and model-based reliability estimation (Alanoglu, Karabatak and Yang, 2025; Çimşir, Uzunboylu and Yavuz, 2024). Across this evolution, several dimensions have consistently emerged as core components of online readiness, including technology access, technology skills, self-regulation, communication competencies, and learner motivation, suggesting broad agreement regarding the foundational characteristics required for online learning success. However, important methodological gaps remain. Most studies continue to rely heavily on Cronbach's alpha as the primary indicator of reliability, relatively few have evaluated measurement invariance across demographic groups, and only a limited number have examined how multiple demographic characteristics simultaneously influence readiness dimensions (Putnick and Bornstein, 2016; Çimşir, Uzunboylu and Yavuz, 2024). Consequently, while online readiness instruments have become more comprehensive and psychometrically sophisticated over time, further work is needed to establish the fairness, validity, and practical utility of these measures across increasingly diverse student populations.

2.2 Demographic Factors and Online Readiness Assessments

Across the online readiness literature, several dimensions consistently emerge as important predictors of student success in online learning environments, including self-regulated learning, time management, learner motivation, communication competencies, technology access, and technology skills (Reyes-Millán et al., 2023). Students who possess strong organizational skills, confidence in their academic abilities, reliable access to technology, and the technical competencies needed to navigate online learning platforms are generally more likely to engage successfully in virtual learning environments and persist in their studies (Dray et al., 2011; Martin, Stamper and Flowers, 2020). These findings suggest that readiness extends beyond technical preparedness and includes the academic and behavioral capacities necessary for effective online learning.

The ORSSA was developed to reflect this multidimensional understanding of readiness through five interconnected dimensions: Learning Organization, Learning Preferences, Learning Skills, Technical Readiness Access, and Technical Readiness Skills. Learning Organization captures students' ability to manage time, prioritize coursework, and maintain productive study habits. Learning Preferences examines students' comfort and engagement with various online instructional and collaborative learning approaches. Learning Skills assess academic competencies such as reading, writing, collaboration, and information literacy. Technical Readiness Access evaluates students' access to reliable technology and internet connectivity, while Technical Readiness Skills measure students' confidence and proficiency in using digital tools required for online learning. Together, these dimensions provide a comprehensive assessment of the factors most associated with online learning success in the literature.

Although these readiness dimensions are important for all learners, research suggests that demographic characteristics may influence how students experience and develop readiness. Studies have shown that race, ethnicity, first-generation status, socioeconomic background, disability status, and prior educational experiences can affect access to technology, self-efficacy, academic preparedness, and opportunities to develop online learning competencies (Joosten and Cusatis, 2020). For example, first-generation and underrepresented minority students experienced disproportionate challenges during the COVID-19 pandemic, including caregiving responsibilities, employment obligations, limited technology access, and financial stressors that may affect readiness for online learning (Barber et al., 2021). Consequently, readiness assessments that incorporate demographic information can help institutions identify students who may benefit from targeted supports and interventions before the start of their programs (Schwam, Greenberg and Li, 2020). However, meaningful comparisons across demographic groups require evidence of measurement invariance—the degree to which an instrument measures the same construct in the same way across groups—so that observed differences can be interpreted as true differences in readiness rather than measurement bias (Putnick and Bornstein, 2016). Establishing measurement invariance is therefore a critical step in using readiness assessments to support equitable and data-informed decision-making.

3. Materials and Methods

3.1 Development of the Online Readiness and Student Success Assessment (ORSSA) Survey

A Likert scale survey design was used to obtain a numeric description of opinions (Creswell and Creswell, 2017) to measure the general trends and attitudes of first-year university students regarding their readiness for online learning. A new assessment tool, 'The Online Readiness and Student Success Assessment (ORSSA)" was developed, revised and validated (Kellam et al., 2025). The scale design involved identifying the five factors from a review of the research literature, developing a set of questions for each factor, refining the survey questions, and piloting the scale. The survey was then distributed in an exploratory study to 392 students who participated in the online orientation modules from January to October 2024, and an initial Principal Component Analysis was performed that identified the potential of the survey and a need for a more rigorous quantitative study with an increased number of participants. The list of five ORSSA factors (Kellam et al., 2025) and their associated questions can be found in Table 1. In the current study, the survey was examined for validation with psychometric evidence with a large sample (see the information in Data Analysis and Results).

Table 1: Factors and Associated ORSSA Likert Questions

Factor	Likert Questions
1 **Learning Organization**	LO1 - I am able to prioritize at least 9 hours per week for each online class.
	LO2 - I have a quiet, dedicated place to work on my online classes and studying.
	LO3 - I am usually able to stay on task and avoid distractions while studying (common distractions include texting, social media, web surfing, and multi-tasking).
	LO4 - I consistently finish and submit work on time and complete.
	LO5 - I use software to maintain to-do lists for my class and university projects and deadlines.
	LO6 - I understand the importance of checking school email at least 3 times per week during the semester.
	LO7 - I finish the projects I start.
	LO8 - When I encounter a technical issue while learning online, I persevere until it gets resolved.
	LO9 - I can depend on the support of family and friends while completing my online program.
2 **Technical Readiness Skills**	TRS1 – I am comfortable conducting internet searches.
	TRS2 - I am comfortable opening files on my computer such as documents, presentations, spreadsheets.
	TRS3 - I am comfortable using videoconferencing software.
	TRS4 - I am comfortable participating in online polls or surveys.
	TRS5 - I am comfortable participating in online discussion forums.
	TRS6 - I am comfortable creating and sharing online videos or presentations.
	TRS7 - I am comfortable using virtual support to resolve a technical issue.
3 **Learning Preferences**	LP1 - I enjoy learning through online lectures (recorded by the professor).
	LP2 - I enjoy learning through online classes (delivered live via videoconference).
	LP3 - I enjoy learning through videos.
	LP4 - I enjoy learning through podcasts or audio recordings.
	LP5 - I enjoy learning through online readings.
	LP6 - I enjoy learning through discussions with peers.
	LP7 - I enjoy collaborating virtually through videoconference.
	LP8 - I enjoy collaborating virtually through email.
	LP9 - I enjoy collaborating virtually through online whiteboards (like Microsoft Whiteboard).
	LP10 - I enjoy collaborating virtually through online word processing (like MS Word).
4 Technical Readiness Access	TRA1 - I have reliable access to a high-speed Internet connection (recommended minimum download speed of 25 Mbps and upload speed of 3 Mbps).
	TRA2 - I have access to a webcam and microphone for multimedia participation, either on my computer or my smartphone.
	TRA3 - My computer runs reliably on Windows or on Mac OS.
	TRA4 - My browser can play common multimedia (video and audio) formats such as mp3, mp4, mov files.
	TRA5 - I have experience taking online tests using lockdown browsers (extension often used to limit web access during exams).

Factor	Likert Questions
5 Learning Skills	LS1 - When working on a class project independently, I am comfortable performing online academic research utilizing tools such as library databases or Google Scholar. LS2 - I am comfortable working on a collaborative online project with classmates.
	LS3 - I am confident in my ability to carefully read written instructions without missing key information.
	LS4 - I am confident in my ability to write at a post-secondary level (university level).
	LS5 - I am confident in my ability to write and respond to emails.
	LS6 - I learn from constructive feedback given by my instructor or my classmates.
	LS7 - I respect academic integrity and the university honor code when completing my online work.

3.2 Sample and Data Collection

This IRB-approved study collected quantitative data using the ORSSA survey at a large public university in the southern United States. All incoming online undergraduate students in all Colleges were required to participate in six online orientation modules created by the Office of Student Success. The modules provided information on campus resources, contacting orientation leaders, academic advising, and completing orientation documents. The fifth module focused on online readiness skills and included the ORSSA survey that began with a consent page where students were provided with details of the research study and could give their consent. Students who refused to consent could still participate in the ORSSA survey, but their data were not collected. Data were collected from incoming online students from January 2, 2024, through January 30, 2025, which included a total of 2884 undergraduate students. A total of 215 students with incomplete responses in the Likert questions were omitted from the data analysis.

In the end, a total of 2,669 undergraduate students were included in the sample. The majority of them were female (83.0%, n = 2,214), with males comprising 17.0% (n = 455). More than three-quarters of participants were first-generation college students or students whose parents or legal guardians did not complete a four-year bachelor's degree (76.7%, n = 2,046) and 23.3% (n = 623) were non-first generation. Regarding ethnicity, 33.6% (n = 898) identified as Hispanic/Latino, 28.7% (n = 766) as White, 22.6% (n = 604) as Black/African American, and 15.0% (n = 401) as Other.

3.3 Data Analysis

We first examined the factor structure of the ORSSA using confirmatory factor analysis (CFA), allowing correlations among factors. Analyses were conducted in Mplus 8.11 using WLSMV, the default estimation method for ordered categorical (Likert-scale) data (Muthén and Muthén, 1998–2010). Confirmatory factor analysis was conducted to confirm the five correlated factors under the proposed scale: learning organization, technical readiness skills, learning preference, technical readiness access, and learning skills. We also examined the one-factor model as we expected to have a general factor indicating the overall readiness level. As the chi-square statistics were highly sensitive to sample size, model evaluation relied primarily on commonly recommended fit indices: the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Following Kline (2016), cutoffs for adequate fit were defined as CFI ≥ .90, TLI ≥ .90, RMSEA ≤ .08, and SRMR ≤ .10. More stringent thresholds (CFI ≥ .95, TLI ≥ .95, RMSEA ≤ .06, SRMR ≤ .08) were considered to indicate good model good fit (Hu and Bentler, 1999). In addition, factor loadings .50 is preferable for practical significance and .70 or above indicates strong item–factor association (Hair et al., 2019). Only factor loadings over .70 were included in this study.

After the factor structure was confirmed, we evaluated the model-based reliability (i.e., omega values) for each subscale. Following conventional guidelines, values ≥ .70 were considered acceptable, ≥ .80 as good, and ≥ .90 as excellent (Dunn, Baguley, and Brunsden, 2014; Nunnally and Bernstein, 1994). Convergent validity was evaluated using the Average Variance Extracted (AVE), which was the proportion of variance in the observed indicators accounted for by the specific factor. Values higher than .50 are considered adequate to demonstrate convergent validity, while discriminant validity requires that the square root of the AVE for each factor is higher than its factor correlations (Fornell and Larcker, 1981; Hair et al., 2019).

Next, we conducted measurement invariance tests to confirm that the validated factor structure functioned equivalently across demographic groups. Specifically, we evaluated configural invariance (same factor structure), metric invariance (same structure and factor loadings), and scalar invariance (same structure, loadings, and item thresholds) across gender, ethnicity, and first-generation status. For testing measurement invariance, we compared the configural, metric, and scalar models using scaled chi-square difference tests (via the *DIFFTEST* option in Mplus) to evaluate whether invariance could be supported by progressively adding equality constraints across groups. While a nonsignificant chi-square difference ($p > .05$) traditionally indicates invariance, prior research has noted that this criterion is overly stringent and often unrealistic with large samples (Chen, Sousa and West, 2005). Therefore, we also relied on changes in alternative fit indices—RMSEA, CFI, and SRMR—when evaluating model invariance. In particular, non-invariance is indicated when in CFI is greater than –.010, accompanied by an increase of ≥ .015 in RMSEA or ≥ .010 in SRMR (Chen, 2007). It was noted that these criteria may be misleading when the estimator was WLSMV and we may evaluate the model fit indices directly following the criteria above (Sass, Schmitt and Marsh, 2014).

Finally, a Multiple Indicators Multiple Causes (MIMIC) model was constructed to include gender, ethnicity, and first generation as predictors of the latent constructs, enabling us to evaluate the extent to which these observed variables influence the underlying readiness factors. MIMIC models embed these covariates directly as predictors of latent variables within a confirmatory factor modeling framework, allowing for simultaneous estimation of measurement and structural components (Wang, 2022). This approach offers a parsimonious alternative to multiple-group CFA, especially when including numerous covariates simultaneously. The same model fit criteria of CFA were applied to evaluate the quality of the MIMIC modeling. We focused on explaining the relationships between demographic variables and latent factors. The following groups were considered the reference group in results interpretation: first generation students, white and female.

4. Results

The first set of analysis was conducted to find the optimal factor structure of the ORSSA. The one factor CFA demonstrated poor model fit: ($\chi^2_{(702)}$ = 39222.699, RMSEA = .143, 90% CI .142 - .145, CFI = .783, TLI = .771, SRMR = .126). The five-factor CFA model showed acceptable to good fit with indices above the cut-off values ($\chi^2_{(692)}$ = 10592.094, RMSEA = .073, 90% CI .072 - .074, CFI = .944, TLI = .940, SRMR = .048). Therefore, the five-factor model was selected as the optimal model due to the better model fit and alignment with the theoretical framework. The completely standardized loadings of the final solution are displayed in Table 2. Item descriptive statistics can be found in Table 3. All items were significantly loaded on the principal factor, and all factor loadings were higher than 0.71. Factor correlations ranged from .391 to .896. Omega estimates ranged from .911 to .932, suggesting high internal consistencies of all subscales. Evidence for convergent validity was supported, as AVE values were above .628 for all subscales. Regarding discriminant validity, three subscales had square root AVE values greater than their inter-factor correlations. However, high correlations between Learning Skills and Learning Organizations resulted in slightly lower discriminant validity for the five-factor models. After further evaluating the four- and five-factor alternatives, we selected the five-factor model due to its conceptual coherence, better model fit and its ability to reveal unique associations with demographic predictors in subsequent MIMIC analyses (see below).

Measurement invariance was examined across gender, ethnicity, and first-generation status (Table 4). While the scaled chi-square tests showed significant results at each step given their sensitivity to a large sample size, all testing models showed good model fit in terms of CFI, TLI, and RMSEA. Moreover, CFI and RMSEA values improved slightly from the configural to the metric and scalar models, and SRMR values decreased while remaining within the acceptable range. Taking together, these results provide strong evidence for measurement invariance across demographic groups. Then the demographic variables were added to the model. The final model showed acceptable to good fit: $\chi^2_{(862)}$ = 10765.891, RMSEA = .066, 90% CI .065 - .067, CFI = .949, TLI =.944, SRMR=.046. The MIMIC model included significant regression coefficients from each covariate considered in the model and the identified factors (Figure 1).

Gender was significantly associated with learning organization (standardized b = -.075, p <.001), indicating that female reported higher learning organization levels than male students. First-generation status was significantly related to three of the five subscales: non–first-generation students demonstrated higher Learning Skills (β = .043, p < .001), Technical Readiness Access (β = .065, p < .001), and Technical Readiness Skills (β = .048, p < .001) compared to first-generation students.

Using White students as the reference group, Hispanic students reported lower levels of Learning Organization (β= -.056, p =.030), Learning Skills (standardized b = -.052, p =.040), Technical Readiness Access (β = -.063, p =.017) and Technical Readiness Skills (β = -.051, p =.049). A similar pattern was observed for students classified as "Other" compared to White students, with significantly lower scores on Learning Organization (β = –.090, p <

.001), Learning Skills (β = –.087, p < .001), Technical Readiness Access (β = –.085, p = .001), and Technical Readiness Skills (β = –.081, p = .001).

Interestingly, both Hispanic (β = .076, p = .001) and Black students (β = .151, p < .001) reported higher levels of Online Learning Preference compared to White students. Finally, Black students also reported significantly lower Technical Readiness Access than White students (β = –.096, p < .001) while there were no significant differences for three other subscales including Learning Organization, Learning Skills and Technical Readiness Skills.

Table 2: Standardized Factor Loadings, Omega, AVE and Factor Correlations

Items	LO	LP	LS	TRA	TRS
1	0.833	0.807	0.807	0.914	0.888
2	0.847	0.720	0.745	0.941	0.913
3	0.774	0.846	0.878	0.935	0.885
4	0.873	0.727	0.831	0.945	0.892
5	0.728	0.737	0.917	0.827	0.899
6	0.889	0.714	0.882		0.853
7	0.896	0.785	0.794		0.874
8	0.834	0.797	0.868		
9	0.743	0.818			
10		0.853			
Omega	0.913	0.917	0.911	0.923	0.932
AVE	0.709	0.628	0.736	0.858	0.790
Square Root AVE	0.842	0.792	0.858	0.926	0.889
Factor Correlations					
LO	1	0.708	0.896	0.557	0.672
LP	0.708	1	0.678	0.391	0.558
LS	0.896	0.678	1	0.522	0.719
TRA	0.557	0.391	0.522	1	0.631
TRS	0.672	0.558	0.719	0.631	1

Table 3: Item Descriptive Statistics

Item	Mean	SD	Skewness	Kurtosis
LO1R	4.361	0.737	-1.342	2.808
LO2R	4.433	0.705	-1.443	3.235
LO3R	4.136	0.858	-1.004	1.048
LO4R	4.455	0.666	-1.292	2.773
LO5R	4.040	0.956	-0.839	0.140
LO6R	4.546	0.619	-1.553	4.258
LO7R	4.486	0.630	-1.254	2.865
LO8R	4.381	0.713	-1.268	2.606
LO9R	4.369	0.810	-1.456	2.534
LP1R	4.254	0.825	-1.191	1.778
LP2R	3.907	0.982	-0.717	0.095
LP3R	4.303	0.754	-1.193	2.273
LP4R	3.976	0.966	-0.843	0.344
LP5R	3.871	0.997	-0.695	0.005

Item	Mean	SD	Skewness	Kurtosis
LP6R	3.814	0.995	-0.630	0.005
LP7R	3.701	1.040	-0.541	-0.206
LP8R	3.851	0.952	-0.652	0.210
LP9R	3.738	0.931	-0.321	-0.167
LP10R	3.889	0.900	-0.509	-0.005
LS1R	4.312	0.773	-1.147	1.598
LS2R	4.067	0.903	-0.961	0.859
LS3R	4.383	0.674	-1.049	1.918
LS4R	4.244	0.776	-0.982	1.212
LS5R	4.508	0.621	-1.293	2.973
LS6R	4.471	0.613	-1.067	2.336
LS7R	4.250	0.813	-1.097	1.342
LS8R	4.629	0.580	-1.827	5.605
TRA1R	4.413	0.953	-2.229	5.133
TRA2R	4.450	0.942	-2.338	5.645
TRA3R	4.426	0.967	-2.221	4.917
TRA4R	4.393	0.956	-2.133	4.725
TRA5R	4.214	1.127	-1.575	1.676
TRS1R	4.572	0.727	-2.392	7.691
TRS2R	4.555	0.729	-2.242	6.784
TRS3R	4.302	0.868	-1.375	2.060
TRS4R	4.468	0.767	-1.858	4.638
TRS5R	4.414	0.810	-1.713	3.660
TRS6R	4.118	0.982	-1.038	0.548
TRS7R	4.280	0.850	-1.294	1.944

Table 4: Test of Measurement Invariance across Gender, First Generation Status and Ethnicity

Models	χ^2 (df)	RMSEA	Diff χ^2 (df) p-value	CFI	TLI	SRMR
Gender						
Configural Model	9815.745 (1384)	.068		.956	.953	.050
Metric Model	6378.693 (1423)	.074	93.847 (39) <.001	.974	.973	.051
Scalar Model	6004.885 (1540)	.047	267.742(117) <.001	.977	.978	.051
First Generation						
Configural Model	10382.020 (1384)	.070		.949	.946	.050
Metric Model	6494.247 (1423)	.052	60.413(39) =.001	.971	.970	.051
Scalar Model	5946.287 (1540)	.046	194.441(117) <.001	.975	.976	.051
Ethnicity						
Configural Model	11157.934 (2768)	.067		.953	.950	.052

Models	χ^2 (df)	RMSEA	Diff χ^2 (df) p-value	CFI	TLI	SRMR
Metric Model	7647.934 (2885)	.050	255.444(117) <. 001	.973	.973	.055
Scalar Model	7921.370 (3236)	.047	948.915(351) <.001	.974	.976	.056

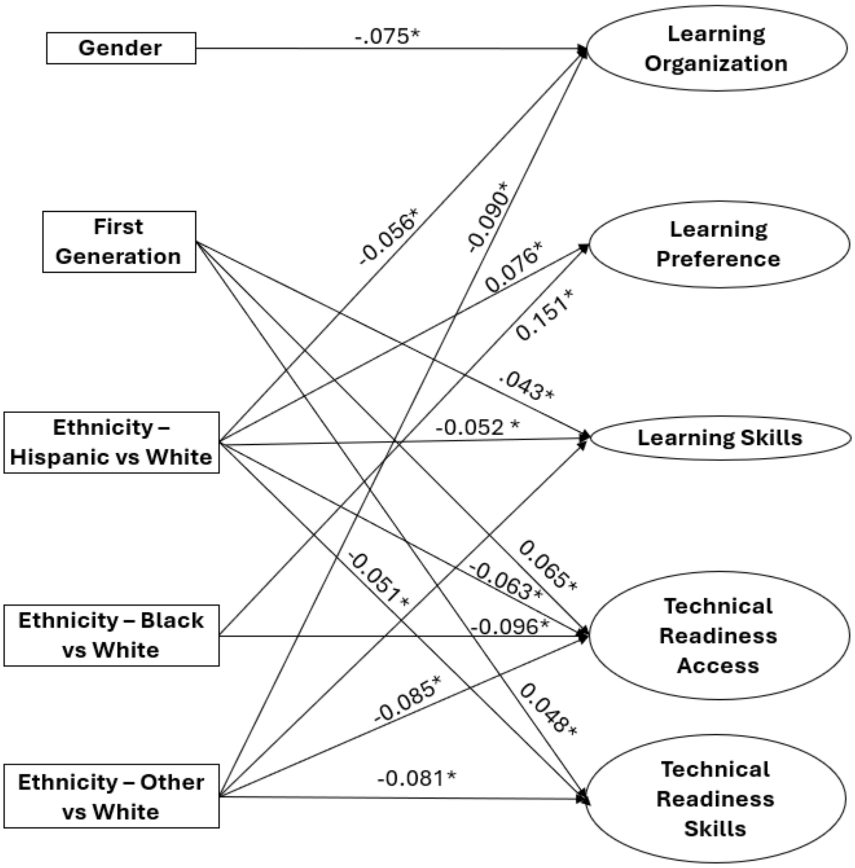

Figure 1: MIMIC Modeling Results

5. Discussion

This study investigated the underlying factor structure, model-based reliability, discriminant and convergent validity, and measurement invariance of gender, ethnicity, and first generation of the ORSSA for undergraduate students who enroll in online courses. After measurement invariance was established, we further investigated the complex relationships between the demographic factors and five subscales of the ORSSA: Learning Organization, Learning Preferences, Learning Skills, Technical Readiness Access, and Technical Readiness Skills.

To evaluate the most appropriate latent structure, both four-factor and five-factor models were estimated and compared using global fit indices. Although both models demonstrated acceptable fit, the five-factor model consistently outperformed the four-factor model across all major fit indices. Specifically, the five-factor model demonstrated lower RMSEA (.073 vs. .077) and SRMR (.040 vs. .051), along with higher CFI (.944 vs. .939) and TLI (.940 vs. .935), indicating improved model fit. Relative to the four-factor model, the five-factor solution resulted in improvements of ΔCFI = +.005, ΔTLI = +.005, ΔRMSEA = −.004, and ΔSRMR = −.011. Collectively, these findings suggest that distinguishing Learning Organization and Learning Skills as separate but related constructs provides a more accurate representation of online readiness than combining them within a four-factor structure. Therefore, the five-factor model was retained for all subsequent analyses because it demonstrated superior empirical fit while maintaining greater theoretical interpretability. The five-factor solution was consistent with the principal component analysis results reported by Kellam et al. (2025), supporting the stability of the factor structure. Unlike PCA, the present study employed confirmatory factor analysis (CFA), which provided formal model-fit indices to evaluate competing models. CFA allows researchers to test the adequacy of theoretically specified models and assess model fit using multiple statistical criteria, thereby providing stronger support for construct validity and model selection (Brown, 2015). This approach enhances the robustness of the findings and establishes a solid foundation for future comprehensive investigations of online learning readiness.

Although the standardized coefficients were relatively small ($\beta \approx .04$–.15), their consistency across readiness dimensions suggests meaningful patterns at the population level. The finding that Hispanic and Black students reported stronger preferences for online learning while simultaneously reporting lower levels of technical access aligns with broader digital divide research, indicating that enthusiasm for online learning does not necessarily correspond with equitable access to technological resources. These findings suggest that readiness interventions should distinguish between students' willingness to engage in online learning and their ability to access the technological infrastructure required for success. Institutions may therefore benefit from targeted technology-access supports while simultaneously leveraging students' positive attitudes toward online learning.

Factor correlations ranged from low to moderate, indicating that the dimensions capture distinct aspects of the construct. However, the discriminant validity between the two highly correlated factors—Learning Skills and Learning Organization—was limited. Conceptually, these domains overlap, suggesting that a four-factor alternative model, combining these two dimensions, may provide a more parsimonious representation. While we selected the five-factor model based on the theoretical framework and model fit indices, future research should test and cross-validate both the five-factor and four-factor models across different settings. Model-based reliability estimates were provided to indicate the internal consistency of all subscales. Unlike coefficient alpha, model-based reliability incorporates factor loadings and measurement errors from the CFA model, providing a more accurate estimate of internal consistency (Raykov, 1997). Next, as most prior studies have not examined measurement invariance across subgroups, the study findings contribute important evidence to measurement of online readiness levels. Although the importance of measurement invariance is widely recognized, it is often overlooked in applied measurement research (Putnick and Bornstein, 2016). Measurement invariance was tested across students' gender, ethnicity, and first-generation status to ensure meaningful group comparisons. The decent model fit after imposing equality constraints supported the presence of measurement invariance across subgroups despite the significant chi-square difference tests due to the large sample size.

5.1 Practical Implications

This study identified the value of administering an online readiness instrument at orientation that includes the five ORSSA factors, and the importance of collecting disaggregated race/ethnicity data to identify equity gaps at the beginning of college/university studies. It is also important to use a validated tool to perform invariance checks to make group comparisons. Few peer-reviewed higher-education studies report ethnic technology access results directly and more work should present race-specific (not just the broad underrepresented minority) estimates for each factor of the ORSSA.

Universities should treat computer access/reliability and broadband availability as first-order academic needs, as these issues persist for undergraduate students. Also, online-learning skills should be embedded in orientation and gateway courses. Short, graded micro-modules on LMS navigation, time management, help-seeking, and environmental structuring, with practice tasks and nudges, benefit all students and correlate with motivation (Michikyan et al., 2025). Universities must partner with libraries to assess and teach online skills and literacy in first-year seminars/comp courses, and target FGCS sections for extra support (Lemire, 2025). Professors can provide quick checks on technology reliability and skills for their first-year classes, and shouldn't assume national patterns exactly fit their campus, as large studies show variability (Michikyan et al., 2025). A final reminder is that FGCS often have less exposure to technology during their high school years due to socioeconomic factors, leading to a lack of foundational skills in using online educational tools, which can compound their challenges in online learning environments (Wang, 2022).

A notable finding was the strong correlation between Learning Organization and Learning Skills ($r = .896$), indicating substantial shared variance (approximately 80%). Although the two constructs were theoretically specified as distinct dimensions, the magnitude of the relationship suggests that they may represent closely related aspects of academic self-regulation in online learning environments. From a psychometric perspective, this finding raises the possibility of a higher-order readiness factor or a more parsimonious four-factor structure. Nevertheless, the five-factor solution demonstrated superior conceptual interpretability and allowed the identification of unique demographic relationships in subsequent MIMIC analyses. Future research should directly compare four-factor, five-factor, higher-order, and bifactor representations across independent samples to determine the most appropriate structural model.

The current study focused on correlated factor models based on the theoretical framework. Higher-order or bifactor models were not examined because they address a different question: whether factor correlations can be explained by a general higher-order factor or whether item responses are explained by a general factor. The intended interpretation of the scale emphasizes the sub-dimensional factors rather than a single general factor. In addition, the factor correlations were not uniformly high, ranging from .391 to .896. Most factor correlations were low to moderate. This pattern suggests that the dimensions are related but not consistently reducible to a general/higher order factor.

6. Limitations and Future Research Directions

Several limitations should be considered when interpreting the findings. First, the sample was drawn from a single R1 institution in the southwestern United States, which may limit generalizability to other institutional contexts. Second, the sample was predominantly female (83%), potentially affecting the stability of gender-based comparisons despite evidence of measurement invariance. Third, students who declined research consent were excluded from the analytic sample, introducing the possibility of consent bias if consenting and non-consenting students differed systematically. Fourth, the study focused on psychometric validation and did not evaluate predictive validity; future research should examine the extent to which ORSSA scores predict academic performance, retention, and online course success. Finally, this study provided a broad understanding on online readiness across gender, ethnicity and FGCS, a contextual, qualitative study to comprehend specific challenges across the five ORSSA factors is warranted.

7. Conclusion

The ORSSA meets core standards for psychometric quality and fairness, providing a defensible mechanism for interpreting online readiness across diverse student groups. Its validated five-factor structure, strong reliability, and demonstrated measurement invariance enable institutions to compare groups responsibly and to identify where student resources and support programs will have the greatest impact. The demographic patterns observed through the MIMIC modeling point to practical priorities: address technology access and skill gaps as first-order academic needs; embed short, just-in-time modules on time management, LMS navigation, help-seeking, and study environments in orientation and gateway courses; partner with libraries for foundational digital literacy; and provide additional scaffolds for first-generation students. Used diagnostically rather than as a gatekeeper, the ORSSA can equip universities to deliver targeted interventions that improve students' readiness for and success in online learning. While the ORSSA demonstrated strong psychometric properties, the high correlation between Learning Organization and Learning Skills warrants continued investigation. Furthermore, although demographic effects were statistically significant, their practical magnitude was generally small, suggesting that readiness differences across groups should be interpreted cautiously. Replication across institutions and examination of predictive validity will be important next steps in establishing the broader utility of the instrument.

Ethics Statement: The study protocol was reviewed and approved by the university's Institutional Review Board. All participants provided written informed consent prior to their inclusion in the study, and the research was conducted in accordance with the ethical standards of the 1964 Declaration of Helsinki and its later amendments.

AI Statement: Artificial intelligence was not used in any way in the preparation of this paper.

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