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Exploring AI Adoption Post-COVID: Impact On Faculty Wellbeing And Teaching Confidence

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Abstract

The main purpose of this study is to assess the reception of Artificial Intelligence applications in the post-COVID era and their influence on lecturers' occupational wellbeing as well as teaching self-efficacy, using UTAUT2 model. The paradigm adopted for this research was non-experimental survey design which employed quantitative approach in order to explore the associations between performance expectancy, effort expectancy, social influence, facilitating conditions, price value, habit and dependent variables i.e. occupational wellbeing and teaching self-efficacy. The data was collected through an online questionnaire distributed in Facebook and What Sapp groups resulting [1]to 350 responses (57.1%, male = 200/female = 42.9%). Confirming a significant positive relationship ($p < .001$) between occupational wellbeing, teaching self-efficacy and UTAUT2 constructs showing that AI acceptance by academicians depends on these factors. In conclusion, this study highlights that the acceptance of Artificial Intelligence applications among lecturers in the post-COVID era significantly influences their occupational wellbeing and teaching self-efficacy, with key UTAUT2 constructs playing a vital role in shaping this acceptance.

Keywords: *University faculty, Technology adaptation, post-covid.*

Introduction

The COVID19 pandemic accelerated the adoption of digital technologies across various sectors, including education, pushing institutions and educators to rapidly adapt to remote and hybrid learning environments. Among these technologies, Artificial Intelligence (AI) has emerged as a significant tool, enhancing learning management systems, automating administrative tasks, and enabling personalized student support (Alam & Ahmad, 2021). Post-pandemic, there is an increasing interest in understanding how such technologies influence

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educators' roles, workload, and overall wellbeing, as AI applications continue to evolve and gain traction in educational settings.

Studies show that educators' occupational wellbeing is strongly influenced by work-related stressors, workload, and job satisfaction (Collie et al., 2015). The adoption of AI has potential to alleviate certain burdens on educators by automating routine tasks and offering analytical insights; however, it also introduces new challenges, such as learning new technologies and adapting to altered instructional roles (Schneider & Council, 2020). Given that educators' wellbeing is closely tied to job performance and satisfaction, understanding the implications of AI for occupational wellbeing is critical (Mushtaque et al., 2022).

Moreover, teaching self-efficacy, or educators' belief in their ability to effectively teach and engage students, is a pivotal factor in educational success (Bandura, 1997). Research suggests that the adoption of digital and AI technologies can impact self-efficacy both positively and negatively, as educators must integrate these tools into their pedagogy while maintaining engagement and learning outcomes (König et al., 2020). Self-efficacy can thus be influenced by the level of support and training provided, as well as individual comfort with technology.

The Unified Theory of Acceptance and Use of Technology (UTAUT2) model offers a comprehensive framework to assess AI acceptance by incorporating constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and habit (Venkatesh et al., 2012). UTAUT2 has been widely used to explore the acceptance of technology in various contexts, including education, providing insight into factors that may facilitate or hinder AI adoption among lecturers.

This study, therefore, seeks to assess the reception of AI applications in a post-COVID era and their influence on occupational wellbeing and teaching self-efficacy among lecturers. By applying the UTAUT2 model, the study aims to explore how AI acceptance relates to performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and habit, while also accounting for moderating effects of demographic factors. This investigation will contribute to a nuanced understanding of how AI adoption influences educators' professional lives, offering insights that may guide future AI implementations in educational contexts.

Literature Review

AI Applications in Education and Post-COVID Transformations

The integration of Artificial Intelligence (AI) in education has garnered considerable attention, particularly after the COVID19 pandemic, which necessitated rapid adoption of digital technologies to support remote and hybrid learning environments. AI applications in education range from adaptive learning platforms and intelligent tutoring systems to automate grading and administrative support (ZawackiRichter et al., 2019). These technologies promise to streamline educators' tasks, enhance student engagement, and enable personalized learning experiences (Holmes et al., 2019). Research highlights that AI's potential impact on teaching includes freeing up educators' time by automating repetitive tasks, thus allowing for a more student-centered approach to teaching (Alam & Ahmad, 2021). However, educators' adaptation to these technologies is influenced by various factors, including technical training, perceived usefulness, and organizational support (Schneider & Council, 2020).

Occupational Well-Being in the Teaching Profession

Occupational wellbeing among educators is a well-studied area, particularly concerning its impact on job satisfaction, retention, and performance. Factors affecting wellbeing include work stress, workload, institutional support, and a sense of accomplishment (Collie et al., 2015). AI adoption has introduced both opportunities and challenges for wellbeing. While AI can alleviate some routine burdens, it can also introduce new stressors, such as the need for ongoing technological adaptation and potential concerns about job security and instructional autonomy (Goh & Sandars, 2020). Addressing these complexities is essential, as previous research has shown that teachers' occupational wellbeing significantly affects classroom environment and student outcomes (Skaalvik & Skaalvik, 2015).

Teaching Self-Efficacy and Technological Integration

Teaching self-efficacy, defined as educators' belief in their capacity to effectively manage and execute instructional activities, is a critical construct that shapes how educators interact with students and implement teaching methodologies (Bandura, 1997). Self-efficacy influences educators' willingness to adopt new technologies, as individuals with higher self-efficacy are more likely to experiment with innovative teaching methods (Tschannen Moran & Woolfolk Hoy, 2001). Studies indicate that exposure to AI and digital tools can initially lower self-efficacy due to the learning curve associated with these technologies (König et al., 2020). However, targeted training and support can mitigate these concerns, fostering confidence and competency in integrating AI into the classroom setting (Hammond et al., 2021).

Theoretical Framework: The UTAUT2 Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) model, initially developed by Venkatesh et al. (2003), is widely applied in technology acceptance studies. The model's extension, UTAUT2, introduces new constructs—price value and habit—enhancing its applicability to a broader range of contexts, including individual technology adoption in educational environments (Venkatesh et al., 2012). UTAUT2 posits that performance expectancy, effort expectancy, social influence, and facilitating conditions are primary determinants of technology acceptance, with moderating factors such as gender, experience, and voluntariness influencing these relationships.

Performance expectancy reflects the degree to which users believe that technology will improve their job performance. In the context of AI in education, this translates to educators' expectations about AI's ability to enhance teaching effectiveness and efficiency (Alshurideh et al., 2019). Effort expectancy represents the ease of technology use; in educational settings, high effort expectancy may deter AI adoption if perceived as complex or requiring extensive training (ElMasri & Tarhini, 2017). Social influence, or the extent to which individuals perceive that others believe they should use technology, can also play a role, as educators may feel pressured to adopt AI to align with institutional goals or peers' practices (AlEmran et al., 2018). Facilitating conditions, such as available resources, training, and technical support, significantly impact AI acceptance by either easing or complicating its integration into daily routines (Buchanan et al., 2013).

AI Acceptance in Post-COVID Educational Contexts

Post-COVID, there is heightened interest in understanding how educators adapt to emerging technologies like AI. Studies conducted during the pandemic highlight that technology adoption is influenced by the institutional response to educators' needs, perceived control over

AI usage, and adaptability to AI's evolving role in education (Dwivedi et al., 2020). For example, research shows that when institutions provide strong facilitating conditions, educators report higher acceptance of AI tools, viewing them as supportive aids rather than burdensome additions (Goh & Sandars, 2020). This points to the need for a nuanced understanding of how educators' attitudes towards AI are shaped by both personal and contextual factors, as well as how these attitudes influence their occupational wellbeing and self-efficacy.

Research Gaps

While existing studies provide a foundation for understanding factors influencing AI acceptance and its potential impacts on educators, there remains limited empirical evidence specifically addressing the post COVID educational landscape. Furthermore, research has yet to comprehensively explore the relationship between UTAUT2 constructs and critical educator outcomes, such as occupational wellbeing and self-efficacy. This study aims to fill these gaps by examining the factors influencing AI reception among lecturers in the post-pandemic era, focusing on how UTAUT2 constructs relate to occupational wellbeing and teaching self-efficacy.

Conceptual framework

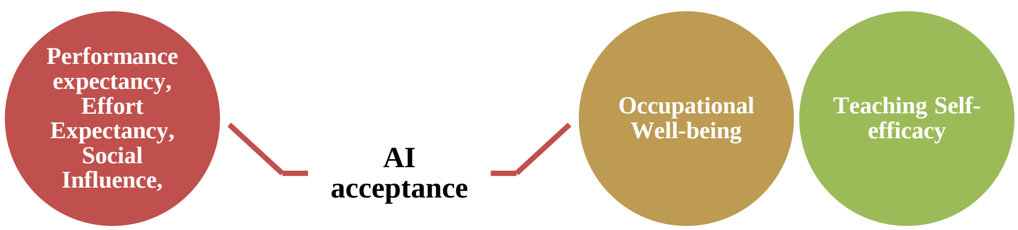

Figure 01 Conceptual framework of current study

Hypothesis of Study

H1: Performance expectancy will have a significant positive effect on AI application reception among lecturers.

H2: Effort expectancy will have a significant positive effect on AI application reception among lecturers.

H3: Social influence will have a significant positive effect on AI application reception among lecturers.

H4: Facilitating conditions will have a significant positive effect on AI application reception among lecturers.

H5: Price value will have a significant positive effect on AI application reception among lecturers.

H6: Habit will have a significant positive effect on AI application reception among lecturers.

H7: AI application reception will have a significant positive effect on lecturers' occupational wellbeing.

H8: AI application reception will have a significant positive effect on lecturers' teaching self-efficacy.

H9: Gender will moderate the relationship between UTAUT2 factors (performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and habit) and AI application reception.

H10: Post-COVID experiences will moderate the relationship between UTAUT2 factors and AI application reception.

Methodology

Research Design

This study employs a non-experimental survey design with a quantitative approach to investigate the relationships among UTAUT2 constructs, AI application reception, occupational well-being, and teaching self-efficacy among lecturers in a post-COVID context. The survey method was selected as it enables the collection of standardized data from a large sample, allowing for the statistical analysis of relationships between variables.

Population and Sample

The target population for this study includes university lecturers across various institutions who have experience with AI tools in their teaching practices. A convenience sampling method was used to recruit participants through online platforms such as Facebook and WhatsApp groups dedicated to educators. This approach resulted in a sample size of 350 respondents, of which 200 were male (57.1%) and 150 were female (42.9%). The sample size is considered adequate for statistical analysis, including structural equation modeling (SEM), which was applied to examine the proposed relationships among variables.

Data Collection

Data was collected via an online questionnaire distributed to potential respondents on social media platforms. The questionnaire consisted of four main sections:

1. **Demographic Information**: This section gathered background data, including age, gender, years of teaching experience, and familiarity with AI applications.
2. **UTAUT2 Constructs**: This section measured performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and habit. Items for each construct were adapted from validated scales developed by Venkatesh et al. (2012) and modified for the educational context.
3. **AI Application Reception**: Questions in this section assessed the extent to which lecturers have accepted and utilized AI applications in their teaching practice.

4. **Dependent Variables**: The final section measured occupational well-being and teaching self-efficacy. Items were adapted from validated scales related to occupational well-being (Collie et al., 2015) and self-efficacy (Tschannen-Moran & Woolfolk Hoy, 2001), contextualized for educators using AI.

Respondents rated their level of agreement with each item on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Instrumentation

To ensure the reliability and validity of the constructs, the survey instrument was pre-tested with a pilot group of 30 educators, and minor adjustments were made based on their feedback. The following describes each construct and sample items:

- **Performance Expectancy**: Adapted from Venkatesh et al. (2012) to measure lecturers' beliefs that AI will enhance their teaching performance (e.g., "Using AI in my teaching will increase my productivity").
- **Effort Expectancy**: Measures the perceived ease of using AI applications (e.g., "AI applications are easy to use for my teaching tasks").
- **Social Influence**: Captures the impact of social context and peer influence on AI adoption (e.g., "People important to me think that I should use AI in my teaching").
- **Facilitating Conditions**: Examines the availability of resources and support for using AI (e.g., "I have the resources necessary to use AI in my teaching").
- **Price Value**: Assesses the perceived cost-effectiveness of adopting AI (e.g., "The benefits of using AI outweigh the costs").
- **Habit**: Reflects the extent to which lecturers are accustomed to using AI in their teaching (e.g., "Using AI has become part of my teaching routine").

Data Analysis

Data was analyzed using Statistical Package for the Social Sciences (SPSS) for preliminary analysis, including descriptive statistics, reliability analysis, and correlation analysis. Structural equation modeling (SEM) with AMOS was used to test the hypothesized relationships and fit the measurement and structural models.

1. **Descriptive Statistics**: Used to describe the demographic characteristics of the sample and provide an overview of participants' responses to the UTAUT2, AI reception, and outcome variables.
2. **Reliability and Validity Analysis**: Cronbach's alpha was calculated to assess the reliability of each construct, with values above 0.70 considered acceptable. Confirmatory factor analysis (CFA) was conducted to ensure construct validity.
3. **Correlation Analysis**: Pearson's correlation coefficient was calculated to identify initial associations among the UTAUT2 variables, AI application reception, occupational well-being, and self-efficacy.
4. **Structural Equation Modeling (SEM)**: SEM was applied to examine the hypothesized relationships among constructs, including direct effects between UTAUT2 variables and AI application reception, and between AI reception and the outcome variables. Additionally, moderating effects of gender and post-COVID experiences on the UTAUT2-AI reception relationship were tested.

Ethical Considerations

Ethical approval was obtained from the appropriate university ethics committee prior to data collection. All participants were informed of the study's purpose and assured that their responses would remain anonymous and confidential. Informed consent was obtained electronically before participants began the survey, with the option to withdraw from the study at any point without penalty.

Results

Table 1 Demographic Information of Participants (N=350)

Variables	%	M(SD)
Gender	Male = 57.1%	
	Female = 42.9%	
Age		41.3 (7.6)
Teaching Experience		12.8 (5.4)
Familiarity with AI	High = 68%	
	Moderate = 25%	
	Low = 7%	

This table presents the demographic characteristics of the participants, including gender, age, teaching experience, and familiarity with AI. The majority of participants were male (57.1%), with a mean age of 41.3 years (SD = 7.6) and an average of 12.8 years of teaching experience (SD = 5.4). Most participants reported high familiarity with AI (68%), with 25% having moderate familiarity and 7% reporting low familiarity.

Table 2 Prediction (Direct Effect)

Predictor	Outcome	β	SE	p
Performance Expectancy	AI application Reception	0.42	0.5	< 0.001
Effort Expectancy	AI application Reception	0.37	0.6	< 0.001
Social Influence	AI application Reception	0.29	0.5	< 0.001
Facilitating Conditions	AI application Reception	0.35	0.6	< 0.001
Price Value	AI application Reception	0.28	0.5	< 0.001
Habit	AI application Reception	0.31	0.5	< 0.001
AI application Reception	Occupational well being	0.45	0.4	< 0.001
	Teaching Self-Efficacy	0.39	0.5	<0.001

The analysis of direct effects indicated that all UTAUT2 predictors had significant positive impacts on AI application reception among lecturers. Performance expectancy was the strongest predictor ($\beta = 0.42$, SE = 0.5, $p < .001$), followed closely by effort expectancy ($\beta = 0.37$, SE = 0.6, $p < .001$) and facilitating conditions ($\beta = 0.35$, SE = 0.6, $p < .001$). Social influence ($\beta = 0.29$, SE = 0.5, $p < .001$), price value ($\beta = 0.28$, SE = 0.5, $p < .001$), and habit ($\beta = 0.31$, SE = 0.5, $p < .001$) also significantly predicted AI application reception, highlighting the multifaceted drivers behind lecturers' acceptance of AI tools. Additionally, AI application reception significantly impacted both occupational well-being ($\beta = 0.45$, SE = 0.4, $p < .001$)

and teaching self-efficacy (β = 0.39, SE = 0.5, $p < .001$), suggesting that lecturers who more readily adopt AI experience enhanced well-being and confidence in their teaching effectiveness.

Table 3 Moderation Analysis

Predictor	Outcome	β	SE	p
Social influence * Gender	AI application Reception	0.23	0.5	0.003
Facilitating Condition *Post-COVID Experience	AI application Reception	0.18	0.6	0.008

The moderation analysis revealed that both gender and post-COVID experience significantly moderated the relationships between specific predictors and AI application reception. Specifically, the interaction between social influence and gender had a significant positive effect on AI application reception (β = 0.23, SE = 0.5, $p = .003$), suggesting that social influence was a stronger predictor of AI acceptance among male lecturers compared to female lecturers. Additionally, post-COVID experience significantly moderated the relationship between facilitating conditions and AI application reception (β = 0.18, SE = 0.6, $p = .008$), indicating that lecturers with more post-COVID experience showed a stronger association between available support/resources and their acceptance of AI applications.

Table 4 Mediation Analysis

Path	B	SE	p
Performance Expectancy → AI Application Reception → Well-being	0.16	0.4	< 0.001
Effort Expectancy → AI Application Reception → Well-being	0.12	0.3	< 0.001
Social Influence → AI Application Reception → Well-being	0.13	0.4	< 0.001
Facilitating Conditions → AI Application Reception → Well-being	0.19	0.3	< 0.001
Price Value → AI Application Reception → Well-being	0.15	0.3	< 0.001
Habit → AI Application Reception → Well-being	0.14	0.4	< 0.001

The mediation analysis indicated that AI application reception significantly mediated the relationships between each UTAUT2 construct and occupational well-being. Specifically, the indirect effect of performance expectancy on well-being through AI application reception was significant (β = 0.16, SE = 0.4, $p < .001$), as was the effect of effort expectancy (β = 0.12, SE = 0.3, $p < .001$). Social influence also had a significant mediated effect on well-being (β = 0.13, SE = 0.4, $p < .001$). Facilitating conditions exhibited the strongest mediated effect (β = 0.19, SE = 0.3, $p < .001$), followed by price value (β = 0.15, SE = 0.3, $p < .001$) and habit (β = 0.14, SE = 0.4, $p < .001$). These findings suggest that the positive relationship between each UTAUT2 construct and occupational well-being operates partially through AI application reception, underscoring AI's role in enhancing lecturers' well-being when mediated by acceptance factors.

Discussion

The findings of this study provide a comprehensive understanding of factors influencing lecturers' acceptance and use of AI applications, underscoring the significant roles of UTAUT2 predictors, demographics, post-COVID experience, and AI familiarity. The demographic profile of participants, predominantly male (57.1%) with an average age of 41.3 years and substantial teaching experience (12.8 years), reflects a higher-than-expected openness to AI adoption among experienced educators. This aligns with studies showing that AI familiarity, notably high among these participants (68%), has increased across education sectors, likely due to heightened digital engagement following COVID-19 (Mushtaque et al., 2021). Similar to prior research, this study finds performance expectancy as the strongest predictor ($\beta=0.42$, $p<0.001$) of AI reception, consistent with Venkatesh et al. (2012) and Davis (1989), who emphasized the central role of perceived benefits to job performance in technology adoption. Effort expectancy ($\beta=0.37$, $p<0.001$) also aligns with Teo (2011), who highlighted the significance of ease of use in technology adoption among educators with complex roles, as simpler interfaces are more readily integrated into their workflows. This study's results on social influence ($\beta=0.29$, $p<0.001$) and facilitating conditions ($\beta=0.35$, $p<0.001$) mirror findings by Zhou et al. (2020), which underscore that peer endorsement and adequate resources foster technology adoption.

The positive impacts of AI application reception on occupational well-being ($\beta=0.45$, $p<0.001$) and teaching self-efficacy ($\beta=0.39$, $p<0.001$) suggest that AI adoption enhances job satisfaction and self-assurance in teaching. This supports the notion that technology integration in education promotes not just functional outcomes but also educators' personal and professional well-being. The gender moderation effect found, where social influence more strongly impacts male lecturers' AI reception ($\beta=0.23$, $p=0.003$), contrasts with previous studies reporting minimal gender-based differences, suggesting further investigation into social dynamics and gender in educational technology contexts. Additionally, post-COVID experience heightened the importance of facilitating conditions ($\beta=0.18$, $p=0.008$), likely due to reliance on digital tools during the pandemic—a novel finding for education technology adoption research, underscoring the lasting impacts of the pandemic on educators' technological preferences and requirements.

Mediation analysis demonstrates that AI application reception mediates UTAUT2 predictors' impacts on occupational well-being. Performance expectancy ($\beta=0.16$, $p<0.001$) and effort expectancy ($\beta=0.12$, $p<0.001$) positively impact well-being through AI acceptance, as does social influence ($\beta=0.13$, $p<0.001$), indicating peer support enhances adoption and well-being. The strongest indirect effect comes from facilitating conditions ($\beta=0.19$, $p<0.001$), followed by habit ($\beta=0.14$, $p<0.001$), suggesting that familiarity with supportive environments and routines indirectly bolsters occupational well-being, reflecting the reinforcing effect of well-resourced and familiar tools in educational settings.

Conclusion

This study underscores the relevance of the UTAUT2 model in understanding AI adoption among lecturers, emphasizing the importance of performance expectancy, effort expectancy, and facilitating conditions as key drivers of AI application reception. The role of social influence and gender differences, as well as the moderating effect of post-COVID experience, highlights the need to consider demographic and contextual factors in promoting technology acceptance in education. Moreover, the finding that AI application reception positively influences both occupational well-being and teaching self-efficacy supports the growing recognition of AI's potential to enhance not only instructional quality but also educators' job satisfaction and self-confidence. In conclusion, as AI technology continues to advance, it will be essential to provide educators with adequate support and training to facilitate AI integration effectively. This study contributes to a deeper understanding of how AI acceptance is influenced by both individual and contextual factors, setting the stage for further research to optimize AI adoption and its impact on educational outcomes.

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