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FACTORS AFFECTING EMPLOYEES' WILLINGNESS TO ACCEPT ARTIFICIAL INTELLIGENCE TECHNOLOGY: IMPLICATIONS FOR DIGITAL MARKETING IN HOSPITALITY AND TOURISM

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Abstract: This research aims to explore the factors that affect employees' willingness to accept artificial intelligence (AI) technology at work, guided by the Theory of Reasoned Action (TRA). A conceptual model was proposed to examine the direct effects of the four main antecedents – role clarity, extrinsic motivation, intrinsic motivation, and employee ability - on employees' acceptance of AI technologies. The research also examined the moderating functions of trust in AI and perceived interactivity. The data were collected from questionnaires of the Egyptian hospitality industry participants and analyzed according to structural equation modeling. The findings show that role clarity, intrinsic and extrinsic motivation, and capability all have a significant and positive impact on AI acceptance by employees. Above all, trust in AI was a negative moderator of the relationship between role clarity and intrinsic motivation for adopting AI, wherein high levels of trust would inhibit employees' anticipation of clarity and motivation. Perceived interactivity did not play any vital moderating function. The findings contribute to literature in proposing the potential substitutive impact of trust in AI, and refuting hypotheses regarding interactivity as the prime driver of technology adoption. In practice, according to the research, there is a requirement to induce transparency, incentive and capacity among staff, and excessive dependence on AI systems may only provide subjective returns with diminishing benefits. The results from the study provide significant implications for hospitality managers interested in managing effective use of artificial intelligence technologies by promoting harmony of human-and-machine teamwork.

Keywords: artificial intelligence, digital marketing, role clarity, ai-powered marketing, consumer trust in AI, marketing innovation, perceived interactivity, consumer experience, Theory of Reasoned Action

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INTRODUCTION

The world has recently witnessed significant progress and developments in various fields, most notably the service sector (Manoharan et al., 2024). In an effort to improve the quality and efficiency of these services, information technology plays a crucial and major role, particularly in the hospitality industry (Anwar et al., 2024; Jawabreh, 2022). Digital transformations have combined with methods for analyzing data to understand customer needs, as well as the use of the Internet of Things to enhance the guest experience within hotels, among many others (Abdel-Hamid et al., 2022). Hence, artificial intelligence, in all its forms, has become the driving force behind the success of such services, underscoring its pivotal role in enhancing the future of this industry (Naeem et al., 2024; Sharma & Kumar, 2023; Tariq et al., 2021).

Since the human element is the foundation of all service industries, it is essential to comprehend the human aspect of these digital transformations (Minh-Nhat et al., 2022). In the field of information technology and the use of artificial intelligence, most previous research (i.e., Shin et al., 2022; Pizam et al., 2022) has focused on technical dimensions, such as applicability, operationalization, and the benefits of its use, while largely neglecting employee attitudes,

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perceptions, and behavioral intentions toward accepting and using such technologies (Kelly et al., 2023). This has created a serious knowledge gap about the psychological readiness of employees for AI implementation in organizational settings. The majority of AI tools and applications within the service sector fail because they are rejected psychologically and organizationally by employees who are unable to adapt to such tools (Hornung & Smolnik, 2022; Khalifa et al., 2025). A significant number of factors can influence employees' acceptance or rejection of such technological advancements. Employees' perceptions of the impact of AI tools on their roles and responsibilities, whether through perceived threat, anxiety, or opportunities for performance improvement, influence whether they accept or reject such tools (Filippelli et al., 2024). Furthermore, professional motivation and the ability to adapt to these tools enhance their readiness to accept them (Kumi et al., 2024). In addition, another significant factor affecting acceptance or rejection of AI tools is the employees' locus of control over their working future, either being externally controlled by the management of the business or internally controlled by their own decisions (Singh et al., 2024; Bragard, 2023).

The Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), one of the most widely used theories in behavioral research, serves as the foundation for the research conceptual model (Figure 1).

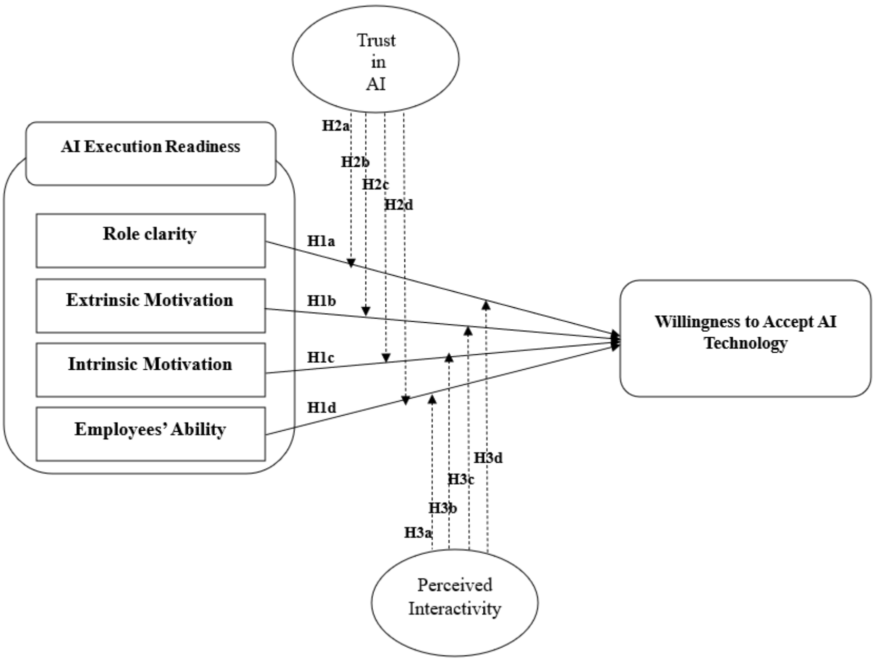

Figure 1. The conceptual model

TRA assumes that intentions or willingness are determined by action-specific attitudes, such as assessments or appraisals, and subjective norms, such as the perceived expectations of significant others (Kumar et al., 2023). The model used in this paper was constructed with respect to the scientific implications and recommendations provided by previous scholars (e.g., Choi, 2021; Elshaer et al., 2022), and extends their work by combining individual-level enablers and psychological moderators into an integrated framework. In this model, the independent variables represent positive stimuli that influence employees' behavior. In other words, when using AI applications, the more clearly an employee's role is defined, along with strong professional motivation, sufficient ability, and a high internal locus of control, the more likely they are to accept such applications. On the other hand, the complex relationship between humans and machines imposes a set of psychological and organizational factors that can significantly impact the relationship between the independent variables and the dependent variable. This is a matter of privacy, system trust, and employee-machine relationship, all of which are sensitive in nature. These moderator factors can facilitate or hinder technology acceptance and therefore make a direct contribution to internal resistance and low receptivity towards AI.

Despite the growing interest in AI adoption, empirical research remains limited in two key ways: it often overlooks behavioral and psychological aspects of technology acceptance, and it tends to focus on Western organizational contexts. As for the practical aspect, research that has focused on employees' psychological and behavioral responses to AI has largely ignored developing countries, such as Egypt (Mhlanga, 2021). There are numerous individual distinctions between Egyptian employees and their Western counterparts in terms of culture and organization (Sidani & Jamali, 2010), which makes it necessary to apply this research to the Egyptian context. For example, employee conduct in Egypt is influenced by the nature of employment, as many employees tend to follow managerial instructions without exercising independent judgment (Shahin & Wright, 2004). Additionally, Egyptian and Western workers differ in terms of continuous training and technical advancement (Radwan, 2020). Although these distinctions do not indicate that one is better than the other, they do point to the differences in organizational culture and labor market profiles between regions. Accordingly, this study aims to explore the determinants of Egyptian hospitality employees' willingness to embrace AI technologies and shed light on a context yet downplayed in existing literature.

LITERATURE REVIEW

1. The Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (Fishbein & Ajzen, 1975) is a recognised social psychological framework that focusses on the factors influencing consciously intended behaviours. From a theoretical perspective, the TRA is intuitive, succinct, and illuminating in its capacity to elucidate behaviour (Bagozzi, 1982). The Theory of Reasoned Action posits that individuals are typically rational and will evaluate the consequences of their actions before determining whether to engage in a specific behaviour (Ajzen & Fishbein, 1980). The TRA posits that behavioural intention is the direct precursor to an individual's behaviour. Ajzen & Fishbein (1980) assert that the TRA contends that "most behaviours of social relevance are under volitional control and are thus predictable from intention" (p. 41). The theory posits that the stability of intention is affected by numerous extraneous factors, thus the correlation between intention and behaviour is contingent upon two criteria: (a) the intention measure must align with the behavioural criterion regarding action, target, context, and time; and (b) intention remains unchanged prior to the observation of behaviour (Ajzen & Fishbein, 1980). The TRA delineates that behavioural intention is influenced by two determinants: an individual aspect known as attitude towards behaviour, and an individual's sense of social forces referred to as subjective norm (Fishbein & Ajzen, 1975).

Attitude pertains to an individual's execution of a specific behaviour, rather than their overall performance (Fishbein & Ajzen, 1975). Subjective norm is determined by a collection of views known as normative beliefs. Ajzen & Madden (1986) define normative beliefs as pertaining to the probability that significant referent people or groups would endorse or condemn the execution of a behaviour (p. 455). As per the TRA, to derive an estimate of a subjective norm, each normative belief of an individual is initially multiplied by the incentive to comply with the referent, and the resultant products are aggregated for all prominent referents. In the context of this study, the TRA model illustrates that the acceptance of AI technology by employees in the Egyptian hospitality industry depends on their attitudes (e.g. motivation, trust, perceived benefits) and subjective norms (e.g. managerial expectations and norms, peer pressure). The study defined psychological and social acceptance processes by plotting role clarity and motivation and trust in relation to the TRA model.

2. AI Execution Readiness

2.1. The Impact of Role Clarity on AI Acceptance

Thomas Lyons (1971) elucidated the concept of role clarity as the availability of role-relevant information, which may be influenced by either the limitation of this information or the variability in its quality. Role clarity and employee feedback are significant predictors of diverse performance metrics within an organisation; nevertheless, the correlation between role clarity and managerial performance more pronounced when pertinent job information is supplied (Tisu et al., 2022). Role clarity is significantly enhanced in organizations that employ performance feedback and decision-making participation for achieving exceptional staff performance (Teas et al., 1979). It ensures a distinct definition of roles and responsibilities, along with the interactivity of job security, that increases employee performance and clarity of expectations.

Additionally, supervisory support alongside customer involvement fosters role clarity, competence, and intrinsic motivation, thereby enhancing the connection between employee engagement in service innovation and organisational work performance (Cadwallader et al., 2010). Managerial coaching that is constructive and supportive directly impacts employee job satisfaction and role clarity, while indirectly influencing work performance and organisational commitment (Kim et al., 2013). Role clarity, as pinpointed by Ify Diala and Rao Nemani (2011), promotes greater job satisfaction, which in turn has a positive impact on an individual's responsibilities and roles. Clear roles have the potential to reduce uncertainty and fear, which have been widely cited as barriers in the uptake of new emerging technologies such as AI (Petter et al., 2008; de Neufville & Baum, 2021). After employees are made aware of how their work aligns with technological innovations, they will be more willing to see AI as a technology that augments and not threatens their work tasks (Sampson et al., 2020; Tschang & Almirall, 2021; Khairy et al.,2024). In addition, role clarity produces perceived behavioral control, a central construct in both the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB), which both posit that confidence in one's role and capacity increases openness to adopting innovations (Venkatesh & Davis, 2000; Ajzen, 1991). It is thus reasonable to anticipate that employees with high role clarity will be more open to accepting AI technology. Thus, the following hypothesis is developed in light of the literature review:

H1a: Employees' role clarity will positively influence their willingness to accept AI technology

2.2. Intrinsic and Extrinsic Motivation as Predictors of AI Acceptance

Motivation is characterised as a physiological process from which behaviour originates (Batarfi et al., 2025). Motivation is hence the foundation of all voluntary human behaviour (Vroom, 1964). The motivation to utilise technology can be influenced by a myriad of reasons. Motivation is typically categorised into intrinsic and extrinsic forms, arising from distinct wants and desires, and eventually fulfilling various functions (Cook & Artino, 2016). Extrinsic motivation refers to behaviour propelled only by the pursuit of an external consequence, such as incentives like monetary rewards or fame; it constitutes the predominant form of motivation, as individuals frequently respond to social pressures (Legault, 2016; Ryan & Deci, 2000a). It is also explicitly instrumental in character (Legault, 2016). Although extrinsic and intrinsic incentives can both influence behaviour, their effectiveness is not necessarily equivalent. Intrinsic motivation occurs when an individual engages in an activity solely for the pleasure derived from it, whereas extrinsic motivation arises when an individual participates in an activity to achieve a specific, favourable outcome (Ryan & Deci, 2000a; Legault, 2016). Extrinsic motivation can arise from multiple factors, whereas intrinsic motivation depends on a singular factor. Prior research, including studies by Yoo et al. (2012), indicates that intrinsic motivators are typically more efficacious in facilitating behavioural changes, while Yoo et al. (2012) saw minimal to no correlation between extrinsic motivation and behavioural intention. Both intrinsic and extrinsic drive can effectively facilitate behavioural change; however, intrinsic motivation generally exerts a more profound influence on behaviour. In the analysis of systems categorised as utilitarian (productivity-focused) versus hedonic (pleasure-focused), the results significantly diverge. Wu & Lu (2013) discovered that intrinsic motivators are more efficacious in encouraging the use of hedonic systems, whilst extrinsic motivators are more successful in encouraging the utilisation of utilitarian systems.

This implies that extrinsic motivators may be more effective in encouraging the utilisation of systems in the workplace, owing to the inherently utilitarian nature of such systems (Khalifa et al., 2025b; Khairy et al., 2025; Agina et al., 2025c). Both internal and extrinsic motivation are likely to influence the utilisation, acceptance, and adoption of technology. Nevertheless, intrinsic and extrinsic incentive processes have rarely been examined in conjunction with the utilisation, acceptability, and adoption of technology. Employees' extrinsic as well as intrinsic motivation plays a central role in determining their acceptance of AI technology at work. Extrinsic motivation, which consists of external stimuli such as bonuses, promotions, or performance rewards, can highly support employees' receptivity to AI adoption by making technological involvement co-aligned with concrete individual rewards (Lin et al., 2022). These rewards reinforce the belief in the usefulness of AI, a critical construct in the Technology Acceptance Model (Venkatesh & Davis, 2000), thereby facilitating greater chances of adoption. In contrast, intrinsic motivation, produced by internal satisfaction, interest, and mastery motivation, creates positive AI attitudes since it is viewed as an equipment for learning, a generator, and a booster of one's self (Yoo et al., 2023). Innately driven employees are more likely to be proactive, adaptable, and open to innovation (Elshaer et al., 2025), seeing AI as an opportunity rather than as a deceptive threat, thus making them stronger. These motivators collectively, whether intrinsic or extrinsic, are strong facilitators in overcoming resistance and initiating a positive attitude towards the integration of AI into organizational contexts.

The literature lacks incentive mechanism analysis for enabling automation in the context of their impact on intrinsic versus extrinsic motivation (Alshuqaiqi et al., 2025). It is crucial to understand how intrinsic and extrinsic motivators can drive the utilisation, acceptance, and adoption of technology. Based on this discussion, the following hypotheses are suggested:

H1b: Employees’ extrinsic motivation will positively influence their willingness to accept AI technology

H1c: Employees’ intrinsic motivation will positively influence their willingness to accept AI technology

2.3. Employee Ability and the Acceptance of AI Technology

The deployment of AI is fundamentally connected to the organisational culture, which influences employees' readiness to adapt, engage, and innovate. Technology constitutes merely a portion of the challenge in innovation during digital transformation, and the range of expectations for technology among employees and managers is extensive (Ek & Ström, 2021). Certain personnel exhibit optimism towards AI and demonstrate enthusiasm for learning and deploying automation, while others remain sceptical or even fearful. Some are even daunted by AI's capabilities and actual efficacy (Groopman, 2018; Agina et al., 2025a). Groopman (2018) asserts that preparing personnel for AI involves not only training in new technology but also adopting a new mindset. Employees have more favourable rational attitudes when they perceive that AI can enhance productivity or diminish routine tasks. Conversely, when employees see that AI would diminish their work performance or disturb established routines, their rational views will be less favourable (Davenport, 2019). Employees possessing diverse resources (e.g., personal expertise, social support) generally have diminished apprehension regarding prospective AI adoption, whereas those with constrained resources, who perceive a loss of control, are inclined to adopt a defensive posture (Zhu et al., 2020). Accordingly, employees with greater ability are not just more capable of understanding the potential of AI technologies but also more likely to apply them in their work procedures. Therefore, it is hypothesised that.

H1d: Employees’ ability will positively influence their willingness to accept AI technology

2.4. The Moderating Role of Employees’ Trust in AI Technology-Acceptance

Researchers have examined many personal characteristics that affect trust in automation, including trust in automated systems (Kraus et al., 2019), technical comfort (Kohn et al., 2021), and technology self-efficacy (Holcomb et al., 2004). In this context, trust in automation refers to the confidence in engaging with intelligent autonomous systems, such as smart autonomous vehicles, robots, or drones. Recent autonomous technology systems utilise artificial intelligence (Khayyam et al., 2020) to enhance its functionality and adaptability. Due to the fact that technology lacks volition and moral agency, trust in technology reflects beliefs about technology’s characteristics rather than its motives or will, because it has no will (McKnight et al., 1998). According to the relevant literature, general trust in technology refers to the issue of people’s (among them employees’) assessment of whether, in their opinion, the suppliers of technology have the knowledge and resources necessary to implement particular solutions (Rossi, 2019). Furthermore, as noted by McKnight et al. (1998), general trust in technology refers to the assessment of people’s perception of whether the solutions in the field of technology are consistent, reliable, functional, and provide the help needed.

The trust of employees in AI is a special category of trust in the broadest sense. It is a complex, multifaceted and multidimensional variable (Łapińska et al., 2021). In addition, it is latent and difficult to measure directly. As a result, it is both difficult to define and measure, and it is also difficult to describe its relationships with other variables. A specific feature of this category of trust, however, is that the object of trust in this case is neither people nor organizations that are created by people, but technology, i.e., artificial intelligence, which can be considered the most advanced form of technology development to date. Moreover, it refers to (Lewis & Weigert, 1985) employees of companies, which means a significant narrowing of the group of entities (individuals) to which the term can be applied.

General trust in technology is closely related to the issue of the ethical governance of new technologies. In particular, ethical issues in regard to technology involve the following: identification of potential harms, providing guidelines on safe design, creating measures protecting the safety of new technology or privacy concerns (Winfield & Jirotka, 2018). Another aspect referring to ethical governance of technology and its impact on general trust in technology is ensuring the confidentiality of data and information provided by the technology user. Therefore, creating data privacy policies and procedures that enhance user's trust in technology nowadays seems to be particularly significant for creating general trust in technology (Winfield & Jirotka, 2018; Agina & Abuelnasr, 2021). Given the context of our research, general trust in technology seems to be the variable of high importance as we follow McKnight et al. (1998) who claim that people's general trusting beliefs regarding the attributes of technology influence individual decisions to use technology and influence individual technology acceptance and post-adoption behavior. Some research provides an interesting point of view, arguing that general trust in technology has a nature of confidence, meaning that a technology user deliberately trusts himself/herself to use technology (Taddeo, 2010; Agina et al., 2025b). Taking such a point of view, Kiran & Verbeek (2010) argue that rather than being perceived as risky or useful, the technology in general is approached by its users as trustworthy. This perspective relates to evidence mentioned by several authors that people's technology trust highly impacts the adoption as well as the acceptance of the technology (Thatcher et al., 2010).

H2a. Employees' trust in AI technology-use favorably affected the relationship between employees' role clarity and their willingness to accept AI technology in hotels

H2b. Employees' trust in AI technology-use favorably affected the relationship between employees' extrinsic motivation and their willingness to accept AI technology in hotels

H2c. Employees' trust in AI technology-use favorably affected the relationship between employees' intrinsic motivation and their willingness to accept AI technology in hotels

H2d. Employees' trust in AI technology-use favorably affected the relationship between employees' locus of control and their willingness to accept AI technology in hotels

2.5. The Moderating Role of Employees' Interaction in AI Technology- Acceptance

Growing applications of AI technologies in service industries, such as hospitality, have introduced advanced dynamics between AI-driven systems and human employees. Although the benefits of automation and AI in improving efficiency and service are well documented, the uptake also revealed new relational and psychological concerns (Libert et al., 2020). Particularly, the typical collaboration among workers and AI technologies remains yet to be thoroughly studied within HRM studies, especially its moderating function in powerful psychological and behavioral factors behind technology acceptance.

There has been literature pointing out that the successful cooperation among human employees is subject to psychological influences such as cognitive biases, emotions, and differences between people (Driskell et al., 2018; Khalifa et al., 2024; Smids et al., 2020). These issues come to the fore when human workers are likely to engage frequently with AI-enabled robots. In this case, employees may be resistant or uneasy, primarily due to fear of job substitution, perceived loss of control, or unease related to unfamiliarity with AI technology (Ivanov & Webster, 2019; Smids et al., 2020).

This resistance can be manifested in the form of technology anxiety, which is a temporary affective state of frustration, fear, or apprehension when exposed to new technologies (Mikkelsen et al., 2002; Okumus et al., 2017). However, scholars such as Harrington et al. (1990) and Novak & Wisdom (2018) have believed that this anxiety is situational in nature and can be overcome if the individual is exposed to it, learns skills, and receives organizational support. In this regard, employees' interaction with AI technology, i.e., the frequency and intensity of direct interaction with AI systems, can play the role of an important moderator that regulates the quality of relations between psychological precursors (e.g., role clarity, motivation, ability) and willingness to accept AI. Employees who engage with AI technologies more regularly will become more familiar and confident in use, reducing fear and enhancing the conversion of internal drivers to real willingness to adopt the technology (Okumus et al., 2017; Arthanat et al., 2019; Marzouk et al., 2025). For example, employees with high role clarity and frequent exposure to AI systems will most probably develop a clearer vision of how their roles will complement new technology and hence reinforce their acceptance of the same. Similarly, people with high extrinsic and intrinsic motivation will likely be able to accept AI tools more when they receive good, experiential exposure that is aligned with their goals or values.

Finally, more competent employees can perform to their best in work related to AI when they have opportunities to engage directly, thereby becoming more effective and willing to adopt. Therefore, it is hypothesized that:

H3a. Employees' interaction in AI technology-use favorably affected the relationship between employees' role clarity and their willingness to accept AI technology in hotels

H3b. Employees' interaction in AI technology-use favorably affected the relationship between employees' extrinsic motivation and their willingness to accept AI technology in hotels

H3c. Employees' interaction in AI technology-use favorably affected the relationship between employees' intrinsic motivation and their willingness to accept AI technology in hotels

H3d. Employees' interaction in AI technology-use favorably affected the relationship between employees' ability and their willingness to accept AI technology in hotels.

METHODOLOGY

1. Sampling and Data Gathering

The study comprised employees from five-star chain hotels in Greater Cairo, Egypt. Greater Cairo was chosen because it is Egypt's most important tourist city, has the bulk of foreign chain hotels, and is the top employment in the tourism and hotel sectors. Moreover, the reason for selecting five-star hotels from multinational chains is that this industry is one of the first and largest to embrace information technology and pioneer the application of artificial intelligence technology, given its financial resources to capitalize on this potential. Previous investigations demonstrate that the correct and perfect sample selection contributes to the validity and dependability of the results, and that areas with high operational and economic density are fertile ground for application (Elshaer & Marzouk, 2022; Aguinis & Lawal, 2012). Convenience sampling was used to contact employees to test research hypotheses.

Although the convenience sampling technique restricts the scope of the data, it helps collect data from a large number of people in a short period of time and at a lower cost (Stratton, 2021). Moreover, this technique has been used extensively in the Egyptian hospitality context. The first version of the questionnaire was developed in English and then tested with 20 academics and hotel industry professionals to see how the questions were phrased and organized.

The final form of the questionnaire was provided to authorities from 10 hotel samples involved in the study to define its scientific purpose and obtain permission to distribute it to staff (Alshuqaiqi et al., 2025). In addition, as the majority of hotel employees are Egyptian and speak Arabic as their native language, the questionnaire has been translated into Arabic so that participants could correctly grasp all of the questionnaire items, resulting in accurate findings.

To guarantee linguistic equivalency between the two versions, researchers employed the back-translation technique (Molina et al., 2007; Sayed et al., 2025). Finally, between January 2025 and April 2025, 450 employees delivered the questionnaire by hand. With a ratio of 80.2%, the researchers were able to gather 389 questionnaires, of which 28 were removed for analysis, leaving 361 questionnaires available for study.

2. Measures

To better fit the context of the current study, the measuring scales for each variable were adjusted from earlier research. Every question on the survey was graded using a five-point Likert scale, where 1 denoted strongly disagree and 5 denoted strongly agree (Appendix). The variables were as follows:

- Independent Variables: are a first-order core construct consisting of four proposed factors that may affect employees' willingness to accept artificial intelligence technology: i.e., Role Clarity (RC), Extrinsic Motivation (ExM), Intrinsic Motivation (InE) and Ability (AB). A variety of scales adapted from previous research (i.e., were used to evaluate the degree to which these constructs were used in hotels. Role clarity (5 Items) was adapted from Rizzo et al. (1970) and re-tested by Choi (2021); Extrinsic Motivation (6 Items) and Extrinsic Motivation (6 Items) were adapted from Tyagi (1985) then re-tested by Choi (2021); and Ability (5 Items) was adapted from Jones (1986).
- Dependent Variable: consists of one factor, which is (willingness to accept) and was measured as a formative construct with six items adapted from Montargot & Ben Lahouel (2018) and Wang & Hou (2025).
- Moderating Variables: consistent with existing studies, two variables were chosen to measure its impact on the direct relationship between the independent and the dependent variables. First, trust in AI (TR) (4 Items) was adapted from Mustofa et al. (2025). Second, perceived AI interactivity (4 Items) adapted from Kim et al. (2012) and Kim et al. (2022).

3. Data Analysis

The two-step data analysis method developed by Anderson & Gerbing (1988) was applied by the researchers using version 20 of "the Statistical Package for the Social Sciences (SPSS) and Analysis of Moment Structure (AMOS)" (first "confirmatory factor analysis (CFA)" and then "structural equation model").

FINDINGS

1. Measurement Model Assessment

The researchers conducted confirmatory factor analysis on our five-component hypothesized model using a covariance matrix and the maximum likelihood technique. Moreover, we performed confirmatory factor analysis on our seven-component hypothesized model using a covariance matrix and the maximum likelihood technique. Items like (RC3; RC5; ExM2; AB5) that had a factor load of less than 0.6 were disqualified, but those with a factor load greater than 0.6 were approved (Shrestha, 2021). Following model estimation, the overall fit indices were assessed and showed a reasonable fit: $\chi2$ = 1193.450 with df = 434, p <.0001; $\chi2$/df = 2.75 (<3, Hair et al., 2010).

When assessing the model's fit, the lowest permitted value of 0.90 is exceeded by the NFI =.906, IFI =.938, CFI =.938, and TLI =.929 indices (Tucker & Lewis 1973; Hu & Bentler, 1999). The root mean square error of approximation (RMSEA), which is 0.07 (0.08, Arbuckle, 2011), is another noteworthy number. Standard residual covariance was investigated to determine whether it may considerably reduce model fit. As a result, just a few items served as covariates for the latent variables. ExM1 and ExM3; ExM3 and ExM4 in the ExM latent variable; InM1 and InM2; InM1 and InM4 in the InM latent variable; AB2 and AB3; AB3 and AB4 in the AB latent variable; TR1 and TR3 in the TR latent variable; and W3 and W4; W5 and W6 in the W latent variable were covariates.

Researchers calculated AVE, Cronbach's α, and CR values for each construct to confirm the scales' reliability and convergent validity. Fornell and Larcker (1981) state that when AVEs are greater than 0.50 and CRs are greater than 0.70, the prerequisites for convergent validity and reliability are satisfied.

Table 1's statistics showed that the AVE and CR values exceeded 0.617 and 0.864, respectively. These results show that our study's variables are reliable and have convergent validity (Hair et al., 2010; Pallant, 2005).

Table 1. Factor loadings, validity analysis, and reliability test of the measurement model

Construct	Mean	SD	Factor Loading	CR	A	AVE
Role Clarity (RC)				.865	.864	.681
RC1	3.06	1.16	.774	Rizzo et al. (1970) and re-tested by Choi (2021)		
RC2	3.01	1.22	.841			
RC3	Excluded					
RC4	3.17	1.19	.859			
RC5	Excluded					
Extrinsic Motivation (ExM)				.947	.949	.782
ExM1	3.40	.93	.856	Tyagi (1985) then re-tested by Choi (2021)		
ExM2	Excluded					
ExM3	3.41	.97	.888			
ExM4	3.42	.91	.932			
ExM5	3.45	.95	.910			
ExM6	3.49	.96	.833			
Intrinsic Motivation (InM)				.951	.951	.763
InM1	3.41	.99	.861	Tyagi (1985) then re-tested by Choi (2021)		
InM2	3.50	.96	.883			
InM3	3.52	.98	.933			
InM4	3.38	1.05	.862			
InM5	3.34	1.06	.864			
InM6	3.44	1.09	.834			
Ability (AB)				.863	.883	.617
AB1	3.51	1.03	.883	Jones (1986)		
AB2	3.62	.99	.909			
AB3	4.00	.93	.688			
AB4	4.07	.90	.622			
AB5	Deleted					
Trust in AI (TR)				.908	.926	.711
TR1	3.49	1.09	.816	Mustofa et al. (2025)		
TR2	3.52	1.00	.903			
TR3	3.48	1.10	.805			
TR4	3.32	1.14	.846			
Perceived AI Interactivity (PI)				.913	.907	.727
PI1	3.73	.97	.911	Kim et al. (2012) and retested by Kim et al. (2022)		
PI2	3.75	.93	.914			
PI3	3.70	.95	.893			
PI4	3.48	1.16	.667			
Willings to Accept AI Technology (W)				.936	.939	.708
W1	3.44	1.00	.866	Montargot & Ben Lahouel (2018) and Wang & Hou (2025)		
W2	3.78	.99	.807			
W3	3.49	1.05	.827			
W4	3.63	1.02	.839			
W5	3.24	1.08	.889			
W6	3.44	1.04	.818			
SD = standard deviation; CR = composite reliability; α = Alpha reliability; AVE = average variance extracted						

Table 2. Discriminant Validity for the Measurement Model

The AVE and the square multiple correlations between variables							
Variables	RC	ExM	InM	AB	TR	PI	W
Role Clarity (RC)	.681						
Extrinsic Motivation (ExM)	.175	.782					
Intrinsic Motivation (InM)	.246	.660	.763				
Ability (AB)	.237	.591	.570	.617			
Trust in AI (TR)	.118	.623	.506	.546	.711		
Perceived AI Interactivity (PI)	.169	.384	.397	.484	.361	.727	
Willing's to Accept AI Technology (W)	.231	.572	.587	.610	.407	.697	.708
The square root of the AVE and correlations between variables							
Variables	RC	ExM	InM	AB	TR	PI	W
Role Clarity (RC)	.825						
Extrinsic Motivation (ExM)	.419	.884					
Intrinsic Motivation (InM)	.496	.813	.873				
Ability (AB)	.487	.769	.755	.785			
Trust in AI (TR)	.344	.789	.711	.739	.843		
Perceived AI Interactivity (PI)	.411	.620	.630	.696	.601	.853	
Willing's to Accept AI Technology (W)	.481	.756	.766	.781	.638	.835	.841

Fornell and Larcker's (1981) criterion, which contrasts either the square root of the AVE with inter-correlations between the variables the AVE with the square multiple correlations, were used to guarantee discriminant validity. This criterion states that the discriminant validity condition is met when the square root of the AVE is greater than the intercorrelations between the study variables. In addition, the AVE is greater than the square multiple correlations of the variables. Both methods, as presented in Table 2, offer proof that our research variables are discriminately valid.

2. Hypotheses Testing

2.1. Direct Relations

Assuming the foregoing, standardized path coefficients (ß) were utilized to assess the hypothesized correlations using the structural equation model (Table 3).

Of the four hypotheses, the first hypothesis had an absolute t-value greater than 2.58 (t 2.719, ß = 0.076, $p < 0.01$), indicating a positive relation. Meanwhile, the other three hypotheses (H1b, H1c, and H1d) had strong positive relationships with estimated absolute t-value greater than 3.29 (t= 9.004, ß =.308, $p < 0.01$); (t= 9.076, ß =.291, $p < 0.01$) and (t= 6.951, ß =.247, $p < 0.01$) respectively. These findings matched our predictions of the theoretical hypotheses that role clarity, employees' extrinsic motivation, extrinsic motivation and ability positively impact their willingness to accept AI technology in hotels.

Table 3. Standardized Parameter Estimates of the Structural Model

H	Path			Beta coefficients (ß)	t-values	*P*-values	Results
H1a	Role Clarity	→	Willing's to Accept AI	.076	2.719	*P* = .007**	Supported
H1b	Extrinsic Motivation	→	Willing's to Accept AI	.308	9.004	*P* < .001***	Supported
H1c	Intrinsic Motivation	→	Willing's to Accept AI	.291	9.076	*P* < .001***	Supported
H1d	Ability	→	Willing's to Accept AI	.247	6.951	*P* < .001***	Supported
*Absolute t-value > 1.96, p< 0.05; **Absolute t-value > 2.58, p< 0.01; ***Absolute t-value > 3.29, p< 0.001.							

2.2. Moderation Effects

The study assesses the moderating role of trust in AI and perceived interactivity in the relationship between role clarity, extrinsic motivation, intrinsic motivation, ability, and their willingness to accept AI technology. The results shown in Table 4 revealed a negative and significant moderating impact of trust in AI in the relationship between employees' role clarity (ß = -.121, t = -3.933 $p < 0.001$) and intrinsic motivation (ß = -.104, t = -3.143, p = 0.002) with their willing to accept AI technology, supporting H2a and H2c, respectively. On the other hand, the results indicate that there is no moderating role of trust in the relationship between extrinsic motivation (ß = -.028, t = -.703, p = .482), ability (ß = -.067, t = -1.728, p = .084), and their willingness to accept AI technology, rejecting both H2b and H2d. Moreover, moderation role results show that there is no moderation effect of perceived interactivity in the relationship between role clarity (ß = -.030, t = -1.042, p = .298), extrinsic motivation (ß = .012, t =.345, p = .730), intrinsic motivation (ß = -.045, t =-1.497, p = .134), ability (ß = .011, t = .317, p = .751) and their willing's to accept AI technology, rejecting H3a, H3b, H3c and H3d.

Table 4. Standardized Parameter Estimates of the Structural Model

H	Path		Beta coefficients (ß)	t-values	*P*-values	Results
H2a	Role Clarity X Trust in AI	Willing's to Accept AI	-.121	-3.933	< 0.001	Supported
H2b	Extrinsic Motivation X Trust in AI	Willing's to Accept AI	-.028	-.703	.482	Rejected
H2c	Intrinsic Motivation X Trust in AI	Willing's to Accept AI	-.104	-3.143	.002	Supported
H2d	Ability X Trust in AI	Willing's to Accept AI	-.067	-1.728	.084	Rejected
H3a	Role Clarity X Perceived Interactivity	Willing's to Accept AI	-.030	-1.042	.298	Rejected
H3b	Extrinsic Motivation X Perceived Interactivity	Willing's to Accept AI	.012	.345	.730	Rejected
H3c	Intrinsic Motivation X Perceived Interactivity	Willing's to Accept AI	-.045	-1.497	.134	Rejected
H3d	Ability X Perceived Interactivity	Willing's to Accept AI	.011	.317	.751	Rejected

DISCUSSION

This study addressed some of the factors that affect employees' acceptance of artificial intelligence technology in the workplace, especially in the hotel sector. It thus examined the moderating role of both trust in such technology and perceived interactivity with it on the direct relationships of both role clarity, extrinsic motivation, intrinsic motivation, and ability, and their acceptance. Our major findings were as follows. The results demonstrate that employees are more likely to accept AI technology when they know what their role is, are motivated to use AI-based technology, and can do so. Interestingly, the results revealed unexpected moderating effects. More clearly, trust pertaining to the use of AI-based technology weakens the relationship between both role clarity and intrinsic motivation with employees' willingness to accept AI technology. In contrast, the results revealed a lack of effect for the AI perceived interactivity on the direct relationship, which was inconsistent with the research hypotheses and requires clear justifications.

In more detail, the results showed a direct positive relationship between the clarity of employee and AI's roles with their willingness to accept AI technology in the workplace. In other words, the more fully an employee is aware of their duties within the hotel work environment and what they are expected to accomplish, the more they will understand how useful AI technology is (Jarrahi, 2018). This value comes from improving the services provided to guests, which in turn makes employees more eager to embrace such technology and integrate it into their job duties (Montargot & Ben Lahouel, 2018;

Lam et al., 2007). These findings are consistent with the views of other academics who have emphasized that the clearer users' roles in artificial intelligence technology, the more they appreciate the benefits of incorporating such technology into their business strategies regularly (Shemshaki, 2024; Rane et al., 2024; Choi, 2021).

Moreover, the study confirmed the significant role of employees' motivation to adopt AI-based technology, whether extrinsic or intrinsic, in their willingness to accept it. Extrinsically, the changing expectations of customers, the need to provide great hotel services, the demands of the work environment, and the desire to respond to constant pressures are all elements that stimulate the acceptance of AI technology (Vafaei-Zadeh et al., 2025; Sohn & Kwon, 2020; Ostrom et al., 2018). In addition, intrinsically, hotel employees are continuously seeking to attain their full potential and demonstrate their capacity to go beyond the tasks entrusted to them, especially in front-line services. Furthermore, employees' drive to develop their individual skills to better guest service makes AI a supportive tool for achieving great performance (Ruel & Njoku, 2021; Prentice et al., 2020). In succession, the results of direct relationships found a positive impact of employees' ability in the context of the adoption of AI-based technology on their willingness to accept AI technology. Professional development begins with an employee's ability to use AI technology (Billiot, 2023). Numerous scientific studies (i.e., Houari, 2025; Pérez-López & Alegre, 2012) have verified that there is a direct and unambiguous correlation between an employee's technological proficiency, knowledge, skills, and ability. As a result, an employee's ability to embrace AI technology depends on both their personal aptitudes and talents as well as the organizational technologies that allow them to do so and realistically accept it (Morandini et al., 2023). As a result, researchers have identified employee ability as one of the key determinants of workplace readiness for AI technology acceptance in the hotel sector.

However, the findings of the research's moderation variables contradicted the hypotheses derived from the theoretical context. This is regarded as a distinct scientific addition that necessitates explanations that could help offer a fresh viewpoint on the body of knowledge in the field. First, the researchers hypothesized that the presence of trust as a moderating variable might strengthen the relationship between the independent and dependent variables.

However, the results were negative for both role clarity and intrinsic motivation, while there were no moderating effects for both extrinsic motivation and ability. In other words, as employees' trust in using AI technology increased, the importance of role clarity and intrinsic motivation in influencing their willingness to accept such technology diminished. This may make sense, given that employees have a strong belief in AI's ability to perform all activities with unimaginable professionalism, especially in the area of guest service (Çolak, 2023; Koo et al., 2021).

As a result, they become more reliant on AI without needing to comprehend the job roles and work organization (Jarrahi, 2018; Huang, 2018). These findings are consistent with some behavioral theories, such as substitution theory by Netto (1892), which explains how some elements in human behavior weaken or lessen other factors.

According to this viewpoint, employees rely on their trust in AI technology to fulfill their role, neglecting to understand their own human role. On the other side, although intrinsic motivation are the cornerstone of trust (Weibel & Six, 2013), their significance decreases as trust grows (Martinez, 2016). To put it another way, an employee may use their own internal motivation to adopt various, significant technology systems that support them in realizing their achievement goals (Ke, 2012; Hwang, 2005). But as time goes on and the efficacy of these systems is verified, they gain self-assurance and strive to put them into place independently of intrinsic motivation (Gill, 1996).

Finally, the study's findings revealed that perceived interactivity had no moderating effect on direct relationships. This implies that role clarity, motivation, and ability are more important elements than involvement and are unaffected by it. In other words, employees' role clarity, as well as their motivation and ability to engage in a technological environment characterized by a range of AI tools, may have a greater impact on their adoption of such tools in the workplace, even if they do not interact directly with them. This may be due to a lack of organizational support for such instruments. Furthermore, a substantial body of research shows that perceived interactivity does not directly alter the strength of factors, but rather serves as an explanatory factor.

IMPLICATIONS AND LIMITATIONS

1. Theoretical Implications

This study contributes the following to the theoretical literature body on employees' acceptance of AI technology, particularly in the hospitality industry: First, it extends the application of the Theory of Reasoned Action (TRA) by integrating four key antecedents—role clarity, extrinsic motivation, intrinsic motivation, and ability—as predictors of employees' intention to accept AI technology. The study confirms that person-level enablers such as role clarity, personal motivation, and technical skill greatly influence behavioral intention towards AI, further support for psychological and cognitive processes in the formation of technology acceptance beyond performance and ease of use expectations.

Second, the study makes a worthwhile theoretical contribution through its examination of moderating variables, namely trust in AI and perceived interactivity, those much-discussed variables in the academic literature but not frequently surveyed empirically in a hospitality working environment setting. Compared to theoretical expectations, the negative moderating effect of trust in the relationship between both intrinsic motivation and role clarity suggests a substitution effect, in which employees who possess deep trust in AI systems will opt-out of their personal role or motivations. This finding confirms substitution theory of behavior and adds a new layer to understanding how over-reliance on technology reduces the value of human agency within online settings.

Third, the non-significant moderating effect of perceived interactivity is contrary to previous speculations that user engagement and engagement in AI systems inherently enhance behavioral effects.

This finding shifts the theoretical emphasis towards more job design or organizational readiness drivers, i.e., job design or organizational readiness, instead of users' perceptions of interactivity. The study, therefore, calls for a redefinition of where interactional factors are situated in AI adoption theories.

2. Managerial Implications

These results are particularly interesting for hotel managers and HR specialists who are trying to leverage AI technology to improve service work. The significant positive influence of role clarity on AI acceptance suggests that hospitality companies should strive to communicate clearly to employees their job expectations and the changing landscape of human–AI interaction. The managers must also ensure that they design onboarding and training protocols that clearly communicate to employees how AI technologies augment their work as opposed to substituting their work.

Second, the critical role of extrinsic and intrinsic motivation emphasizes both the necessity of incentive structures and development opportunities. Performance pay must be contingent on AI usage, but also foster a work environment in which self-directed innovation, learning, and mastery can flourish. Third, the direct positive effect of employee capability demonstrates that capacity building must be a high priority. This not only includes technical skill training but also gaining soft skills such as adaptability and digital confidence. Investment in professional development will support employees' readiness to embrace new technologies and reduce employee resistance to technology change. Fourth, the unexpected moderation effect of trust indicates balance in dependence on technology. While trust in AI systems is important, leaders must not fall into the trap of over-relying on them, as this can inhibit sound human reasoning or involvement. Models with reflective supervision, role reinforcement in the professional domain, and ethics-focused AI role orientation workshops could all provide a basis for other kinds of more balanced perspectives to emerge. Finally, the consideration of interactivity indicates that organizations must avoid a focus on the richness of the interface and the participation of users, as these may not properly address more significant and enabling motivational and structural facilitators. Instead, this focus must shift to readiness of system structures, congruence to job roles, and enabling policies in the service of acceptance.

3. Marketing Implications

These findings have some crucial implications for marketing in the hospitality and tourism sectors beyond the managerial and HR perspectives. The results show that employees' acceptance of AI technologies is not only an operational issue but one that will have direct implications for brand image and customer experience. For this reason, marketing efforts should position AI as a tool that enhances, rather than replaces, the human element of service. In communicating this message, hotels and tourism companies should emphasize AI as an enabler of personalization, efficiency, and responsiveness-attributes that build customer trust and satisfaction while retaining the authenticity of human interaction. There should be transparency in customer communications. Marketing campaigns and digital touchpoints across the entire customer journey should explain how AI is supporting service delivery through enhanced check-in speed, personalized recommendations, or dynamic room pricing, yet inform guests that human employees are still reachable. In this way, an organization would reduce discomfort on the part of the customer or potential customer that automation equates to depersonalized service. The findings suggest that too much emphasis on AI capability may raise unrealistic expectations or reduce perceptions of human accountability. Hence, messaging needs to be balanced, focusing on augmenting employee expertise rather than fully automating service.
In addition, the positive role of intrinsic and extrinsic motivation in the acceptance of AI underlines internal marketing strategies that turn employees into brand ambassadors. If the staff is confident and motivated to use AI tools, the enthusiasm will automatically overflow to ensure higher service quality and a more genuine encounter with the customers. Such empowered employees featured in promotional materials may reinforce the narrative that technology is used to enhance human performance and care. It can build both external brand perception and the internal culture of an organization.

Finally, since customer attitudes toward AI-based service innovations are also shaped by perceived interactivity and trust, marketers should focus on ensuring that the technology-driven service encounter is consistent and reliable. Instead of touting the sophistication or newness of interfaces, marketing campaigns should focus on reliability, ethical use of AI, and the organization's commitment to data privacy and human oversight. If hospitality marketers link brand messaging to these study insights, they can nurture deeper emotional connections with customers, foster employee acceptance of new technologies, and develop a competitive advantage based on trustworthy, human-centered innovation.

4. Limitations and Future Research

This research has limitations even though it contributes to the research. To begin, the study used hotel employees in Egypt and the potential challenges in generalizing the findings to other cultures or regions. Future studies can apply the model in other countries or sectors (e.g., healthcare, banking) to ascertain the nature of findings across various organizational contexts. Second, the cross-sectional research design limits our ability to make causal inferences between the variables. Future research will need to use longitudinal or experimental designs if we are to explore the changes in trust, motivation, and role clarity over time, especially as the tools of AI become increasingly embedded in the daily operations of organizations.

In the third position, the study investigated two moderating variables but did not examine the potential mechanisms (such as perceived usefulness, perceived behavioral control, or technostress) that might mediate the relationship from antecedents to AI acceptance. Future research will need to utilize mediators to derive additional and potentially valuable explanations of employee behavior. In the fourth position, the construct of perceived interactivity may require re-examination or more context-specific operationalization. It is possible that for the hospitality context, interactivity is not meaningfully perceived unless it ties back to service personalization or guest engagement possibilities. As the industry evolves, future research may consider how qualitatively based research could reframe or extend this construct in these different contexts. Finally, as AI technology continues to unfold, future research should examine the ethical and emotional issues (e.g., job insecurity, privacy concerns, or AI anxiety) that can interact with employee characteristics and organisational considerations in shaping the AI adoption behaviour of employees.

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Appendix

Questionnaire Items

Role Clarity (5 Items) adapted from Rizzo et al. (1970) and re-tested by Choi (2021).

- I have full authority to perform the tasks assigned to me.
- I have clear, planned goals for my job.
- I understand how I should be evaluated for promotion on a regular basis.
- I know exactly what is expected of me.
- I have a clear explanation of what I need to do.

Extrinsic Motivation (6 Items) adapted from Tyagi (1985) then re-tested by Choi (2021).

- I receive high respect from my supervisor at work.
- I have greater freedom to do what I want in my job.
- I enjoy a high degree of job security.
- I receive respect from colleagues.
- I earn a high salary.
- I get awards and special recognition.

Intrinsic Motivation (6 Items) adapted from Tyagi (1985) then re-tested by Choi (2021).

- I feel like I accomplish something meaningful.
- I have great opportunities for professional development and progress
- I experience a fascinating work environment.
- I experience a sense of creativity and innovation.
- I feel a sense of loyalty to my workplace.

Ability (5 Items) adapted from Jones (1986)

- I possess the skills and knowledge necessary to adapt to the tasks assigned to me.
- I feel I have sufficient technical skills to sustain my work.
- I have previous experience and expertise that will help me succeed in my job.
- I have the qualifications and experience that are equal to or superior to those of my colleagues.
- I possess the qualifications that exceed the requirements of the job I perform.

Trust in AI (4 Items) adapted from Mustofa et al. (2025)

- I trust the data and information I obtain from AI based technology.
- I believe that AI based technology helps in completing tasks and making decisions.
- I believe that recommendations derived from AI based technology are based on comprehensive and accurate data analysis.
- I believe that AI based technology helps in solving problems within the workplace effectively.

Perceived AI Interactivity (4 Items) adapted from Kim et al. (2012) and retested by Kim et al. (2022)

- The hotel uses a range of responsive AI systems and tools.
- The AI-based technology used helps create new and stimulating experiences.
- The AI-based technology used helps with synchronous and instant communication.
- Using AI tools makes me more focused while working.

Willing's to accept AI technology (6 Items) adapted from Montargot & Ben Lahouel (2018) and Wang & Hou (2025).

- I feel that using AI based technology will help me do work more swiftly.
- I believe that AI based technology improves the efficiency of my work.
- I believe that employing AI based technology is simple and effortless.
- Learning how to use AI based technology would be simple for me.
- I believe that implementing AI based technology in the hotel is a wonderful idea.
- I am optimistic about using AI based technology.

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