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Recceing Learner Objectives in Educational AI Adoption through Structural Equation Modeling

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Introduction

The integration of AI into education ushers in a transformative power into students' learning process, offering new tools and methodologies, yet raising questions about student readiness (Marr, 2023). AI's journey from science literature to routine reality has revolutionized various industries, including education, healthcare, and finance (Marr, 2023). From figurative reasoning to deep learning, AI's evolution has reshaped technology and garnered massive user engagement (Haenlein & Kaplan, 2019; Anu & Ansah, 2023; Hu, 2023).

In the Philippines, the integration of artificial intelligence into education has been gradually gaining traction, with higher education institutions integrating it as a key resource to enrich learning experiences (Lee & Koh, 2020). This aligns with the country's broader commitment to achieving Sustainable Development Goal 4 (SDG 4): Quality Education, which aims to ensure inclusive and equitable education and promote lifelong learning opportunities for all. Initiatives such as the National AI Roadmap and the establishment of the National Centre for AI Research (N-CAIR) demonstrate the government's intent to future-proof education through innovation (Estrellado, 2023).

Despite these efforts, the Philippine education system still exhibits a conservative approach to learning, highlighted by a World Economic Forum report ranking the country low in digital skills readiness (Estrellado, 2023). Addressing this gap is critical to realizing SDG 4 and requires not only the enhancement of digital literacy and skills but also the modernization of regulatory and institutional frameworks to fully harness the benefits of the digital economy.

Summary of Facts

The Philippine government has been working to reform the country's educational system through the Department of Education (DepEd) and the Commission on Higher Education (CHED) (Olea, 2019). As highlighted by Olea (2019), these reforms are crucial for preparing students to thrive in a rapidly evolving global landscape. Additionally, Ang and Aragon (2020) draw attention to the growing interest among East Asian universities in leveraging innovation as a catalyst for economic growth. They emphasize the importance of universities in cultivating an environment where students across disciplines can contribute to the development of a thriving AI ecosystem. Notably, educational institutions like De La Salle University are offering AI-related courses, indicating a commitment to preparing students for an AI-driven future.

Statement of Issues

While incorporating AI in education empowers learners and improves various aspects of curriculum development and learning approaches, a lack of findings remains regarding its significance and impact on AI readiness among university students in the Philippine context (Seo et al., 2021; Hooda et al., 2022). This brief fills the gap by investigating students' AI readiness and its relationship with factors such as perceived usefulness, attitudes toward AI, confidence in AI use, and AI's relevance in education, while also exploring potential moderating roles of gender, habit, confidence, and social good in AI usage for learning enhancement and academic performance. That said, this study posed the question: ***What are the variables that influence the acceptance and usage of generative AI learning tools, such as ChatGPT and Bard, by tertiary education students in Metro Manila?***

Outline of Arguments

Perceived Usefulness

Perceived usefulness significantly shapes individuals' intent to adopt technology, as it reflects their belief in its ability to enhance performance (Sugandini et al., 2018; Yu, 2022). However, Yang and Mei (2020, as cited in Yu, 2022) highlight that usefulness is not guaranteed by features alone, but it must align with user workflows. In education, this alignment drives adoption: teachers are more likely to integrate AI when they perceive it as beneficial (Wang et al., 2021), and student nurses adopt it when it supports their learning needs (Labrague et al., 2023). Gado et al. (2022) further emphasize that belief in AI's benefits is a strong predictor of intention to use it.

Attitude Towards AI

Attitudes, or the favorable or unfavorable feelings toward a behavior, shapes technology adoption (Ayanwale et al., 2022). Studies across contexts affirmed this: Pan et al. (2019) found that physicians' positive attitudes predicted smart healthcare adoption, while Emon et al. (2023) and Khan et al. (2021) reported that Bangladeshi professionals' favorable views of AI tools like ChatGPT were linked to higher adoption intent. Gado et al. (2021) similarly found attitudes to be a key predictor of AI use among psychology students, demonstrating the cross-sectoral relevance of this factor.

AI for Social Good

Students' intention to adopt AI is strongly linked to their belief in its societal benefits (Chai et al., 2020, 2021, 2022). Viewing AI as a tool for social good fosters deeper engagement, autonomy, and motivation to learn. However, for teachers, this perception alone does not directly translate to readiness to teach AI (Ayanwale et al., 2022); rather, it serves as a motivational backdrop. This contrast highlights a nuanced difference: students are more immediately driven by social relevance, whereas educators may require additional support to translate belief into practice.

Relevance of AI

While less explored, the perceived relevance of AI is an emerging determinant of adoption. Ayanwale et al. (2022) found it significantly influences teachers' readiness and intention to teach AI.Most literature, however, focuses on AI literacy (i.e., how knowledge shapes readiness) rather than direct perceptions of relevance (Chai et al., 2020; Dai et al., 2020). This points to a gap and an opportunity to investigate how relevance influences students' behavioral intention toward AI.

AI Readiness

AI readiness, driven by "technological optimism" and confidence in AI tools, is a strong predictor of adoption (Chai et al., 2020; Ayanwale et al., 2022). Educators with higher readiness show stronger intentions to teach AI. Chai (2022) expands this, identifying autonomy, resource design, and perceptions of AI's societal value as key factors shaping readiness to learn AI. These findings underscore the multifaceted nature of readiness and its influence on behavioral intent.

Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT (Venkatesh et al., 2003) provides a foundational model to explain technology adoption through effort expectancy, social influence, performance expectancy, and facilitating conditions. UTAUT2 (Venkatesh et al., 2012) extends this by adding hedonic motivation, habit, and price value, while removing voluntariness of use as a moderator. In this study, adapted UTAUT2 variables such as hedonic motivation inform attitudes towards AI, while performance and effort expectancy assess perceived relevance and usability. These models provide a comprehensive lens to examine AI adoption in education.

Discussion

Data and Methods

A causal quantitative research design was used to ascertain the cause-and-effect relationship of the latent variables. Using a homogenous purposive sampling method, survey data were collected from students in the Philippines, ranging from senior high school students to post-graduate students, who had integrated and applied generative AI tools for academic purposes. The data collection process was executed through an online survey through Google Forms, which received a total of 498 valid responses.

The research hypotheses were tested using structural equation modeling (SEM), which follows a two-step process: (1) testing the reliability and validity of the measurement model using confirmatory factor analysis and (CFA) (2) testing the structural models using path analysis (Fan, 2016). Structural equation models combine factor analysis with path analysis and other path modeling methods to specify a set of linear equations that represent the hypothesized relationships between latent variables and their multiple indicators (Knoke, 2005).

Normality Check and Common Method Bias

To assess the distribution of the survey data, Mardia's test and the Anderson-Darling test were employed to evaluate multivariate and univariate normality, respectively. Both tests indicated a non-normal distribution. In light of this deviation and to mitigate the impact of outliers, the study adopted the maximum likelihood robust (MLR) estimator, as recommended by Rosseel (2012). Further, Harman's single-factor test was conducted to check for common method bias. The test revealed a proportion variance of 0.29, which is below the 0.5 threshold, confirming that the item measurement scales are not significantly affected by common method bias (Rosseel, 2012).

Measurement Model

Confirmatory factor analysis (CFA) was employed to validate the factor structure of the primary research model.

To maintain data integrity, however, factor loadings below 0.7 were excluded from the structural model. Factor loadings of 0.7 or higher are considered robust, indicating a strong relationship between the observed variable and the latent construct.

As shown in Table 2, the initial CFA presented that all model fit indices were within acceptable limits. After excluding four item measurement scales (i.e., PU1, SG5, RE5, and RE6) with factor loadings below 0.7, all model fit indices improved significantly, enhancing the overall validity and reliability of the research model.

Table 2. *Model Fit Indices*

Model Fit Indices	**Acceptable Range**	**Initial CFA**	**Final CFA**
Tucker Lewis Index (TLI)	Above 0.90 (Weston & Gore, 2006)	0.912	0.934
Comparative Fit Index (CFI)	Above 0.90 (Hu & Bentler, 1999)	0.921	0.943
Standardized Root Mean Square Residual (SRMR)	Less than 0.08 (Hu & Bentler, 1999)	0.047	0.043
Root Mean Square Error of Approximation (RMSEA)	Less than 0.08 (Fabrigar et al., 1999).	0.062	0.059

Convergent and Discriminant Validity

To enhance the robustness of the measurement model, we assessed both convergent and discriminant validity of the measurement scales. The results, presented in Table 3, confirmed the validity of the constructs. The average variance extracted (AVE) values for each construct exceeded the recommended threshold of 0.5, indicating strong convergent validity. Furthermore, the heterotrait-monotrait (HTMT) ratios of correlation ranged from 0.66 to 0.834, all below the prescribed 0.90 threshold, further confirming the discriminant validity of the scales (Fornell & Larcker, 1981; Henseler, 2015).

Table 3. *AVE and HTMT Ratios of Correlation*

	AVE	**PU**	**AT**	**SG**	**RA**	**RE**	**BI**
PU	0.63	1					
AT	0.78	0.763	1				
SG	0.75	0.66	0.698	1			
RA	0.67	0.757	0.707	0.766	1		
RE	0.54	0.714	0.755	0.746	0.834	1	
BI	0.58	0.675	0.701	0.677	0.735	0.818	1

Structural Model

The structural model showed that five of the seven paths were statistically significant (Table 4). All of the model fit indices are within the acceptable range (CFI = 0.941, TLI = 0.933, RMSEA = 0.06, SRMR = 0.046), entailing an adequate model fit.

Table 4. *Structural Model*

Hypothesis	**Estimates**	**SE**	**p-value**	**Result**
	0.08	0.08	0.441	Not supported
	0.238	0.087	0.006**	Supported
	0.079	0.077	0.307	Not supported
	0.227	0.126	0.072*	Supported
	0.32	0.085	< 0.001***	Supported
	0.534	0.105	< 0.001***	Supported
	0.404	0.111	< 0.001***	Supported

PU: Perceived usefulness; AT: Attitude towards using AI; SG: AI for social good; RA: Relevance of AI; RE: AI readiness; BI: Behavioral intention.
Note. *** denotes significance at the 1% level; ** denotes significance at the 5% level

The outcomes demonstrated no significant statistical relationship between the perceived usefulness of AI tools and behavioral intention. This may be rooted in the incompatibility of AI tools in student's learning workflows. That said, the actual implementation and user experience of AI tools might critical in this context. If generative AI tools are perceived as complicated, unreliable, or poorly integrated into existing workflows, their usefulness is diminished, impacting their adoption (Yu, 2022). Further, the innovative features might be seen as gimmicky rather than genuinely valuable if they do not align with students' needs and workflows (Yang & Mei, 2020, as cited in Yu, 2022).

The model revealed that AI for social good did not significantly impact students' behavioral intention, contradicting Chai et al.'s studies from 2020 and 2021, which found a strong positive correlation between social good consciousness and students' intention to engage with AI. Chai (2022) also emphasized that using AI for societal benefit enhances students' sense of independence and motivation toward societal contribution. This discrepancy may arise from differences in how students perceive the relevance of AI's societal benefits to their educational goals. Students might prioritize immediate practical benefits, such as educational advancement and career opportunities, over broader societal impacts. At the 5% significance level, students' attitude of using AI positively impacts behavioral intention. This means that students who view AI tools favorably are more likely to intend to use them. Such positive attitude towards AI tools can stem from perceived benefits such as increased efficiency, personalized learning experiences, and enhanced engagement. When individuals recognize these advantages, they are naturally more inclined to integrate AI into their coursework.

Similarly, Emon et al. (2023) found that a positive attitude towards using such ChatGPT strongly correlates with a heightened behavioral intention to employ this AI technology among Bangladeshi professionals.

Despite being underexplored in the current literature, this study purveyed evidence of a positive impact of AI relevance on behavioral intention. Most research to date has focused on the relationship between AI literacy and students' readiness to engage with AI technologies, as shown by Chai et al. (2020) and Dai et al. (2020), who investigated how AI knowledge affects students' preparedness. Thus, understanding AI's relevance in academic pursuits proved to be crucial, as it directly affects students' willingness to integrate AI into their learning processes. This study highlighted the importance of perceiving AI as relevant, suggesting that when students see AI as pertinent to their studies, their intention to engage with AI technologies increases, filling a critical gap in the existing literature.

In light of AI readiness, both SG and RA exhibited a positive effect on students' readiness in utilizing AI tools. Chai et al. (2020) highlighted how Japan's design of AI robots to assist the elderly exemplifies AI's potential to benefit diverse populations in various aspects. This notion of AI for social good resonates with students, enhancing their readiness to learn about AI by showing tangible, positive impacts on society. When students see AI making a difference in real-world scenarios, they are more inclined to develop an interest in learning about and utilizing these technologies. Concerning AI relevance, when students understand how AI can be applied to their academic and personal lives, their intention to engage with AI tools increases. Providing students with clear, practical examples of AI applications that are pertinent to their interests and studies makes the technology more relatable and valuable to them. Thus, the influence of understanding AI's societal benefits and its relevance to students' own lives fosters a more profound readiness and intention to engage with AI.

Finally, the structural model showed a statistically significant positive relationship between readiness of using AI and behavioral intention, suggesting that as students become more prepared to use AI, their intention to engage with AI tools increases. This relationship is further reinforced by Chai's (2022) extensive analysis, which identified additional factors contributing to behavioral intention. These factors include the design of learning resources, learner autonomy, and the perceived societal benefits of AI for social good. Well-structured educational materials, autonomy in learning, and recognition of AI's societal impact collectively enhance students' readiness and motivation to use AI. Thus, fostering these elements can effectively increase students' intention to integrate AI into their education.

Table 5. *SEM with Mediation*

Hypothesis	**Indirect Effect**	**SE**	**p-value**	**Result**
	0.13	0.049	0.008***	Supported
	0.216	0.071	0.002***	Supported
Relationship	**Direct effect**	**SE**	**p-value**	**Result**
	0.079	0.077	0.307	Not supported
	0.227	0.126	0.072*	Supported

PU: Perceived usefulness; AT: Attitude towards using AI; SG: AI for social good; RA: Relevance of AI; RE: AI readiness; BI: Behavioral intention.
Note. *** denotes significance at the 1% level; ** denotes significance at the 5% level

The mediation analysis of the structural model showed that a full mediating effect of AI readiness on the relationship between AI for social good and behavioral intention. This implied that students' readiness fully accounts for how they perceive AI's societal benefits and their intention to use AI tools. When students recognize AI's potential to benefit society, it influences their readiness to engage with AI, which in turn shapes their behavioral intention. Therefore, fostering AI readiness is crucial for enhancing students' intention to use AI, particularly by emphasizing AI's societal benefits and providing them with the necessary skills and knowledge to engage with AI technologies effectively.

On the other hand, the partial mediation of AI readiness in the relationship between AI relevance and behavioral intention suggests a nuanced interplay between students' perception of AI's relevance and their readiness to engage with AI, which collectively influence their intention to use AI tools. When students perceive AI tools as relevant to their academic pursuits and personal lives, it directly impacts their behavioral intention by increasing their motivation to use AI technologies. This direct effect highlights the importance of students recognizing the practical applicability and significance of AI in their educational contexts.

Conclusion

Structural equation modeling and mediation analysis were used to explore factors influencing students' behavioral intention to use AI tools in their learning workflows. Interestingly, the study found no significant statistical relationship between the perceived usefulness of AI tools and students' behavioral intention. To address this, higher education institutions may mandate annual AI tool audits within departments to ensure that any integrated AI tools meet clear usability benchmarks, such as time-to-learn and interface accessibility. Furthermore, faculty development grants may be offered to support instructors in co-designing AI-enhanced modules with instructional designers.

This is to ensure that AI applications directly align with learning outcomes rather than acting as optional add-ons.

In the student space, institutions may also establish a student AI user experience review that tests AI tools each semester and provides structured feedback for immediate refinements to maintain high perceived usefulness and seamless integration.

In stark contrast to previous studies, this research revealed that AI for social good did not significantly impact students' behavioral intention. However, universities may strengthen this link through integrating AI-for-social-good projects as credit-bearing components within courses. This may encourage students to apply AI tools to address real community or societal challenges related to their fields of study. For instance, feasible, capstone projects and undergraduate theses may include an AI-for-impact dimension, supported by faculty mentors and partnerships with local NGOs or government agencies.

The results also highlighted a positive impact of students' attitudes towards using AI on their behavioral intention. To cultivate such positive attitude, institutions may launch AI student ambassador programs in each college or faculty, empowering students to host peer-to-peer showcases, demo days, and hackathons that highlight the concrete academic and career benefits of AI tools. Complementing this, discipline-specific AI case studies should be embedded across lectures and assessments, with faculty incentives for innovative teaching practices.

Moreover, the research demonstrated a positive impact of AI relevance on students' behavioral intention. In streamlining practical relevance, universities may develop a personalized AI career planner within student portals, showing students how AI tools connect with their specific majors, career tracks, and personal aspirations. Student research grants might be offered to fund student-led investigations into innovative AI applications within their disciplines, with findings showcased at public student symposia.

Both AI for social good and AI relevance positively influenced students' readiness to utilize AI tools.

Educators and policymakers may leverage this by making AI competency a core graduate attribute, embedded through curriculum mapping and scaffolded across multiple courses. All degree programs should provide baseline AI fluency workshops, addressing tool use, ethics, and data privacy, and make these modules prerequisites for AI-integrated coursework. To monitor progress, institutions may conduct a regular (e.g., biannual, annual) AI readiness diagnostic survey which identifies skill gaps and following up with targeted interventions such as bridge modules, mentoring, or additional technical support.

The study revealed a significant positive relationship between AI readiness and behavioral intention. That said, universities may ensure the availability of well-structured educational materials that promote learner autonomy and recognize AI's societal benefits. Combined with regular assessments and systematic feedback loops in the previous recommendations, these actions can help students develop the confidence and competence needed to effectively integrate AI tools into their educational journeys.

References

Ang, S. M. O., & Aragon, M. J. D. (2020). Development of AI-Enhanced Information Technology Program: Preparing Today's Students in AI Era. EasyChair (No. 4049). https://easychair.org/publications/preprint_open/dQmN

Chai, C. S., Lin, P., Jong, M. S., Dai, Y., Chiu, T. K., & Huang, B. (2020). Factors influencing students' behavioral intention to continue artificial intelligence learning. 2020 International Symposium on Educational Technology (ISET). https://doi.org/10.1109/iset49818.2020.00040

Chai, C. S., Lin, P. Y., Jong, M. S. Y., Dai, Y., Chiu, T. K., & Qin, J. (2021). Perceptions of and behavioral intentions towards learning artificial intelligence in primary school students.Educational Technology & Society, 24(3), 89-101.

Dai, Y., Chai, C. S., Lin, P. Y., Jong, M. S. Y., Guo, Y., & Qin, J. (2020). Promoting students' well-being by developing their readiness for the artificial intelligence age. Sustainability, 12(16), 6597.

Estrellado, C. J., & Miranda, J. C. (2023). Artificial Intelligence in the Philippine EducationalContext: Circumspection and Future Inquiries. International Journal of Scientific and Research Publications, 13(5), 16–22. https://doi.org/10.29322/ijsrp.13.05.2023.p13704

Garland, K., & Noyes, J. (2005). Attitudes and confidence towards computers and books as learning tools: A Cross-sectional study of student cohorts. British Journal of Educational Technology, 36(1), 85–91.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California Management Review, 61(4), 5-14. https://doi.org/10.1177/0008125619864925

Hooda, M., Rana, C., Dahiya, O., Rizwan, A., & Hossain, M. S. (2022). Artificial intelligence for assessment and feedback to enhance student success in higher education. Mathematical Problems in Engineering, 2022.

Lee, M. C. (2010). Explaining and predicting users' continuance intention toward e-learning: An Extension of the expectation–confirmation model. Computers & Education, 54(2), 506–516.

Melchor, P. J. M. , Lomibao, L. S. , & Parcutilo, J. O. (2023). Exploring the Potential of AI Integration in Mathematics Education for Generation Alpha — Approaches, Challenges, and Readiness of Philippine Tertiary Classrooms: A Literature Review. Journal of Innovations in Teaching and Learning, 3(1), 39-44.

Olea, M. D. (2019). Application of Web 2.0 tools in teaching 21st – Century students in higher education institutions in Calabarzon, Philippines. International Multidisciplinary Research Journal, 1(1), 1-8. https://doi.org/10.54476/iimrj405

Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. International journal of educational technology in higher education, 18(1), 1-23.

Wu, I. L., Li, J. Y., & Fu, C. Y. (2011). The adoption of mobile healthcare by hospital's professionals: An integrative perspective. Decision Support Systems, 51(3), 587–596. https://doi.org/10.1016/j.dss.2011.03.003

Wu, J., & Wang, S. (2021). Factors influencing consumers' acceptance of AI-powered smart speakers: An empirical study. International Journal of Human-Computer Interaction, 37(12), 1269-1283.