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Acceptance of Artificial Intelligence Application in the Post-Covid Era and Its Impact on Faculty Members' Occupational Well-being and Teaching Self Efficacy: A Path Analysis Using the UTAUT 2 Model

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ABSTRACT
The purpose of the present study was to assess acceptance of Artificial Intelligence Application in the Post-covid Era and its impact of faculty members' occupational well-being and teaching self efficacy using The UTAUT 2 Model. This study used a quantitative, non-experimental survey design to answer the research questions and study the relationships between the independent variables of performance expectancy, effort expectancy, social faculty members' occupational well-being and teaching self efficacy. Faculty members from Umm AL-Qura University were targeted. An online questionnaire was used to collect data via Facebook and WhatsApp groups. I received a total of 350 questionnaire responses. They were 200 males (57.1%), and 150 females(42.9%). In confirmation of the research results, there is a significant positive relationship ($p < .001$) between occupational well-being (OWB)and teaching self efficacy(TSE) and performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), price value (PV), and habit (HB), indicating that faculty members are influenced by the constructs established in the UTAUT2 model in the adoption of AI.

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Introduction

In April 2020, the peak of global lockdowns, the pandemic disturbed learning for over 1.6 billion students in about 190 countries (Düzyol and Yıldırım 2022; Sanal-Erginel 2022; Çoban and Yazıcı 2022). Globally, universities are expected to offer education to students despite the pandemic (Taner et al. 2021). Thus COVID-19 has severe implications for the attainment of Sustainable Development Goal 4 (SDG4) since education is among the sectors that were strongly impacted by the pandemic (Kurtdede Fidan and Yıldırım 2022; Ulaş et al. 2021).

The great progress of science and technology has promoted the rapid development of Artificial Intelligence(AI). Artificial intelligence is observed as an area

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of computer science that observes intelligent machines that operate and think like humans. This includes speech recognition, natural language processing (NLP), image recognition, etc (Gültekin 2022). ML presents the usage of AI in enabling the systems to learn and develop based on experience without explicitly programming them to do so. In machine learning, for example, computers learn from data, not coded instructions (Duangekanong 2022; Varzaru 2022).

The use of AI in different fields boomed in the last years, teaching and learning in higher education being only one dimension of this evolution. Innovative digital solutions emerge almost every month from sectors that are as different as possible, such as health, manufacturing, logistics, creative industries, design, defense, public goods, accountability, and many others. Therefore, investigating the implications of emerging technologies for education is an important aspect. Artificial intelligence is progressing at an accelerated pace, which already impacts the profound nature of services within higher education. On one hand, students should learn how AI will change the future of jobs (Bucea-Manea-Țoniş et al. 2022).

Recently, the educational community has recognized AI's potential to facilitate learning in various contexts (Hwang et al. 2020). Artificial Intelligence in Education (AIEd) is primarily concerned with the development of computers that perform cognitive tasks, typically associated with human minds, especially learning and problem-solving education for all ages should prepare society for the future and help humans achieve self-fulfillment (2019). In the age of artificial intelligence, education is both difficult and an opportunity (Ocaña-Fernández, Valenzuela-Fernández, and Garro-Aburto 2019). New learning channels, including learning management systems based on digital textbooks, tailored learning via big data learning analysis, interactive technologies based on voice recognition and speech synthesis, and chatbots driven by natural language processing (NLP), are being created (Ekin 2022). The majority of AI technologies have educational and instructional uses. Education is necessary for a person's complete growth (Sulak 2021). Theoretically, technology, particularly AI, in contemporary education enhances educational material, transforms educational perspectives, and disrupts old educational paradigms.

With the increased usage of AI technologies for teaching and learning, instructors may eliminate time-consuming and repetitive duties and deliver rapid replies to students, promoting adaptive and personalized learning. Specifically, hardware developments, such as high-speed graphics processing units and the availability of software libraries have enhanced AI technologies, particularly with the expansion of deep learning research and data analysis methods. In addition, the future development of education will be intimately linked to the future expansion of AI. Future education will become more innovative and thrive as new technologies, and the computing capacities of intelligent computers continue to grow. AIEd research covers several subdisciplines (İçen 2022).

Occupational (or career) wellbeing refers to feeling good about the work you do. The rise of AI has the potential to enable workers to feel more engaged in their role and happier in their workplace. Self-efficacy is one's belief in their ability to execute a particular task or behavior (Acar 2022; Arslan and Karameşe 2018; Bandura 1982; Gündoğdu, Dursun, and Saracaloğlu 2020; Uyar and Öztürk 2022). Park (2009) found that self-efficacy was the most significant variable in predicting intention to use. Previous research revealed that in individual with a high level of self efficacy intention might be more likely to facilitate goal achievement and perceived overall self-efficacy contributes significantly to the motivation and performance of an individual (Bandura and Locke 2003).

People use various AI-enabled technologies and devices to self-administer multiple benefits according to their requirements. Essentially, an AI system tailors an appropriate response or service to fit users' requirements based on users' inputs into the system. Information inputs, including question-answer sessions, allow AI machines to learn about users' specific requirements and conditions and determine particular features such as size, color, time, measurement and weight, and so on to conform closely to users' needs (Uzir et al. 2021). Holmstrom (2022) noted the importance of an organization's readiness to deploy AI technologies if they wish to be successful.

A good number of studies were reported on factors influencing the adoption of digital technologies in teaching and learning in time of crises such as COVID-19. For example, Fatimah, Rajiani, and Abbas (2021) the influence of culture and individual characteristics in the adoption of computer-based collaborative learning during the pandemic such as COVID-19 was carried out. Structural Equation Modelling (SEM) was used to assess the relationship among the construct. The results showed that students' perception of computer-based collaborative learning positively associated with the student's personality and cultural beliefs.

Technology Acceptance Model (TAM) was adopted and the following significant internal factors were identified by the author: perceived ease of use and perceived usefulness, while infrastructure and device access were considered partially as external factors (Aly 2020).

Despite the aforementioned merits, there is no study known to the authors at the time of this study on **acceptance of artificial intelligence application in the post-covid era and its impact of faculty members' occupational well-being and teaching self efficacy using the utaut 2 model**. That is why this study is needed.

Statement of the Problem and Purpose

The specific research problem this study addressed was the lack of knowledge regarding acceptance of Artificial Intelligence Application in the Post-covid Era and its impact of faculty members' occupational well-being and teaching self efficacy in the light of The UTAUT 2 Model. The scholarly literature indicates that AI offers many benefits when implemented (Brown and Brown 2019; Butler 2020; Dobrescu and Dobrescu 2018; Matt, Hess, and Benlian 2015; Vial 2019; Ziyadin, Suieubayeva, and Utegenova 2020). The research also indicates that AI is challenging to implement, and many educational institutions fail (Heaven and Power 2018; Willcocks 2021). The present study addressed the gap in the literature by investigating how the UTAUT2 factors of performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and habit influence faculty members' occupational well-being and teaching self efficacy.

The purpose of the present study was to assess acceptance of Artificial Intelligence Application in the Post-covid Era and its impact of faculty members' occupational well-being and teaching self efficacy using The UTAUT 2 Model.

Literature Review

The UTAUT 2 Model

The distinction in recognition of any modern technical know-how is also focused mainly on technology acceptance models in the literature. These models also clarified the reasons that measure these technologies' acceptance (Raghavan, Jayasimha, and Nargundkar 2020). Davis, Bagozzi, and Warshaw (1989) used TAM to explain computer usage behavior. Davis, Bagozzi, and Warshaw (1989) study compared the Technology Acceptance Model (TAM) with Theory of Reasoned Action (TRA) and resulted in the convergence of TAM and TRA. In addition to its utility, it has been observed that TAM is once forecasting less than 50% of embracing scientific cases (Park 2009). Thus, on the grounds of a comprehensive literature review on technical acceptability (Venkatesh et al. 2003), the UTAUT model was suggested that will eventually help to overcome TAM's vulnerabilities.

UTAUT was developed by Venkatesh et al. (2003). This model has four core constructs. It predicts users' behavior intention and the actual use (performance expectancy PE, effort expectancy EE, social influence SI, and facilitating conditions FC). It is worth mentioning that the UTAUT model includes the theory of reasoned action (TRA), information diffusion theory (IDT), theory of planned behavior (TPB), technology acceptance model (TAM), a combined model of TAM and TPB (C-TAM-TPB), motivational model (MM), model of personal computer utilization (MPCU), and social cognitive theory (SCT) (Venkatesh et al. 2003).

Shen and Chuang (2010) pointed out that while verifying students' attitudes and behavioral intentions by the extended TAM with interactivity and self-efficacy, it was found that attitudes and behavioral intentions were affected by interactivity, self-efficacy, usability, and perceived usefulness.

The findings of Alkhwaldi and Abdulmuhsin (2022) revealed that performance expectancy, facilitating conditions, TR and AUT were the significant predictors of distance learning acceptance in both samples. By identifying the factors affecting the acceptance of distance learning systems, it will be more useful to offer better services of distance learning.

Upadhyay, Upadhyay, and Dwivedi (2022) aimed to determine the entrepreneur's intention to accept artificial intelligence (AI) and provide advancement in the domain of digital entrepreneurship. The findings revealed that performance expectancy, openness, social influence, hedonic motivations and generativity have a positive impact on entrepreneur's acceptance intention of AI. Additionally, affordance has no direct relationship with AI acceptance intention, but it affects AI acceptance intention through attitude.

Results of Eimler, Krämer, and von der Pütten (2011) indicate that people infer specific emotional states from the robot rabbit's different ear positions. Also illustrated is that observers' attribution of feelings to the rabbit depends on their cultural backgrounds. Implications and questions for future research are discussed.

Performance Expectancy (PE)

Performance expectancy (PE) is defined as the level to which an individual believes that the system helps to improve job performance (Venkatesh et al. 2003). The concept is associated with the usefulness of a technology (Zhou et al. 2022). Venkatesh et al. (2003) advocate that PE is the strongest factor of behavioral intention (BI) for adopting technology. Attitude plays a pivotal role and is expected to be affected by PE. Attitude is conceptualized as an individual's characteristics affecting the behavior to adopt AI (Chatterjee et al. 2021). These discussions provide the basis for the following hypotheses:

- H1a: Performance expectancy has a positive impact on faculty members' occupational well being due to accepting Artificial Intelligence Application in their university.
- H1b: Performance expectancy has a positive impact on faculty members' teaching self efficacy due to accepting Artificial Intelligence Application in their university.

Effort Expectancy (EE)

Effort expectancy (EE) is a strong predictor of acceptance of technology. It is defined as the degree of ease linked with the use of the system (Venkatesh et al. 2003). The concept of EE is identical with the construct ease of use as envisaged in diffusion of innovation (DoI) theory. The ease of use is conceptualized as a degree to which the use of AI in an organization is perceived to be simple or difficult. Moreover, the use of technology by users depends on their individual behavioral characteristics (Chatterjee et al. 2021). These result in the formulation of the following hypotheses:

- H2a: Effort Expectancy has a positive impact on faculty members' occupational well being due to accepting Artificial Intelligence Application in their university.
- H2b: Effort Expectancy has a positive impact on faculty members' teaching self efficacy due to accepting Artificial Intelligence Application in their university.

Facilitating Conditions (FC)

Facilitating conditions (FC) are interpreted as the degree to which a person perceives that the technical infrastructure exists to support the use of new technology, like AI (Venkatesh et al. 2003). Earlier studies found that the acceptance of a specific technology is determined by FC, which considerably impacts the adoption of innovative technology on usage behavior (Chatterjee et al. 2021). It is easier for the employees to use AI if the existing technological infrastructure is user-friendly and supports usage of the system by its employees (Venkatesh et al. 2003). The above discussions formulate the following hypotheses:

- H3a: Facilitating Conditions has a positive impact on faculty members' occupational well being due to accepting Artificial Intelligence Application in their university.
- H3b: Facilitating Conditions has a positive impact on faculty members' teaching self efficacy due to accepting Artificial Intelligence Application in their university.

Social Influence (SI)

SI is about influential and important people's views in the students' surroundings regarding the use and importance of technology use. social environment has a major impact on people's behaviors. Previous studies found SI to have a significant effect on BI (Sultan 2021). The above discussions formulate the following hypotheses:

- H4a: Social influence has a positive impact on faculty members' occupational well being due to accepting Artificial Intelligence Application in their university.
- H4b: Social influence has a positive impact on faculty members' teaching self efficacy due to accepting Artificial Intelligence Application in their university.

Hedonic Motivation (HM)

Defined as "the users' pleasure of using a system" (Chao 2019, 5), HM is one of the critical factors in shaping behavioral intentions of people to perform certain actions. According to Venkatesh, Thong, and Xin (2012) HM relates to a perception that using a particular system is an enjoyable experience (Xuelin 2021). Findings in studies by Venkatesh, Thong, and Xin (2012), Nikolopoulou, Gialamas, and Lavidas (2020), and Gharrah, Aljaafreh, and Al-Ma'aitah (2021), showed that HM has a positive and significant relationship with behavioral intentions of individuals to accept a system. The above discussions formulate the following hypotheses:

- H5a: Hedonic motivation has a positive impact on faculty members' occupational well being due to accepting Artificial Intelligence Application in their university.
- H5b: Hedonic motivation has a positive impact on faculty members' teaching self efficacy due to accepting Artificial Intelligence Application in their university.

Habit (HA)

HA is the "degree to which individuals perform behaviors automatically" (Casey and Wilson-Evered 2012, 2035). Moorthy et al. (2019) defines habit as the extent to which an individual uses a system involuntarily. This suggests that habit relates to a behavior that has become a usual way of doing things or a behavior that has become almost involuntary. Studies by Huang and Kao (2015), Nguyen and Chao (2014) and Abu Gharrah and Aljaafreh (2021) found that HA significantly influences the behavioral intentions of users to accept a system. The above discussions formulate the following hypotheses:

- H6a: Habit has a positive impact on faculty members' occupational well being due to accepting Artificial Intelligence Application in their university.

- H6b: Habit has a positive impact on faculty members' teaching self efficacy due to accepting Artificial Intelligence Application in their university.

Price Value (PV)

Defined as the level of an individual's understanding of the monetary costs and benefits of using a system, PV is one of the factors affecting behavioral intentions of individuals to accept something (Moorthy et al. 2019; Venkatesh, Thong, and Xin 2012). This means that HM is a cognitive trade-off between the perceived benefits and monetary costs of a system or technology (Venkatesh, Thong, and Xin 2012). The above discussions formulate the following hypotheses:

- H7a: Price value has a positive impact on faculty members' occupational well being due to accepting Artificial Intelligence Application in their university.
- H7b: Price value has a positive impact on faculty members' teaching self efficacy due to accepting Artificial Intelligence Application in their university (see Figure 1).

Research Design

This study used a quantitative, non-experimental survey design to answer the research questions and study the relationships between the independent

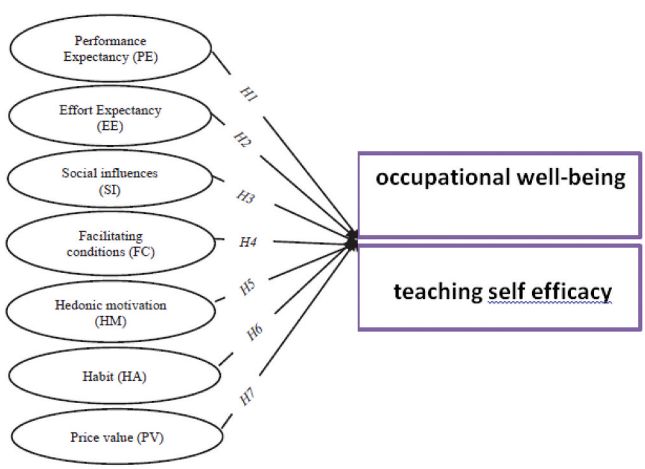

Figure 1. Research model.

variables of performance expectancy, effort expectancy, social faculty members' occupational well-being and teaching self efficacy. The UTAUT2 served as a theoretical framework for the present study. The main assumptions of the UTAUT2 relate to interactions between the independent and dependent variables.

Sample

A convenience method of sampling was used. Faculty members from Umm AL-Qura University were targeted. An online questionnaire was used to collect data via Facebook and WhatsApp groups. A total of 350 responses was received. They were 200 males(57.1%), and 150 females(42.9%). The sample included 30 professors, 70 associate professors, 200 assistant professors, and 50 lecturers. All participants are of Saudi nationality and speak Arabic as their mother tongue. They were recruited on a voluntary basis. The respondents' ages are mainly between 35 and 57 years old. The response rate was calculated to be 98%. The inclusion criteria comprised faculty members' willingness to participate in the study. Study was conducted in the first semester of the academic year 2021–2022.

Protection of Participants

The data was collected anonymously by an electronic survey via a web address. The consent to inform the purpose of the study with the research information was provided to the participants. The information provided in the survey guaranteed the exchange of adequate information, voluntary participation, the benefits of research, and knowledge to the participants who can withdraw at any time during the study.

Instrument

A structured questionnaire with nine sections that used a five-point Likert scale was developed for collecting data. The research questionnaire mainly adopts Venkatesh, Thong, and Xin (2012). In order to design the questionnaire items, we examined the questionnaires based on the UTAUT2 used in other studies (Suki, and Suki 2017; Tarhini et al. 2017; Venkatesh et al. 2003). The nine sections were as follows: performance expectancy (PE) – 3 items, effort expectancy (EE) – 3items, social influences (SI) – 3 items, facilitating conditions (FC) – 3 items, hedonic motivation (HM) – 3 items, price value (PV) – 3 items, habit (HA) – 3 items, occupational well-being (OWB) – 6 items and teaching self efficacy (TSE) – 6 items. Validity: mean explained variance (AVE) for each question was greater than .70, which exceeded the squares of correlations and confirmed the reliability criteria (Venkatesh, Thong, and Xin 2012). The Internal Consistency Reliability (ICR) measures for each construct were greater than 0.75, which confirmed the instrument's validity. Reliability : The instrument was evaluated by the constructs using Cronbach's alpha (α) coefficients, where the results were more significant than .7 and confirmed that it is acceptable.

Data Analysis

Research model was analyzed by using the software, IBM SPSS Statistics 20 to do the demographic analysis and reliability analysis, followed by IBM SPSS Amos 25 to estimate composite reliability (CR) and average variance extracted (AVE) for convergent validity analysis.

To investigate sample data and assess model fit, this study employs structural equation modeling (SEM). SEM is a technique for performing high-quality statistical analysis on multivariate data that was developed in the second generation. The measurement model depicts the relationships between constructs (latent variables) and their indicators (observed variables), whereas the structural model depicts the latent variables' potential causal relationships. The author used the correlational analysis through the Pearson correlation coefficient to support the path analysis of the SEM.

Ethical Considerations

In this research, ethics is essential. The study maintained the ethical principles and guidelines for protecting human subjects in Research. Because this research used human subjects, supervision was required within the process. The IRB of the Umm Al-Qura University provided such supervision and governance. The distribution of the questionnaire included a confidentiality letter explaining the purpose and use of the data collected, which was respected. Any user who disagreed with the terms could not continue with the questionnaire. Each user had the opportunity to abandon responding to the survey at any time. This was configurable since the questionnaire was digital.

Results

Measurement Model Analysis

Convergent validity, discriminant validity, internal consistency reliability and model fit measurement were used as tools for data validation, as shown in the results in Tables 1 and 2. Measurement model analysis was done to confirm that the collected data met the minimum requirements for data to be confirmed as reliable and valid. The minimum requirements to be satisfied for data to be confirmed as reliable and valid are also highlighted. The researcher first cleaned the data for outliers before validating the data. Outliers were identified as items that had either λ < 0.6, α < 0.7or average variance accepted (AVE) < 0.6 (Hair et al., 2017). The following items were found to be outliers: PE 3, HM2, SI1 and PV2and were removed from the measurement scale to ensure that all the measurement tools satisfied the minimum requirements, as shown in Table 1. After cleaning the data to remove outliers, the data were then tested for normality before validation. Skewness and kurtosis were used for testing data normality. The results in Table 1 show that the data were normally distributed as for all values, S < 2 and for all values, K < 4 (Tabachnick and Fidell, 2019). The researcher then measured internal consistency reliability, convergent validity, content validity, construct validity and discriminant validity in that order to validate the data. To measure internal consistency reliability, Cronbach's alpha (CA) and composite reliability (CR) were used. The researcher observed that all values of CA ranged between 0. 769 and 0. 943, thus satisfying the minimum requirement of α ≥ 0.7; and all CR values ranged between 0. 795 and 0. 939 thus also satisfying the minimum requirement of CR ≥ 0.6 demonstrating the presence of internal consistency

Table 1. Confirmatory factor analysis results (λ, CA, CR, AVE, S and K).

Model constructs	Construct items	SFL (λ > 0.6)	CA (α ≥ 0.7)	CR (Crel > 0.6)	AVE (AVE > 0.6)	Skewness S < j2j	Kurtosis K < j4j
PE	PE1	0.728	0.822	0.825	0.705	1.720	3.554
	PE2	0.660				1.044	2.314
	PE3	0.720				1.978	1.885
EE	EE1	0.777	0.781	0.819	0.623	1.040	3.213
	EE2	0.820				0.832	1.928
	EE3	0.679				1.452	1.811
SI	SI1	0.744	0.819	0.855	0.638	1.119	2.544
	SI2	0.840				1.311	3.002
	SI3	0.660				0.890	2.797
FC	FC1	0.780	0.921	0.929	0.640	0.930	3.229
	FC2	0.813				1.442	1.948
	FC3	0.850				1.205	2.228
HM	HM1	0.820				0.832	1.928
	HM2	0.833				0.937	1.799
	HM3	0.659				1.035	2.331
HA	HA1	0.740	0.943	0.939	0.640	0.996	1.977
	HA2	0.744	0.819	0.855	0.638	1.119	2.544
	HA3	0.671				1.115	2.471
PV	PV1	0.825	0.769	0.795	0.639	1.519	2.551
	PV2	0.861				0.974	1.856
	PV3	0.773				1.337	2.441
OWB	OWB1	0.705	0.823	0.831	0.644	1.217	2.736
	OWB2	0.819				1.335	1.394
	OWB3	0.729				1.715	2.188
	OWB4	0.849				1.317	3.035
	OWB5	0.679				1.452	1.811
	OWB6	0.850				1.205	2.228
TSE	TSE1	0.662	0.916	0.925	0.615	0.917	1.628
	TSE2	0.820				0.832	1.928
	TSE3	0.850				1.304	2.007
	TSE4	0.829				0.944	2.099
	TSE5	0.740	0.943	0.939	0.640	0.996	1.977
	TSE	0.849				1.317	3.035

Note(s): SFL= standardized factor loadings; CA= Cronbach's alpha; CR =composite reliability; AVE = average variance extracted

Table 2. Sources measurement model assessment using model fit indices.

	Absolute fit measures			Incremental fit measures		Parsimonious fit measures	
Construct	χ^2/df	GFI	AGFI	NFI	TLI	CFI	RMSEA
PE	1.932	0.943	0.933	0.976	0.970	0.949	0.043
EE	1.739	0.983	0.944	0.975	0.988	0.951	0.043
SI	1.995	0.981	0.948	0.987	0.974	0.960	0.042
FC	1.852	0.977	0.932	0.963	0.977	0.961	0.042
HM	1.774	0.982	0.944	0.971	0.986	0.942	0.044
HA	1.852	0.977	0.932	0.963	0.977	0.961	0.042
PV	1.739	0.983	0.944	0.975	0.988	0.951	0.043
OWB	1.861	0.971	0.947	0.966	0.973	0.951	0.042
TSE	1.937	0.979	0.963	0.979	0.984	0.938	0.044

reliability in the data. To measure convergent validity, the researcher used standardized factor loadings, AVE, internal consistency reliability and model fit indices. The results in Table 1 show that all standardized factor loadings satisfied the minimum requirement of $\lambda > 0.6$; internal consistency reliability was confirmed by CA ≥ 0.7 and CR > 0.6. Also, all AVE values satisfied the minimum requirement of AVE>0.6. Based on the above metrics, convergent validity was therefore confirmed in the study.

Further confirmation of convergent validity was done through the assessment of measurement model fit indices, namely, MIN/degrees of freedom (χ2/df), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), normed fit index (NFI), Tucker – Lewis index (TLI), comparative fit index (CFI) and the root mean square error of approximation (RMSEA) (Table 1). Based on the results in Table 2, the measurement model fit metrics satisfied the minimum requirements for model fit demonstrating overall model fit and confirming convergent validity .

To measure discriminant validity, the researcher used square roots of AVE as well as the maximum shared value (MSV) metric (Table 3). The square roots of AVE (bold diagonal values) in Table 3 are greater that corresponding inter-construct correlations demonstrating the presence of adequate discriminant validity in the data (Segars, 1997). Also, the values of AVE are also greater than the MSV metrics further demonstrating adequate discriminant validity in the data.

Hypothesis Testing

Hypotheses were tested using the structural equation modeling approach. First model fit metrics were assessed to establish if they were within acceptable levels for structural modeling to be conducted. The results showed that χ2/df = 1.874; GFI = 0.942; AGFI = 0.926; NFI = 958; TLI = 0.957; CFI = 0.964; RMSEA = 0.044 confirming that all the metrics were within acceptable ranges

Table 3. Measurement of discriminant validity.

	CR	AVE	MSV	MaxR (H)	PE	EE	SI	FC	HM	HA	PV	OWB	TSE
PE	0.834	0.777	0.319	0.817	0.827								
EE	0.832	0.615	0.308	0.815	0.230	*0.790*							
SI	0.837	0.636	0.189	0.837	0.091	0.188	*0.797*						
FC	0.930	0.649	0.228	0.950	0.390	0.324	0.069	*0.790*					
HM	0.840	0.729	0.313	0.850	0.141	0.280	0.118	0.045	*0.860*				
HA	0.955	0.638	0.298	0.949	0.226	0.077	0.081	0.051	0.077	*0.796*			
PV	0.798	0.639	0.181	0.809	0.210	0.066	0.093	0.108	0.068	0.071	*0.799*		
OWB	0.844	0.644	0.227	0.836	0.344	0.102	0.331	0.091	0.189	0.094	0.831	0.805	
TSE	0.929	0.688	0.354	0.961	0.328	0.076	0.276	0.077	0104	0.210	0.091	0.718	0.*820*

Note(s): CR= composite reliability; AVE = average variance extracted; MSV = maximum shared variance; MaxR (H)= maximum reliability

(Hooper et al., 2008) for structural equation modeling to be used to test hypotheses. Path analysis was then conducted to assess path coefficients.

The results of hypotheses testing using structural equation modeling in Table 4 show that PE ($\beta = 0.411$; $\beta = 0.433$;$\rho < 0.001$;), EE ($\beta = 0.344$; $\beta = 0.362$; $\rho < 0.001$), SI ($\beta = 0.315$; $\beta = 0.319$; $\rho < 0.001$), FC ($\beta = 0.323$; $\beta = 0.316$;$\rho < 0.001$), HM ($\beta = 0.335$; $\beta = 0.341$; $\rho < 0.001$), HA ($\beta = 0.330$; $\beta = 0.339$; $\rho < 0.001$), and PV ($\beta = 0.344$; $\beta = 0.362$; $\rho < 0.001$) significantly influenced faculty members' occupational well-being and teaching self efficacy respectively. Thus, all hypotheses were supported (see Figure 2 for the results of the structural model test).

Discussion

The main aim of the study was to assess acceptance of Artificial Intelligence Application in the Post-covid Era and its impact of faculty members' occupational well-being and teaching self efficacy using The UTAUT 2 Model. To achieve the research objective, the study focused on the UTAUT 2 Model in order to gain an insight deeper into these factors that influence faculty members' occupational well-being and teaching self efficacy due to AI adoption at the collegial level.

All the 7 hypotheses formulated for this study were supported after validation. In confirmation of the research results, there is a significant positive relationship ($p < .001$) between *occupational well-being (OWB)and teaching self efficacy*(TSE) and *performance expectancy* (PE), *effort expectancy* (EE), *social influence* (SI), *facilitating conditions* (FC), *price value* (PV), and *habit* (HB), indicating that faculty members are influenced by the constructs established in the UTAUT2 model in the adoption of AI. This is in consonance with UTAUT model (Venkatesh et al. 2003). The results contribute to knowing the factors that influence the acceptance of AI and help drive innovation in faculty members' colleges (Holmstrom 2022; Sikdar 2018; Verma 2018).

Although AI is a relatively new and rapidly evolving technology, it can be found in various, well-established fields of science, including computer

Table 4. Test of hypotheses.

Hypotheses	Hypothesised relationships: DV path IV	Unstandardised estimates	SE	Standardised estimateR2	
H1a	OWB ← PE	0.319	0.049	411***	0.517
H1b	TSE ← PE	0.321	0.050	0.433***	0.520
H2a	OWB ← EE	0.332	0.047	0.344***	0.529
H2b	TSE ← EE	0.334	0.049	0.362***	0.503
H3a	OWB ← SI	0.320	0.057	0.315***	0.491
H3b	TSE ← SI	0.325	0.048	0.319***	0.501
H4a	OWB ← FC	0.414	0.051	0.323***	0.519
H4b	TSE ← FC	0.389	0.049	0.316***	0.523
H5a	OWB ← HM	0.330	0.050	0.335***	0.520
H5b	TSE ← HM	0.357	0.049	0.341***	0.522
H6a	OWB ← HA	0.301	0.052	0.339***	0.538
H6b	TSE ← HA	0.368	0.053	0.339***	0.516
H7a	OWB ← PV	0.304	0.054	0.344***	0.509
H7b	TSE ← PV	0.309	0.049	0.362***	0.514

Note(s): Significant at ***p < .001; DV = dependent variable; IV = independent variables; SE = standard error; P =significance level; R^2 = coefficient of determination

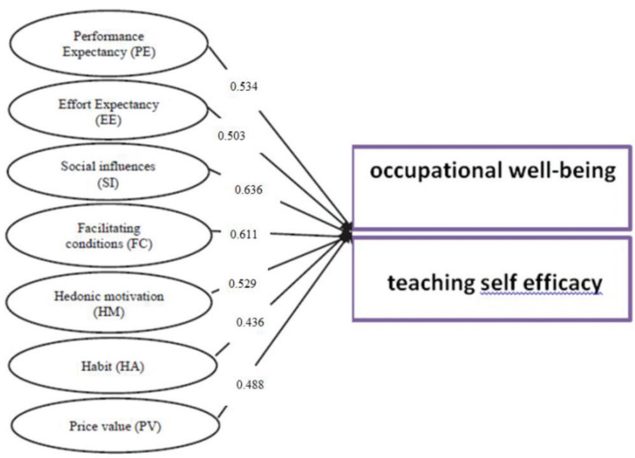

Figure 2. Structural model results.

science, psychology, language science, philosophy, statistics, mathematics, and electrical engineering. AI is becoming increasingly important, as financial and enrollment pressures in higher education become more prevalent. This has necessitated the development of low-cost technologies capable of providing students with personalized support and service. For example, chatbots and other instant self-service technologies can enable higher education institutions to be more innovative. Furthermore, using the most recent AI and ML methodologies enables the development of new technological innovation equivalent to ten years of work in a relatively short time. The use of AI is critical to providing a more consistent and accessible customer experience (Kuleto et al. 2021).

This study revealed that performance expectancy positively impacted faculty members' occupational well-being and teaching self efficacy. It indicated that the performance of the technology is vital to people's perceptions, which positively impacts use. As previous research has shown, anxiety and technology self-efficacy could be relevant predictors of technology acceptance (McKenna, Tuunanen, and Gardner 2013; Wang et al. 2014).

This finding goes in the same line with other studies, for example Sultana (2020), Cheong et al. (2004), Abu-al-aish and Love (2013). Another finding is that effort expectancy exhibited a significant and positive impact on the behavioral intention to use the Blackboard platform, which is in line with two studies, namely, Sultana (2020), and Abu-al-aish and Love (2013).

Conclusions

Adopting AI is a lengthy process that includes not only the procurement of software and technology but also the establishment of necessary infrastructure and resources over time. This study is an early investigation of AI applications adoption at the collegial level, incorporating The UTAUT 2 Model. The findings of this study indicated that there is a significant positive relationship ($p < .001$) between occupational well-being (OWB)and teaching self efficacy-(TSE) and performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), price value (PV), and habit (HB), indicating that faculty members are influenced by the constructs established in the UTAUT2 model in the adoption of AI. This is not surprising because people tend to accept AI provided the use of it will help to improve their performance at work and enhance their relationships with people. This study aimed to be innovative, by giving a twist to the existing technology acceptance theories and paving a new road for acceptance of Artificial Intelligence theories to be developed. This research provides a foundation for future research on the importance of Artificial Intelligence Application in the Post-Covid Era and its impact of faculty members' occupational well-being and teaching self efficacy using The UTAUT 2 Model. It can be used as a starting point for further study on AI adoption in various universities in our country, Saudi Arabia. The current study provides different insights into how accepting Artificial Intelligence Application in the Post-covid Era influences faculty members' occupational well-being and teaching self efficacy in the light of The UTAUT 2 Model. Furthermore, this study adds to the current body of knowledge about Artificial Intelligence Application. The findings confirm that The UTAUT 2 Model can provide a more comprehensive understanding of successful AI adoption at the collegial level.

AI should be continually utilized to improve the work environments within the universities in order to enhance the mental health and wellbeing of college teaching members. It should be noted that there is a need to develop and design new AI to improve the mental health of college teaching members and to expand the benefits of AI for the psychological wellbeing of the educational system as a whole. Taking into account their psychological needs, new AI should be developed and designed to reduce workloads of college teaching members and contribute to their physical and mental wellbeing, thereby expanding the psychological benefits of AI to the entire educational system.

Most reputable high education institutions have understood that AI represents the present and future in both education and the world's progressive development. Such technologies provide an interactive and advanced educational experience to their students. Moreover, these systems provide valuable assistance to teachers and lecturers in the best schools, facilitating and improving learning in various ways. For example, estimates indicate that AI in education in the United States increased by 47.5% between 2017 and 2021 (Kuleto et al. 2021).

Limitations and Future Works

This study, like others, has a few limitations. Firstly, the study has involved faculty members from the King Saud, KSA only. In order to generalize the findings, the applicability to other universities in the kingdom must also be investigated. Second, the data is self reported by faculty members; hence biased can not be denied in reporting the responses. This study is limited by the use of cross-sectional data. The cross-sectional nature of the data makes it difficult to conduct an in-depth examination of Artificial Intelligence Application in the Post-covid Era and its impact of faculty members' occupational well-being and teaching self efficacy using The UTAUT 2 Model.

Practical Implication

The advent of disasters, such as COIVD-19, has meant that universities need to come up with more innovative ways of enhancing access to education by students and their instructors. This study contributes to the explanation of AI applications adoption at the collegial level, incorporating The UTAUT 2 Model. The research illustrated that all components of The UTAUT 2 Model significantly influenced faculty members' occupational well-being and teaching self efficacy respectively, which means faculty members have high expectation of AI. AI developers should improve user experience by increasing efficiency of their leisure activities so as to reach leisure goals. College students today have an excellent opportunity to learn in an interactive and personalized setting. AI, in particular, is capable of assisting with both of these issues. AI, fed and learned from big data, can provide students with individualized learning experiences. Simultaneously, professors can discover new ways different students learn and advise them on tailoring their teaching methods to meet their needs. By understanding the individual, technological and environmental factors that significantly affect their IT adoption behavior, policy makers could facilitate and provide guidance on the adoption and usage of IT innovation.

Disclosure Statement

No potential conflict of interest was reported by the author.

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Data Availability Statement

Data sharing not applicable. The data are not publicly available due to participants' privacy.

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