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Rethinking AI Acceptance in Corporate: A Human-Centric Extension of UTAUT

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Abstract

In the business corporate world, artificial intelligence (AI) is becoming a disruptive force. This study explores the intricacies of adopting AI in corporate environments, emphasizing factors that affect both behavioral intentions and real usage patterns. This study, which drew on the Unified Theory of Acceptance and Use of Technology (UTAUT), identified the distinctive features of AI and added new determinants, including perceived humanness, bias, job threat, functionality, transparency, and privacy and security issues. These determinants cover technological, human-centric, and situational aspects which can either catalyze or hinder AI acceptance. Our quantitative research, involving 223 professionals across diverse sectors in Saudi Arabia, expanded the UTAUT model by revealing critical factors driving AI acceptance, including ethics and privacy considerations. Intriguingly, certain latent factors were identified to inversely affect AI application. This research addresses important ethical, security, and operational issues related to AI deployment, while also expanding the theoretical understanding of AI's role in business. Such insights are paramount for decision-makers, practitioners, and academics alike, ensuring the sustainable and responsible incorporation of AI in the business realm.

Keywords: *Artificial Intelligence, AI in Business, Technology Acceptance, Ethical Considerations, UTAUT, Technology Adoption.*

Introduction

The acceptability and deployment of artificial intelligence (AI) in work contexts has received attention due to its development. The effort of investigating AI acceptance and adoption is categorized into four areas: (1) new antecedents/determinants (e.g. individual, environmental, technological, interventional characteristics) (Fan et al., 2020; Roh et al., 2023), (2) new moderator (Gurmeet et al., 2022), (3) new predictors (Jain et al., 2022), and (4) new consequences such as job satisfaction and employee performance (Venkatesh, 2022). This study proposed a holistic extension of UTAUT that synthesizes all the previous four categories to close the gap of having robust theory that captures the unique issues of AI at organizational and individual levels. Therefore, this study bases its proposed extension on the original UTAUT's root constructs that were formulated and validated based on synthetization and comparison of eight well-known acceptance and adoption models and theories. In addition, the current study is in the line with the Venkatesh (2022) AI research agenda grounded in UTAUT. It is suggested that this study serve as a reference for future research and workplace practices related to AI adoption at the individual and organizational levels. The following sections provide a thorough summary of the primary and secondary structures included in the UTAUT extended model.

Performance Expectancy

Performance expectancy pertains to performance to attain job gains as perceived by users (Venkatesh et al., 2003). In order to capture many AI performance qualities, such as perceived humanness, functionality, inference, automaticity, and autonomy, this study extended performance expectancy to include such qualities.

H1: User behavioral intention to use AI is influenced by performance expectations.

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AI Perceived Humanness

Perceived humanness refers to how much a user views the AI agent as human-like during their interactions (Du et al., 2022). Based on social robotics, van Doorn et al. (2017) claimed that people often "imbue the real or imagined behavior of nonhuman agents with humanlike characteristics, motivations, intentions, or emotions," which then affects how they interact with those agents. This tendency to anthropomorphize AI agents is rooted in social robotics (Epley et al., 2007, p. 864). Złotowski et al. (2018) proposed two levels of anthropomorphism, conscious and mindless, based on the media equation theory. Mindful anthropomorphism indicates if anthropomorphism is a deliberate or inadvertent activity. Mindless anthropomorphism occurs when user rapidly process AI agent as human-like while the mindful one occurs when user takes effort and thought to decide AI agent is a human-like (Lu et al., 2022).

Anthropomorphizing agents cause users to feel more positively (they find a system more appealing and desired, for example), which makes them prefer the product in the end (Wan & Aggarwal, 2015). Anthropomorphization is therefore anticipated to increase the beneficial effects of AI behavioral intention even further (van Doorn et al., 2017). Canning et al. (2014) discovered, for example, that robots with a higher degree of resemblance to humans are regarded as more intelligent and receive better ratings for competence and utility than mechanical ones. As a result, humanizing AI agents need to strengthen the beneficial effect that automated social presence has on presumed competence (van Doorn et al., 2017).

From a psychological perspective, anthropomorphism influences the interplay between AI agent and user's psychological ownership through increasing AI agent receptiveness, and attractiveness (van Doorn et al., 2017). Users' self-congruence and self-AI integration are impacted by anthropomorphism, and they are critical elements in the acceptance and use of AI systems (Alabed et al., 2022).

Anthropomorphism, or the perception of humanness, has been proven to have a major impact on users' attitudes, acceptance, and continuous usage of AI agents (Blut et al., 2021; Li & Suh, 2022; Lu et al., 2022; Mende et al., 2019; Zhang et al., 2021). However, findings show inconsistency in positivity or negativity of such an influence where perceived humanness may negatively influence user acceptance of AI agent. High human-like AI agent may lead to unrealistic expectations, threatened identity, and feelings of eeriness (Kätsyri et al., 2015; Lu et al., 2019; Lu et al., 2022; Mende et al., 2019).

From a different angle, several research emphasized the significance of multidimensional measurements to accurately represent AI's perceived humanness by combining three related constructs: social presence, anthropomorphism, and conversational human voice (Alabed et al., 2022; Li & Suh, 2022; Uysal et al., 2023).

Three factors make up AI perceived humanness for the purposes of this study: the degree of communication, collaboration, and naturalness of the AI agent. When users perceive the communication with AI agent as natural, collaborative in tasks, and use communicative interactions, it increases the overall perception of AI humanness which leads to more acceptance and adoption. Hence, the following hypothesis is put out by this study:

Sub-H1a: Perceived humanness positively influences behavioral intention to utilize AI.

AI Perceived Functionality

The perceived function of AI is a significant determinant of AI performance expectations. This element was created using the multidimensional value theory, in which the acceptability of AI is significantly influenced by the utilitarian value (Yin & Qiu, 2021). According to Sánchez-Fernández and Iniesta-Bonillo (2007), utilitarian value is the use of a particular service or technology as a means to a goal; these are the instrumental, task-related, logical, and functional aspects of a technology. Further, according to Expectancy-Disconfirmation Paradigm, pre-performance expectations influence user's post-performance technology assessment and satisfaction (Woodruff, 1997); therefore, perceived function of AI is interrelated with performance expectancy construct in UTAUT.

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Functional attributes of AI included in this factor are accuracy, integratability, personalization, and enhanceability (Akdim & Casaló, 2023; Boksberger & Melsen, 2011; Du et al., 2022; Gupta et al., 2019; Lu et al., 2019; Tzeng, 2011). Integrability is the degree to which users believe AI technology can readily integrate with their current processes and tools, while accuracy is the degree to which users believe AI is more accurate than humans in gathering and interpreting data to make better judgements for jobs (Kelly et al., 2023: Chatterjee et al., 2021; Tzeng, 2011; Yin & Qiu, 2021). Enhancability, also known as perceived usefulness in the literature, refers to the extent to which users believe that AI agents can enhance and improve their experience with the task at hand. Personalization is the belief held by users that AI systems can be customised to suit their preferences and needs (Du et al., 2022). Thus, underlying hypothesis of this factor is that:

Sub-H1b: The behavioral intention to use AI is positively impacted by the perceived functioning of AI.

AI Perceived Inference

Machine learning as an AI application works in two phases: training on pre-existing data, then inference new data to draw conclusions and make predictions (Jamal et al., 2018). Therefore, AI inference refers to the process of applying the learned knowledge from a trained model to real-world data through AI inference engine (Hastie et al., 2009).

As inference capability is the notion of AI technology, this study proposed it as a factor that holds a potential in enhancing the performance expectancy of AI. So, the degree to which a user believes that artificial intelligence (AI) can mimic human cognitive complexity, engage in logical reasoning, forecast outcomes, identify human manipulation, learn from data independently, and produce high-quality outputs is known as AI perceived inference. This study hypothesizes that:

Sub-H1c: The behavioral intention to use AI is positively impacted by AI perceived inference.

AI Perceived Automaticity and Autonomy

The term "AI perceived automaticity" describes the user's perception of an AI agent's capacity to automate repetitive operations or conduct tasks in an automated way (Jain et al., 2022). The capacity of an AI agent to function and make decisions on its own without constant human involvement is referred to as AI autonomy (Tanantong & Wongras, 2024; Tzeng, 2011). While automaticity enables an AI agent to perceive and respond to its surroundings, autonomy empowers the agent to independently develop and adapt its behaviors within a dynamic environment while operating. (Florian, 2003). This brings controllability as an overlap between AI function and user effort expectancy to control an AI agent. However, controllability is considered in the literature as a perception of AI agent's attribute and affordance than a user effort and preference (Degachi et al., 2023; Mirbabaie et al., 2022; Yan et al., 2022). Thus, the formulated hypothesis is:

Sub-H1d: The behavioral intention to use AI is positively impacted by the perceived automaticity and autonomy of AI.

Effort Expectancy

The degree of convenience connected with using the AI system is the focus of the UTAUT effort expectation construct (Venkatesh, 2022). However, this cannot be confined solely to ease of use in the original UTAUT, considering AI's unique characteristics (Venkatesh, 2022). The relationship between productivity and effort is integral, with the latter frequently being a prerequisite for achieving elevated performance levels. This in turn influences acceptance and adoption of AI, demonstrating that higher productivity is not merely a consequence but a catalyst for technological engagement (Noy & Zhang, 2023).

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The term "perceived productivity" describes a person's subjective assessment of their own degree of production (Vuolle et al., 2008). It is based on their personal assessment of how efficiently and effectively they are accomplishing tasks and achieving goals (Noy & Zhang, 2023).

As productivity subjective measurement may serve as a foundation for integrating usability and productivity views, it is frequently used to measure usability (Vuolle et al., 2008). Also, it could be a useful method of accounting for intangible factors like quality when calculating productivity (Vuolle et al., 2008). Thus, this study extends the effort expectancy construct in UTAUT to include:

H2: The behavioral intention to use AI is positively influenced by effort expectation.

Sub-H2a: The behavioral intention to use AI is positively impacted by the perceived ease of use of AI.

Sub-H2b: The behavioral intention to adopt AI is positively impacted by AI perceived productivity.

Socio-cultural Influence

In UTAUT, social influence acknowledges the role that social pressure plays in modifying users' attitudes and intentions about technology (Venkatesh et al., 2003). However, AI introduces more factors that are not only associated with society but with culture as well. AI bias, for example, reproduces social biases in the training data, but this may lead to favoring certain cultural standards (Lee et al., 2019). For instance, in this context, a chatbot trained predominantly on Western data may not understand or generate culturally appropriate responses for users from different cultural backgrounds, reflecting ethnocentrism as a cultural bias (Dong et al., 2021). Thus, this study adopts a broad perspective through including cultural influences such as AI perceived bias, job threats, and social norms.

H3: Users' behavioral intention to use AI systems is influenced by sociocultural factors.

AI Perceived Bias

AI perceived bias examines the degree of which AI users find AI systems output bias or discriminant against different groups or individuals (Belenguer, 2022) that is recognized as a deviation from the social, psychological, moral, or statistical standards (Danks & London, 2017). Unfair results may result from AI systems unintentionally incorporating biases found in the training data or algorithms (Ferrer et al., 2021). Individuals, especially in workplaces, are more likely to accept AI technology that is designed to be fair and unbiased, considering diverse perspectives and avoiding discrimination (Ferrer et al., 2021).

AI bias is a socio-cultural factor that is based on human inputs inherited with present social inequality around us (Ferrer et al., 2021). In return, AI reproduce or exaggerate these biases and discriminations in different procedures (Ganel et al., 2022). A well-known case of AI bias is Amazon's AI recruitment tool that was found to favor men over women for software programming jobs, where the AI system trained based on ten years of majorly men applicants' data (Lee et al., 2019). Thus, this study proposes that:

Sub-H3a: The behavioral intention to employ AI is positively influenced by AI perceived bias.

AI Perceived Job Threats

The emergence of AI technology has sparked concerns about its societal impact and effects on the labor market, as it has the potential to displace workers and possibly lead to an increase in technophobia among them. (McClure, 2018). AI perceived job threats refers to the degree of user's fear that AI threaten his or her job security (Vu & Lim, 2022). Strong correlations were seen between the low level of AI acceptability and the high degree of AI perceived job risks, according to Schepman and Rodway (2020) and Vu and Lim (2022). Also, Cave et al. (2019) and Khanfar et al., (2024) reported the public concerns of AI threaten job and becoming obsolete. Thus, this study hypothesizes that:

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Sub-H3b: The behavioral intention to use AI is positively impacted by AI regarded as a job threat.

AI Perceived Social Norms

Originating from the UTAUT, users often validate the attitudes and actions of their social circles in order to preserve their social standing (Hong, 2022). If AI is widely accepted and positively regarded in users' social circles, they are more likely to accept AI technology, which creates sense of legitimacy and guideline (Venkatesh et al., 2003). Perceived social norms for AI in this context refer to the extent to which users think that others think they should utilise AI (Khanfar et al., 2024; Du et al., 2022; Venkatesh et al., 2003). Accordingly:

Sub-H3c: The behavioral intention to use AI is positively impacted by AI perceived social norms.

Facilitating Conditions

AI requires redefining facilitating conditions in a way enhancing user's belief in organizational support of AI use (Jain et al., 2022). This includes establishing AI trust policy and practice, ethics, security, privacy, transparency, and introducing proper interventions for users (Naik et al., 2022; Xiuquan & Tao, 2017).

The rationale for redefining the facilitating conditions of the original UTAUT model for AI systems lies on the unique characteristics and requirements of AI technology. AI systems are complex and often opaque, necessitating transparency to allow users understand their workings and build trust (Choung et al., 2023). Trust, specifically holds a significant role in AI systems, given their high-stakes applications, such as medical diagnostics or autonomous vehicles, where users need to rely on the system's dependability (Tanantong & Wongras, 2024; Hasan et al., 2021; Vakkuri et al., 2020). Furthermore, AI has the potential to have a big influence on society, which raises important ethical questions about responsibility and monitoring (Naik et al., 2022; Vakkuri et al., 2020). Since AI systems often handle sensitive personal and institutional data, users' belief in the system's ability to securely protect their data is pivotal (Vakkuri et al., 2020). Finally, due to AI's complexity, users need more extensive support and training to effectively understand and use the system (Benbya et al., 2020). Hence, a more thorough understanding of the elements impacting user adoption of AI systems will need broadening the facilitating conditions to include perceived trust, transparency, ethics, privacy and security, and intervention and training options.

The degree to which users perceive the existence of a suitable technical, moral, and supportive infrastructure that guarantees the AI system's reliability, security, transparency, and morality, as well as the availability of sufficient training to enable its efficient use, is thus the definition of the facilitating conditions construct in this study. Such a holistic environment encourages user confidence and adoption of the AI system (Lada et al., 2023).

Facilitating conditions, in this context, is an institutional dimension. This is because organizations need to establish mutual trust practices, ethical guidelines, privacy and security measures, and level of support and training of AI system for it to be integrated effectively into operations (Lada et al., 2023; Knowles & Richards, 2021). This includes the organization's leaders trusting that the AI system will deliver the expected benefits, comply with regulatory requirements, manage risks effectively, and act ethically (Acosta-Enriquez et al., 2024; Huang et al., 2022). Trust at the institutional level may also be influenced by factors such as the organization's culture and its previous experience with AI or other technologies (Venkatesh et al., 2012). Thus, this study proposes that:

H4: Facilitating conditions directly influence user's actual use of AI technology.

Sub-H4a: AI Perceived trust directly influence user's actual use of AI technology.

Sub-H4b: AI Users' actual usage of AI technology is directly influenced by their perceptions of security and privacy.

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Sub-H4c: AI Perceived transparency directly influence user's actual use of AI technology.

Sub-H4d: AI Perceived ethics directly influence user's actual use of AI technology.

Sub-H4e: AI received intervention directly influence user's actual use of AI technology.

Study model:

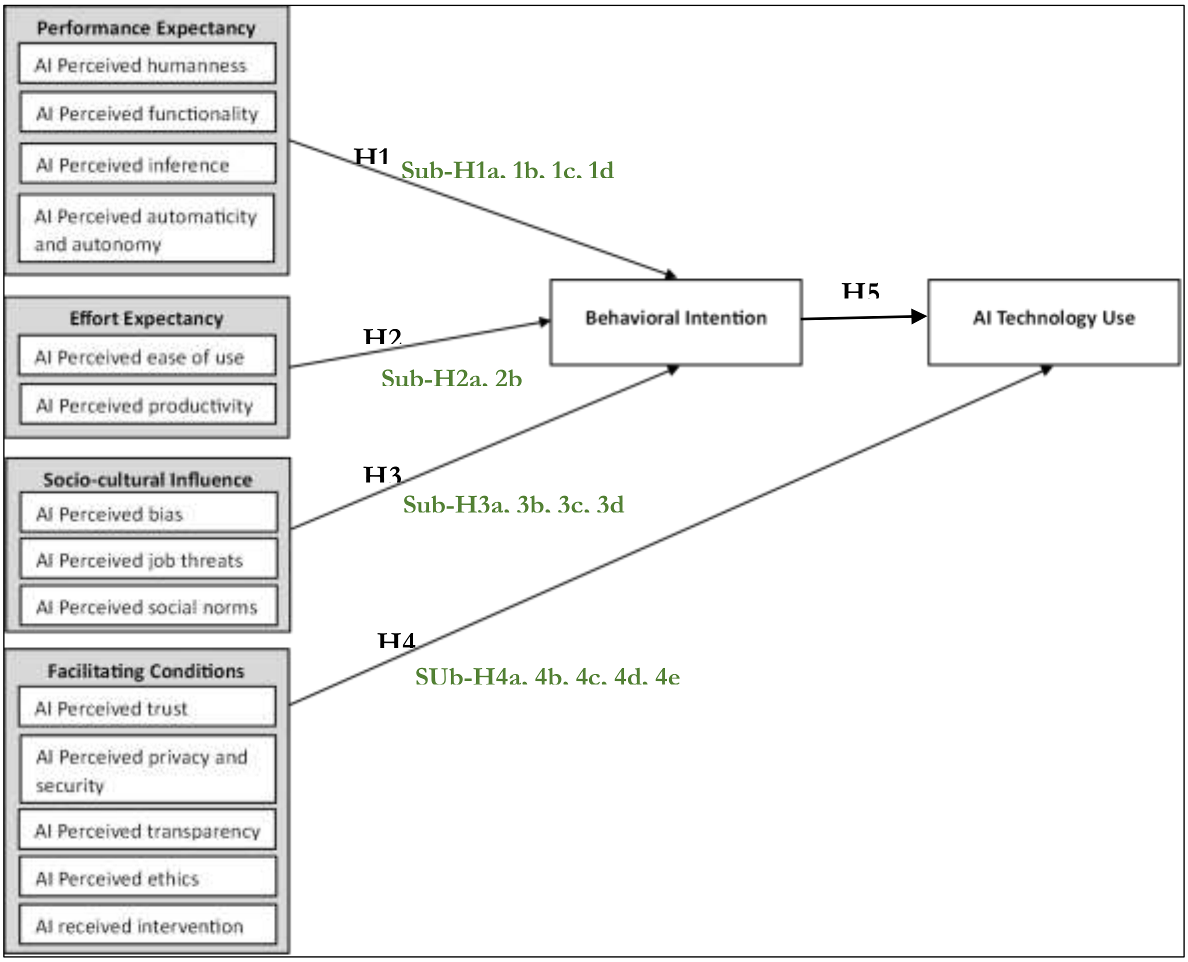

Figure 1. Study Proposed Model

Method

This study used a quantitative approach to examine the suggested model using a questionnaire created based on research on AI adoption (Appendix).

Sample and Measure

This study recruited participants from workers in different industries in Saudi Arabia during June and July 2023. The participants were recruited through emails and professional online communities. The total sample size is 223 respondents from nine different industries.

Based on the UTAUT conceptual model, six key factors were assessed: AI technology usage, behavioral intention to useAI, socio-cultural impact, performance expectancy, effort expectancy, and facilitating conditions. Under the first four main variables, sub variables were introduced as factors constituting the main variable. Figure 1 depicts the study model including measured main and sub variables.

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Structural Model

This study employed the Partial-Least-Square-Structural-Equation-Modelling (P-L-S-S-E-M) approach in two phases. In order to demonstrate how effectively an item represents the underlying construct, factor loading was first determined using Confirmatory Factor Analysis (CFA). Secondly, the conceptual model's importance was investigated using Path Coefficients. The instrument's reliability was determined using Cronbach's alpha, and each latent variable's discriminant validity was checked and confirmed using the Fornell-Larcker criteria. In order to determine whether there was a multicollinearity problem among the variables, multicollinearity was evaluated using inner and outer VIF.

Results

Demographic Analysis

As shown in Table 1, the survey captured data from 223 respondents primarily with an intermediate level of experience in AI technology (47.5%), while 25.1% were beginners and 27.4% were advanced users. Participants came from diverse industries, predominantly Telecommunication and Information Technology (21.5%), Retailing (20.2%), and Supply Chain, Transportation, and Logistics (13.9%), with Culture, Tourism, and Entertainment being the least represented (1.3%). The majority of respondents (51.6%) were between the ages of 28 and 38, and the gender distribution was significantly biassed towards men (56.5%). Interestingly, a significant majority of AI usage was compulsory (61%) as opposed to voluntary (39%).

Table 1. Demographic Analysis of Participants

Variable	Category	Frequency	Percent
AI experience level	Beginner	56	25.1
	Intermediate	106	47.5
	Advanced	61	27.4
Industry	Telecommunication and Information Technology	48	21.5
	Retailing	45	20.2
	Supply Chain, Transportation and Logistics	31	13.9
	Financial Services	27	12.1
	Energy and Renewable Energy	24	10.8
	Healthcare	12	5.4
	Education	16	7.2
	Culture, Tourism and Entertainment	3	1.3
	Other	17	7.6
Gender	Male	126	56.5
	Female	97	43.5
Age	18 - 28 years	76	34.1
	28 - 38 years	115	51.6
	39 or older years	32	14.3
AI use	Compulsory	136	61.0
	Voluntary	87	39.0

Interpretation Of Mean Scores

The questionnaire items can be answered by the respondent using a number between 1 and 5, where 5 denotes the highest level of acceptance and 1 denotes the lowest. The following ranges of mean scores are used to interpret the results: 1.80 – 2.59 low, 2.60 – 3.39 medium, 3.40 – 4.19 high, and 4.20 – 5.00 extremely high acceptance.

Descriptive data for the primary constructs in the questionnaire are shown in Table 2. With a mean of 4.15 and a standard deviation (SD) of 0.71, "AI Technology Usage" came in first. Both "Socio-cultural

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Influence" and "Facilitating Condition" tied for the second rank, having means of 4.04, with (*SD*) of 0.56 and 0.48, respectively. "Behavioral Intention" came in third with a mean of 4.00 and a (*SD*) of 0.49, while "Performance Expectancy" and "Effort Expectancy" both ranked fourth with means of 3.98 and (*SD*) of 0.53 and 0.59, respectively.

Table 2. Descriptive Statistics for Each Construct in Questionnaire

No	Domain	Mean	*SD*	Ranking	Interpretation
6	AI Technology Use	4.15	0.71	1	High
3	Socio-cultural influence	4.04	0.56	2	High
4	Facilitating Condition	4.04	0.48	2	High
5	Behavioral Intention	4.00	0.49	3	High
1	Performance Expectancy	3.98	0.53	4	High
2	Effort Expectancy	3.98	0.59	4	High

Confirmatory Factor Analysis (CFA)

A dependent variable connected to the use of AI technology, a mediator variable called behavioral intention, and independent variables like performance expectancy, effort expectancy, socio-cultural influence, and facilitating condition make up the PLS path model, which was developed using Smart PLS4 software. The degree to which each item represents its underlying construct is revealed by the factor loading in the model. It is generally advised that factor loading (FL) be more than.70 (Vinzi et al., 2010), while in social science studies, researchers often find lower outer loadings (<0.70). Yet, if the loading is less than.70, we are unable to remove an item. Rather, we want to evaluate if eliminating a particular item will substantially enhance the Composite Reliability(CR) and Average Variance Extracted (AVE). Table 3 shows that all factors loading over 0.70.

Table . 3Factor Loadings, Reliability, and Validity Of Items

Variables	Item	FL	Cronbach's alpha	CR	AVE
Performance Expectancy	EX_Prcvd_Human_1	0.896	0.745	0.887	0.797
	EX_Prcvd_Human_2	0.889			
	EX_Prcvd_Infrnc_1	0.901	0.804	0.91	0.835
	EX_Prcvd_Infrnc_2	0.926			
	EX_Prcvd_Auto_1	0.822	0.792	0.861	0.677
	EX_Prcvd_Auto_2	0.706			
	EX_Prcvd_Auto_3	0.926			
	EX_Prcvd_Function_4	1			
Effort Expectancy	EE_Prcvd_Prdctvty_1	0.892	0.907	0.93	0.815
	EE_Prcvd_Prdctvty_2	0.978			
	EE_Prcvd_Prdctvty_3	0.832			
	EE_Prcvd_EaseUse_1	0.87	0.865	0.916	0.785
	EE_Prcvd_EaseUse_2	0.91			

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	EE_Prcvd_EaseUse_3	0.878			
Socio-cultural Influence	SCI_Prcvd_Bias	1			
	SCI_Prcvd_Job_Thrt	1			
	SCI_Prcvd_ScialNorm	1			
Facilitating Conditions	FC_Prcvd_Prvcy_Scrty_1	0.888	0.87	0.923	0.857
	FC_Prcvd_Prvcy_Scrty_2	0.977			
	FC_Prcvd_Trnsprncy	1			
	FC_Prcvd_Trust	1			
	FC_Prcvd_Ethics	1			
	FC_Intervention	1			
Behavioral Intention to Use AI	Bhvr_intention1	0.912	0.945	0.965	0.901
	Bhvr_intention2	0.967			
	Bhvr_intention3	0.968			
AI Technology Use	Use_bhvr_AI	1			

Reliability and Validity

Cronbach's alpha values were calculated to verify the model's validity and dependability. The values of the extracted Cronbach's alpha, composite reliability, and AVE are shown in Table 3. When the AVE values are larger than 0.5, it indicates that there is an appropriate degree of convergent validity. Cronbach's alpha values must be better than 0.70 to be deemed acceptable (Chin, 2010; Hair et al., 2016).

The Fornell-Larcker criteria was used to check and confirm discriminant validity in order to determine the degree to which each and every latent variable was unique from other constructs (Chin, 2010; Hair et al., 2016). Table 4 displays the outcomes of this criteria.

Table 4. FLC-Fornell-Larcker Criterion

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Bhvr_intention	0.95															
EE_Prcvd_Prdctvty_	0.28	0.9														
EX_Prcvd_Auto_	0.39	0.74	0.82													
EX_Prcvd_Infrnc_	0.49	0.16	0.06	0.91												
FC_Intervention	0.17	0.74	0.61	-0	1											
FC_Prcvd_Ethics	0.56	0.23	0.11	0.74	0.04	1										
FC_Prcvd_Prvcy_Scrty_	0.2	0.72	0.59	-0	0.69	0.1	0.93									
FC_Prcvd_Trnsprncy	-0.1	0.46	0.19	-0.1	0.45	0.06	0.64	1								
FC_Prcvd_Trust	0.04	0.48	0.44	-0.3	0.52	-0.1	0.64	0.49	1							
Prcvd_EaseUse	0.64	0.11	0.25	0.61	-0.1	0.53	-0.2	-0.4	-0.3	0.89						
Prcvd_Function	0.71	0.27	0.51	0.39	0.12	0.36	0.13	-0.1	0.05	0.63	1					
Prcvd_Human	0.63	-0.1	0.17	0.36	-0.2	0.3	-0.1	-0.2	-0	0.5	0.65	0.89				
SCI_Prcvd_Bias	0.76	0.45	0.44	0.62	0.22	0.68	0.31	0.11	0.12	0.59	0.6	0.47	1			

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SCI_Prcvd_Job_Thrt	0.75	0.45	0.42	0.61	0.25	0.64	0.33	0.15	0.13	0.54	0.56	0.45	0.84	1		
SCI_Prcvd_ScialNorm	0.62	0.46	0.58	0.12	0.41	0.26	0.5	0.17	0.38	0.31	0.54	0.41	0.6	0.57	1	
Use_bhvr_AI	0.57	-0.2	-0.1	0.22	-0.2	0.27	-0.2	-0.2	-0.2	0.37	0.35	0.42	0.29	0.23	0.17	1

Collinearity Assessment

To investigate the problem of multicollinearity in the model, the values of the inner and outer VIFs were also calculated. Table 5 displays the inner VIF values findings.

The findings indicate that inner VIF levels are below 5. As a result, it is determined that none of the variables have the multicollinearity problem or concern. When the VIF values exceed 5, it indicates the existence of multicollinearity, necessitating the removal or exclusion of such structures. Here, this isn't the case.

Table 5. Inner VIF Values

	Behavioral Intention	AI Technology Use
Behavioral Intention		1.646
EE_Prcvd_Productivity	3.043	
EX_Prcvd_Auto_	3.315	
EX_Prcvd_Infrnc_	2.617	
FC_Intervention		1.951
FC_Prcvd_Ethics		1.525
FC_Prcvd_Prvcy_Scrty_		3.106
FC_Prcvd_Trnsprncy		1.852
FC_Prcvd_Trust		1.804
Prcvd_EaseUse	2.346	
Prcvd_Function	3.08	
Prcvd_Human	2.197	
SCI_Prcvd_Bias	4.503	
SCI_Prcvd_Job_Thrt	3.826	
SCI_Prcvd_ScialNorm	2.421	
AI Technology Use		

R Square

Table 6 displays the R square and Adjusted R square values for the latent variables. That indicates that all independent factors account for 44.4% of the variation in AI technology use.

Table 6. R-Square And R-Square Adjusted

	R-square	R-square adjusted
Behavioral Intention	0.756	0.75
AI Technology Use	0.453	0.444

Path Coefficients (Significance of Structural Paths in Bootstrapping)

One technique for determining and testing a model's relevance is bootstrapping. The importance of the path coefficients is reflected in the t-statistics value (Ringle et al., 2015). The path coefficient results are displayed in Figure 2.

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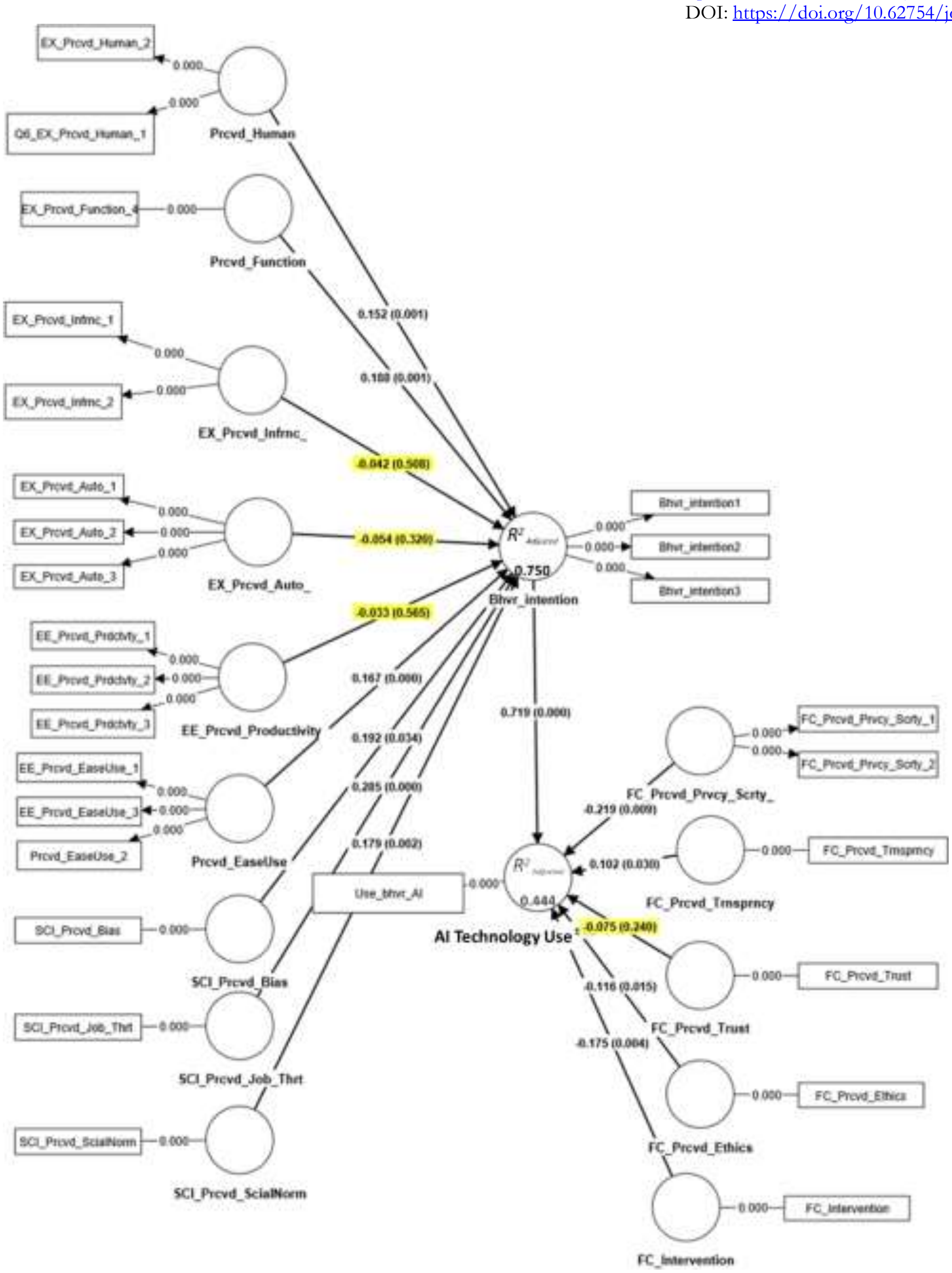

Figure 2. Results of Path Coefficients for All Sub Latent Variable .

Note: Significance at $p < 0.001$ (highlighted not significant)

Hypotheses Conclusions

The behavioral intention to use AI is significantly influenced by the three main constructs (i.e., performance expectancy, effort expectancy, and socio-cultural influence), as Table 7 illustrates ($t= 4.831 > 1.96$, $p = 0.000 < 0.05$, $t= 2.279 > 1.96$, $p = 0.023 < 0.05$, $t= 7.280 > 1.96$, $p = 0.000 < 0.05$, respectively).

Table 7 shows that, for the performance expectancy sub-factors, behavioral intention to use AI is highly correlated with (a) AI perceived humanness and (b) AI perceived functionality. Nevertheless, there was no significant correlation found between the behavioral intention to use AI and (c) AI perceived inference and (d) AI perceived automaticity and autonomy.

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Additionally, Table 7 shows that the following sub-factors of effort expectancy are proposed to be significant predictors of behavioral intention to use AI: (a) AI perceived ease of use; (b) AI perceived productivity; and (c) behavioral intention to use AI was not significantly influenced by either of the sub-factors.

The study revealed that behavioral intention to use AI was significantly predicted by three of the suggested sub-factors that comprise the socio-cultural impact construct: (a) AI perceived bias; (b) AI perceived job threats, (c) AI perceived social norms.

Facilitating condition construct was proposed as a direct antecedent of AI usage. Table 7 confirms that facilitating conditions construct is a significant antecedent od AI technology usage with value of $t = 7.125 > 1.96$, p-value $= 0.000 < 0.05$. Surprisingly, AI perceived trust was an insignificant antecedent of AI usage; however, (b) AI perceived privacy and security, (c) AI perceived transparency, (d) AI perceived ethics, and (e) AI received intervention were significant antecedents of AI usage.

Table 7 indicates that behavioral intention to use AI has a considerable positive impact on AI usage (t = 20.967 > 1.96, p-value = 0.000 < 0.05).

Table 7. Hypotheses Conclusions

	Path Coefficients	β	*SD*	*t*	*P*	Conclusion
H1	**Performance Expectancy -> Behavioral Intention**	**0.331**	**0.069**	**4.831**	**0.000**	**Supported**
H1a	AI perceived humanness -> Behavioral Intention	0.152	0.044	3.475	0.001	Supported
H1b	AI perceived functionality -> Behavioral Intention	0.188	0.056	3.342	0.001	Supported
H1c	AI perceived inference -> Behavioral Intention	-0.042	0.063	0.662	0.508	Not Supported
H1d	AI perceived automaticity & autonomy -> Behavioral Intention	-0.054	0.054	0.996	0.32	Not Supported
H2	**Effort Expectancy -> Behavioral Intention**	**0.107**	**0.047**	**2.279**	**0.023**	**Supported**
H2a	AI Perceived ease of use -> Behavioral Intention	0.167	0.04	4.144	0.000	Supported
H2c	AI Perceived productivity -> Behavioral Intention	-0.033	0.058	0.575	0.565	Not Supported
H3	**Socio-cultural influence -> Behavioral Intention**	**0.484**	**0.067**	**7.280**	**0.000**	**Supported**
H3a	AI Perceived bias -> Behavioral Intention	0.192	0.091	2.124	0.034	Supported
H3b	AI Perceived job threats -> Behavioral Intention	0.285	0.082	3.494	0.000	Supported
H3c	AI Perceived social norms -> Behavioral Intention	0.179	0.057	3.121	0.002	Supported
H4	**Facilitating Conditions -> AI Technology Use.**	**-0.28**	**0.039**	**7.125**	**0.000**	**Supported**
H4a	AI Perceived trust -> AI Technology Use	-0.075	0.064	1.175	0.24	Not Supported
H4b	AI Perceived privacy and security -> AI Technology Use	-0.219	0.084	2.601	0.009	Supported

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H4c	AI Perceived transparency -> AI Technology Use	0.102	0.047	2.176	0.03	Supported
H4d	AI Perceived ethics -> AI Technology Use	-0.116	0.048	2.432	0.015	Supported
H4e	AI Perceived intervention -> AI Technology Use	-0.175	0.06	2.901	0.004	Supported
H5	**Behavioral Intention -> AI Technology Use**	**0.719**	**0.034**	**20.967**	**0.000**	**Supported**

Calculating the overall and particular indirect effects allowed for further mediation research. According to Table 8's results, behavioral intention plays a major mediating role in the link between the AI technology use and the constructs of socio-cultural influence, performance expectancy, and effort expectancy.

Table 7. Specific Indirect Effects

	Path Coefficients	β	*SD*	*T*	*p*	Results
M1	Performance Expectancy -> Behavioral Intention -> AI Technology Use.	0.182	0.041	4.442	0.000	Supported
M2	Effort Expectancy -> Behavioral Intention -> AI Technology Use.	0.059	0.026	2.244	0.025	Supported
M3	Socio-cultural influence -> Behavioral Intention -> AI Technology Use.	0.266	0.034	7.736	0.000	Supported

Discussion

This research put up a number of hypotheses, the findings of which offer a clear picture of the variables impacting both the behavioral intention to use artificial intelligence and its actual use.

Performance Expectancy and Behavioral Intention were shown to be positively correlated ($\beta = 0.331$, $p<0.001$), supporting the hypothesis that H1. Significant evidence was found to support the idea that behavioral intention is influenced by AI's perceived humanness (H1a, $\beta = 0.152$, $p<0.01$) and functionality (H1b, $\beta = 0.188$, $p<0.01$). The fact that automaticity & autonomy (H1d) and perceived inference (H1c) of AI, on the other hand, were not significant suggests that these criteria do not significantly affect the intention to use AI.

The impact of Effort Expectancy on Behavioral Intention (H2) was validated ($\beta = 0.107$, $p<0.05$), as was the hypothesis pertaining to the influence of AI's perceived ease of use on this intention (H2a, $\beta = 0.167$, $p<0.001$). Remarkably, behavioral intention was not significantly impacted by AI's perceived productivity (H2c).

The third hypothesis, socio-cultural influence (H3), demonstrated a strong positive correlation with behavioral intention ($\beta = 0.484$, $p<0.001$). This intention was strongly influenced by the perception of AI's bias (H3a), job threats (H3b), and social norms (H3c).

Facilitating conditions, however, showed a negative influence on AI Technology Use (H4, $\beta = -0.28$, $p<0.001$). Among these conditions, perceived trust in AI (H4a) did not significantly impact AI use, while perceived privacy and security (H4b), transparency (H4c), ethics (H4d), and intervention (H4e) all showed a significant inverse relationship.

Finally, the hypothesis that Behavioral Intention affects AI Technology Use (H5) was strongly supported ($\beta = 0.719$, $p<0.001$), indicating that as users' intentions to utilize AI increase, so does their actual usage of the technology.

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Performance expectancy significance means that the more users perceive AI as human-like and functional, the more they accept AI. For AI perceived humanness, user consider naturalness and communication are determinants of AI humanness while AI collaboration capability is less important to them to perceive AI as a human-like. Therefore, collaboration item was omitted from the model. This confirmed a study by Du et al. (2022) that users' adoption of AI virtual assistants is strongly influenced by their perception of AI's humanness.

Additionally, users' behavioural intention to use AI is only predicted by AI perceived usefulness when they evaluate AI's capacity to enhance their existing tasks; from their perspective, users did not find AI to be accurate, integratable, or personalised. This finding add to the inconsistency in the literature where AI integrataibility found to be influencer of users general attitudes towards AI but not significant influencer on their behavioral intention to use AI (Chatterjee et al., 2021). It is important to consider the overlap between some functionality items and usefulness in the literature like accuracy and personalization, that requires more simplified and accurate wordings of survey items to overcome such an overlap. Integratability or compatibility is proposed as performance construct in this study while it could be viewed in wider organizational perspective through AI integration with business processes and cases to yield more significant results.

AI perceived inference found to be significant when users consider AI ability to conduct deep research that reflects human brain complexity and logical reasoning. However, users do not consider AI predictability, detectability, learnability (machine learning), and quality output as determinants of AI inference capabilities that influence their acceptance of AI. Lastly, AI automaticity and autonomy items were not significant enough to be a determinant of users' performance expectations. In contrast, AI perceived inference and absolute rationality is significantly influencer of user acceptance in legal and consultation industries where users rely heavily on inferential capabilities of AI (Xu & Wang, 2021). These industries were not represented in this study sample, which may reflect the shallow inferential level needed in the participating industries.

AI productivity is a negligible factor when it comes to effort expectancy as a predictor of behavioral intention to use AI; ease of use was the only relevant factor. This is partially in consensus with the literature reporting that ease of use determines the intention to use AI (Chatterjee et al., 2021; Hao et al., 2021; Hong, 2022). Contrary to Noy and Zhang (2023) productivity was measured in the current study using subjective measurement: however, using more objective measurements like earning per minutes or task completion rate may reveal more significant results.

Regarding socio-cultural influences on AI acceptance, AI perceived biases, job threats, and social norms were significant determinant of such an influence. This result supports that of Vu and Lim (2022), who found that users' adoption of AI is negatively impacted by their perception of a job threat. Furthermore, this result is consistent with other studies that shown that perceptions of AI bias have a major impact on how AI is actually used (Pillai & Sivathanu, 2020). Thus, bias mitigation methods should be in place to prevent any reversal influence on adoption and acceptance especially in social related industries like HR and financial industries.

Facilitating conditions construct is a significant antecedent of AI usage including serious users' concerns such as privacy and security, model transparency, ethical guidelines, and received intervention. However, the inverse relationship between these concerns and AI usage suggests that the more these concerns increase, the less AI usage appears. This is consistent with conclusions of Acosta-Enriquez et al., (2024), Ismatullaev and Kim(2022), and Poonpanich and Buranasiri (2022) where privacy and security, transparency, and organizational interventions negatively influence AI usage.

Surprisingly, trust on AI judgement and decision-making was not a major concern of users that may influence their actual use of AI. Similarly, Raffaghelli et al. (2022) and Choung et al. (2023) found trust as insignificant predictor of AI usage suggesting that this item must be reconsidered cautiously as trust interrelated with anxiety and discomfort that were significantly impedes AI acceptance (Hmoud & Várallyai, 2020; Sharma & Kaur, 2022). Moreover, this study model placed trust factor under facilitating conditions construct based on the assumption that trust is an organizational behavior: however, placing trust under more individual construct like effort expectancy may yield different results.

Conclusion

With the remarkable progress made in artificial intelligence (AI), it is critical now more than ever to develop more intricate models that faithfully capture the ways in which this revolutionary technology is applied across a wide range of industries. The present study represents a significant step forward in this ongoing pursuit, as it aims to contribute to the development of such definitive models. This study introduces critical new factors to AI that reflect user intentions and usage when adopting AI. Perceived humanness, functionality, bias, job threats are among these significant determinants of users' intentions who using AI. Conversely, lack of perceived privacy and security, transparency, ethical guidelines, and proper intervention negatively influence user's AI usage. The current study succeeded in extending UTAUT to capture new factors of AI acceptance with explained variance of behavioral intention 75% and AI use behavior 44%.

Nevertheless, this study is not without its limitations, particularly concerning the underrepresentation of industries heavily reliant on AI inferential capabilities and the subjective measures used for assessing AI productivity. In addition, moderation variables like gender, age, AI experience, and use voluntariness were beyond this study scope. Future research would do well to address these gaps and extend this work into different industries. It is important to highlight that this study has identified several overlaps or misconceptions regarding trust, confidence, and usefulness; hence, future research assessing acceptance criteria should take these into account and investigate more straightforward and unambiguous item construction. It is strongly recommended for future studies to properly group induvial and organizational factors contributing to acceptance which may lead to more factor loadings and significant findings.

This research also has noteworthy theoretical and practical implications, especially for AI adoption research. By integrating dynamic technological, human, and contextual factors, it gives a holistic view of how workforces adopt and use AI. Also, considering critical socio-cultural concerns like job displacement and bias in more details may address serious users' concerns that hinder AI acceptance. As for practice, AI development will be benefited from users' acceptance behaviors in developing more user-centered solutions that meet their privacy and security concerns and exceed their expectations in naturalness and function. Organizations, on the other hand, should consider proper interventions before AI technology implementation as lack or improper innervations may have an inverse impact.

In the swiftly progressing domain of artificial intelligence, maintaining a keen awareness of users' viewpoints is of utmost importance. As the comprehension of these dynamics progressively broadens, our ability to adeptly navigate the intricacies of AI adoption and utilization will correspondingly amplify, ultimately enabling us to fully harness the transformative capabilities of this groundbreaking technology.

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Appendix A

Items Used to Estimate Artificial Intelligence Acceptance

Performance Expectancy

EX_ Perceived Humanness:
I find AI's responses natural and human-like.
I find AI able to identify, understand and synthesize written human language.

EX_ Perceived Function:
I find AI's responses accurate. **
I find AI enhancing my current work task(s).

EX_ Perceived Inference:
I find AI able to conduct deep research that reflects the complexity of human brains.
I think AI has a logical reasoning.

EX_ Perceived Automaticity and Autonomy: **
I find AI automates the routine work.
I find AI operate and make decisions independently, without constant human interaction.
I find AI can be directed, guided, or controlled by human users or external entities.

Effort Expectancy

EE_ Perceived Productivity: **
Using AI reduced my tasks' time.
Using AI helped me to spend more time in fulfilling high-value tasks.
I think AI is agile and produce real-time results.

EE_ Perceived Ease of Use:
I find AI easy to use.
Learning to use AI is easy for me.
My interaction with AI is clear and understandable.

Social and Cultural Influences

SCI_ Perceived Bias:
I think AI is biased or discriminating against certain groups.

SCI_ Perceived Job Threat:
I think AI is a threat to my job.

SCI_ Perceived Social Norms:
People who influence my behavior think that I should use AI.

Facilitating Conditions

FC_ Perceived Privacy and Security:
I think my data and my interactions with AI is protected and private.
I think AI has security measures in place to prevent unauthorized access or misuse of my information.

FC_ Perceived Transparency:
I think AI model is transparent and can provide clear explanations for its decisions and recommendations.

FC_ Perceived Trust:
I have trust in AI's judgements and decision-making capabilities. **

FC_ Perceived Ethics:
I think AI adheres to ethical guidelines, and has mechanisms to ensure accountability.

FC_ Received Intervention
I think the intervention I received in my work helps me to use AI.

Behavioral intention to use AI

I intended to use AI in the next 12 months.
I predict I will use AI in the next 12 months.
I plan to use AI in the next 12 months.

AI Technology Usage

How often do you use AI?
1 - 3 times per month
1 -2 days per week
3 - 5 days per week
1 -2 times per day
Several times per day

** Items need further testing for significance in future research