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Examining GenAI readiness and behavioral intention of adult learners: a PLS-SEM and IPMA approach

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ABSTRACT

In the current rapidly changing technological landscape, emerging technologies such as generative artificial intelligence (GenAI) continue to disrupt adult learners' preparedness for the AI-driven future in the workplace and in society. This study aimed to explore the factors of adult learners' behavioral intention towards adopting GenAI. A quantitative approach was used where a self-administered online survey was randomly distributed to existing adult learners at an open and distance learning (ODL) institution in Malaysia. There were 484 responses, however, due to straightlining and outlier issues, only 460 were usable. Data analysis used SPSS version 28 for data cleaning and descriptive statistics, and SmartPLS 4 to perform partial least squares structural equation modelling (PLS-SEM) and the assessment of importance-performance matrix analysis (IPMA). The findings indicated that GenAI readiness constructs of ability and ethics positively predict adult learners' intention to adopt GenAI. Management of the university should address the performance gap in ability, maintain ethical awareness, and improve the performance of vision and cognition.

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1. INTRODUCTION

Artificial intelligence (AI) has evolved significantly since its inception, transforming numerous aspects of modern society [1], [2]. Over the decades, AI has progressed from its early stages in the 1940s and 50s to experiencing exponential growth in the 21st century, driven by advancements in computational power and technology [1]–[3]. This evolution has led to the emergence of generative artificial intelligence (GenAI) technologies, such as ChatGPT, Midjourney, and Heygen. GenAI possesses the ability to learn from vast datasets, recognize complex patterns, and generate novel outputs that resembles human-like intelligence [4]. This advancement has ushered in a new era of AI applications, from natural language processing and image generation to creative storytelling and music composition, sparking tremendous attention for their potential applications across various industries, including education [2], [3]. As emerging technologies such as GenAI continue to shape various industries and sectors, it is crucial for universities to cultivate learners' readiness to engage with GenAI effectively and responsibly [5]–[7]. This readiness involves having technical proficiency and ability, cognitive understanding, ethical awareness, and a forward-thinking vision regarding GenAI applications. When GenAI readiness is present, these learners will then have the behavioral intention to use or accept GenAI.

However, in reality, particularly among adult learners at open and distance learning (ODL) universities, limited face-to-face interaction and usage of traditional teaching methods may prevent the development of GenAI readiness among ODL adult learners [8]. For instance, they may not be able to experience nuances of communication from direct interpersonal interaction, neither will they be able to receive immediate feedback and support which are essential to building confidence and proficiency using GenAI technologies. This situation could lead to potential gaps in adult learners' preparedness for the AI-driven future in the workplace and in society. Without targeted interventions and support from the universities, adult learners may face challenges in fully embracing GenAI and leveraging its potential to enhance their learning experiences and future work.

The existing literature on GenAI readiness and behavioral intention among students reveals several significant gaps. First, there is a lack of comprehensive studies focusing on what influences students' readiness for GenAI technologies [5]. Recent research indicates a strong interest in AI readiness of students in the medical or science fields [7], [9], [10]. Second, despite the growing prominence of GenAI in the educational context, there are relatively few studies that have explored perceptions and intentions of students to use GenAI technologies such as ChatGPT to enhance learning environments that create effective learning experiences [2]. Finally, the slow uptake of AI technologies in current educational settings may be due to neglecting socio-techno factors. For instance, extant studies emphasize the significance of understanding students' and educators' preferences, social dynamics, and ethical considerations; however, these factors are often not prioritized in the development and deployment of AI technologies in the educational systems [3], [11]. These gaps suggest further research is needed to inform discussions on learners' readiness and behavioral intentions towards AI or GenAI tools. Against this backdrop, we intend to examine adult learners' readiness for GenAI and their behavioral intention within the specific context of ODL education. Insights gained from the findings of the study should be able to inform the design of appropriate interventions and policies to enhance GenAI preparedness among adult learners in the university. The study is based on two research questions:

i) What is the relationship between GenAI readiness and behavioral intention of adult learners?
ii) What is the most significant GenAI readiness factor predicting behavioral intention of adult learners?

2. RELEVANT STUDIES AND HYPOTHESES DEVELOPMENT

Technology readiness and acceptance model (TRAM) was derived from the integration of technology readiness index (TRI) and technology acceptance model (TAM) to provide a robust framework for understanding user acceptance of new technologies [12]. According to TAM, as posited by Davis [13], perceived usefulness and perceived ease of use are fundamental determinants of behavioral intention. This model has been empirically validated across studies. For example, Estriegana *et al.* [14] reported that students are more inclined to adopt the technology if they find it useful in enhancing their writing performance. Similarly, Yang and Wang [15] observed that the perceived ease of use is a critical and positive influence on students' intention to use machine translation.

Technology readiness refers to "people's propensity to embrace and use new technologies to accomplish goals in home life and at work" [16]. It measures whether an individual is ready to use a new technology [17]. Lin *et al.* [12] integrated the TRI into TAM, proposing the TRAM. Based on their analysis, perceived ease of use and perceived usefulness mediate the relationship between readiness and intention. Supporting these findings, Başgöze [18] reported that technology readiness's impact on mobile shopping intention is mediated by both perceived usefulness and ease of use. Likewise, Chen and Lin [19] found that technology readiness significantly and positively affects the perceived ease of use and usefulness of dietary and fitness apps. With this readiness, it is also able to predict the intention to download and use the apps.

As Lin *et al.* [12] articulated, technology readiness is a construct that is specific to the individual and not tied to any particular system. This means it encompasses factors that are inherent to the individual, whereas perceived usefulness and perceived ease of use are constructs linked to the characteristics of a given system. The current study is set to investigate how the personal factors of adult learners contribute to their behavioral intentions regarding GenAI use. Considering the range of GenAI tools available, which vary in ease of use and usefulness, it is possible that learners are evaluating different GenAI tools based on these varying system-specific factors. Therefore, this study excludes perceived usefulness and perceived ease of use, focusing instead on the individual factors' readiness, that drive behavioral intention.

Studies have also documented the direct impact of readiness on behavioral intention. Study by Omar *et al.* [20] highlighted that farmers' technology readiness predicted their behavioral intention to adopt the e-AgriFinance app. Rahim *et al.* [8] discovered that academic staff's technology readiness directly affects their behavioral intention to use ODL technology during the COVID-19 pandemic. Similarly, Anh *et al.* [21] noted that technology readiness positively influences the intention to apply AI in the accounting and auditing fields. In the context of this study, we explore the influence of GenAI readiness among adult learners on their behavioral intention to use GenAI.

Several research [6], [7] proposed the concept of AI readiness that has been redefined for medical students and educators, respectively. According to them, AI readiness consists of four constructs: cognition, ability, vision, and ethics. Cognitive readiness refers to an individual's understanding of the importance and function of AI in education, and the relationship between human and AI. The ability aspect is related to an individual's skills and competence in selecting and using AI for learning. Vision relates to an individual's recognition of AI's potential and limitations in the educational sector. Lastly, the ethics construct refers to the adherence to ethical and legal norms and regulations in AI's educational usage. As such, we hypothesize that: i) GenAI readiness has a positive significant influence on behavioral intention (H1); ii) ability has a positive significant influence on behavioral intention (H1a); iii) cognition has a positive significant influence on behavioral intention (H1b); iv) ethics has a positive significant influence on behavioral intention (H1c); and v) vision has a positive significant influence on behavioral intention (H1d).

3. METHOD

The current study is a quantitative self-administered survey based on purposively sampling. The required sampling size followed Hair *et al.* [22] rule of thumb of "10-times the maximum number of arrowheads" towards the dependent variable. Since there are four arrowheads of the constructs of ability, cognition, ethics, and vision pointing towards behavioral intention, the minimum sample size should be 40. The participants selected are all undergraduate and postgraduate students at an ODL institution who are active during the May 2023, September 2023, and January 2024 terms. The survey contains demographic items and the measurement items used to operationalize the construct were adapted from extant studies on technology readiness and behavioral intention. Specifically, we adapted items for GenAI readiness comprising of ability (6 items), cognition (5 items), ethics (4 items), and vision (3 items) from [6], [7], while items for behavioral intention (3 items) were adapted from Lai and Lee [23]. All items were rated on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Figure 1 illustrates all the hypothesized relationships examined in the study. Approval was given by the university's ethics committee to conduct the study. Respondents' participation was on a voluntary basis where they were informed of the purpose of the study and assured of confidentiality and anonymity as the data collected will be aggregated.

Prior to data collection, a face and content validity were conducted on the survey items and layout where four experts provided feedback. The survey was then revised accordingly. In total, 484 surveys were completed; however, 24 had to be deleted due to straight-lining or outlier issues. Thus, 460 responses were used in this study. The responses collected met the required minimum sample size of 40. Table 1 shows the respondents' profile summary. In general, there is nearly equal male and female respondents, with an approximate average age of 34 years; the majority of respondents are from the School of Business and Administration (54.13%) and mostly entering the university through regular type of entry. Additionally, a high percentage (68.04%) of the respondents have limited experience in using GenAI.

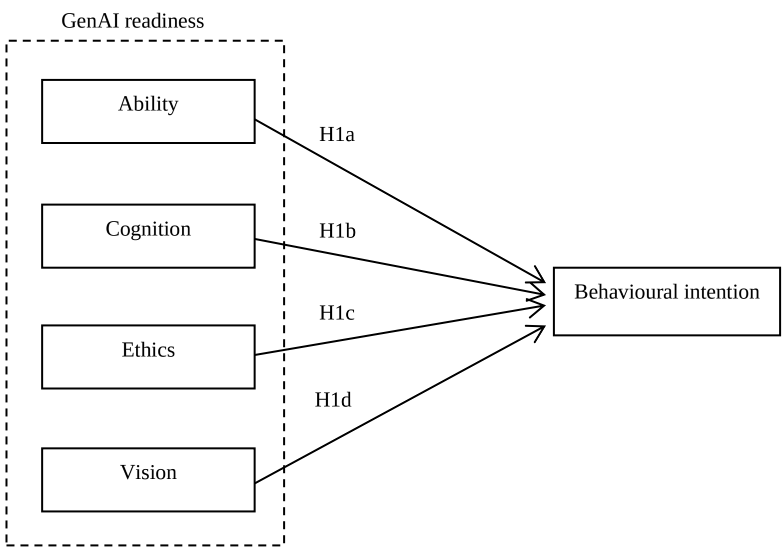

Figure 1. Research model

Table 1. Demographic profile of respondents (n=460)

Profile items		Frequency	Percentage (%)
Gender	Male	198	43.04
	Female	262	56.96
School	School of Business and Administration	249	54.13
	School of Technology and Science	106	23.04
	School of Education, Humanities, and Social Sciences	101	21.96
	School of Digital Technology	4	0.87
Type of entry	Regular	271	58.91
	APEL	189	41.09
GenAI usage experience	No experience	156	33.91
	Little experience	157	34.13
	Some experience	102	22.17
	Good experience	41	8.91
	Extensive experience	4	0.88
Age	Mean	34.32	
	Standard deviation	9.30	

Data was first analyzed using SPSS version 28 (for data cleaning and descriptive statistics). Next, SmartPLS 4 was used to assess the measurement (validity and reliability) and structural models (hypotheses testing), and conducting importance-performance matrix analysis (IPMA). According to Hair *et al.* [22], IPMA extends the basic PLS-SEM findings as it contrasts the total effects (importance) of the structural model and average values of the latent variable scores (performance) of the dependent construct, thus, highlighting significant areas of improvement. IPMA can also be used for constructs and indicators.

4. RESULTS

4.1. Measurement model

We used SmartPLS 4 to conduct the partial least squares structural equation modelling (PLS-SEM) on the research model. We followed the two-stage analysis procedures recommended by Hair *et al.* [22]. First, we tested the measurement model for validity and reliability. According to Hair *et al.* [22], convergent validity ensures multiple items that measure the same concept are not contradicting one another. It is determined with loadings, average variance extracted (AVE), and composite reliability. The loadings were all more than the threshold value of 0.7, while both the composite reliabilities and AVE were all also higher than the required values of 0.7 and 0.5 respectively, as presented in Table 2. Additionally, discriminant validity was also established between the constructs (Table 2) as the heterotrait-monotrait (HTMT) values were less than the 0.90 [24].

Table 2. Results of measurement model

Model construct	Reliability and convergent validity			Discriminant validity-HTMT				
	Factor loading range	CR (>0.7)	AVE (>0.5)	BI	AB	CO	ET	VI
Behavioral intention (BI)	0.923–0.942	0.952	0.868	***				
Ability (AB)	0.862–0.917	0.962	0.808	0.635	***			
Cognition (CO)	0.841–0.887	0.936	0.745	0.514	0.800	***		
Ethics (ET)	0.800–0.897	0.921	0.745	0.584	0.718	0.663	***	
Vision (VI)	0.848–0.895	0.911	0.773	0.566	0.815	0.746	0.827	***

Note: CR=composite reliability; AVE=average variance extracted

4.2. Structural model

As the measurement model was assured of construct validity and reliability, we continued with testing the structural model according to Hair *et al.* procedures [22]. The structural model captures all the hypothesized relationships between the constructs examined in this study. We also tested collinearity issues among the constructs. The constructs met the collinearity outer model threshold value of less than 5.0. In the structural model, we analyzed the path coefficients, the t-values and their significance levels, and confidence intervals, through a 5,000 resampling bootstrapping process, as they indicate how well the data supported the hypothesized relationships of the research model, as shown in Table 3 and Figure 2.

Two hypotheses (H1a and H1c) were supported as GenAI readiness of ability (β=0.438, $p<0.01$) and ethics (β=0.241, $p<0.01$) were positively significant to behavioral intention. The other two hypotheses (H1b and H1d) were not supported as GenAI readiness of cognition ((β=0.604, $p<0.01$) and vision (β=0.025, $p>0.05$) were found not significant to behavioral intention. The R^2 of behavioral intention is 0.392 meaning that 39.2% of the variance in behavioral intention can be explained by GenAI readiness of ability and ethics. Following Hair *et al.* [22], for assessing the effect size (f^2), the findings indicate small effect size for ability and ethics as the values are more than 0.02 (small effect) but less than 0.15 (medium effect). The Q^2 value for the endogenous construct (behavioral intention) is at 0.370 which is more than the criteria of more than zero. Hence, predictive relevance of the research model was established.

Table 3. Results of structural model

Relationship	Std beta (β)	t-value	95% Confidence interval	Effect size (f^2)	Decision
H1a. Ability→behavioral intention	0.427	5.749**	[0.277, 0.565]	0.096	Supported
H1b. Cognition→behavioral intention	0.006	0.091	[-0.124, 0.135]	0.000	Not supported
H1c. Ethics→behavioral intention	0.227	3.199**	[0.088, 0.364]	0.037	Supported
H1d. Vision→behavioral intention	0.024	0.365	[-0.103, 0.154]	0.000	Not supported

Note: **p<0.01; *p<0.05

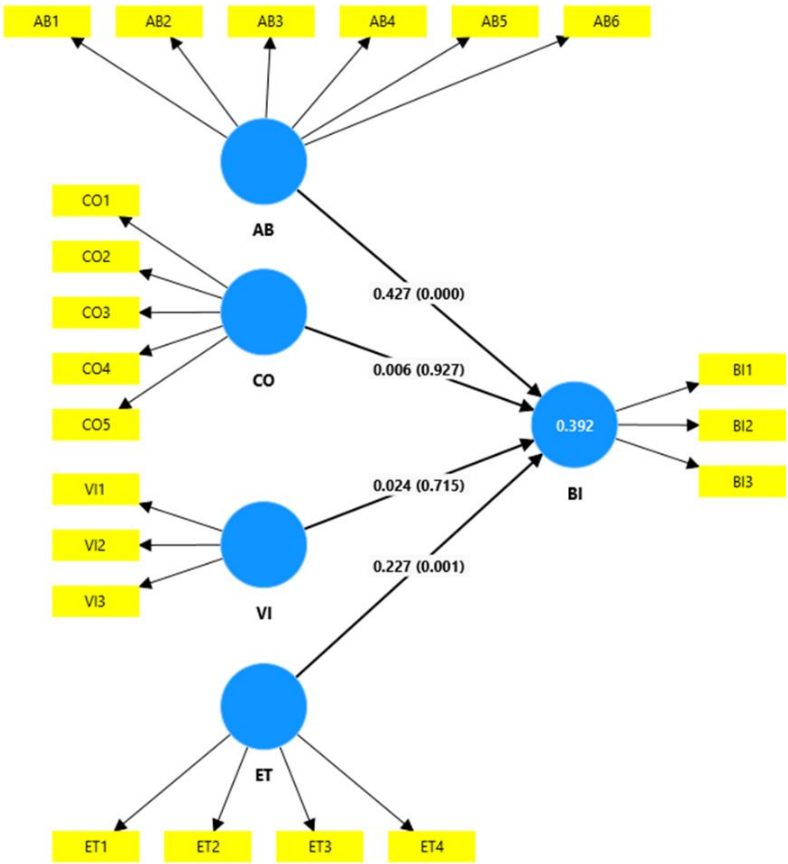

Figure 2. Results of structural model bootstrapping

4.3. Importance-performance matrix analysis

Next, we conducted the IPMA analysis. As mentioned earlier, IPMA is useful as it is able to extend the findings of PLS-SEM. An IPMA map was constructed for the GenAI readiness constructs as presented in Figure 3 using the performance and importance measures and data of this study. Table 4 shows the IPMA results based on total effects and performance. Based on performance, ethics has the highest perceived performance score (71.061), followed by vision (69.251), ability (69.210), and cognition (64.899). To identify areas for improvement, the IPMA scores for each construct can be compared. If the performance score is lower than the importance score, it indicates a performance gap that needs to be addressed. For example, although ability has high importance (0.427), its performance score is slightly lower, suggesting a gap that may require attention. Moreover, ethics ranks second highest in importance and highest in performance, indicating that it is significant and effective. On the other hand, cognition ranks the lowest in both importance and performance, suggesting an area where improvements may be needed.

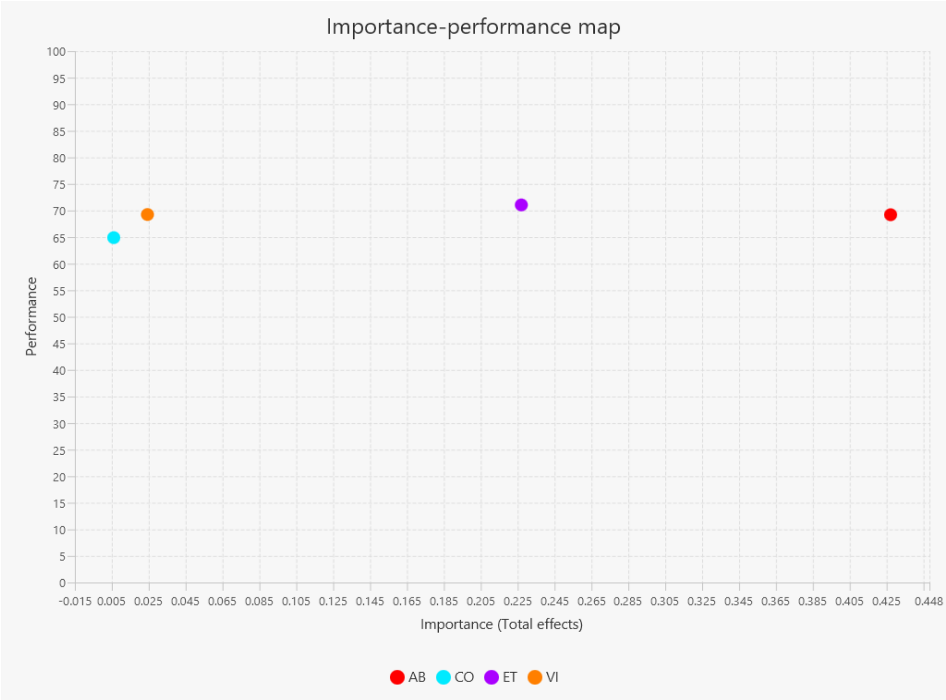

Figure 3. IPMA construct map

Table 4. Results of IPMA constructs

Indicators	GenAI readiness	
	Importance (total effects)	Performance (index values)
Ability	0.427	69.210
Cognition	0.006	64.899
Ethics	0.227	71.061
Vision	0.024	69.251

5. DISCUSSION

The PLS-SEM analysis revealed mixed findings for the relationship between GenAI readiness (ability, cognition, ethics, and vision) and behavioral intention to adopt GenAI. Firstly, neither GenAI readiness of cognition nor vision significantly affects the intention to use GenAI. This insignificance may be due to theoretical knowledge of GenAI does not necessarily lead to an intention to use GenAI [25]. Specifically, adult learners may understand the importance of GenAI for education; however, this does not automatically mean they will intend to use the GenAI in their learning. According to Chan and Zhou [25], knowing GenAI's definition, strengths and weaknesses are not enough for students to want to use GenAI. What is more important is for the students to have AI literacy and guiding them to use AI in a practical and effective manner. Dahlkemper *et al.* [26] revealed that students with prior experiences using AI will be more positive towards AI, thus, use it more often. In our study, the adult learners' demographic profile indicated that a high percentage of them have little or no experience using GenAI. This could explain the insignificance of cognition towards the intention to use GenAI. As students' cognitive readiness increases, they will be able to understand AI's role and significance in education and have awareness of the collaborative nature between humans and AI [6], [7]. Chan and Hu [27] argue that frequency of using GenAI can increase the intention to use AI. Perhaps if the university encourages or incorporates the use of GenAI in the adult learners' assignments or in the curriculum will the cognitive readiness increase [3]. Besides, GenAI garnered more interest since the popularity of ChatGPT at the end of November 2022 [28], and adult learners may still be uncertain regarding the benefits and potential of GenAI in their learning process.

As for vision, being one of GenAI readiness constructs, it relates to having a forward-looking outlook on GenAI's potential role in transforming education [6], [7]. Vision may be influenced by the strategic goals of the institution and the broader educational policies at play. For instance, Arizona State University, which have a clear strategic vision for AI, are currently working with OpenAI to enhance student achievements, create new innovative research opportunities, and increase organizational efficiency [29].

Through this strategic move, faculty and students may be more likely to align their own vision with that of the institution, thereby enhancing their readiness to adopt AI [29]. However, the ODL institution in this study has yet to have such strategic vision, thus, it is not surprising that the vision was found insignificant towards intention to adopt GenAI.

Secondly, GenAI readiness of ability and ethics have a significant positive relationship with behavioral intention, indicating that they are strong predictors of behavioral intention towards GenAI. Adult learners' ability in this study is a significant predictor of their intention to use GenAI. Here, the ability aspect involves the learners' skills and competence to select and use AI for learning [6], [7]. It is important to note that the measure of ability in this study does not capture the actual skills in using GenAI but rather the adult learners' perception of their capability. This concept is similar to the concept of perceived competence in the self-determination theory [30], self-efficacy [31], and perceived knowledge [32]. Kwak *et al.* [33] reported that self-efficacy predicts nursing students' behavioral intention in using AI-based healthcare technology. In research by Luik and Taimalu [32], it was found that student teachers' perceived knowledge about integrating technology had an indirect effect on the intention to use it. In the context of this study, the perceived ability to use GenAI in an ODL institution can be significantly influenced by the availability of resources, training, and institutional support. In higher learning institutions that provide robust support for GenAI integration such as through workshops, AI-powered tools, and accessible technology infrastructure, faculty and students are more likely to feel confident in their ability to use AI. For example, Mudawy [34] confirmed that familiarity to AI applications can be strengthened through training and support which can help facilitate better integration of new AI tools. Therefore, in order to increase the adult learners' behavioral intention to use GenAI in their learning, hands-on workshops should be provided to them so that they have the knowledge and skills to use GenAI in their learning.

The ethics construct relates to complying with ethical and legal norms and regulations when using AI [6], [7]. Data analysis shows that ethics positively affects adult learners' behavioral intention to use GenAI. This finding suggests that students who understand digital ethics and ethical responsibilities tend to feel a greater sense of accountability when using GenAI in their learning which in turn increases their intention to use GenAI. Besides, they show a greater inclination towards its use when equipped with knowledge on how to protect their personal information. However, extant studies were unable to determine if having ethics awareness influence behavioral intention to use GenAI among students [33], [35]. Despite GenAI's benefits in education, there is a need for clearer ethics guideline and transparency for adult learners to ensure responsible and ethical use of GenAI [36], [37]. As such, GenAI ethics should be integrated into the curricula and ethical frameworks established to prevent transparency, security and accountability issues when using GenAI [37]. The discussion of GenAI ethics has intensified with the rapid advancement of GenAI. However, most of the studies examined the ethical challenges [38] and different facets of ethics [39]. Research exploring the relationship between ethics and user behavioral intention is still in the infancy stage. Thus, this study contributes to the emergent body of knowledge by demonstrating how understanding and adhering to ethical norms shapes adult learners' intentions to use GenAI in their learning.

Finally, based on the IPMA results, there is a misalignment between the perceived importance and actual performance of GenAI readiness constructs among adult learners. Ability and ethics emerge as the two most essential constructs of GenAI readiness. Having the highest importance, ability is a critical factor in predicting behavioral intention to adopt GenAI among adult learners. The performance level is moderate, indicating that learners perceive themselves as somewhat capable of using GenAI, but there might still be room for improvement. Under the ODL context, adult learners are exposed more to the digital online realm than face-to-face interactions [8]. Besides that, they have to balance work, family, and education [40]. Thus, having the ability readiness to adopt GenAI is definitely needed. Institutions of higher learning should support and enhance adult learners' abilities through focused training programmers, user-friendly GenAI tools, and on-going technical support [34]. Ethics, being ranked second in terms of importance, is also deemed important in influencing behavioral intention to adopt GenAI. Having the highest performance indicates that ethical concerns about privacy, data security, and fairness in GenAI usage are being adequately addressed. Ethical considerations are important, especially for adult learners who may be wary of using GenAI due to data privacy issues or biased algorithms. Hence, institutions should continue to emphasize and communicate ethical AI usage and guidelines that reassure adult learners [36], [37].

Cognition and vision, on the other hand, are perceived as less critical, although their performance levels vary. Cognition placed lowest in importance as well as in performance. This result reinforces the insignificance of cognition and that it has minimal impact on behavioral intention, suggesting that adult learners may not have a deep understanding of GenAI, its functions, and features. Adult learners could be more interested in the practical aspects of GenAI [3], [25] instead of in-depth cognitive understanding. While it may not be necessary to enhance the cognitive GenAI readiness of adult learners, institutions could provide optional resources for those interested to learn more about AI or GenAI, without making it a core component of the GenAI adoption strategy. Despite its low importance, the performance level of vision is moderate.

The finding indicates that for adult learners, immediate benefits and practical applications of GenAI are likely to be deemed more important than long-term visions of GenAI's role in ODL. Adult learners may focus on GenAI tools that provide direct support in their current learning context over broader visionary ideas [27], [34]. Promotion of potential future GenAI benefits is inevitable due to its rapid influence in the education sector [4], [28]. Institutions may want to consider discussions on AI in their long-term strategy.

6. IMPLICATION

6.1. Theoretical implications

On a theoretical basis, the current study's findings confirm that the research model and measurement scales adapted from several studies [6], [7], [23] are valid and reliable for measuring GenAI readiness among adult learners from an ODL university. This expands the scope of the literature, which has largely focused on educators, medical students, and building information modeling (BIM) users. Additionally, the study also provides evidence that out of the four GenAI readiness constructs, ability and ethics are significant predictors of adult learners' behavioral intention to use GenAI. Between these two constructs, ability is the stronger predictor of behavioral intention. As such, the study contributes towards new insights into a different set of GenAI readiness constructs (ability, cognition, ethics, and vision) that influence the behavioral intention of GenAI among adult learners, instead of constructs of optimism, innovativeness, discomfort, and insecurity which are commonly used in extant studies [8], [16]–[19], [23].

6.2. Practical implications

The PLS-SEM findings and IPMA data reveal several practical implications for each GenAI readiness construct of adult learners in an ODL university. In general, adult learners in the ODL context often juggle with various work commitments and family responsibilities [40]. They may prefer straightforward, practical tools that enhance their learning experience without requiring deep cognitive engagement or visionary thinking. These adult learners are likely more concern with how GenAI can solve their immediate challenges such as time management [27], access to resources [27], [34], and ethical concerns [37], [38] rather than how GenAI might transform education in the long run. More specifically, the GenAI readiness constructs of ability and ethics are the most critical in influencing adult learners' behavioral intention to adopt GenAI. Institutions of higher learning should prioritize maintaining and enhancing these two areas. For ability, it could mean offering more hands-on training, simplified interfaces, and user support. For ethics, it is key to continue building trust through transparent AI policies and ethical practices. Cognition and vision have low importance. This finding suggests that while these two constructs may contribute to a deeper understanding and long-term engagement with AI, they are not immediately impactful on the decision to adopt GenAI. Institutions of higher learning could consider them as lower priorities and focus more on practical aspects that directly enhance the learning experience of adult learners.

7. CONCLUSION

The study examined the behavioral intention of adult learners towards GenAI adoption within an ODL higher learning institution. The novelty of this study is its exploration of the dimensions of GenAI readiness–ability, cognition, ethics, and vision–rather than the commonly used dimensions of innovativeness, optimism, discomfort and insecurity. Moreover, its context is based on a more specific context of adult learners and ODL. Additionally, data analysis was extended to include the IPMA approach, offering valuable insights in the dimensions of GenAI readiness. Overall, the study's findings contribute significantly to the technology/AI readiness literature, highlighting areas for improvement and providing recommendations to university managers and policymakers. Specifically, the PLS-SEM results indicate that ability and ethical readiness significantly predict adult learners' intention to adopt GenAI, aligning with IPMA results. However, the insignificance and relatively low performance of cognition and vision suggests a need for further exploration of these constructs in future research.

Additionally, although statistically significant, the small effect sizes of ability and ethics highlight a need for further investigation to better understand the relationship between these factors and behavioral intention. The study's scope which is limited to one ODL institution, restricts generalization. Subsequent studies should consider expanding the sample to include diverse learning environments such as other private higher learning institutions and public universities. Exploring antecedents of GenAI readiness and examining deeper into the ethics-behavior relationship are recommended. These future research avenues could provide valuable insights into ensuring wider GenAI adoption.

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REFERENCES

[1] C. Almaraz-López, F. Almaraz-Menéndez, and C. López-Esteban, "Comparative study of the attitudes and perceptions of university students in business administration and management and in education toward artificial intelligence," *Education Sciences*, vol. 13, no. 6, p. 609, Jun. 2023, doi: 10.3390/educsci13060609.

[2] E. M. Bonsu and D. Baffour-Koduah, "From the consumers' side: determining students' perception and intention to use ChatGPT in Ghanaian higher education," *Journal of Education, Society & Multiculturalism*, vol. 4, no. 1, pp. 1–29, Jun. 2023, doi: 10.2478/jesm-2023-0001.

[3] R. Luckin, M. Cukurova, C. Kent, and B. du Boulay, "Empowering educators to be AI-ready," *Computers and Education: Artificial Intelligence*, vol. 3, p. 100076, 2022, doi: 10.1016/j.caeai.2022.100076.

[4] T. K. F. Chiu, "The impact of generative AI (GenAI) on practices, policies and research direction in education: a case of ChatGPT and Midjourney," *Interactive Learning Environments*, pp. 1–17, Sep. 2023, doi: 10.1080/10494820.2023.2253861.

[5] Y. Dai, C.-S. Chai, P.-Y. Lin, M. S.-Y. Jong, Y. Guo, and J. Qin, "Promoting students' well-being by developing their readiness for the artificial intelligence age," *Sustainability*, vol. 12, no. 16, p. 6597, Aug. 2020, doi: 10.3390/su12166597.

[6] X. Wang, L. Li, S. C. Tan, L. Yang, and J. Lei, "Preparing for AI-enhanced education: conceptualizing and empirically examining teachers' AI readiness," *Computers in Human Behavior*, vol. 146, p. 107798, Sep. 2023, doi: 10.1016/j.chb.2023.107798.

[7] O. Karaca, S. A. Çalışkan, and K. Demir, "Medical artificial intelligence readiness scale for medical students (MAIRS-MS) – development, validity and reliability study," *BMC Medical Education*, vol. 21, no. 1, p. 112, Dec. 2021, doi: 10.1186/s12909-021-02546-6.

[8] N. N. A. Rahim, N. Humaidi, S. R. A. Aziz, and N. H. M. Zain, "Moderating effect of technology readiness towards open and distance learning (ODL) technology acceptance during COVID-19 pandemic," *Asian Journal of University Education*, vol. 18, no. 2, pp. 406–421, Apr. 2022, doi: 10.24191/ajue.v18i2.17995.

[9] G. Ö. Güven, Ş. Yilmaz, and F. Inceoğlu, "Determining medical students' anxiety and readiness levels about artificial intelligence," *Heliyon*, vol. 10, no. 4, p. e25894, Feb. 2024, doi: 10.1016/j.heliyon.2024.e25894.

[10] A. Y. Z. Tung and L. W. Dong, "Malaysian medical students' attitudes and readiness toward AI (artificial intelligence): a cross-sectional study," *Journal of Medical Education and Curricular Development*, vol. 10, pp. 1–8, Jan. 2023, doi: 10.1177/23821205231201164.

[11] S. B. Shum, R. Ferguson, and R. Martinez-Maldonado, "Human-centred learning analytics," *Journal of Learning Analytics*, vol. 6, no. 2, pp. 1–9, Jul. 2019, doi: 10.18608/jla.2019.62.1.

[12] C. Lin, H. Shih, and P. J. Sher, "Integrating technology readiness into technology acceptance: the TRAM model," *Psychology & Marketing*, vol. 24, no. 7, pp. 641–657, Jul. 2007, doi: 10.1002/mar.20177.

[13] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly: Management Information Systems*, vol. 13, no. 3, pp. 319–339, 1989.

[14] R. E. Valdehita, J. A. M. Merodio, and R. B. Plata, "Student acceptance of virtual laboratory and practical work: an extension of the technology acceptance model," *Computers and Education*, vol. 135, pp. 1–14, 2019.

[15] Y. Yang and X. Wang, "Modeling the intention to use machine translation for student translators: an extension of technology acceptance model," *Computers & Education*, vol. 133, pp. 116–126, May 2019, doi: 10.1016/j.compedu.2019.01.015.

[16] A. Parasuraman, "Technology readiness index (TRI): a multiple-item scale to measure readiness to embrace new technologies," *Journal of Service Research*, vol. 2, no. 4, pp. 307–320, May 2000, doi: 10.1177/109467050024001.

[17] Y.-W. Chang and J. Chen, "What motivates customers to shop in smart shops? The impacts of smart technology and technology readiness," *Journal of Retailing and Consumer Services*, vol. 58, p. 102325, Jan. 2021, doi: 10.1016/j.jretconser.2020.102325.

[18] P. Basgoze, "Integration of technology readiness TR in to the technology acceptance model TAM for M shopping," *International Journal of Scientific Research and Innovative Technology*, vol. 2, no. 3, pp. 26–35, 2015.

[19] M.-F. Chen and N.-P. Lin, "Incorporation of health consciousness into the technology readiness and acceptance model to predict app download and usage intentions," *Internet Research*, vol. 28, no. 2, pp. 351–373, Apr. 2018, doi: 10.1108/IntR-03-2017-0099.

[20] Q. Omar, C. S. Yap, P. L. Ho, and W. Keling, "Can technology readiness predict farmers' adoption intention of the e-AgriFinance app?" *Journal of Agribusiness in Developing and Emerging Economies*, vol. 13, no. 1, pp. 156–172, Jan. 2023, doi: 10.1108/JADEE-04-2021-0090.

[21] N. T. M. Anh *et al.*, "The effect of technology readiness on adopting artificial intelligence in accounting and auditing in Vietnam," *Journal of Risk and Financial Management*, vol. 17, no. 1, p. 27, Jan. 2024, doi: 10.3390/jrfm17010027.

[22] J. F. J. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modelling (PLS-SEM)*, 3rd ed. Thousand Oaks, CA: SAGE Publications, Inc., 2022.

[23] Y. L. Lai and J. Lee, "Integration of technology readiness index (TRI) into the technology acceptance model (TAM) for explaining behavior in adoption of BIM," *Asian Education Studies*, vol. 5, no. 2, p. 10, Oct. 2020, doi: 10.20849/aes.v5i2.816.

[24] G. Franke and M. Sarstedt, "Heuristics versus statistics in discriminant validity testing: a comparison of four procedures," *Internet Research*, vol. 29, no. 3, pp. 430–447, Jun. 2019, doi: 10.1108/IntR-12-2017-0515.

[25] C. K. Y. Chan and W. Zhou, "An expectancy value theory (EVT) based instrument for measuring student perceptions of generative AI," *Smart Learning Environments*, vol. 10, no. 1, p. 64, Dec. 2023, doi: 10.1186/s40561-023-00284-4.

[26] M. N. Dahlkemper, S. Z. Lahme, and P. Klein, "How do physics students evaluate artificial intelligence responses on comprehension questions? A study on the perceived scientific accuracy and linguistic quality of ChatGPT," *Physical Review Physics Education Research*, vol. 19, no. 1, p. 010142, Jun. 2023, doi: 10.1103/PhysRevPhysEducRes.19.010142.

[27] C. K. Y. Chan and W. Hu, "Students' voices on generative AI: perceptions, benefits, and challenges in higher education," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 43, Jul. 2023, doi: 10.1186/s41239-023-00411-8.

[28] K. Hu, "ChatGPT sets record for fastest-growing user base - analyst note," *Reuters*, 2023. [Online]. Available: https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/ (accessed Mar. 26, 2024).

[29] A. Davis, "A new collaboration with OpenAI charts the future of AI in higher education," *ASU News*, 2024. [Online]. Available: https://news.asu.edu/20240118-university-news-new-collaboration-openai-charts-future-ai-higher-education (accessed Mar. 26, 2024).

[30] C. S. Chai, T. K. F. Chiu, X. Wang, F. Jiang, and X.-F. Lin, "Modeling Chinese secondary school students' behavioral intentions to learn artificial intelligence with the theory of planned behavior and self-determination theory," *Sustainability*, vol. 15, no. 1,

p. 605, Dec. 2022, doi: 10.3390/su15010605.
[31] M. R. M. Rosman, M. A. A. Aziz, M. A. F. Osman, and N. M. Razlan, "Self-efficacy and user behavioral intention to use online consultation management system," *International Journal of Evaluation and Research in Education (IJERE)*, vol. 11, no. 3, pp. 1240–1249, Sep. 2022, doi: 10.11591/ijere.v11i3.22875.
[32] P. Luik and M. Taimalu, "Predicting the intention to use technology in education among student teachers: a path analysis," *Education Sciences*, vol. 11, no. 9, p. 564, Sep. 2021, doi: 10.3390/educsci11090564.
[33] Y. Kwak, J.-W. Ahn, and Y. H. Seo, "Influence of AI ethics awareness, attitude, anxiety, and self-efficacy on nursing students' behavioral intentions," *BMC Nursing*, vol. 21, no. 1, p. 267, Sep. 2022, doi: 10.1186/s12912-022-01048-0.
[34] A. M. A. Mudawy, "Investigating EFL faculty members' perceptions of integrating artificial intelligence applications to improve the research writing process: a case Study at Majmaah University," *Arab World English Journal*, vol. 1, no. 1, pp. 169–183, Apr. 2024, doi: 10.24093/awej/ChatGPT.11.
[35] W. Zhu *et al.*, "Could AI ethical anxiety, perceived ethical risks and ethical awareness about AI influence university students' use of generative AI products? An ethical perspective," *International Journal of Human–Computer Interaction*, pp. 1–23, Mar. 2024, doi: 10.1080/10447318.2024.2323277.
[36] M. da Silva, M. Ferro, E. Mourão, E. F. R. Seixas, J. Viterbo, and L. C. C. Salgado, "Ethics and AI in higher education: a study on students' perceptions," in *International Conference on Information Technology & Systems (ICTS)*, 2024, pp. 149–158. doi: 10.1007/978-3-031-54235-0_14.
[37] A. S. Valerio, "Anticipating the impact of artificial intelligence in higher education: student awareness and ethical concerns in Zamboanga City, Philippines," *Cognizance Journal of Multidisciplinary Studies*, vol. 4, no. 6, pp. 408–418, Jun. 2024, doi: 10.47760/cognizance.2024.v04i06.024.
[38] Z. Slimi and B. V. Carballido, "Navigating the ethical challenges of artificial intelligence in higher education: an analysis of seven global AI ethics policies," *TEM Journal*, vol. 12, no. 2, pp. 590–602, May 2023, doi: 10.18421/TEM122-02.
[39] D. Kim and Y. Ko, "Development and validation of ethical awareness scale for AI technology," *Journal of Digital Convergence*, vol. 20, no. 1, pp. 71–86, 2022.
[40] B. M. Joshi, U. Acharya, and P. Koirala, "Motivation for joining the open and distance learning mode program: student's perspectives," *OCEM Journal of Management, Technology & Social Sciences*, vol. 3, no. 1, pp. 160–167, Jan. 2024, doi: 10.3126/ocemjmtss.v3i1.62235.

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