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Development and Validation of Instruments for Assessing the Impact of Artificial Intelligence on Students in Higher Education

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Abstract: The role of artificial intelligence (AI) in education remains incompletely understood, demanding further evaluation and the creation of robust assessment tools. Despite previous attempts to measure AI's impact in education, existing studies have limitations. This research aimed to develop and validate an assessment instrument for gauging AI effects in higher education. Employing various analytical methods, including Exploratory Factor Analysis, Confirmatory Factor Analysis, and Rasch Analysis, the initial 70-item instrument covered seven constructs. Administered to 635 students at Nueva Ecija University of Science and Technology – Gabaldon campus, content validity was assessed using the Lawshe method. After eliminating 19 items through EFA and CFA, Rasch analysis confirmed the construct validity and led to the removal of three more items. The final 48-item instrument, categorized into learning experiences, academic performance, career guidance, motivation, self-reliance, social interactions, and AI dependency, emerged as a valid and reliable tool for assessing AI's impact on higher education, especially among college students.

Keywords: *Artificial Intelligence, item measurement, reliability test, validity test.*

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Introduction

The integration of artificial intelligence (AI) technologies in higher education has gained significant attention in recent years due to its potential to transform and enhance the learning experience. As AI continues to evolve and shape various aspects of society, understanding its impact on higher education, specifically college students, becomes increasingly crucial. This research aims to contribute to the field by constructing and validating a questionnaire to assess the impact of AI in higher education, specifically among college students, providing valuable insights into this emerging area.

The use of AI technologies in higher education holds immense promise for improving educational outcomes, personalizing learning experiences, and fostering student engagement (Malhotra, 2020). AI-powered tools, such as intelligent tutoring systems, virtual reality simulations, and adaptive learning platforms, offer unique opportunities for personalized instruction, data-driven decision-making, and enhanced student support (Masero, 2023). However, with the rapid adoption of AI in higher education, it is essential to critically examine its impact on students' learning experiences, academic performance, career guidance, motivation, self-reliance, social interactions, and AI dependency. Constructing and validating a questionnaire will allow for a comprehensive investigation of these dimensions and shed light on both the benefits and potential challenges associated with AI integration.

In higher education settings, several AI-powered tools are actively utilized. Examples of these tools encompass Chat GPT, Google Bard, Photo Math, Grammarly, paraphrasing tools like Quillbot, Turnitin, and similar applications. Denecke et al. (2021) suggest that while chatbots like Chat GPT and Google Bard show promise in psychoeducation and adherence, ethical considerations, such as their potential impact on the patient-therapist relationship, the risk of over-reliance, and their limited skills and emotional intelligence, need to be carefully considered, as these factors may

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constrain their practicality. Conversely, Kooli (2023) asserts that the inclusion of AI systems and chatbots in education should be viewed as a chance for advancement rather than a potential threat. Moreover, the use of AI, exemplified by tools like PhotoMath, has become prevalent in college settings. PhotoMath, designed for instant problem-solving through image recognition, offers convenience but raises concerns about its impact on students' conceptual understanding, potential overreliance, and ethical considerations (Booc et al., 2023). The literature underscores the dual nature of AI's influence on education, where its effects manifest both positively and negatively. The nuanced impact of AI in educational settings necessitates a comprehensive examination of its advantages and disadvantages for a more informed understanding of its implications.

Significant research has been conducted on the impact of AI in education, focusing on various dimensions such as student performance, engagement, and learning outcomes. The existing research literature on the impact of AI in education demonstrates the potential of AI-powered tools in improving student performance (Hwang et al., 2020), and enhances engagement in educational games (Eltahir et al., 2021; Hsu & Chen, 2022; Tan Ai Lin et al., 2018), supporting personalized learning for improved outcomes (Pataranutaporn et al., 2021), and aiding formative assessments to facilitate learning (Irons & Elkington, 2007; Sagarika et al., 2021). Furthermore, other research focuses on the development and implementation of various questionnaires to measure the influence of AI in education. Zhu and Ren (2022), for example, created a questionnaire to assess the impact of AI on role cognition in the educational system. The questionnaires include six role cognition items: morality and discipline, knowledge and professionalism, activities and communication, guidance and consultation, research and practice, and goals and feedback. On the other hand, Sangapu (2018) employed a structured open-ended questionnaire to measure students' and instructors' attitudes toward AI in education. Similarly, Seo et al. (2021) employ a questionnaire based on Kang and Im's (2013) five-factor model of learner-instructor interaction in online learning settings to measure student and teacher interaction in an online environment. Furthermore, Kairu (2020) uses a questionnaire to assess students' perceptions of AI in higher education classroom engagement evaluation.

Certain studies have centred on the medical domain, exemplified by Lennartz et al. (2021), who employed a questionnaire to explore patients' perspectives regarding the utilization of AI across various facets of the medical workflow and the degree of oversight and supervision required for AI applications in healthcare to be deemed acceptable. Jindal and Bansal (2020) use ten items questionnaires aiming to assess the knowledge and education related to AI and computer language in the medical field. Furthermore, Ongena et al. (2020) conducted research wherein they developed and validated a standardized patient questionnaire focused on the integration of AI in radiology. However, there is a need for a comprehensive and validated instrument that specifically addresses the impact of AI in the context of higher education. Existing studies often utilize different measurement tools, making it challenging to compare findings across studies or draw generalizable conclusions. Therefore, this research aims to contribute to the existing body of knowledge by constructing and validating a questionnaire tailored to the specific context of AI in higher education, providing a standardized instrument to assess its impact consistently.

The rationale for constructing and validating a questionnaire on the impact of AI in higher education lies in several key considerations. First, understanding the impact of AI in higher education is essential for educators, policymakers, and institutions seeking to leverage AI technologies effectively (Ma & Siau, 2018). A validated questionnaire will provide a reliable and standardized tool to assess the impact across multiple educational settings, allowing for meaningful comparisons and evidence-based decision-making. Second, by constructing a questionnaire that covers diverse dimensions, such as learning experiences, academic performance, career guidance, motivation, self-reliance, social interactions, and AI dependency, this research aims to provide a comprehensive understanding of the multifaceted impact of AI in higher education. The questionnaire will enable researchers to explore the interrelationships between these dimensions and identify potential areas of concern or opportunities for improvement. Lastly, constructing and validating a questionnaire on the impact of AI in higher education, specifically on students, will contribute to the research methodology itself. By ensuring the validity and reliability of the questionnaire through rigorous validation processes, this study will enhance the quality of data collection in future research and provide a foundation for further investigations in this evolving field.

Based on the aforementioned literature, this research seeks to construct and validate a questionnaire to assess the impact of AI in higher education, specifically focusing on college education. Specifically, the primary goal is to develop and validate a comprehensive questionnaire assessing AI's impact on learning experiences, academic performance, career guidance, motivation, self-reliance, and social interactions. Objectives include addressing ethical considerations, understanding AI's dual nature, and creating a standardized measurement tool for consistent assessment. By providing a standardized instrument, this study aims to contribute to the field by offering a comprehensive understanding of the impact of AI on various dimensions of higher education. The findings will inform educators, policymakers, and researchers, facilitating evidence-based decision-making and fostering responsible integration of AI technologies in higher education settings.

Methodology

The goal of this study was to develop and validate an instrument to assess the influence of AI on learners, particularly college students. The following steps were taken during the instrument's development: (a) interviews with university professors; (b) analyzing interviews and face validity; (c) content validation using the Lashe method; (d) Exploratory Factor Analysis (EFA); (e) Confirmatory Factor Analysis (CFA); (f) RASCH analysis; and (g) reliability testing using the internal consistency method (Cronbach's alpha).

Interviews With Experts

One Professor and three Associate Professors from Nueva Ecija University of Science and Technology were interviewed by the researcher. These individuals, recognized as education specialists in diverse subjects, bring extensive expertise to their respective roles. The Professor, holding a PhD, possesses 25 years of dedicated service in academia, specializing in language and educational management. Additionally, the Professor serves as the campus director of the university. The three Associate Professors specialize in educational technology, guidance and counseling, and educational management. They are queried on the potential structure of the questionnaire on the influence of AI on students' learning in higher education. The interview is unstructured, and the following are some of the specific questions asked during the interview:

1. What are the key aspects or dimensions of AI that could impact the learning experiences of students in higher education?
2. How would you define the influence of AI on students' learning in higher education?
3. From your perspective, what specific constructs or factors should be considered when exploring the influence of AI on students' learning?
4. What are some specific aspects of students' learning experiences that you believe can be measured in the context of AI integration in higher education?
5. Could you suggest potential items or indicators that could be used to quantify or assess these identified constructs?

The interview was conducted in person. Interviews were taped to ensure that their perspectives were preserved. Olson (2010) argues that in terms of creating questionnaires with credibility for data collection, experts are the most dependable source.

Analyzing Interviews and Face Validation

The researcher analyzed the data collected from expert interviews and used face validity to create 7 constructs, each with 10 items. This resulted in an instrument with a total of 70 items. Zach (2021) defines face validity as the degree to which a test seems to measure what it purports to measure based on its surface characteristics. Furthermore, in face validity items were subjectively evaluated without any systematic testing or statistical analysis (Bhandari, 2022).

Content Validation

Following face validation, the researcher enlists the assistance of 15 academic members from Nueva Ecija University of Science and Technology to validate the items of each construct. In the validation phase, the researcher used the Lawshe approach, which was created by Lawshe (1975). In the Lawshe technique, the faculty rater ranks each component in the instrument as essential and non-essential (Ayre & Scally, 2014). The content validity ratio of each item is calculated using the formula CVR = [ne - (N/2)] / (N/2), where it is the number of raters who consider the item essential and N is the total number of raters. The content validity index (CVI) is the average value of all CVR in a construct. The content validity ratio and content validity index minimum value for 15 raters is 0.49.

Sample Size and Data Collection

Using Google Forms, the questionnaire was given to 1235 students at the Nueva Ecija University of Science and Technology Gabaldon campus. The questionnaire was distributed on May 1, 2023, and 635 replies were received after two months. A minimal sample size of 500 in an exploratory and confirmatory factor analysis, according to Comrey and Lee (1992), is considered very good. Furthermore, the sample size must be at least five times the number of questionnaire items (Hair et al., 1998). Since the number of items in this study is 70 times five, or 350, a sample size of 635 is excellent for performing EFA and CFA.

Data Analysis

EFA is used to assess the construct's validity, confirm whether the observed variables correspond with the hypothesized theoretical constructs, and identify any measurement errors or inconsistencies (Knekta et al., 2019). The Kaiser-Meyer-Olkin (KMO) test was employed to assess the suitability of the data for factor analysis (Shrestha, 2021). According to Kaiser (1974), the minimal value of KMO is .5, values between .7 and .8 are good, and values over .9 are outstanding. Bartlett's Test of Sphericity must be significant (p<.05) (Hair et al., 2006). Furthermore, in this research, the varimax rotation method is used (Osborne, 2015). In this study, all components with eigenvalues larger than 1.0 were kept, which is also known as the K1 rule, Kaiser rule, and Kaiser-Guttman rule (Goodwyn, 2012). According to

Zwick and Velicer (1986), a factor with an eigenvalue greater than 1.0 is predicted to have a stronger predictive ability when compared to individual variables on their own. Furthermore, the minimum loading factor value is .5.

The CFA is used to validate the EFA results. In this study, the following fit criteria were used to determine the goodness of fit of a CFA model: Comparative Fit Index (CFI) value of .95 or higher; Tucker-Lewis Index (TLI) value of .95 or higher; Goodness of fit index (GFI) value of .95; Root Mean Square Error of Approximation (RMSEA) value of .06 or lower; and Standardized Root Mean Square Residual (SRMR) value of .08 or lower. These values are commonly seen as indicative of a good fit (Gaskin & Lim, 2016; Kline, 2023). Furthermore, the construct validity of the instrument was determined using the Rasch analysis (Mui Lim et al., 2009). The following criteria were used in this study for item retention: Reasonable Item Mean-square Ranges for Infit and Outfit for rating scale is .6 - 1.4 (Wright & Linacre, 1994); a Point-measure Correlation value (PTMEA) of .3 - .6 (Bond & Fox, 2015); separation value of ≥ 2 (Linacre, 2007); and Person reliability of .8 or greater (Bond & Fox, 2007).

Each factor's reliability coefficient was calculated using SPSS-Cronbach's alpha. The reliability coefficient < .5 is unacceptable, .6 > a > .5 is poor, .7 > a > .6 is questionable, .8 > a > .7 is acceptable, .9 > a > .8 is good, and 1.0 > a > .9 is excellent (George & Mallery, 2003).

Findings/Results

Content Validity Using Lawshe Method

Table 1 shows the 70 item instruments after a thorough analysis of the interviews and face validation: 10 items for Learning Experience; 10 items for Academic Performance; 10 items for Career Guidance; 10 items for Motivation; 10 items for Self-reliance; 10 items for Social Interaction; and ten items for AI Dependency. Table 1 also demonstrates that the content validity ratio and content validity index of each item and construct are more than the critical threshold of .49, indicating that 70 items are all considered in the analysis. This further suggests that, in accordance with the assessment conducted by experts, the 70 items are deemed valid for gauging the seven constructs.

Table 1. Content Validity

	Learning Experience	Content Validity Ratio
LE1	AI has enhanced my learning experience by providing personalized content and resources.	1
LE2	AI has helped me understand complex concepts more effectively.	0.73
LE3	AI-powered simulations and virtual reality have improved my understanding of the subject matter.	0.73
LE4	AI has adapted to my learning style and pace, making learning more enjoyable and effective.	0.87
LE5	AI has provided interactive and engaging learning materials.	0.87
LE6	AI has facilitated hands-on and practical learning experiences.	0.87
LE7	AI has encouraged critical thinking and problem-solving skills development.	0.87
LE8	AI has provided real-world examples and case studies to enhance my learning.	0.87
LE9	AI has promoted creativity and innovation in my learning process.	0.73
LE10	AI has improved my retention and recall of learned information.	0.73
	Content Validity Index (CVI)	**0.83**
	Academic Performance	
AP1	AI has contributed to improving my academic performance.	0.87
AP2	AI-powered tools have helped me identify and address my weaknesses in specific subjects.	0.73
AP3	AI-based feedback has helped me improve the quality of my assignments and exams.	0.87
AP4	AI has assisted me in achieving my learning goals.	0.87
AP5	AI has provided timely and accurate assessments of my progress.	0.87
AP6	AI has helped me prepare for exams more effectively.	0.73
AP7	AI has improved my problem-solving and analytical skills.	0.87
AP8	AI has enhanced my ability to apply theoretical knowledge in practical situations.	0.73
AP9	AI has provided resources and techniques to improve my study habits.	0.87
AP10	AI has contributed to my overall academic growth and success.	0.87
	Content Validity Index (CVI)	**0.83**
	Career Guidance	
CG1	AI has provided accurate and up-to-date information about potential career paths.	0.73
CG2	AI tools have matched my skills and interests with suitable career options.	0.87
CG3	AI has recommended internships or job opportunities aligned with my career goals.	0.87
CG4	AI has helped me make informed decisions about my academic and career choices.	0.87
CG5	AI has guided me in developing the necessary skills for my desired career.	0.73
CG6	AI has offered mentorship and networking opportunities in my field of interest.	0.87

Table 1. Continued

	Learning Experience	Content Validity Ratio
CG7	AI has connected me with industry professionals and experts.	0.87
CG8	AI has facilitated access to career development resources and workshops.	0.73
CG9	AI has helped me identify emerging trends and technologies in my field.	0.87
CG10	AI has supported my long-term career planning and development.	0.87
	Content Validity Index (CVI)	**0.83**
	Motivation	
MT1	AI has motivated me to actively engage in my educational journey.	1
MT2	AI-powered tools have provided incentives and rewards for achieving learning milestones.	0.87
MT3	AI has personalized learning experiences to match my interests and goals, boosting my motivation.	0.87
MT4	AI has provided opportunities for gamified learning, making the process more enjoyable and engaging.	0.73
MT5	AI has inspired me to set ambitious goals and strive for continuous improvement.	0.87
MT6	AI has offered feedback and recognition for my achievements.	0.87
MT7	AI has provided insights and progress tracking to keep me motivated.	0.87
MT8	AI has connected me with peers who share similar goals and interests.	0.73
MT9	AI has provided challenges and competitions to fuel my motivation.	0.87
MT10	AI has facilitated goal-setting and action planning for academic success.	0.87
	Content Validity Index (CVI)	**0.85**
	Self-reliance	
SR1	AI has empowered me to take ownership of my learning and academic progress.	0.87
SR2	AI tools have enabled me to find solutions to academic challenges independently.	0.73
SR3	AI has encouraged self-directed learning and exploration of topics beyond the curriculum.	0.87
SR4	AI-powered tools have supported my ability to think critically and solve problems on my own.	0.87
SR5	AI has enhanced my confidence and self-reliance in academic pursuits.	0.87
SR6	AI has helped me develop self-discipline and accountability in my studies.	0.87
SR7	AI has provided resources and tools for self-assessment and self-improvement.	0.73
SR8	AI has encouraged reflective thinking and self-evaluation of my learning progress.	0.87
SR9	AI has supported my development of independent research and analytical skills.	0.87
SR10	AI has promoted autonomy and initiative in my academic journey.	1
	Content Validity Index (CVI)	**0.85**
	Social Interaction	
SI1	AI has facilitated collaboration and teamwork among students in group projects.	1
SI2	AI-powered platforms have provided spaces for online discussions and knowledge sharing.	0.87
SI3	AI has encouraged peer-to-peer learning and support among students.	0.73
SI4	AI tools have promoted inclusive and respectful interactions in virtual learning environments.	0.87
SI5	AI has connected me with a diverse community of learners, expanding my social network.	0.87
SI6	AI has facilitated networking opportunities with professionals and experts in my field.	0.73
SI7	AI has supported group-based learning and problem-solving activities.	0.87
SI8	AI has promoted cultural exchange and understanding among students.	0.73
SI9	AI-powered platforms have facilitated mentoring relationships between students.	0.87
SI10	AI has encouraged participation in extracurricular activities and student organizations.	0.87
	Content Validity Index (CVI)	**0.84**
	AI Dependency	
AID1	AI has become an essential part of my learning process and academic success.	0.87
AID2	I heavily rely on AI tools to support my study-related activities.	1
AID3	AI has significantly influenced my educational choices and decision-making processes.	0.87
AID4	I feel more confident and capable with the assistance of AI in my studies.	0.73
AID5	AI has transformed the way I approach learning and problem-solving tasks.	0.73
AID6	AI has become a trusted source of information and guidance for me.	0.73
AID7	I actively seek out AI-powered tools and resources to enhance my learning experience.	0.73
AID8	AI has increased my efficiency and productivity in academic tasks.	0.87
AID9	I believe AI has positively impacted my overall educational journey.	0.87
AID10	I feel that AI has improved the quality of my learning outcomes.	0.73
	Content Validity Index (CVI)	**0.81**

Exploratory Factor Analysis (EFA)

Table 2 shows that the Kaiser-Meyer-Olkin Measure of Sampling Adequacy is outstanding (.935) and Bartlett's test of Sphericity is significant (p<.001). Thus, the data meets the preliminary criteria in the factorial analysis. This indicates that the dataset is appropriate for factor analysis.

Table 2. KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.935
Bartlett's Test of Sphericity	Approx. Chi-Square	45254.392
	df	1326
	Sig.	*p<.001*

Loading Factors

Following the execution of EFA using the varimax rotation method, certain items that did not reach the loading factor value of .5 were deleted (Field, 2013). AID1, SI10, AP7, AP8, LE2, LE3, LE9, LE10, SR2, SR9, SR10, MT2, MT3, MT5, and MT9 were all eliminated. Furthermore, the entries MT1, SR1, AP10, and AP9 had cross-loadings these were eliminated as well (Maskey et al., 2018). After removing all items that did not meet the loading factor of .5 and with cross-loadings, the EFA analysis was performed again (Albano, 2020). Table 3 provides the 51-item questionnaire on the Impact of AI in Education, which includes: AI Dependency (9 items); Social Interaction (9 items); Career Guidance (10 items); Academic Performance (6 items); Learning Experience (6 items); Self-reliance (6 items); and Motivation (5 items). The application of EFA plays a pivotal role in refining and optimizing the underlying model in anticipation of forthcoming analyses. Through this refinement, the EFA contributes to a more nuanced and well-defined understanding of the underlying constructs, ensuring a solid foundation for subsequent analytical endeavors.

Table 3. Rotated Component Matrix

	Component						
	1	2	3	4	5	6	7
AID4	.739						
AID2	.720						
AID3	.714						
AID5	.705						
AID9	.690						
AID10	.666						
AID6	.645						
AID7	.642						
AID8	.616						
SI2		.780					
SI4		.731					
SI5		.728					
SI7		.694					
SI1		.679					
SI6		.661					
SI8		.658					
SI9		.647					
SI3		.619					
CG6			.738				
CG5			.672				
CG2			.661				
CG7			.658				
CG3			.626				
CG10			.588				
CG1			.588				
CG4			.578				
CG8			.565				
CG9			.542				

Table 3. Continued

	Component						
	1	2	3	4	5	6	7
AP3				.713			
AP5				.698			
AP4				.669			
AP2				.641			
AP1				.591			
AP6				.561			
LE5					.775		
LE7					.688		
LE6					.638		
LE1					.615		
LE8					.592		
LE4					.555		
SR4						.659	
SR5						.634	
SR8						.618	
SR7						.598	
SR6						.588	
SR3						.516	
MT7							.628
MT4							.601
MT6							.547
MT8							.524
MT10							.501

Fit Indices

Table 4 displays the CFA fit indices. The following conditions were met: Normed Chi-squared CMIN/DF = 2.523 is between 1 and 3; CFI = .95 is acceptable; TLI = .952 is greater than .95; GFI = .945 is acceptable; SRMR = .044 is less than .08; RMSEA = .062 is less than .08; and the p-value of .051 is greater than .05, indicating that the model fits the individual subject's data. Overall, these CFA fit indices collectively indicate a robust fit between the proposed model and the observed data.

Table 4. Fit Indices Criteria

Measure	Estimate	Threshold	Interpretation
CMIN	6445.47	--	--
DF	2554	--	--
CMIN/DF	2.523	Between 1 and 3	Excellent
CFI	.95	>.95	Acceptable
TLI	.952	>.95	Excellent
GFI	.945	>.95	Acceptable
SRMR	.044	<.08	Excellent
RMSEA	.062	<.08	Excellent
PClose	.051	>.05	Excellent

Confirmatory Factor Analysis Loading

Table 5 displays the CFA loading factors. All the loading factors are more than .5, indicating a strong correlation within the components. Awang (2012) argues that each item must have a loading factor of at least .6. The data indicate a significant correlation between the assessed items and their respective latent constructs.

Table 5. CFA Loading

Code	Items	Loading Factor
AID4	I feel more confident and capable with the assistance of AI in my studies.	.844
AID2	I heavily rely on AI tools to support my study-related activities.	.742
AID3	AI has significantly influenced my educational choices and decision-making processes.	.888
AID5	AI has transformed the way I approach learning and problem-solving tasks.	.805
AID9	I believe AI has positively impacted my overall educational journey.	.91
AID10	I feel that AI has improved the quality of my learning outcomes.	.919
AID6	AI has become a trusted source of information and guidance for me.	.896
AID7	I actively seek out AI-powered tools and resources to enhance my learning experience.	.89
AID8	AI has increased my efficiency and productivity in academic tasks.	.856
SI2	AI-powered platforms have provided spaces for online discussions and knowledge sharing.	.818
SI4	AI tools have promoted inclusive and respectful interactions in virtual learning environments.	.869
SI5	AI has connected me with a diverse community of learners, expanding my social network.	.879
SI7	AI has supported group-based learning and problem-solving activities.	.866
SI1	AI has facilitated collaboration and teamwork among students in group projects.	.868
SI6	AI has facilitated networking opportunities with professionals and experts in my field.	.832
SI8	AI has promoted cultural exchange and understanding among students.	.867
SI9	AI-powered platforms have facilitated mentoring relationships between students.	.867
SI3	AI has encouraged peer-to-peer learning and support among students.	.829
CG6	AI has offered mentorship and networking opportunities in my field of interest.	.815
CG5	AI has guided me in developing the necessary skills for my desired career.	.877
CG2	AI tools have matched my skills and interests with suitable career options.	.834
CG7	AI has connected me with industry professionals and experts.	.857
CG3	AI has recommended internships or job opportunities aligned with my career goals.	.818
CG10	AI has supported my long-term career planning and development.	.863
CG1	AI has provided accurate and up-to-date information about potential career paths.	.834
CG4	AI has helped me make informed decisions about my academic and career choices.	.853
CG8	AI has facilitated access to career development resources and workshops.	.881
CG9	AI has helped me identify emerging trends and technologies in my field.	.825
AP3	AI-based feedback has helped me improve the quality of my assignments and exams.	.782
AP5	AI has provided timely and accurate assessments of my progress.	.87
AP4	AI has assisted me in achieving my learning goals.	.837
AP2	AI-powered tools have helped me identify and address my weaknesses in specific subjects.	.782
AP1	AI has contributed to improving my academic performance.	.814
AP6	AI has helped me prepare for exams more effectively.	.787
LE5	AI has provided interactive and engaging learning materials.	.764
LE7	AI has encouraged critical thinking and problem-solving skills development.	.753
LE6	AI has facilitated hands-on and practical learning experiences.	.777
LE1	AI has enhanced my learning experience by providing personalized content and resources.	.763
LE8	AI has provided real-world examples and case studies to enhance my learning.	.781
LE4	AI has adapted to my learning style and pace, making learning more enjoyable and effective.	.835
SR4	AI-powered tools have supported my ability to think critically and solve problems on my own.	.883
SR5	AI has enhanced my confidence and self-reliance in academic pursuits.	.908
SR8	AI has encouraged reflective thinking and self-evaluation of my learning progress.	.911
SR7	AI has provided resources and tools for self-assessment and self-improvement.	.926
SR6	AI has helped me develop self-discipline and accountability in my studies.	.888
SR3	AI has encouraged self-directed learning and exploration of topics beyond the curriculum.	.878
MT7	AI has provided insights and progress tracking to keep me motivated.	.89
MT4	AI has provided opportunities for gamified learning, making the process more enjoyable and engaging.	.875
MT6	AI has offered feedback and recognition for my achievements.	.874
MT8	AI has connected me with peers who share similar goals and interests.	.90
MT10	AI has facilitated goal-setting and action planning for academic success.	.858

Rasch Analysis

Rasch analysis was employed to support the EFA and CFA findings. It was carried out to determine the instrument's construct validity (Baghaei, 2008). Table 6 demonstrates that the reliability and separation of the item and person indices satisfy the Rasch analysis requirements.

This indicates that the instrument possesses ample sensitivity to discern between high and low performers, and the sample size of individuals is sufficiently large to validate the construct validity of the instrument by confirming its item difficulty hierarchy (Linacre, 2007).

Table 6. Reliability and Person Indices

	Person		Item	
CONSTRUCT	**Reliability**	**Separation**	**Reliability**	**Separation**
Learning Experience	.84	2.63	.99	5.23
Academic performance	.86	2.58	.98	6.37
Career Guidance	.91	2.64	1.00	8.99
Motivation	.83	1.98	.98	10.45
Self-reliance	.94	2.92	1.00	41.6
Social Interaction	.87	2.65	1.00	9.37
AI dependency	.88	2.74	.99	8.11

Fit Analysis

Table 7 demonstrates that the majority of the items fit the inclusion requirements. The infit and outfit MNSQ are within the permissible range of .6 - 1.4, while PTMEA is within the acceptable range of .3 - .6. Item CG4, CG7, and AID9, on the other hand, failed to meet the inclusion requirements and were thus deleted. This means that items CG4, CG7, and AID9 are not functioning well. The fit indices for each remaining item show that the observed responses align well with the expected patterns predicted by the Rasch model, thereby supporting the reliability and validity of the measurements.

Table 7. Infit-Outfit MNSQ and Point-measure Correlation Value

Items	Infit (0.6-1.4)	Outfit (0.6-1.4)	PTMEA (0.3-0.6)
LE1	.624	.58	.5684
LE4	.563	.606	.5776
LE5	.943	1.036	.2632
LE6	.9	.97	.596
LE7	1.087	1.139	.601
LE8	.947	1.013	.609
AP1	.786	.883	.64
AP2	.92	1.014	.611
AP3	1.041	1.128	.604
AP4	.75	.764	.562
AP5	.727	.764	.568
AP6	.817	.87	.446
CG1	.669	.552	.608
CG2	.626	.536	.585
CG3	.671	.577	.571
CG4	**1.961**	**2.025**	**.709**
CG5	.781	.785	.504
CG6	.691	.701	.536
CG7	**1.813**	**1.725**	**.671**
CG8	.62	.609	.546
CG9	.649	.645	.51
CG10	.614	.622	.518
MT4	.679	.71	.578
MT6	.612	.602	.505
MT7	.725	.701	.509
MT8	.68	.683	.537
MT10	.621	.642	.595
SR3	.64	.651	.556
SR4	.62	.652	.511
SR5	.68	.696	.528
SR6	.662	.675	.524
SR7	.735	.735	.558
SR8	.897	.882	.52
SI1	.691	.695	.486
SI2	.675	.679	.496
SI3	.761	.792	.58

Table 7. Continued

Items	Infit (0.6-1.4)	Outfit (0.6-1.4)	PTMEA (0.3-0.6)
SI4	.605	.607	.551
SI5	.673	.698	.575
SI6	.727	.713	.595
SI7	.679	.638	.579
SI8	.742	.739	.456
SI9	.69	.684	.493
AID2	1.117	1.093	.453
AID3	.7	.673	.537
AID4	.628	.627	.563
AID5	.632	.628	.541
AID6	.973	.953	.428
AID7	.97	.951	.524
AID8	.83	.896	.583
AID9	**1.751**	**2.042**	**.732**
AID10	.757	.75	.54

Reliability of Each Construct

The reliability coefficient for each construct is shown in Table 8. Academic performance (a = .92), career guidance (a = .91), and self-reliance (a = .93) have good reliability coefficients, whereas learning experience (a = .88), motivation (a = .89), social interaction (a = .87), and AI dependency (a = .86) have excellent reliability coefficients. The reliability coefficient indicates the reliability of the items in measuring the construct. Furthermore, the moderate reliability coefficient suggests a lack of redundancy among the items.

Table 8. Reliability Coefficients

Factors	Cronbach's Alpha	Interpretation
Learning Experience	.88	Good
Academic Performance	.92	Excellent
Career Guidance	.91	Excellent
Motivation	.89	Good
Self-reliance	.93	Excellent
Social Interaction	.87	Good
AI Dependency	.86	Good

Discussion

In recent years, AI has dramatically advanced and changed the trajectory of education. AI technology is transforming education by delivering various learning platforms. AI was used by educators and students to improve the teaching and learning process by providing effective assistance for online learning and teaching, such as customizing learning for students, automating instructors' mundane activities, and powering adaptive assessments (Seo et al., 2021). However, its influence on the educational process is not yet evident, hence this study was carried out to create a validated and reliable tool to reveal the impact of AI in higher education.

The 70 items were developed through expert interviews and face validation. The face validation procedure was carried out by closely studying the expert interviews. The 70-item instrument was divided into seven constructs: learning experiences (10 items); academic performance (10 items); career guidance (10 items); motivation (10 items); self-reliance (10 items); social interactions (10 items); and AI dependency (10 items). Following face validity, the instrument was statistically assessed using the Lawshe technique to determine the instrument's content validity. Each item's content validity ratio and content validity index are more than the critical threshold of .49, indicating that the items were valid. Furthermore, the Lawshe technique results confirm the face validity results. The consistency between face validation and the Lawshe technique enhances the instrument's credibility, combining qualitative and quantitative rigor.

Factor analysis was used to assess the correlation between the instrument's variables (Gerber & Price, 2018). The EFA analysis demonstrates that the KMO is excellent and the significance of Bartlett's test of sphericity suggests that the data are sufficient for factorial analysis (Zhang, 2006). Each factor's Eigenvalue is larger than one, which suggests that it is positively reliable (Cliff, 1988). Additionally, according to Kaiser (1960), the number of eigenvalues larger than one is equal to the number of reliable factors. Additionally, the majority of the elements were loaded into their anticipated proper constructs. Four items, on the other hand, that had cross-loadings were eliminated (Yan et al., 2022). Similarly, 15 more items were deemed ineligible because their loading factors fell below the minimum criterion of .5 (Hair et al., 1998). The EFA produces a 51-item instrument organized into seven constructs: AI Dependency (9 items), Social Interaction (9 items), Career Guidance (10 items), Academic Performance (6 items), Learning Experience (6 items), Self-reliance (6 items), and Motivation (5 items). The CFA was carried out to corroborate the EFA results. Table 4 demonstrates that all of the fit indices conditions were met: the CFI and GFI are within the acceptable range, while the CMIN/DF, TLI, SRMR, RMSEA, and P-value are all within the excellent range. As a result, the consistency of the constructs is confirmed (Tomé-Fernández et al., 2020). This methodical approach enhances the confidence in the instrument's ability to measure the intricacies of AI's impact on education across distinct dimensions, providing researchers and educators with a reliable tool for comprehensive assessment.

The Rasch analysis was performed to determine the validity and reliability of the items. Item reliability is from .99-1.00 and item separation is >2 which is considered as in the good category. The high values of item reliability and item separation confirmed the construct validity of the instrument (Akour, 2022). Furthermore, a person separation value greater than 2 and a person reliability exceeding .80 suggest that the existing number of items for each construct is sufficiently sensitive to differentiate between individuals with high and low performance (Akour, 2022). These results provide a strong foundation for confidence in the study's ability to accurately assess the impact of AI on higher education students, reinforcing the credibility of the research findings. In addition, most of the item has MNSQ Infit and Outfit value that are within the acceptable range, which indicates that the data fits the model (Linacre, 2012). The most of PTMEA values fall within the acceptable range as defined by Bond and Fox (2015). Additionally, the positive PTMEA values indicate that the respective items effectively measure the intended construct (Bond & Fox, 2007). Moreover, as stated by Hassan (2011), items with high positive values suggest that respondents will not encounter difficulty in responding to those items. Items CG4, CG7, and AID9, on the other hand, failed to meet the infit and outfit MNSQ and PTMEA requirements, hence they were eliminated. This selective elimination ensures that the final instrument comprises only the most reliable and valid items, enhancing its precision in assessing AI's impact on education.

Cronbach's alpha for the seven constructs is in the good to excellent range. Data indicates that there is internal consistency on each construct, which means that respondents' responses are consistent across items (Frost, 2023). Furthermore, internal consistency assesses the link between numerous test questions aiming to measure the same concept (Middleton, 2019). Additionally, Cronbach's alpha values are not excessively high (.95 - .99), indicating that the items are not redundant (Frost, 2023). Extremely high alpha values could indicate redundancy among the items, suggesting that they are measuring the same thing multiple times. The fact that the values are not excessively high implies that each item within a construct is contributing unique information, reinforcing the idea that the survey is measuring distinct aspects of the impact of AI on higher education students.

The newly developed and validated questionnaire to assess the impact of AI on higher education students addresses a comprehensive set of dimensions, including learning experiences, academic performance, career guidance, motivation, self-reliance, social interactions, and AI dependency. By incorporating items that specifically address ethical considerations and the dual nature of AI, the questionnaire ensures a balanced examination of both positive and negative aspects of AI integration. Notably, this instrument contributes to the field by providing a standardized measurement tool tailored to the specific context of AI in higher education, addressing the challenge of diverse measurement tools in existing literature. Its inclusion of multiple dimensions allows for an exploration of interrelationships between aspects, adding depth to the understanding of AI's complex influence on higher education. Moreover, the questionnaire equips educators, policymakers, and institutions with a reliable tool for evidence-based decision-making, supporting responsible integration of AI technologies in diverse educational settings. The study's contribution to research methodology lies in the enhanced validity and reliability of the questionnaire, providing a foundation for future investigations into the evolving field of AI in higher education.

Conclusions

This study presents the development of a valid and reliable measurement instrument to assess the influence of AI in higher education. Rigorous assessments were conducted using EFA, CFA, and Rasch analysis to ensure item validity and reliability. Following the EFA, 15 items failed to meet the loading factor criterion of 0.5, and 4 items exhibited cross-loadings, resulting in the exclusion of these 19 items. The CFA results indicated favourable fit indices (CMIN/DF, CFI, TLI, GFI, SRMR, RMSEA, and P-value), ranging from good to excellent. The resulting instrument consisted of 51 items divided into 7 constructs: AI Dependency (9 items), Social Interaction (9 items), Career Guidance (10 items), Academic Performance (6 items), Learning Experience (6 items), Self-reliance (6 items), and Motivation (5 items). To assess construct validity, Rasch analysis was employed, revealing satisfactory values for infit-outfit MNSQ and PTMEA for the majority of items. However, 3 items were eliminated due to their failure to meet the acceptable values for infit-outfit MNSQ and PTMEA. As a result, the instrument comprised 48 items across the seven constructs, demonstrating good to excellent reliability coefficients that avoid excessive redundancy. As such, the instrument is considered valid and reliable for assessing the impact of AI on higher education, particularly focusing on students. The researcher can confidently assert the validity and reliability of the instrument based on the evidence gathered.

Recommendations

The newly constructed and validated instrument to measure the impact of AI in higher education provides significant value for educators, curriculum developers, school administrators, students, and researchers. Educators can utilize the instrument to assess the influence of AI on students' learning experiences and academic performance, while curriculum developers can evaluate and improve existing AI-related curricula based on the instrument's feedback. School administrators can integrate the instrument into institutional assessments to monitor AI's impact and make data-driven decisions. Students can reflect on their AI dependency, social interaction, and motivation using the instrument, guiding their personal development. Researchers are encouraged to employ the instrument for further studies and collaborate with stakeholders to track the evolving impact of AI. Overall, the instrument serves as a valuable tool for enhancing AI integration in higher education and optimizing its benefits for learners.

Limitations

The study's applicability may be limited as it concentrated on students at Nueva Ecija University of Science and Technology – Gabaldon campus. The unique characteristics of this specific institution may restrict the generalizability of findings to other educational settings. Caution is warranted when extending results to different universities with diverse demographics and structures. Further research across various institutions is needed to validate the instrument's effectiveness in diverse settings.

Ethics Statements

The campus director granted permission to carry out the study, ensuring alignment with ethical standards. Participants provided informed consent, highlighting the confidentiality of data and the voluntary aspect of their involvement. The research strictly adhered to ethical guidelines, with a focus on prioritizing the well-being and rights of participants.

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