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Factors Affecting Behavior, Perceived Impact of AI on Work Engagement, and AI Application: Indonesian Context

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ABSTRACT

This study aimed to elaborate on the predictors of behavioral intention, actual behavior, perceived impact of AI on work engagement, and the perceived impact of AI on teaching and learning in Asian higher education institutions (HEIs). We extended the Unified Theory of Acceptance and Use of Technology (UTAUT) to test the relationships among these variables. In total, 516 lecturers from three different universities contributed to the dataset. Partial least squares structural equation modeling (PLS-SEM) was employed to analyze the respondents' data through both measurement and structural models. The findings indicate that actual behavior has a significant positive relationship with the perceived impact of AI on teaching and learning and the perceived impact of AI on work engagement. Behavioral intention is strongly correlated with actual behavior. Performance expectancy is the most prominent link to behavioral intention, followed by social influence and facilitating conditions. The results of the study underscore the importance of fostering a conducive environment through adequate facilitating conditions and aligning performance expectations to drive behavioral intention and perceived engagement with AI technologies in HEIs.

Keywords: Artificial intelligence; behavior; higher education; Indonesian students; perceived impact of AI; work engagement; teaching and learning

1. Introduction

AI plays a significant role in higher education, especially in changing how classes are taught. AI-powered techniques help teachers assess efficacy, organize materials, and enhance teaching. They can manage admin tasks and customize methods using chatbots, virtual assistants, and adaptive learning systems. Chatbots such as ChatGPT, Gemini, and Meta AI assist lecturers by answering questions, providing teaching advice, and managing administrative tasks like scheduling. AI also improves grading speed and gives thorough assignment feedback, allowing educators to concentrate more on student engagement and instructional design. AI algorithms can spot locations where instructional enhancements are needed and find trends in teaching data that assist teachers in delivering better courses. Additionally, AI improves communication and monitors progress, helping lecturers identify and resolve student issues for a more flexible, responsive learning environment (Ashraf, 2023; Deng & Lin, 2023; Lin et al., 2022). More creative and consequential applications of AI in education are on the horizon and hold great potential for improving education quality, relevance, and efficiency through increased individualization and work engagement.

AI in Higher Education Institutions (HEIs) can boost perceived AI impact on lecturers' work engagement, influencing behavioral intentions and actions. Assessing factors affecting AI use, behavior, and its impact on engagement helps guide stakeholders on AI's importance. Many studies examine AI's role in enhancing learning. (An et al., 2023; Habibi, Muhaimin et al., 2023; Ragheb et al., 2022; Wu et al., 2022). However, a few studies reported the use of AI and factors affecting behavioral intention to use AI, behavior, perceived impact of AI on work engagement, and perceived effects of AI on teaching and learning perceived by university lecturers (Clifford & Perez, 2024). The current research expanded the UTAUT model, integrating the perceived impact of AI on work engagement and the perceived effects of AI on teaching and learning. Prior UTAUT studies (e.g., Venkatesh, 2003; Habibi et al., 2023) focused on performance and effort expectancy as adoption drivers, but this study shows how AI behavior sustains engagement by reducing routine tasks, increasing autonomy, and fostering meaningful pedagogical interactions—critical in high-workload Indonesian HEI context behavioral intention and behavior predict to boost lecturers' motivation and long-term adoption by reducing administrative load. This dual-path influence—utility to intention, engagement to sustained behavior—provides a new theoretical lens from transactional acceptance to revolutionary workplace results. These findings strengthen UTAUT's educational explanations and inform robust AI ecosystem implementation in education. Therefore, the current research aims to understand the factors by extending the unified theory of acceptance and use of technology (UTAUT) framework.

2. Literature Review

The current study extends UTAUT to examine AI integration in HEIs. Technology adoption and use behavior can be predicted and explained using the UTAUT framework, which emphasizes performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs directly affect behavioral intention and behavior. In this study, the perceived impact of AI on work engagement and the perceived effects of AI on teaching and learning were hypothesized to correlate with behavioral intention and behavior. The involved constructs are linked to the classic UTAUT model to provide a nuanced view of technology adoption and motivating variables needed to sustain and improve AI in education. Thus, this model offers a robust theoretical foundation for HEIs to implement AI applications in education. Although the basic elements of UTAUT reliably forecast AI adoption in HEIs (Venkatesh et al., 2003; Habibi et al., 2023), the conflicting findings regarding effort expectancy necessitate examination. EE substantially influences intention among early adopters (Lin et al., 2022; Li et al., 2024) but declines among seasoned users (Grassini et al., 2024), indicating that skill maturation moderates its impact. Landmark assessments underscore AI's transformative potential (Holmes et al., 2019)while exposing inconsistent integration attributable to institutional deficiencies (Zawacki-Richter et al., 2019). Augmenting UTAUT with job engagement resolves this by correlating behavioral outcomes with enduring motivation.

2.1. Performance Expectancy

Performance expectancy refers to the degree to which a person believes a technology will enhance their job performance (Venkatesh et al., 2003). UTAUT paradigm relies on this concept to explain technology adoption. In the current study, performance expectancy refers to the belief that AI will enhance academic and administrative efficiency in higher education (Venkatesh, 2022; Wu et al., 2022). When educational institutions implement new technology, performance expectancy becomes an important determinant of user engagement with new systems (Sebastián et al., 2022). Venkatesh et al. (2003) identified performance expectancy as one of UTAUT's four significant components, impacting users' technology use intentions. Prior studies have indicated that performance expectancy is a critical factor for teachers or students in using AI in education (Andrews et al., 2021; Sebastián et al., 2022; Habibi, Muhaimin et al., 2023; Lin et al., 2022; Venkatesh, 2022; Wu et al., 2022). For example, performance expectancy influences ChatGPT use among HEIs' students in Indonesia (Habibi, Muhaimin, et al., 2023). When users have reasonable performance expectancy in AI, the technology promises to improve work outcomes and simplify educational processes (Wu et al., 2022). These prior findings demonstrate the continuous importance of understanding the intention of users in using AI in HEIs:

2.2. Effort Expectancy

Effort expectancy in this study measures how easily HEIs lecturers assess their capacity to adopt and apply AI technology in their daily work (Venkatesh et al., 2003). Users are more likely to adopt easy-to-use technology.

UTAUT suggests that effort expectancy predicts behavioral intention, especially early in technology adoption when users are still learning new systems (Alhwaiti, 2023; Grassini et al., 2024). Venkatesh et al.'s (2003) foundational research on technology acceptance emphasized the relevance of effort expectancy, or perceived ease of use, in influencing technology adoption. Recent studies confirmed AI is more likely to be embraced and integrated into teaching and learning activities in HEIs as rapid AI tool adoption is crucial for improving educational outcomes and operational efficiency (Alhwaiti, 2023; Grassini et al., 2024Habibi, Muhaimin, et al., 2023; Li et al., 2024; Lin et al., 2022; Sebastián et al., 2022). Habibi et al. (2023), who studied the use of ChatGPT in higher education, found that effort expectancy was significantly correlated with the behavioral intention to use AI in education. On the other hand, effort expectancy was not significantly related to behavioral intention to use AI in HEIs (Grassini et al., 2024).

2.3. Social Influence

Social influence is defined as the extent to which an individual believes important individuals think they should use AI technology in HEIs (Venkatesh et al., 2003). Coworkers, superiors, and other influential people often shape impressions and decisions. Social influence refers to the perceived pressure or encouragement from colleagues, management, or the academic community to adopt and utilize AI technologies in higher education (Habibi, Muhaimin et al., 2023; Lin et al., 2022). Social influence can motivate technology adoption, especially when social pressure or group norms favor new technology. Venkatesh et al. (2003) noted that social influence is significant in social and professional settings. For example, if lecturers learn from their peers or leaders by using AI tools in their teaching or administration, they may be inspired to do the same. This social dynamic can speed up the adoption of AI in higher education, fostering institutional change and innovation. Prior studies have explored the essential role of social influence in shaping behavioral intention to use AI (Sebastián et al., 2022; Habibi, Muhaimin et al., 2023; Li et al., 2024; Lin et al., 2022). However, Grassini et al. (2024) found that social influence does not significantly affect university students' perceived use of AI in Norway.

2.4. Facilitating Conditions

Facilitating Conditions refer to the extent to which an individual perceives that the organizational and technological infrastructure supports technology (Venkatesh, 2022; Wu et al., 2022). Training, technical assistance, and enough resources are included. AI adoption and integration in HEIs requires technological resources, faculty and staff training, and management support. Even advanced technology needs solid support for adoption (Habibi, Muhaimin, et al., 2023; Li et al., 2024). Studies suggest that facilitating conditions are crucial for implementing technology, especially AI in education (Andrews et al., 2021; Cabrera-Sánchez et al., 2021; García de Blanes Sebastián et al., 2022; Grassini et al., 2024; Habibi, Muhaimin, et al., 2023; Li et al., 2024; Lin et al., 2022; Venkatesh, 2022; Wu et al., 2022). In the early years of UTAUT studies, Venkatesh et al. (2003) found that facilitating conditions directly impact technology adoption, especially in user-supporting organizations. Andrews et al. (2021) found that institutions (university libraries) with adequate resources and support boost AI use in education. Khan and Rafi (2021) also noted that faculty need ongoing technical support and professional development to cultivate a positive attitude toward emerging technologies such as AI, which, in turn, enhances their effectiveness in higher education (Clifford & Perez, 2024). One hypothesis was established regarding the role of facilitating conditions in behavioral intention to use IA in HEIs, as perceived by Indonesian university lecturers.

2.5. Behavioral Intention

Behavioral intention refers to a person's intention to use technology. Behavioral intention predicts technology use in UTAUT, enabling attitudes and perceptions to become actions. This study defines behavioral intention as the desire of Indonesian HEI lecturers to use AI. Behavioral intention's ability to predict technology adoption or behavior can determine the success of technology integration. Recent research confirms behavioral intention's importance in predicting behavior in educational settings (Andrews et al., 2021; Cabrera-Sánchez et al., 2021; Chatterjee & Bhattacharjee, 2020; Habibi, Muhaimin et al., 2023; Raffaghelli et al., 2022). Cabrera-Sánchez et al. (2021) found that behavioral intention highly predicted AI use in education. Chatterjee and Bhattacharjee (2020) found that excellent intentions boost educational professionals' AI-driven solution use. Supportive surroundings, training, and a clear explanation of AI technology benefits are needed to encourage positive behavior and successful integration of AI technology in education. In the current study, we extended the role of behavioral intention to predict perceived impact of AI on work engagement and AI use in HEIs, which has gained little scholarly attention (AlAjmi, 2022; Al-Takhayneh et al., 2022; Rahiman &

Kodikal, 2024). Behavioral intention, rooted in the TPB, predicts the perceived impact of AI on work engagement. AI's integration in HEIs enhances efficiency and personalized learning, potentially boosting engagement (Rahiman & Kodikal, 2024). Prior studies highlight how positive attitudes toward AI correlate with the increased perceived impact of AI on work engagement, particularly when users perceive AI as beneficial and supportive in their academic and administrative roles (AlAjmi, 2022; Rahiman & Kodikal, 2024). Three hypotheses were developed regarding the role of behavioral intention on behavior, the perceived impact of AI on work engagement, and the impact of AI on teaching and learning.

2.6. Behavior

In this study, behavior refers to how lecturers use AI tools. UTAUT confirms that behavior directly results from behavioral intention, which encompasses AI-graded assignments, tailored learning, and administrative efficiency. Lecturers who use AI-driven tasks may feel more accomplished and efficient, which can boost their job satisfaction. The behavior of lecturers in embracing AI technology can be a major predictor of perceived impact of AI on work engagement and perceived impact of AI on teaching and learning (AlAjmi, 2022; Al-Takhayneh et al., 2022; Rahiman & Kodikal, 2024). Lecturers actively using AI in their education and administrative responsibilities improve their work processes and help the institution adopt AI (Takhayneh et al., 2022). Positive AI experiences lead to broad adoption across departments, fostering an environment where AI is fully integrated into education (AlAjmi, 2022). Behavior is crucial to the perceived impact of AI on work engagement and the successful perceived AI effect on teaching and learning.

2.7. Perceived impact of AI on work engagement and perceived impact of AI on teaching and learning

The way AI affects employees' motivation, commitment, and emotional attachment to their work is reflected in the perceived impact of AI on work engagement (Kong et al., 2021). In this study, AI is being incorporated into more and more professional settings, changing how activities are completed and allowing for increased accuracy and efficiency for students. The decrease in routine and repetitive chores is one substantial effect. AI increases lecturers' happiness and engagement by automating repetitive tasks, allowing them to concentrate on more valuable and innovative work (Sreenivasan & Suresh, 2024). AI is reported to have a revolutionary effect on teaching and learning in HEIs, changing conventional teaching methods and enhancing student and teacher outcomes (Katsamakas et al., 2024). AI allows more individualized and effective educational experiences by introducing adaptive learning technologies, personalized learning paths, and enhanced analytics. AI enables customized learning by assessing each student's needs, pace, and progress through adaptable platforms. It automates tasks like grading, attendance, and report creation, freeing lecturers to focus on mentoring and curriculum development (Rane et al., 2023).

2.8. Hypotheses of the study

With eight variables in the current study (Figure 1), we proposed 10 hypotheses to evaluate their relationships.

H1: Performance expectancy correlates with behavioral intention.
H2: Effort expectancy correlates with behavioral intention.
H3: Social influence correlates with behavioral intention.
H4: Facilitating conditions correlate with behavioral intention
H5: Facilitating conditions correlate with behavior.
H6: Behavioral intention correlates with behavior.
H7: Behavioral intention correlates with perceived impact of AI on work engagement.
H8: Behavioral intention correlates with perceived impact of AI on teaching and learning.
H9: Behavior correlates with the perceived impact of AI on work engagement.
H10: Behavior correlates with perceived impact of AI on teaching and learning.

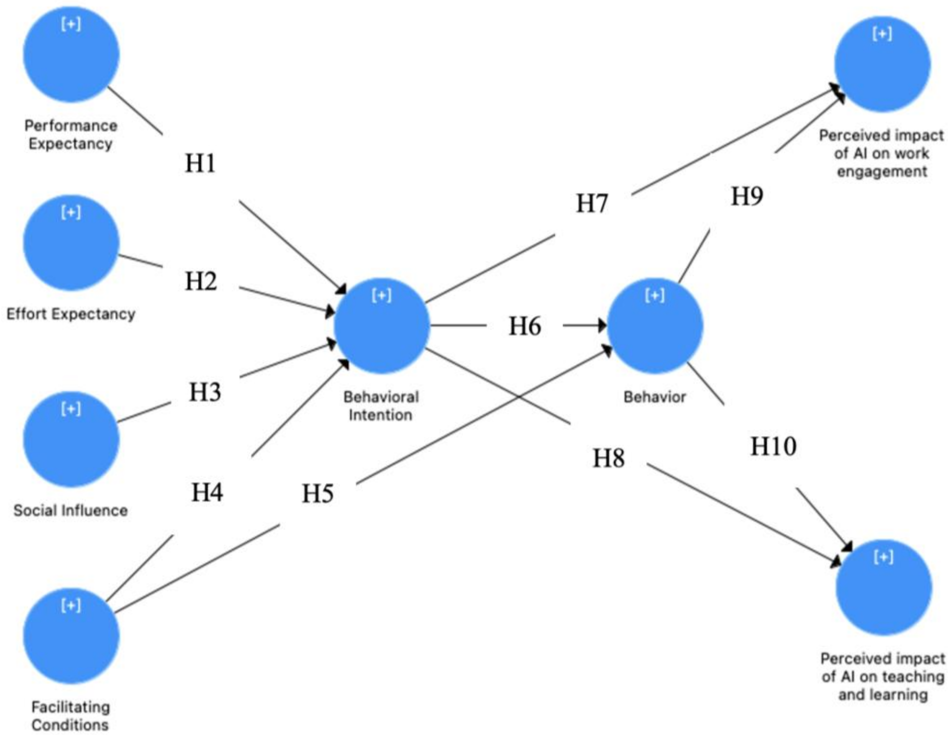

Figure 1. Proposed model: factors affecting behavior, perceived impact of AI on work engagement, and AI application

3. Methods

The survey included a Likert scale consisting of 27 items, each measured on a 5-point scale (Cabrera-Sánchez et al., 2021; Rahiman & Kodikal, 2024; Venkatesh, 2022). We requested five educational technology specialists to assess the items for content validity, and we revised them based on their suggestions. The remaining items (n. 24) in Appendix 1 were used for the pilot study and data collection after eliminating three questions due to the changes. The experts were selected based on their doctoral qualifications in educational technology, at least 10 years of experience in curriculum design and assessment, and prior publications in peer-reviewed journals on survey methodology. Validation involved independent assessments in which each expert rated items on a 4-point scale for relevance, clarity, and simplicity, and provided qualitative feedback via email surveys. No focus groups were used; assessments were administered individually to minimize bias. Inter-rater agreement was measured using Fleiss' Kappa ($\kappa = 0.82$, indicating substantial agreement), while intra-rater reliability was not assessed as it was a one-time evaluation. Expert data-guided revisions: items with average scores below 3.0 or conflicting feedback were modified or removed, ensuring the content validity index (CVI) exceeded 0.80 for the final instrument.

3.1. Data Collection

Using a Google Forms survey, we conducted a pilot study with 51 lecturers to assess the model's reliability. Participants in the pilot study were 18 men and 33 women from a single Indonesian HEI. The pilot research participants were not included in the primary data collection to prevent bias in the work. Good dependability was indicated by a Cronbach's alpha of >.700 (Brown, 2002). The reliability ranges from .773 to .897 (performance expectancy = .773, Effort expectancy = .810, social influence = .776, facilitating conditions = .821, facilitating conditions = .846, behavioral intention = .812, behavior = .757, perceived impact of AI on work engagement GPTU = .878, and perceived impact of AI on teaching and learning .897).

After calculating the first reliability test, we sent the survey to respondents at four Indonesian HEIs for the primary data collection. The questionnaire included a brief description, informed consent, demographic data, and the primary items. Ensuring the respondents employed AI in their activities was the first step in gathering data. We received 550 answers in all. Nonetheless, 516 responses—274 from women and 241 from men—were quantifiable. Ninety-seven lecturers had between one and ten years of professional experience, whereas 191 lecturers had between eleven and twenty years. In the meantime, 231 lecturers have over 20 years of experience in the classroom.

3.2. Data Analysis

We utilised the current SmartPLS statistical tool (SmartPLS 4.0) to test the hypotheses and theoretical framework. We used PLS-SEM for model assessment, measurement and structural models, because of its flexibility with sample sizes and non-normal data (Becker et al., 2023; Rigdon et al., 2017). The current study's intended population comprises lecturers from four Indonesian HEIs who utilize AI in teaching and research. We checked for normality by examining the data's skewness and kurtosis. The normality assumption was reviewed to determine if the data distribution met parametric test requirements, though PLS-SEM is robust to non-normality. This check is crucial for justifying the choice of analytical method, ensuring reliability in parameter estimates, and avoiding biased inferences in structural modeling. Presenting normality results enhances transparency, allowing readers to verify data characteristics and the appropriateness of PLS-SEM for handling any deviations from normality in the sample (Rigdon et al., 2017).

4. Results

4.1. Common Method Bias (CMB) and Normality of the Data

To enhance methodological rigor, we addressed potential biases thoroughly. Self-selection was alleviated by focusing on AI-utilizing lecturers from four distinct Indonesian HEIs, hence minimizing volunteer bias. Social desirability was mitigated by employing anonymous responses and neutral item language. The assessment of common method bias (CMB) was thorough; Harman's single-factor test indicated a variance of 42.3% (below the 50% threshold), and full collinearity variance inflation factors (VIFs) ranged from 1.12 to 2.87 (below 3.3), demonstrating the absence of CMB (Kock, 2015). PLS-SEM was chosen over CB-SEM not only for its versatility but also for the exploratory enhancement of UTAUT with new dimensions (work engagement, teaching impact), non-normative data (skewness/kurtosis ± 2), and a predictive emphasis. These selections guarantee strong, generalizable insights into the dynamics of AI adoption (Abdulmuhsin et al., 2022; Churi et al., 2022).

We checked for normality by examining the data's skewness and kurtosis; we also reported Mean and standar deviation (SD) (Table 1). The skewness and kurtosis values must be between -2 and +2 for the data to be normal. The skewness and kurtosis values fall within the range of -2 to +2 (Zhang et al., 2023). The lowest values of Skewness are reported to emerge on PAITL3 (-1.197), while the highest is reported for SI3 (.15). For Kurtosis, the values range from 1.932 (PAITL2) to -.921 (PAIWE1). Descriptive reports exhibit a sufficient value of PE1 Mean (4.250) and SD (.749) to EE4 (Mean = 3.472; SD = .961). To alleviate evaluation fear and minimize common-method bias, we included consent forms in the survey questionnaire that did not request personal identifiers. The CMB variation inflation factor (VIF) was determined; values of 4 or greater indicate common-method bias (Podsakoff et al., 2024).

Item	Mean	SD	Kurtosis	Skewness
PE1	4.25	.749	.004	-.722
PE2	4.293	.668	-.783	-.418
PE3	4.156	.706	-.983	-.231
EE1	4.181	.67	-.802	-.229
EE2	4.129	.683	-.867	-.169
EE3	3.944	.72	-.455	-.164
SI1	3.472	.961	-.196	-.084
SI2	3.484	.977	-.234	-.06
SI3	3.688	.875	-.949	.15
HM1	4.358	.607	-.663	-.376
HM2	4.11	.808	-.307	-.576

HM3	3.942	.968	.278	-.766
FC1	4.175	.701	.087	-.527
FC2	3.963	.771	-.641	-.216
FC3	4.042	.687	-.88	-.055
HB1	3.289	.984	-.184	.113
HB2	3.351	.993	-.433	-.05
HB3	2.998	1.097	-.617	.135
BI1	4.26	.691	.362	-.677
BI2	4.198	.672	-.816	-.259
BI3	3.909	1.019	-.35	-.662
B1	3.655	1.032	-.768	-.294
B2	3.89	.932	.475	-.883
B3	3.89	.94	.259	-.784
PAIWE1	3.611	1.061	-.921	-.198
PAIWE2	4.012	.871	.539	-.724
PAIWE3	3.705	1.059	-.87	-.298
PAITL1	3.984	.952	.593	-.79
PAITL2	4.121	.811	1.923	-1.073
PAITL3	4.239	.793	1.344	-1.197

Table 1. Mean, SD, Kurtosis, and Skewness

4.2. Mesurement Model

A detailed analysis of factors affecting behavior, behavioral intention, and AI's perceived impact on work engagement, teaching, and learning was conducted using PLS-SEM. This analysis employed a measurement model to assess the validity and reliability of the scale. Multiple items represent each construct, with factor loadings indicating the degree to which each item reflects the measure. Items PAITL1, PAITL2, and PAITL3 measure the Perceived impact of AI on teaching and learning construct, with loadings of .951, .960, and .948, respectively. The items' high loadings indicate potent indicators of the construct, encapsulating AI's role in education. Behavior and behavioral intention are also measured by items with high loadings, demonstrating reliability in capturing the intended dimensions. Other constructs (perceived impact of AI on work engagement, performance expectancy, effort expectancy, and facilitating conditions) have also informed a good loading value for each item, with values of greater than .700 (Habibi et al., 2024; Habibi, Sofyan, et al., 2023; Hair et al., 2022). Cronbach's alpha, rho_A, composite reliability (CR), and average variance extracted (AVE) support the constructs' reliability. The structures' Cronbach's alpha values range from .678 to .949, with most above .700, indicating excellent internal consistency (Benitez et al., 2020; Henseler, 2017; Sarstedt et al., 2022; Schuberth et al., 2022). Dijkstra-Henseler's rho (rho_A) is usually more robust than Cronbach's alpha and CR values. Rho_A values (.763–.949) further support internal consistency, lying between alpha and CR. All values are above .700, confirming the constructs' reliability and ensuring that the items collectively measure the constructs consistently (Dijkstra & Henseler, 2015). In detail, the measurement model exhibits strong to excellent psychometric properties across all constructs. Behavior shows excellent internal consistency (alpha = .896, rho_A = .898, CR = .935), while Behavioral intention demonstrates very good reliability (alpha = .890, rho_A = .895, CR = .931). Effort expectancy possesses the lowest alpha (.678) but remains acceptable thanks to a solid rho_A (.798) and CR (.854). Facilitating conditions has good reliability (alpha = .762, rho_A = .763, CR = .862). The perceived impact of AI on teaching and learning achieves outstanding reliability (alpha = .949, rho_A = .949, CR = .967), and both indicators of the perceived impact of AI on work engagement display excellent consistency (alpha = .926, rho_A = .926, CR = .953). Performance Expectancy exhibits very strong reliability (alpha = .906, rho_A = .907, CR = .941), and Social Influence provides good, acceptable values (alpha = .772, rho_A = .785, CR = .868). The structures account for more variance than measurement error, as AVE values range from .677 to .908. This thorough examination confirms constructs are well-defined and accurately assessed, underpinning future analysis and interpretation (Table 2).

Variable	Alpha	rho_A	CR	AVE
Behavior	.896	.898	.935	.828
Behavioral Intention	.890	.895	.931	.819
Effort Expectancy	.678	.798	.854	.746
Facilitating Conditions	.762	.763	.862	.677
Perceived impact of AI on teaching and learning	.949	.949	.967	.908
Perceived impact of AI on work engagement	.926	.926	.953	.871
Performance Expectancy	.906	.907	.941	.843
Social Influence	.772	.785	.868	.687

Table 2. Reliability and convergent validity: factors affecting behavior, perceived impact of AI on work engagement, and AI application

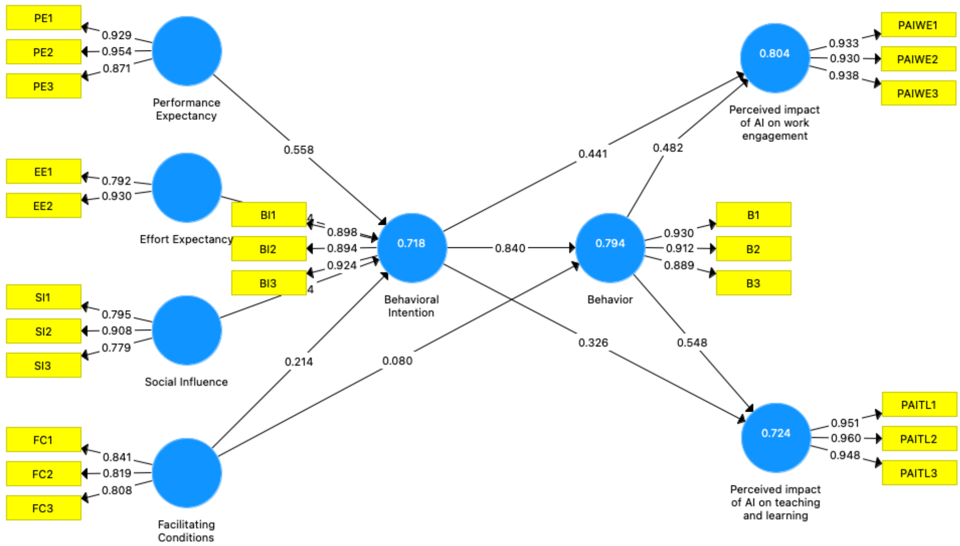

Figure 2. Measurement model: factors affecting behavior, perceived impact of AI on work engagement, and AI application

The Fornell-Larcker Criterion assesses discriminant validity; each construct's diagonal value, the square root of AVE, shows its variance relative to measurement error (Hamid et al., 2017). The perceived impact of AI on teaching and learning has a value of .953, indicating a high construct representation. Off-diagonal construct correlations should be lower than diagonal values to confirm discriminant validity. Behavior (.910), behavioral intention (.905), and perceived impact of AI on work engagement (.934) have high diagonal values, demonstrating internal consistency and validity. The discriminant validity of constructs like perceived impact of AI on teaching and learning with behavior (.838) and behavioral intention and lower correlations than diagonal values support perceived impact of AI on work engagement (.869). Effort expectancy (.864) and facilitating conditions (.823) similarly have good discriminant validity because their correlations with other dimensions are smaller than their AVE square roots. This analysis affirms each construct uniquely measures perceived AI impact on teaching and learning, providing a framework for understanding their relationships. Table 3 shows discriminant validity, supporting reliable educational research and implementation.

	B	BI	EE	FC	PAITL	PAIWE	PE	SI
Behavior	.910							
Behavioral Intention	.888	.905						
Effort Expectancy	.557	.590	.864					
Facilitating Conditions	.593	.612	.727	.822				

Perceived impact of AI on teaching and learning	.837	.813	.563	.640	.953			
Perceived impact of AI on work engagement	.873	.869	.553	.558	.792	.933		
Performance Expectancy	.836	.800	.585	.526	.711	.791	.918	
Social Influence	.677	.622	.414	.428	.613	.664	.567	.829

Table 3. Fornell-Larcker Criterion: factors affecting behavior, perceived impact of AI on work engagement, and AI application

The cross-loading analysis of the current study shows how well each item correlates with its concept relative to others, which is essential for discriminant validity (Hair et al., 2019). For example, PAITL1, PAITL2, and PAITL3 have significant loadings on the perceived impact of AI on teaching and learning construct (.951, .960, and .948), showing strong alignment compared to other loading values on other constructs. Items (B1, B2, and B3) also have high behavior construct loadings (.930, .912, and .889), confirming their significance better than others. The result shows that most items load stronger on their constructs than others, supporting the measurement model's discriminant validity (Table 4). This study guarantees each construct's distinctness and precise quantification, supporting AI research and implementation in higher education.

	B	BI	EE	FC	PAITL	PAIWE	PE	SI
B1	***.930***	.818	.582	.571	.753	.864	.821	.591
B2	***.912***	.820	.482	.545	.786	.802	.818	.612
B3	***.889***	.788	.454	.504	.750	.715	.637	.650
BI1	.781	***.898***	.438	.559	.751	.779	.715	.525
BI2	.729	***.894***	.536	.531	.697	.724	.644	.570
BI3	.893	***.924***	.623	.571	.758	.850	.804	.594
EE1	.289	.367	***.792***	.578	.256	.308	.293	.205
EE2	.610	.610	***.930***	.676	.639	.593	.647	.460
FC1	.453	.442	.601	***.841***	.482	.398	.399	.386
FC2	.474	.520	.607	***.819***	.462	.495	.432	.298
FC3	.530	.538	.588	***.808***	.624	.476	.460	.373
PAITL1	.780	.777	.532	.640	***.951***	.753	.692	.627
PAITL2	.811	.789	.535	.581	***.960***	.784	.724	.574
PAITL3	.804	.758	.544	.612	***.948***	.729	.616	.555
PAIWE1	.843	.809	.555	.500	.681	***.933***	.763	.593
PAIWE2	.801	.833	.519	.489	.760	***.930***	.743	.596
PAIWE3	.803	.792	.473	.575	.782	***.938***	.709	.675
PE1	.800	.742	.494	.475	.662	.723	***.929***	.542
PE2	.799	.733	.517	.434	.647	.712	***.954***	.518
PE3	.704	.728	.601	.541	.650	.745	***.871***	.504
SI1	.439	.416	.247	.348	.425	.436	.342	***.795***
SI2	.581	.557	.395	.338	.511	.578	.514	***.908***
SI3	.638	.552	.366	.380	.572	.614	.526	***.779***

Table 4. Cross-loading: factors affecting behavior, perceived impact of AI on work engagement, and AI application

The HTMT (Heterotrait-Monotrait) ratio of correlations, a crucial metric for evaluating discriminant validity, is shown in Table 5. HTMT compares average heterotrait to monotrait correlations to assess construct differences. Values below .85 indicate sufficient discriminant validity (or .90 for conceptually comparable items). Strong correlations between behavioral intention and important constructs, specifically performance expectancy (.924) and perceived impact of AI on teaching and learning (.908), highlight the significance of perceived utility and effectiveness in influencing adoption intentions. A substantial correlation between effort expectancy and behavioral intention (.720) and performance expectancy (.689) indicates that the ease of use of AI systems is significant. The moderate associations between facilitating conditions and behavioral intention (.736) and perceived AI on teaching and learning (.746) highlight the importance of outside assistance and resources in boosting adoption intentions. With a strong correlation between behavioral intention (.953) and performance expectancy (.863), the perceived impact of AI on work engagement underscores the importance of AI's beneficial effects on engagement and performance expectations. Although less significant than direct performance and engagement elements, Social influence represents the influence of peer and societal perceptions and correlates reasonably with behavioral intention (.740) and performance expectancy (.664). Adequate discriminant validity is confirmed by HTMT results below the threshold, guaranteeing the measured constructs are unique and the model's linkages are strong and clear.

	B	BI	EE	FC	PAITL	PAIWE	PE
Behavior							
Behavioral Intention	.990						
Effort Expectancy	.661	.720					
Facilitating Conditions	.713	.736	.903				
Perceived impact of AI on teaching and learning	.908	.883	.641	.746			
Perceived impact of AI on work engagement	.956	.953	.652	.659	.845		
Performance Expectancy	.924	.886	.689	.629	.766	.863	
Social Influence	.802	.740	.517	.558	.708	.774	.664

Table 5. HTMT: factors affecting behavior, perceived impact of AI on work engagement, and AI application

4.3. Structural Model

Using PLS-SEM procedures, we analyzed the factors that affect behavioral intention, behavior, perceived impact of AI on work engagement, and perceived impact of AI on teaching and learning through bootstrapping the data (5000 subsamples). Performance expectancy was the strongest predictor of behavioral intention, with a path coefficient of .558, indicating that technology's benefits and usefulness greatly influence users' intention to use AI. A t-value of 16.701 and an effect size (f^2) of .579 show that performance expectancy is statistically significant and strongly influences behavioral intention. However, effort expectancy, which evaluates the ease of use of technology, had no significant effect on behavioral intention, with a path coefficient of .024 and a t-value of .512. The finding shows that AI adoption in HEIs is not influenced by ease of use, potentially due to users' knowledge or comfort with the technology, making effort expectancy unimportant.

Social influence, another essential factor, moderately affected behavioral intention with a path coefficient of .204 and a t-value of 7.518. The report suggests that peer pressure, cultural norms, and colleagues' and leaders' influence influence instructional AI engagement goals. The moderate impact size of .097 shows that social influence drives behavioral intention more than social influence. Facilitating conditions, which examine technology resources and assistance, also had a substantial but smaller effect on behavioral intention (path coefficient = .214, t-value = 5.080) and behavior (path coefficient = .080, t-value = 2.856). The model's best direct link between behavioral intention and behavior was .840, indicating that once people want to use AI, they are likely to do so. Both behavior and behavioral intention had significant positive effects on perceived impact of AI on work engagement and perceived impact of AI on teaching and learning, demonstrating their interconnectedness and the central role of behavioral intention and behavior in educational AI integration as well as perceived impact of AI on work engagement (Table 6 and Figure 3).

H	Relationship	ß	t value	p values	f^2	Sign.
H1	Performance Expectancy -> Behavioral Intention	.558	16.786	.000	.5796	Yes
H2	Effort Expectancy -> Behavioral Intention	.024	.520	.603	.0008	No
H3	Social influence -> Behavioral Intention	.204	7.372	.000	.0969	Yes
H4	Facilitating Conditions -> Behavioral Intention	.214	5.080	.000	.0725	Yes
H5	Facilitating Conditions -> Behavior	.080	2.856	.004	.0194	Yes
H6	Behavioral intention -> Behavior	.840	36.540	.000	2.1383	Yes

H7	Behavioral intention -> Perceived impact of AI on work engagement	.441	11.458	.000	.2094	Yes
H8	Behavioral intention -> Perceived impact of AI on teaching and learning	.326	4.692	.000	.0811	Yes
H9	Behavior -> Perceived impact of AI on work engagement	.482	11.952	.000	.2494	Yes
H10	Behavior -> Perceived impact of AI on teaching and learning	.548	8.090	.000	.2293	Yes

Table 6. Structural model: factors affecting behavior, perceived impact of AI on work engagement, and AI application

The current research also presents the R^2 and Q^2 values for various constructs related to AI applications in HEIs, providing insights into the model's predictive accuracy and relevance. The R^2 value, or coefficient of determination, indicates the proportion of variance in the dependent variable that is predictable from the independent variables (Habibi et al., 2020; Hair et al., 2019). For the perceived impact of AI on teaching and learning, the R^2 value is .724, suggesting that the model explains 72.4% of the variance, indicating a strong predictive power. Similarly, the behavior construct has an R^2 of .794, meaning that 79.4% of its variance is accounted for, reflecting a robust model fit.

Behavioral intention shows an R^2 of .718, while the perceived impact of AI on work engagement has an R^2 of .804, indicating substantial explanatory power. The Q^2 value, derived from the Stone-Geisser test, assesses the model's predictive relevance through a blindfolding procedure. A Q^2 value greater than zero suggests the model has predictive relevance for a particular construct. The perceived impact of AI on teaching and learning has a Q^2 of .653, indicating good predictive relevance. Behavior, with a Q^2 of .652, also demonstrates strong predictive relevance (Table 7). Behavioral intention and perceived impact of AI on work engagement have Q^2 values of .579 and .695, respectively, further supporting the model's predictive capabilities. Overall, the high R^2 and Q^2 values across these constructs suggest that the model is accurate and relevant in predicting the impact of perceived impact of AI on teaching and learning (Table 7). This analysis underscores the model's effectiveness in capturing the dynamics of AI integration, behavior, intention, and engagement, providing a solid foundation for further research and practical application in educational settings.

	R^2	Q^2
Perceived impact of AI on teaching and learning	.724	.653
Behavior	.794	.652
Behavioral intention	.718	.579
Perceived impact of AI on work engagement	.804	.695

Table 7. R^2 and Q^2

5. Discussion

The model's validation and reliability in exploring factors affecting behavioral intention, behavior, perceived impact of AI on work engagement, and perceived impact of AI on teaching and learning were rigorously established through Content Validity Index (CVI), a pilot study, and measurement model assessment.CVI obtained initial content validity. Five educational technology experts with doctorates, with over 10 years of curriculum design experience and survey methodology publications, independently evaluated the 27 survey items on a 4-point scale for relevance, clarity, and representativeness. Quantifying inter-rater agreement with Fleiss' Kappa ($\kappa = 0.82$) revealed significant consensus (Habibi et al., 2024). The instrument's alignment with the structures was confirmed by 24 items with an overall CVI greater than 0.80 after revising or eliminating items below 3.0 or with contradicting feedback. Following this, 50 Indonesian HEI lecturers who employ AI in teaching and research participated in a pilot project. It identified minor phrasing and response-pattern issues and tested the instrument's practicality. Initial internal consistency was shown by subscale Cronbach's alpha of 0.78–0.92. Final revisions improved comprehensibility without affecting fundamental validity. Finally, SmartPLS 4.0 was used to evaluate the measurement model via PLS-SEM. All indicators had outer loadings above 0.70, confirming convergence. The Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratios below 0.85 confirmed reliability and discriminant validity. Composite reliability (CR) scores were over 0.80, and Average Variance Extracted (AVE) exceeded 0.50. Skewness and kurtosis validations supported the use of PLS-SEM with non-normal dana (Becker et al., 2023; Rigdon et al., 2017). This comprehensive methodology maintained the model's robustness in capturing AI's implications for lecturers' intentions, behaviors, and perceived impacts, enabling hypothesis testing and theoretical insights.

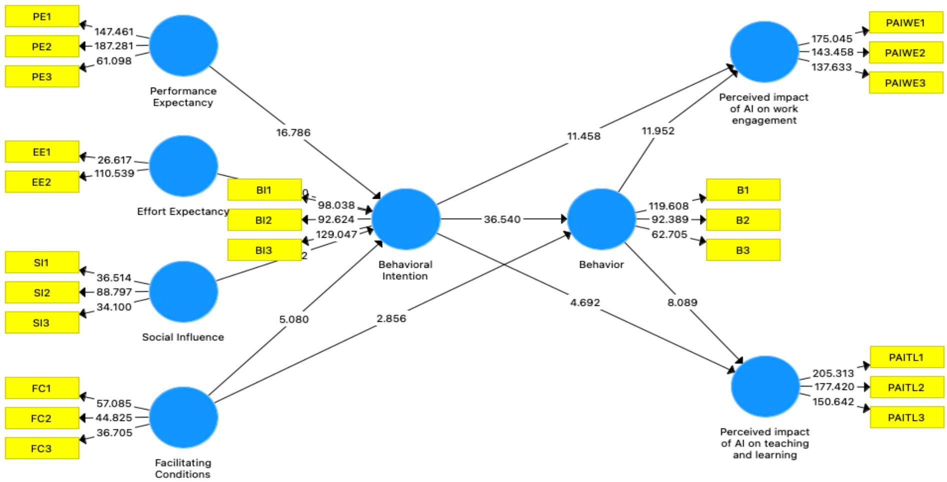

Figure 3. Structural model

The study found that performance expectancy positively affects behavioral intention with a path coefficient of .558, consistent with technology adoption research. In HEIs, users are more likely to adopt and employ AI technologies if they believe they will improve their academic or professional performance. UTAUT confirms that people are motivated by expected performance benefits from new technology (Venkatesh, 2022). Recent research has confirmed this, especially in educational contexts where AI's significance in improving learning results is becoming more apparent (Andrews et al., 2021; Habibi, Muhaimin et al., 2023; Lin et al., 2022; Sebastián et al., 2022; Venkatesh, 2022; Wu et al., 2022). Habibi, Muhaimin, et al. (2023) found that performance expectancy significantly influences university lecturers' propensity to employ AI-driven learning technologies. However, effort expectancy, which evaluates the ease of use of technology, had no significant effect on Behavioral Intention (path coefficient = .024). This suggests that HEIs users may be more concerned with the potential benefits of AI than the effort necessary to utilize AI technologies, especially if they believe the long-term performance benefits surpass any early effort-related hurdles, similar to a prior study (Grassini et al., 2024). These findings contradict previous studies on UTAUT and technology acceptance (Sebastián et al., 2022; Habibi, Muhaimin, et al., 2023; Li et al., 2024; Lin et al., 2022). For instance, Habibi et al. (2023) found effort expectancy to be a key determinant in technology or system uptakes. Growing familiarity with digital tools among educators may have reduced the perceived difficulty of adopting new technologies.

Social influence predicts behavioral intention with a path coefficient of .204. Peers, coworkers, and academic leaders can influence people's AI adoption aspirations. UTAUT model confirms that social impact strongly influences behavioral intention, especially in organizational settings where peer pressure and institutional norms are necessary (Venkatesh, 2022). Prior studies have found that social norms or influences and peer endorsements considerably increase educators' willingness to use AI (Grassini et al., 2024; Habibi, Muhaimin et al., 2023; Li et al., 2024; Lin et al., 2022; Sebastián et al., 2022). Creating a supportive culture surrounding AI use in HEIs, where leadership and peers endorse its use, may increase adoption rates. Facilitating conditions, such as technology resources and support, also significantly affected behavioral intention (path coefficient of .214) and behavior (.080). This finding supports past technology adoption research that facilitating environments are necessary but not sufficient to drive behavior (Andrews et al., 2021; Cabrera-Sánchez et al., 2021; García de Blanes Sebastián et al., 2022; Grassini et al., 2024; Habibi, Muhaimin, et al., 2023; Li et al., 2024; Lin et al., 2022; Venkatesh, 2022; Wu et al., 2022). Supportive settings improve technology adoption early on but decrease as users become more familiar with AI. The findings show that enough infrastructure, training, and technical support are necessary to establish an intention to utilize AI, but it has little effect on actual utilization.

Behavioral intention predicted behavior best in the study, with a path coefficient of .84. Intention is crucial to whether people will engage in an activity, according to the UTAUT model. Lecturers in Indonesian HEIs are more likely to implement AI if lecturers and students are strongly encouraged to use it. This is important in contexts where AI technologies are readily available and accessible, lowering utilization barriers. The literature shows that purpose strongly influences behavior (Andrews et al., 2021; Cabrera-Sánchez et al., 2021; Chatterjee & Bhattacharjee, 2020; Habibi, Muhaimin, et al., 2023; Raffaghelli et al., 2022). Habibi, Muhaimin, et al. 2023)found that strong intentions influence behavior in many circumstances, including technology adoption. Behavioral intention also significantly predicted perceived impact of AI on work engagement (path coefficient of .441) and perceived impact of AI on teaching and learning (path coefficient of .326), suggesting that motivated AI adopters work harder and use AI more in school. Job demands and resources influence perceived impact of AI on work engagement (AlAjmi, 2022; Al-Takhayneh et al., 2022; Rahiman & Kodikal, 2024). AI can improve the perceived impact of AI on work engagement and the perceived effect of AI on teaching and learning if users are motivated to use the technology in their daily activities.

The study concludes that behavior affects perceived impact of AI on work engagement (.482) and perceived impact of AI on teaching and learning (.548). The correlation shows that AI technologies improve the perceived impact of AI on work engagement and lead to more AI adoption in education. These findings are crucial to comprehending HEI AI adoption's long-term effects. The substantial association between behavior and perceived impact of AI on work engagement shows that using AI makes people more invested in their work (AlAjmi, 2022; Al-Takhayneh et al., 2022; Rahiman & Kodikal, 2024). Recent research (Rahiman & Kodikal, 2024) has examined how AI in education might boost the perceived impact of AI on work engagement by making tasks more efficient and fulfilling. Behavior's considerable impact on AI applications suggests that actual usage drives AI's widespread adoption in education. Once people use AI, they will discover benefits and apply it in various cases, leading to broader organizational adoption. Future research should explore how behavior mediates between intention and outcomes, and how different AI applications influence perceptions of AI's impact on work engagement and performance.

This study extends UTAUT by incorporating perceived AI impact on engagement and outcomes, creating a comprehensive framework linking technology acceptance with motivation and pedagogical effectiveness in higher education. Using the extended UTAUT shows that behavioral intention and behavior drive adoption and sustain lecturers' commitment by reducing administrative burdens and enabling meaningful instructional design. This reciprocal mechanism—where AI behavior reinforces engagement—offers a fresh theoretical viewpoint unseen in past UTAUT investigations in high-pressure Indonesian HEI contexts, where faculty often shoulder significant teaching, research, and service loads. The model exhibits better predictive power, explaining job engagement and teaching impact variance, surpassing standard UTAUT criteria (~50-60%). Moreover, experienced Indonesian lecturers' insignificant effort expectancy indicates a maturation effect, with performance expectancy dominating intention formulation as digital familiarity increases. This contextual nuance refines UTAUT's temporal dynamics and emphasizes stage-specific adoption models, adding theoretical depth beyond replication studies like Grassini et al. (2024). The results leave crucial holes that future research must fill to improve generalizability and practicality. Digital literacy, organisational culture, and institutional type (public vs. private, urban vs. rural) may moderate pathway strength. For example, inadequate digital literacy may increase effort expectancy in late adopters. Longitudinal designs are needed to determine if AI fatigue reduces engagement gains. Policymakers and HEI leaders should consider a strategic pivot as conducive conditions predict intention and behavior, suggesting infrastructure alone is insufficient. To avoid digital divides, investments must prioritize role-specific training, performance-focused communication (e.g., measurable time savings), and equity-driven deployment. If human-centered implementation protects teacher-student interactions, scalable customization improves education quality, graduate preparedness for Industry 4.0, and institutional ecosystems. The extended UTAUT provides a model for revolutionary, sustainable AI integration in higher education, especially in Indonesia.

6. Conclusion

This study sheds light on how Indonesian HEIs adopt and use AI technologies. Performance expectancy and behavioral intention were key factors, highlighting the importance of perceived benefits and strong intentions in AI adoption. Social influence and facilitating conditions greatly affected behavioral intention but had little effect on actual behavior, underscoring the complexity of technology adoption. The significant correlation between behavioral intention and behavior predicts that motivated people would engage more with AI, improving the perceived impact of AI on work engagement and broader AI use in education. These findings add to the literature on AI adoption in education and demonstrate the value of expanded UTAUT models in understanding technological acceptance dynamics.

However, this study includes shortcomings that should be addressed in future research. First, cross-sectional statistics only record a snapshot in time, limiting causal inferences. Longitudinal research would help determine how these linkages change and how AI adoption affects the perceived impact of AI on work engagement and education. This study focused on AI in HEIs; hence, its conclusions may not apply to other settings or technologies. Future research should encompass educational contexts and examine moderating variables like organizational culture and individual variations affecting AI acceptance and use. Future studies can overcome these constraints to better understand technology adoption in education and inform ways to integrate AI into teaching and learning.

References

Abdulmuhsin, A. A., Değirmenci, B., Efendioğlu, İ. H., & Durmaz, Y. (2022). The perception of COVID-19 and avoidance behavior in Turkey: the role of income level, gender and education. *International Journal of Emerging Markets*, *17*(10). https://doi.org/10.1108/IJOEM-11-2020-1308

AlAjmi, M. K. (2022). The impact of digital leadership on teachers' technology integration during the COVID-19 pandemic in Kuwait. *International Journal of Educational Research*, *112*. https://doi.org/10.1016/j.ijer.2022.101928

Alhwaiti, M. (2023). 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. *Applied Artificial Intelligence*, *37*(1). https://doi.org/10.1080/08839514.2023.2175110

Al-Takhayneh, S. K., Karaki, W., Hasan, R. A., Chang, B. L., Shaikh, J. M., & Kanwal, W. (2022). Teachers' psychological resistance to digital innovation in jordanian entrepreneurship and business schools: Moderation of teachers' psychology and attitude toward educational technologies. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.1004078

An, X., Chai, C. S., Li, Y., Zhou, Y., & Yang, B. (2023). Modeling students' perceptions of artificial intelligence-assisted language learning. *Computer-Assisted Language Learning*. https://doi.org/10.1080/09588221.2023.2246519

Andrews, J. E., Ward, H., & Yoon, J. (2021). UTAUT as a Model for Understanding Intention to Adopt AI and Related Technologies among Librarians. *The Journal of Academic Librarianship*, *47*(6), 102437. https://doi.org/10.1016/j.acalib.2021.102437

Ashraf, D. (2023). *Digital Finance and Artificial Intelligence: Islamic Finance Challenges and Prospects*. https://doi.org/10.1007/978-3-031-13302-2_11

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information and Management*, *57*(2). https://doi.org/10.1016/j.im.2019.05.003

Brown, J. D. (2002). The Cronbach alpha reliability estimate. *Shiken: JALT Testing & Evaluation SIG Newsletter*, *6*(1).

Cabrera-Sánchez, J. P., Villarejo-Ramos, Á. F., Liébana-Cabanillas, F., & Shaikh, A. A. (2021). Identifying relevant segments of AI applications adopters – Expanding the UTAUT2's variables. *Telematics and Informatics*, *58*. https://doi.org/10.1016/j.tele.2020.101529

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5). https://doi.org/10.1007/s10639-020-10159-7

Churi, P., Pawar, A. V., & Abdulmuhsin, A. A. (2022). Perception of privacy issues and awareness in health-care knowledge management systems: empirical study in Indian health-care context. *International Journal of Organizational Analysis*, *30*(5). https://doi.org/10.1108/IJOA-11-2020-2486

Clifford, R., & Perez, L. (2024). AI in higher education: Faculty perspective towards artificial intelligence through UTAUT approach. *HCMCOUJS-Social Sciences*, *14*(4). https://doi.org/10.46223/HCMCOUJS

Deng, J., & Lin, Y. (2023). The Benefits and Challenges of ChatGPT: An Overview. *Frontiers in Computing and Intelligent Systems*, *2*(2). https://doi.org/10.54097/fcis.v2i2.4465

Dijkstra, T. K., & Henseler, J. (2015). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics and Data Analysis*, *81*. https://doi.org/10.1016/j.csda.2014.07.008

Grassini, S., Aasen, M. L., & Møgelvang, A. (2024). Understanding University Students' Acceptance of ChatGPT: Insights from the UTAUT2 Model. *Applied Artificial Intelligence*, *38*(1). https://doi.org/10.1080/08839514.2024.2371168

Habibi, A., Muhaimin, M., Danibao, B. K., Wibowo, Y. G., Wahyuni, S., & Octavia, A. (2023). ChatGPT in higher education learning: Acceptance and use. *Computers and Education: Artificial Intelligence*, *5*. https://doi.org/10.1016/j.caeai.2023.100190

Habibi, A., Mukminin, A., & Sofyan, S. (2024). Access to the digital technology of urban and suburban vocational schools. *Education and Information Technologies*, *29*(4). https://doi.org/10.1007/s10639-023-12006-x

Habibi, A., Sofyan, S., & Mukminin, A. (2023). Factors affecting digital technology access in vocational education. *Scientific Reports*, *13*(1), 5682. https://doi.org/10.1038/s41598-023-32755-6

Habibi, A., Yusop, F. D., & Razak, R. A. (2020). The role of TPACK in affecting pre-service language teachers' ICT integration during teaching practices: Indonesian context. *Education and Information Technologies*, *25*(3), 1929–1949. https://doi.org/10.1007/s10639-019-10040-2

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1, pp. 2–24). https://doi.org/10.1108/EBR-11-2018-0203

Hair, J., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *PLS-SEM Book: A Primer on PLS-SEM (3rd Ed.)*. Thousand Oaks: Sage.

Hamid, M. R., Sami, W., & Mohmad Sidek, M. H. (2017). Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. *Journal of Physics: Conference Series*, *890*(1). https://doi.org/10.1088/1742-6596/890/1/012163

Henseler, J. (2017). *Partial Least Squares Path Modeling* (pp. 361–381). https://doi.org/10.1007/978-3-319-53469-5_12

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education. Promise and Implications for Teaching and Learning.*

Katsamakas, E., Pavlov, O. V., & Saklad, R. (2024). Artificial Intelligence and the Transformation of Higher Education Institutions: A Systems Approach. *Sustainability*, *16*(14), 6118. https://doi.org/10.3390/su16146118

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration*, *11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of artificial intelligence (AI) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management*, *33*(2). https://doi.org/10.1108/IJCHM-07-2020-0789

Li, L., Peng, W., & Rheu, M. M. J. (2024). Factors Predicting Intentions of Adoption and Continued Use of Artificial Intelligence Chatbots for Mental Health: Examining the Role of UTAUT Model, Stigma, Privacy Concerns, and Artificial Intelligence Hesitancy. *Telemedicine and E-Health*, *30*(3). https://doi.org/10.1089/tmj.2023.0313

Lin, H. C., Ho, C. F., & Yang, H. (2022). Understanding adoption of artificial intelligenceenabled language e-learning system: An empirical study of UTAUT model. *International Journal of Mobile Learning and Organisation*, *16*(1). https://doi.org/10.1504/IJMLO.2022.119954

Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common Method Bias: It's Bad, It's Complex, It's Widespread, and It's Not Easy to Fix. In *Annual Review of Organizational Psychology and Organizational Behavior* (Vol. 11). https://doi.org/10.1146/annurev-orgpsych-110721-040030

Raffaghelli, J. E., Rodríguez, M. E., Guerrero-Roldán, A. E., & Bañeres, D. (2022). Applying the UTAUT model to explain the students' acceptance of an early warning system in Higher Education. *Computers and Education*, *182*. https://doi.org/10.1016/j.compedu.2022.104468

Ragheb, M. A., Tantawi, P., Farouk, N., & Hatata, A. (2022). Investigating the acceptance of applying chat-bot (Artificial intelligence) technology among higher education students in Egypt. In *International Journal of Higher Education Management (IJHEM)* (Vol. 8). CBER. www.cberuk.com

Rahiman, H. U., & Kodikal, R. (2024). Revolutionizing education: Artificial intelligence empowered learning in higher education. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186X.2023.2293431

Rane, N., Choudhary, S., & Rane, J. (2023). Education 4.0 and 5.0: Integrating Artificial Intelligence (AI) for Personalized and Adaptive Learning. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4638365

Sarstedt, M., Radomir, L., Moisescu, O. I., & Ringle, C. M. (2022). Latent class analysis in PLS-SEM: A review and recommendations for future applications. *Journal of Business Research*, *138*. https://doi.org/10.1016/j.jbusres.2021.08.051

Schuberth, F., Rademaker, M. E., & Henseler, J. (2022). Assessing the overall fit of composite models estimated by partial least squares path modeling. *European Journal of Marketing*. https://doi.org/10.1108/EJM-08-2020-0586

Sebastián, M., Sarmiento Guede, J. R., & Antonovica, A. (2022). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.993935

Sreenivasan, A., & Suresh, M. (2024). Design thinking and artificial intelligence: A systematic literature review exploring synergies. *International Journal of Innovation Studies*, *8*(3), 297–312. https://doi.org/10.1016/j.ijis.2024.05.001

Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1–2). https://doi.org/10.1007/s10479-020-03918-9

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Wu, W., Zhang, B., Li, S., & Liu, H. (2022). Exploring Factors of the Willingness to Accept AI-Assisted Learning Environments: An Empirical Investigation Based on the UTAUT Model and Perceived Risk Theory. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.870777

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? In *International Journal of Educational Technology in Higher Education* (Vol. 16, Issue 1). https://doi.org/10.1186/s41239-019-0171-0

Zhang, D., Jia, J., Han, Z., Ouyang, H., Liu, J., & Han, X. (2023). An efficient uncertainty quantification and propagation method through skewness and kurtosis fitting region. *Structural and Multidisciplinary Optimization*, *66*(2). https://doi.org/10.1007/s00158-022-03481-w

APPENDIX 1

Survey instrument

Umur
Jenis kelamin
Pengalaman mengajar

A. Performance Expectancy

1. Menggunakan alat AI meningkatkan kinerja pekerjaan saya.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

2. Aplikasi AI meningkatkan efisiensi kerja saya.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

3. Saya menemukan alat AI membantu mencapai tujuan kerja saya.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

B. Effort Expectancy (Ekspektasi Usaha)

1. Mempelajari cara menggunakan aplikasi AI mudah bagi saya.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

2. Saya merasa alat AI mudah digunakan dalam tugas sehari-hari saya.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

3. Berinteraksi dengan aplikasi AI tidak memerlukan banyak usaha.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

C. Social Influence (Pengaruh Sosial)

1. Orang-orang yang pendapatnya saya hargai menginginkan saya menggunakan aplikasi AI.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

2. Rekan kerja saya berpikir saya harus menggunakan alat AI di tempat kerja.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

3. Di organisasi saya, menggunakan aplikasi AI dianggap penting.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

D. Facilitating Conditions (Kondisi yang Mendukung)

1. Saya memiliki sumber daya yang diperlukan untuk menggunakan aplikasi AI.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

2. Saya memiliki pengetahuan yang dibutuhkan untuk menggunakan alat AI secara efektif.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

3. Alat AI kompatibel dengan sistem lain yang saya gunakan.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

E. Niat

1. Saya berniat menggunakan AI dalam kegiatan pembelajaran saya di masa depan.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

2. Saya berencana untuk memanfaatkan teknologi AI untuk meningkatkan kualitas pengajaran saya.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

3. Saya akan secara aktif mencari cara untuk mengintegrasikan AI ke dalam metode pembelajaran saya.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

F. Perilaku

1. Saya sering menggunakan aplikasi AI dalam pekerjaan saya.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

2. Saya merekomendasikan alat AI kepada orang lain.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

3. Saya berencana untuk terus menggunakan aplikasi AI di masa depan.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

G. Keterlibatan Kerja

1. Alat AI membuat saya lebih terlibat dalam pekerjaan.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

2. Menggunakan aplikasi AI membuat pekerjaan saya lebih menarik.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

3. Alat AI meningkatkan komitmen saya terhadap pekerjaan.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

H. Aplikasi AI di Perguruan Tinggi

1. Aplikasi AI meningkatkan kualitas pengajaran di perguruan tinggi.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

2. Alat AI memfasilitasi proses pembelajaran di perguruan tinggi.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]

3. Aplikasi AI sangat penting untuk inovasi di perguruan tinggi.
   - Sangat Tidak Setuju [1] - Sangat Setuju [5]