FUTURE-READY FACULTY: EMBRACING GENERATIVE ARTIFICIAL INTELLIGENCE (GENAI) IN HIGHER EDUCATION

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ABSTRACT

Artificial intelligence (AI) in higher education (HE) is becoming a prominent area for researchers to explore. Perceived benefits of generative AI in HE includes adaptive learning, personalized pathways, quality content, student engagement, customized and prompt feedback, and intelligent tutoring systems. These benefits can be achieved if educators apply generative AI in their teaching in the right way; therefore, it is critical to explore the readiness of faculty to use AI. This study aims to explore the extent to which faculty members are ready to use AI in their teaching. Furthermore, identifying the factors affecting AI-readiness and behavioral-intention of faculty at open and distance learning institutions (ODL) is also a focus of this study. Using a quantitative research method, the study has collected data from ODL institution in Pakistan. Variables, including AI anxiety, confidence in teaching AI, AI relevance, AI for social good, attitude of using AI and perceived usefulness and AI-readiness of ODL faculty have been examined to measure their behavioral intentions towards using AI in their pedagogy. The online survey was sent to 200 faculty members of ODL from which 180 correctly filled questionnaires were received. Findings indicate that confidence in teaching AI, AI for social good, and relevance are the predictor of AI-Readiness whereas AI-Readiness is a good predictor of behavioral intention of ODL faculty members. This paper contributes to AI literature in higher education by emphasizing the AI benefits specifically in ODL through its faculty. The findings are helpful for higher education institutions (HEIs) to know the factors contributing towards readiness of ODL faculty to integrate AI in higher education, so that policies to adopt AI in education can be formulated. The findings are also important for apex bodies in higher education to identify the areas to be focused on for an effective use of AI.

Key Words: *AI, Generative AI, Behavioral Intention, Adaptive Learning, Readiness to use AI, Attitude to use AI, Open and Distance Learning (ODL)*

INTRODUCTION

The significance of technological advancements in the fiel d of higher education (HE) is duly recognized by researchers, making it as a critical element of education ecosystem (Sanusi et al., 2024). Educationists are now feeling a dire need to integrate artificial intelligence, especially generative artificial intelligence (GenAI) in the learning process as a pedagogical evolution (Chai et al., 2021). Owing to the unprecedented growth of GenAI[1] in education, all stakeholders need to equip themselves accordingly to keep pace with these technological advancements. In an AI

For this study AI and GenAI are used interchangeably. [1]

empowered future, market will demand more creativity, critical thinking and innovative solutions from the students (Camilleri, 2018; Kuleto et al., 2021). Therefore, educational institutions need to develop AI based curriculum to facilitate adaptive learning and boost student success. Here the role of faculty becomes critical in developing such a curriculum which not only prepares the students for an AI-powered workplace but also encourages them to consider AI as their potential career (Qin et al., 2019). The key challenge for the implementation of AI in learning process is the readiness and behavioral intentions of its stakeholders to incorporate it (Ayanwale et al., 2022; El Alfy et al., 2017). This readiness and behavioral intentions are equally important for the faculty, students and the institutions in a learning ecosystem. If anyone of them is not ready, it will hinder the implementation process as a whole. Teachers' knowledge about AI, their skills and readiness to teach is of utmost importance because of their central role in curriculum development (Ayanwale et al., 2022; El Alfy et al., 2017; Yu et al., 2021). Moreover, AI-enhanced education has also increased the level of expectations from teachers (Lin et al., 2023) to not only equip themselves with advance technologies but also empower the students to use technology effectively in their learning process (Lucas et al., 2021). Therefore, it is important to explore the readiness level of faculty at early level of implementation of AI in the education process to develop tailored curriculum (Ayanwale et al., 2022). Universities must focus on identifying the level of readiness and behavioral intentions of faculty to formulate policies regarding implementation of AI in education.

Literature has highlighted that most of the researchers have worked on exploring behavioral intentions and readiness to use AI in education among students of various discipline (Algerafi et al., 2023; Alzahrani, 2023; Ayanwale & Ndlovu, 2024; Chai et al., 2020; Chatterjee & Bhattacharjee, 2020; Chen et al., 2021; Ghimire et al., 2024; Li et al., 2022; Wang et al., 2025). In education, researchers have used several models to test the acceptance of AI among faculty, including the 'Technology Acceptance Model'-TAM (Davis, 1989), 'Unified Theory of Acceptance and Use of Technology'-UTAUT (Venkatesh et al., 2003), 'Theory of Planned Behavior', and 'AI Device Use Acceptance model'-AIDUA (Gursoy et al., 2019). Moreover, recent research also highlights the addition of new constructs to test behavioral intention to use AI in education, including self-efficacy, anxiety, attitude towards use, satisfaction, perception of use of AI for social good, AI-literacy, perceived social norms, intention to use AI, and perceived knowledge (Kelly et al., 2023). Whereas the research on behavioral intentions and readiness of faculty to use AI in education is limited in open and distance learning education. Although, the Open and Distance Learning (ODL) faculty is using technology in their teaching such as Learning Management Systems (LMS), online classrooms, presentation software, and many others. However, emerging technologies including augmented reality, robotics, and application of GenAI in HE is in its initial phases (Campbell & Frawley, 2024). Moreover, it is of utmost importance to explore the readiness and behavioral intentions of ODL faculty to use AI in their teaching because if they are ready to use emerging technologies it can not only broaden the access to content, but it will also increase accessibility for all learners. Therefore, this study aims to investigate readiness and behavioral intentions of ODL faculty to use AI in their teaching. The study also focuses on explaining interactions among various factors affecting AI-readiness, and how they influence intention to use technology statistically.

Objectives of the Study

The study aims to:

- Explore the extent to which faculty members are ready to use AI.

- Explore the behavioral intention of faculty towards using AI.
- Identify the factors affecting AI-readiness and behavioral-intention of faculty.

Significance

AI has revolutionized every field of life and education is not an exception (Hashmi & Bal, 2024; Lucas et al., 2021; Rahiman & Kodikal, 2024). Market size [2]for AI in education has grown from 3.99 billion euro in 2023 to 5.7 billion euro in 2024 with the application of digital platforms, personalized and adaptive learning systems, AI tutoring system and big data analytics. AI, specifically generative GenAI has become the driving force to integrate technological advancements in the transformation process of education and learning system (Wang, 2023). The profound benefits of GenAI in education are compelling the teachers to use AI in their teaching to make student learning more interesting, engaging, adaptive and with improved quality (Alfalah, 2018). Teachers, being at the front line to implement AI in learning process must have an adequate understanding about AI. Moreover, their readiness to use AI in education is also critical for AI enhanced education (Wang et al., 2023). Teachers equipped with AI tools can make learning more engaging, interactive and supportive for students (Van Leeuwen & Rummel, 2020). Therefore, it is significant to explore AI-readiness and the intention of faculty members to use AI in their teaching because it directly impacts the implementation of AI in education.

Furthermore, AI technologies having human-like cognitive capabilities ranging from knowing, learning, perceiving, sensing, acting, communicating, to reasoning which may have long lasting consequences for all actors of an ecosystem (Fernandes & Oliveira, 2021; Huang & Rust, 2018). Hence, it is critical to investigate AI-readiness and behavioral intention of faculty members as the findings will guide higher education institutions to devise policies accordingly. In order to timely embrace the growing use of GenAI, higher education institutions (HEIs) must proactively respond to associated challenges (Wang, 2023). and it is possible if HEIs are well aware about readiness of their front-line actors i.e. faculty members.

HEIs as the traditional centers of knowledge dissemination are also under pressure to transform learning from a teacher centered approach towards learner centered approach. In this effort, HEIs are also striving hard to rightly integrate AI in their education systems (Hashmi & Bal, 2024). This also requires a change in the roles of faculty members as facilitators and supporters of learning (Lin et al., 2023; Lucas et al., 2021), this shift in the role of teachers and HEIs is possible if the key players (teachers) who are responsible for this change are willing to take a step. It is also important for policy makers to know teacher's intention to use AI in education to identify their technological competence and training needs and to formulate policies for improvement (Zhang & Villanueva, 2023).

Hypotheses

The factors considered for the study are adapted from the study of (Ayanwale et al., 2022), AI-anxiety, perceived usefulness, confidence to use AI, AI for social good, attitude towards using AI, relevance of AI, readiness to use AI and behavioral-intention to use AI. Broadly framed on Theory of Planned Behavior (TPB), the aim of this study is to examine inter-relationship among AI anxiety, attitude of using AI, perceived usefulness, confidence in teaching AI, AI relevance, AI

AI in Education Global Market Report 2024: https://www.thebusinessresearchcompany.com/report/ai-in-education-global-market-report [2] for social good, AI-readiness and behavioral-intention of ODL faculty to use AI in their teaching practices. The relevance and significance of these variables to assess the technology acceptance is validated by previous studies (Chai et al., 2020; Chai et al., 2021; Keramati et al., 2011; Sing et al., 2022; Teo, 2011). Based on the above-mentioned studies, the following hypotheses have been developed for the current study:

AI Anxiety

AI anxiety is the measure of unusual feelings of an individual for the use of new technology, it is a unique feeling of discomfort while using a new technology (Ayanwale et al., 2022; Chai et al., 2020). Literature has highlighted the negative impact of AI anxiety on AI-Readiness and behavioral intention of users which varies from significant to insignificant in different contexts (Chai et al., 2020; Güven et al., 2024). Based on literature, the following hypotheses are developed:

H1: AI Anxiety and AI-readiness have a significant relationship.
H2: AI Anxiety and behavioral-intention have a significant relationship.

Confidence in Teaching AI

Another important factor which may affect AI-readiness, and behavioral intention to use AI is confidence. It refers to assurance in understanding the basic concepts and advanced material regarding new technology. High confidence reflects greater self-efficacy, hence, positively affects the behavioral intention to use technology and readiness level (Chai et al., 2020). Furthermore, literature has also proved that confidence is a significant predictor of attitude and intention to use technology (Chai et al., 2020; Chai et al., 2021). Therefore, the following hypotheses are developed to examine the interrelationship among confidence, attitude, readiness to use AI and behavioral intention of faculty members:

H3: Confidence in teaching AI and AI-readiness has a significant relationship.
H4: Confidence in teaching AI and the attitude of using AI has a significant relationship.
H5: Confidence in teaching AI and behavioral-intention has a significant relationship.

AI Relevance

Relevance is an association between individual’s internal needs and the subject matter being learned (Chai et al., 2020). It is an attitude toward an event (Ajzen, 1991), indicating how individuals perceive themselves in relation to AI technology. The relevance of AI in predicting AI- readiness and behavioral intention is also established by literature (Ayanwale et al., 2022; Chai et al., 2020). Sing et al. (2022), highlighted the factors which determine an individuals’ disposition towards learning, and these factors are regarding relevance of AI. For this study, the following hypotheses are developed:

H6: AI relevance and AI-readiness have a significant relationship.
H7: AI relevance and behavioral intention have a significant relationship.

AI for Social Good

A relatively new factor which predicts AI-readiness and behavioral intention is AI for social good Framed on Sustainable Development Goals (SDGs), AI For Social Good (AI4SG) movement highlights the opportunities of AI applications (Tomašev et al., 2020). This factor can play a significant role in determining AI-readiness and behavioral intention among faculty members. AI for social good is described as sustainable AI systems which are designed to reduce adverse impacts of AI on human well-being (Sing et al., 2022). Literature reported it as a strong predictor of students' intention to use AI, indicating their beliefs in the use of AI knowledge in solving social problems and improving lives of the people (Chai et al., 2020; Chai et al., 2021; Sing et al., 2022). This study, therefore, proposed the following hypotheses:

H8: AI for social good and AI-readiness has a significant relationship.
H9: AI for social good and behavioral intention has a significant relationship.

Attitude of using AI

TAM (Davis, 1989) explained how attitude predicts behavioral intention of individuals. The attitude of using AI is described as the level of an individual's favorable or un-favorable assessment of a particular behavior (Ayanwale et al., 2022). Testing TAM, previous studies have reported the significant role of attitude in determining behavioral intention among teachers and students (Ayanwale et al., 2022; Chai et al., 2020; Yu et al., 2021). Therefore, this study developed the following hypotheses:

H10: Attitude of using AI and AI-readiness has a significant relationship.
H11: Attitude of using AI and behavioral intention has a significant relationship.

Perceived Usefulness

Perceived usefulness is described as the level of belief of an individual about the use of technology that it will increase performance as a result of efforts. Perceived usefulness is a significant predictor of readiness, attitude, and behavioral intention (Ayanwale et al., 2022; Toros et al., 2024; Wang, 2023). Thus, this study proposed the hypotheses:

H12: Perceived usefulness and attitude of using AI have a significant relationship.
H13: Perceived usefulness and behavioral intention have a significant relationship.

AI-Readiness

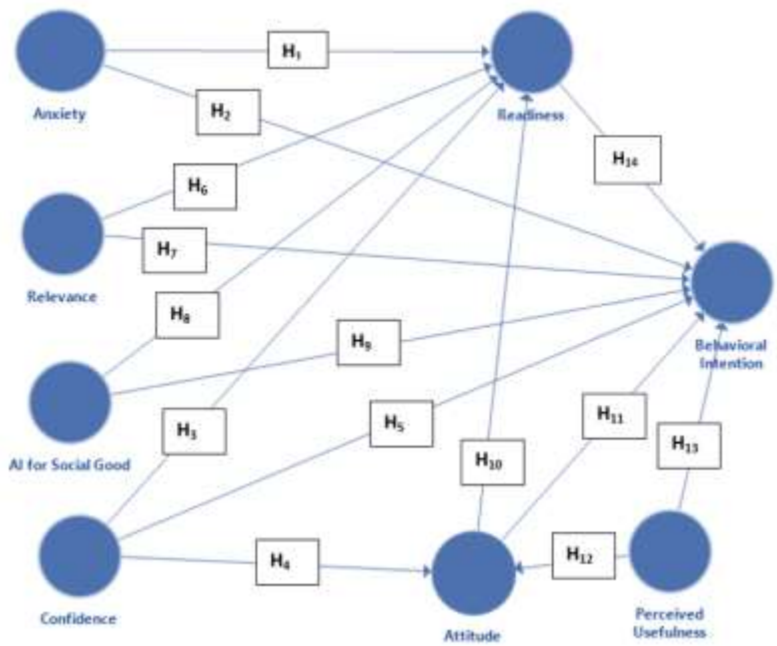
AI-readiness is a relatively new concept, it indicates the perceived comfort level of an individual with the use of AI technology, where the higher AI-readiness level favors the adoption of AI technology. Chai et al. (2020) explained AI-Readiness as a positive outlook toward technology usage. Literature has supported AI-readiness as a significant predictor of intention to use AI among students and faculty members (Ayanwale et al., 2022; Chai et al., 2021; Hammoudi Halat et al., 2024). Based on literature support, the following hypothesis is developed:

H14: AI-readiness and behavioral intention have a significant relationship.

Conceptual Model for Latent Variables

Figure 1 represents measurement model based on hypothesis where contribution of each construct is presented through a causal relationship.

Figure 1
Conceptual Model for Latent Variables



This study has proposed and tested a few additional interrelationships in comparison to the study of (Ayanwale et al., 2022) from which the scale is adopted. These additional interrelationships include anxiety and AI-Readiness (H1), perceived usefulness and attitude (H12), confidence and attitude (H4), and Attitude and readiness (H10). These interrelationships are extracted from literature review and based on which hypothesis have been developed.

METHODOLOGY

The study focuses on investigating the readiness of ODL faculty to adopt AI tools in their teaching methodology. By using multiple variables, including AI anxiety, confidence in teaching AI, AI relevance, AI for social good, attitude of using AI and perceived usefulness, the AI-readiness is measured, followed by the behavioral intentions of ODL faculty. Literature has supported the importance of studying psychosocial factors to investigate the acceptance of AI technologies. These psychological factors have already been studied by using theories including TAM, UTAUT, theory of planned behavior and AIDUA. Among these theories, TAM is the most frequently used model to access the acceptance of AI technologies among teachers and students (Kelly et al., 2023).

The study has targeted the faculty members of ODL mode of education to examine their behavioral indentations towards AI. The faculty of ODL is already familiar with informational technology as their day-to-day tasks are technology dependent (Selvaras, 2020), therefore, their specific intentions towards AI are significant to study to predict the likelihood of adopting AI in teaching. Furthermore, the infrastructure of ODL has the capacity to facilitate AI application in its education system (Carliner, 2004). In this study the online questionnaire was distributed among 200 faculty members who are directly involved in online student interactions. This selection criteria somehow ensures that students are aware of the online system and utilization of AI in ODL is relatively dependent on teachers' intentions and not on students' familiarity.

The data were collected through an online survey. The questionnaire developed by Ayanwale et al. (2022) was used to report responses on a 7-point Likert scale. The survey was comprised of two main sections; in the first section demographics (gender, age, job position, tenure, department, institution) of respondents were recorded. In the second section responses were reported on 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7) for all the variables of the study including AI anxiety, confidence in teaching AI, AI relevance, AI for social good, attitude of using AI and perceived usefulness, AI-readiness and behavioral intentions towards AI. The online survey was sent to 200 faculty members of ODL from which 180 correctly filled questionnaires were received. Among the respondents 60% were females while 40% were males and lie in the age bracket of 36 - 40 years. Most of the participants were lecturers in ODL mode of learning having teaching experience of 11 – 20 years.

FINDINGS

Data were screened for missing values and outliers on Statistical Package for Social Science (SPSS) 24. No missing values were found, however, there were two outliers which were removed from the data before performing analysis. Demographics of the respondents were analyzed using SPSS. The results are shown in Table 1. Most of the respondents were female who filled the questionnaire by representing 60% of the data. Remaining 40% were males. Age group of the majority (36.7%) of the respondents was ranging from 36 – 40 years, however, 25% of the respondents belongs to age group of 41 – 45 years. This shows that most of the respondents were middle-aged. With respect to professional experience, respondents having job tenure of 11 – 15 years and of 16 – 20 years have equal representation of 33.3% of the total responses. Therefore 66.6% of the respondents have notable job tenure as ODL teachers. Descriptive analysis shows that 51.7% of respondents were lecturers, 35% were instructors and 13.3% were assistant professors. This statistic also indicates the selection criteria that these faculty positions comparatively have direct interaction with students as compared to other faculty positions and are more relevant for the implementation of AI in teaching methods.

Table 1

Category		Frequency	Percentage
Gender	Female	108	60
	Male	72	40
Age	26-30	12	6.7
	31-35	33	18.3
	36-40	66	36.7
	41-45	45	25
	46-50	18	10
	More than 50 yrs	6	3.3
Job Position	Instructor	63	35
	Lecturer	93	51.7
	Assistant professor	24	13.3
Teaching Experience	Less than 1 year		
	1-5 years	27	15
	6-10 years	30	16.7

Demographics

Convergent Validity and Reliability of Constructs

Partial least squares structural equation modelling (PLS-SEM) was used to measure scale's reliability and validity. The measurement model includes 28 items with a range of 0.702 – 0.926 out loading which indicates all items are reliable because outer loading for all items is above 0.60 (Hair et al., 2017). Table 2. represents the convergent validity and reliability of constructs, where Cronbach's alpha of all constructs is greater than 0.70 indicating sufficient reliability of the scale. The composite reliability (CR) of each construct is greater than 0.70, whereas Average variance Extracted (AVE), a measure of convergent validity is greater than 0.50, indicating a satisfactory reliability and convergent validity of each construct in the measurement model. The median of each construct is also presented in Table 2. Results of the table indicate favorable responses for all the variables except AI anxiety. This shows that respondents are confident about their ability to teach AI, are likely to show positive attitude towards using AI, are perceived to promote AI for social good, and have positive intention to use AI in their teaching practices. Faculty members have shown a positive readiness for AI and agree on its relevance in their teaching.

Table 2.
Convergent Validity and Reliability of constructs

Constructs	*Cronbach's alpha*	*Composite reliability (CR)*	*Average variance extracted (AVE)*	*Median*
AN	0.793	0.976	0.678	2.0
AT	0.779	0.780	0.695	6.0
BI	0.919	0.919	0.756	6.0

CON	0.706	0.705	0.630	5.5
PU	0.848	0.863	0.688	6.0
RA	0.752	0.767	0.668	6.0
RE	0.830	0.927	0.627	4.5
SG	0.750	0.855	0.659	6.0

Source: Authors own work
Note: AN= AI Anxiety, AT= Attitude to use AI, BI= Behavioral Intention, CON=Confidence to use AI, PU= Perceived Usefulness, RA= relevance, RE= AI-Readiness, and SG= AI for Social Good

Discriminant validity has been tested using heterotrait-monotrait correlation (HTMT). To establish discriminant validity, the HTMT values should not exceed 0.90 (Henseler et al., 2015). Table 3. indicates that discriminant validity is established for the constructs of the current study as all values are less than 0.90

Table 3.
Discriminant validity-HTMT matrix

	AN	***AT***	***BI***	***CON***	***PU***	***RA***	***RE***	***SG***
AN								
AT	0.480							
BI	0.197	0.580						
CON	0.410	0.530	0.597					
PU	0.144	0.588	0.479	0.320				
RA	0.398	0.750	0.764	0.748	0.717			
RE	0.168	0.146	0.285	0.459	0.198	0.222		

Source: Authors own work
Note: AN= AI Anxiety, AT= Attitude to use AI, BI= Behavioral Intention, CON=Confidence to use AI, PU= Perceived Usefulness, RA= relevance, RE= AI-Readiness, and SG= AI for Social Good

Structural Model Analysis

A structural model explains causal relationships among the latent variables, providing R^2 value and path coefficients to determine the predictive power of each construct (Aburumman et al., 2022; Hair et al., 2021). For this study, a structural model is tested using PLS-SEM, the path coefficients, t-statistics, p-values and size effect (f^2) is presented in Table 4:

Table 4

Structural Model Path Coefficients

Hypothesis	Path links	Path coefficients (β)	t-statistics	Effect size(f2)	p-values
H1	AN -> BI	0.036	1.323	0.002	0.638
H2	AN -> RE	0.096	0.471	0.010	0.186
H3	**CON -> AT**	**0.289**	**4.115**	**0.114**	**0.000***
H4	CON -> BI	0.108	1.280	0.011	0.201
H5	**CON -> RE**	**0.564**	**8.396**	**0.293**	**0.000***
H6	**RA -> BI**	**0.452**	**3.918**	**0.164**	**0.000***
H7	RA -> RE	0.137	1.697	0.013	0.090**
H8	SG -> BI	-0.019	0.280	0.000	0.779
H9	**SG -> RE**	**-0.302**	**3.434**	**0.071**	**0.001***
H10	**AT -> BI**	**0.203**	**3.074**	**0.043**	**0.002***
H11	AT -> RE	-0.080	0.979	0.005	0.327
H12	**PU -> AT**	**0.413**	**5.295**	**0.233**	**0.000***
H13	PU -> BI	0.011	0.129	0.000	0.897
H14	**RE -> BI**	**0.176**	**3.413**	**0.042**	**0.001***

Source: Authors own work

Note: AN= AI Anxiety, AT= Attitude to use AI, BI= Behavioral Intention, CON=Confidence to use AI, PU= Perceived Usefulness, RA= relevance, RE= AI-Readiness, and SG= AI for Social Good. *Significant at 5%, ** significant at 10%

P-values in Table 4 indicate acceptance of seven hypotheses (H3, H5, H6, H9, H10, H12, and H14) at 5% significance level whereas, H7 is also accepted at 10% significance level. Six hypotheses were not accepted as p-values are insignificant. Among significant paths, all factors are positively affecting their respective dependent variables EXCEPT AI for social good which has a significant inverse impact on AI-readiness. Size effect (f^2) measures the extent to which each exogenous variable explains an endogenous variable. Table 2. indicates a moderate effect size of CON -> RE (0.293), RA -> BI (0.164), and PU -> AT (0.233) among other significant variables. Effect size (f2) is moderate when its value is >=0.15 whereas for a value of >=0.02 it is considered as small effect. Furthermore, R-square for AI-readiness, Attitude of using AI, and Behavioral Intention is 0.279, 0.313, and 0.492 respectively. The highest value of R-square (49.2%) accounted for the variance observed in Behavioral Intention to use AI in teaching practices of ODL faculty. In addition to this, the collinearity is also tested through variance inflation factors (VIF), all values of VIF are less than 5 that is optimal (Hair et al., 2017). Predictive relevance of the endogenous constructs is also measured using Q2 statistics. The results are presented in Table 5 indicating that models have predictive relevance because Q2 values are greater than 0 (Hair et al., 2017).

Table 5
Predictive relevance of the endogenous constructs

	Q^2predict
AT	0.285
BI	0.409
RE	0.236

Source: Authors own work
Note: AT= Attitude to use AI, BI= Behavioral Intention, and RE= AI-Readiness

The study also examined the indirect effects among variables as mediators. The results indicate SG -> RE -> BI (p-value =0.005), CON -> AT -> BI (p-value =0.010), PU -> AT -> BI (p-value =0.009), and CON -> RE -> BI (p-value =0.001) as significant mediating paths. It shows AI-readiness mediates the relationship between AI for social good and behavioral intention in one path while it mediates the relationship between confidence in teaching AI and behavioral intention in the second path. Similarly, the attitude of using AI also mediates two paths; first it mediates the relationship between confidence in teaching AI and behavioral intention and secondly it mediates relationship between perceived usefulness and behavioral intention. Whereas sequential mediation CON -> AT -> RE -> BI and PU -> AT -> RE -> BI are insignificant.

DİSCUSSİON, CONCLUSİON AND FUTURE RESEARCH DİRECTİON

Teachers, being one of the key stakeholders in AI-enhanced education (Ayanwale et al., 2022; Celik et al., 2022) are the front-line actors for the implementation of AI in education. Therefore, understanding their perspectives about AI in education, needs, and experiences are vital to develop acceptance and use of this innovative technology in learning system. It is important for HEIs to be aware of readiness of faculty for the application of AI tools in order to foster AI-enhanced education and to formulate policies accordingly. Moreover, faculty members are expected to have an adequate level of AI understanding by being its user as well as educator (Wang et al., 2023). It is also important to explore AI-readiness and behavioral intention of faculty because development of AI-based curriculum is also an essential step towards AI-enhanced education, and faculty is central for the development of such a curriculum. Moreover, there are limited studies on exploring AI-readiness and intention of faculty members, specifically in the context of ODL. Underpinned by Theory of Planned Behavior (TPB) this study contributes to the existing literature by investigating AI-readiness and intention to use AI in teaching practices of ODL faculty. Variables under study include, AI anxiety, AI relevance, AI for social good, Attitude of using AI, perceived usefulness, Confidence in teaching AI, AI-Readiness, and Behavioral Intention to use AI.

Strengthening the inferences of previous studies Ayanwale et al. (2022) and Lucas et al. (2021), the results of this study indicate that confidence in teaching AI, AI for social good, and AI relevance are the predictors of AI-readiness among ODL faculty members. This study highlights that the faculty members are confident in teaching AI, and they perceive AI as relevant in their teaching practices. Whereas faculty members also expressed readiness to learn AI based on their perception of AI for social good (Chai et al., 2021). Literature also advocates the role of AI for social good in developing intentions to learn this new technology (Chai et al., 2021). Contrary to Ayanwale et al. (2022), the faculty members in ODL institutions are ready to learn AI with a perception that AI contributes to social good. Among the three predictors of AI-readiness, confidence is the strongest one because ODL teachers are already using technology in their teaching and are ready to adopt future advancements. Literature supports that an individual is more likely to adopt technology if one is confident about its application (Chai et al., 2020). Among other predictors, AI anxiety and attitude of using AI are insignificant in an online education system. AI anxiety does not predict AI-readiness of ODL faculty because they are already in a system where technology is an essential element (Chai et al., 2020).

Behavioral intention of faculty members to use AI in their teaching practices is predicted by relevance of AI, attitude of using AI, and AI-readiness; these results are in-line with the findings of (Ayanwale et al., 2022; Chai et al., 2020; Chai et al., 2021; Wijnen et al., 2023). Among these predictors, relevance of AI is the strongest one in predicting behavioral intentions towards AI. The results also indicate the significance of AI-readiness for a successful implementation of AI-enhanced education. The higher the AI-Readiness, the more the faculty members likely to integrate technology in their teaching practices (Ayanwale et al., 2022; Zhang & Villanueva, 2023). Therefore, the faculty members with positive AI-readiness may perform better in problem solving, critical thinking, and technical skills (Zhang & Villanueva, 2023).

Furthermore, AI anxiety, perceived usefulness of AI, confidence to use AI, and AI for social good are not directly predicting behavioral intention of faculty members. The study has contributed to the literature by testing mediation effects of some variables; AI-readiness mediates the relationship between AI for social good and behavioral intention which was not significant in direct path. It shows that faculty members' perception about the contribution of AI for social good affects their intention to use AI in the presence of AI-readiness. Similarly, AI-Readiness also mediates the relationship between confidence and behavioral intention. It implies that confidence in teaching AI will positively affect the intention to use AI depends on AI-Readiness. Another mediator, identified through this study is attitude to use AI, which mediates relationship between CON -> BI and PU -> BI. Perceived usefulness, an important factor of behavioral intention is significant, if faculty has a positive attitude towards AI use. These findings are significant to formulate strategies for successful AI-enhanced education.

The current study empirically validated the importance of AI-readiness and behavioral intention of ODL faculty to use AI in their teaching practices which has important implications for policy makers, and other stakeholders of educational ecosystem. The findings are important for HEIs to focus on faculty's readiness and intention to use technology as part of their teaching process and to plan training for them. Moreover, understanding AI-Readiness among faculty will help HEIs to formulate AI implementation strategies, as readiness strongly shapes behavioral intentions. HEIs and other stakeholders can benefit from the results of the study to identify the key areas regarding development of the faculty. The findings are also important for faculty members of other HEIs to understand the need to invest more time and effort in integrating technology into teaching for a successful implementation of AI in education (Lin et al., 2023). Moreover, faculty have to face the challenges of ethical and responsible use of AI, data privacy, reluctance towards AI adoption, and AI literacy to successfully integrate AI in higher education (Muzaffar & Fatima, 2026). Therefore, the role of faculty is critical in managing these challenges for an effective integration of AI in education. Moreover, reliable institutional infrastructure is also important to accelerate responsible use of AI. Similarly, along with reliable infrastructural support, universities also need to focus on support structures that facilitates contextualized assistance for pedagogies, policy guidance, and supportive leadership for fair resource allocation and workload recognition (Luo & Day, 2026). Such facilitation will help faculty and HEIs to make AI adoption as an integrated effort rather than an individual initiative.

In addition, the readiness and intention of faculty towards AI is critical to make it a part of the education system, from curriculum development to empowering students with AI tools. If faculty are ready and willing to use AI in their teaching, it will not only leverage the AI-enhanced learning but also contribute towards a successful implementation of AI in the educational ecosystem. Therefore, HEIs need prioritized faculty-focused strategies to build AI competence for a responsible and ethical use of AI leading towards a value-based integration of AI in education. This paper contributes to AI literature in higher education by emphasizing the AI benefits specifically in ODL through its faculty. Future studies can be conducted to explore the role of other factors in adoption of AI in higher education like facilitating conditions. Literature supports the role of facilitating conditions for both intention and actual adoption of AI in HEIs. Furthermore, individual attributes of faculty including AI competence, personal innovation, teaching value etc. may also contributes significantly towards readiness to use AI and its adoption in HEIs. Future research can be conducted to explore these individual level attributes to analyze the significance of these attributes for AI readiness and adoption among faculty.

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