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Determining Behavioral Intention to Use Artificial Intelligence in the Hospitality Sector of Pakistan: An application of UTAUT Model

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ABSTRACT

The main objective of this study is to create and evaluate an empirical model that can forecast the elements that impact user behavioural intentions when using artificial intelligence. The researchers used the expanded Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate the probability of consumers adopting artificial intelligence (AI). The study focused on four key aspects: the impact on society, performance expectancy, effort expectancy, social influence, and facilitating conditions. The research was extended to include three further variables: perceived privacy risk, behaviour intentions, and the adoption of artificial intelligence, to augment the precision of client behaviour forecasts. An on-line poll and obtained 310 answers from the hotel business in Pakistan. The cumulative sample was evaluated using structural equation modelling (SEM) inside the IBM SPSS Statistics V. 29.0 and SMART PLS 4.0.6 framework. Findings of the study suggested that the main factors driving the acceptance of artificial intelligence are the perceived privacy risk, facilitating conditions, and the behavioural intention to use AI. However, the customers' expectations about performance expectancy and effort expectancy, as well as their assessments on social influence, did not substantially impact their choice to utilize this program. Moreover, this study offers essential knowledge on the most effective techniques for employing these technologies.

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1. Introduction

The hospitality industry benefits greatly from the incorporation of Artificial Intelligence (AI) technology in today's fast-changing digital landscape. AI has the potential to completely transform the hotel sector in several ways, from improving operational efficiency to providing guests with personalized experiences. But even with its potential advantages, AI's adoption in Pakistan's hotel industry has been very gradual. The latest advancements in digital technology present novel opportunities for human-machine interaction (Dix, 2017). Virtual assistants (VAs) are notable for their capabilities since they can replicate social skills and mimic human interactions by simulating human-like images and having nearly real-time discussions with humans through interfaces. Speech recognition, the feedback loop, and interacting with the tool of the exchange throughout a conversation are a few human talents that are frequently replicated or portrayed as communicative features (Cassell, 2000). Alexa, Siri, Cortana, and Bixby are a few well-known VAs that assist with daily duties. They perform key functions including making phone calls, checking the weather, doing arithmetic and mathematical computations, playing music lists, and many more (Robinson, 2019). Artificial Intelligence (AI) enables Voice Assistants to offer advanced voice interfaces and real speech interaction (Cobos Guzmán, Nuere Menéndez-Pidal, Miguel Álvarez, & König, 2021). These VAs are integrated into consumer devices, home entertainment, and workplace environments. The market is expected to reach 8.4 billion devices by 2024, doubling the number of AI-powered devices.

According to Sousa, Pani, Dal Mas, and Sousa (2024), technology has become a requisite aspect of our existence, improving welfare, health, and quality of life. The development of AI greatly impacts the services industry due to the rise in digital connectivity(Makridakis, 2017). AI, robotics, and chatbots, for example, are on the verge of revolutionizing a variety of sectors, including the healthcare system, Higher education, tourism, and hospitality industry the technologies are, however, quickly approaching this point. According to Nam, Kim, and Nam (2022), the discussion surrounding accepting or rejecting innovations continually expands in the scholarly and professional literature. According to earlier research, the use of AI and Robotics services in the field of hospitality sector has several advantages for all parties involved (i.e., staff, consumers, and organizations). For instance, using AI and robots can benefit hotels and restaurants by lowering expenses, increasing profits, and improving operating productivity (Ransbotham, Kiron, Gerbert, & Reeves, 2017). Similarly, it helps staff members work more productively by relieving them of monotonous duties (such as collecting orders, checking people in or out, and answering inquiries from customers). Furthermore, the free time to work on other projects calls for a face-to-face connection (Nam et al., 2022).

United Theory of Acceptance and Use of Technology UTUAT model was first introduced by Venkatesh, Morris, Davis, and Davis (2003), providing a variable understanding of the framework of technology adoption of behavior. People thinking about adopting the latest technological advancement which was explained in five important constructs, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Perceived Privacy Risk, and Facilitating Conditions (FC), (Venkatesh et al., 2003). Even though the UTAUT model has been comprehensively utilized in many settings to examine the adoption of technology patterns, its application in the framework of AI adoption in Pakistan's hotel industry is still constrained. The current research on the mediate the title role of behavior intentions in the affiliation amongst UTAUT components and the Adoption of AI in the Pakistan hotel industry is also lacking. This study fills these gaps, the research study investigates how the UTAUT model affects the hospitality sector of Pakistan and compensates particular attention to the mediating role that behavioral intention plays. The current study intends to deliver important comprehensions that can advise legislators, industry practitioners, and scholars on practical measures for encouraging the successful integration of AI technology by analyzing the relationship between UTAUT components, behavioral intention, and AI adoption.

1.1 Problem Statement:

In the world, many hotels have executed Artificial Intelligence and use of robotics in their operations. AI and robotics can change operations and policymaking in an organization or hotel industry (Galaz et al., 2021). Avoid the interactions between employees and customers in the hospitality sector, Singapore and the Netherlands have been the adoption of AI and Robotics (Minor, McLoughlin, & Richards, 2021). Similarly in China, a Beijing-based Chinese delivery restaurant, Meiituan Dianpping, has introduced a robotics system for delivering food from the kitchen to our customers at Takeaways (Toh, Fong, Gonzalez, & Tang, 2023). Artificial intelligence has been extensively used in the hospitality sector (Ivanov, Gretzel, Berezina, Sigala, & Webster, 2019). In the way of hospitality and tourism industry, AI can serve of tourists in the way of helping book rooms, self-check-in and out, room service, complaints about room service, hotel employee mismanagement, and providing recommendations for tour guidance (Cai, Wang, & Sun, 2024). This enhances consumer happiness, data transfer rates, and the tourism industry's overall performance (Cai et al., 2024). AI in hotels and restaurants is capable of placing orders, processing payments for patrons, and booking tables in addition to providing further menu information. AI has been shown to decrease wait times for customers, enhance food freshness and customer satisfaction, and increase income for businesses (Tan & Netessine, 2020).

There are several studies related to AI and hospitality sectors in developed countries but in developing countries lack of research studies in AI and hospitality sectors. Like, Pakistan is a developing country there are lack of studies on AI and the hospitality sector of Pakistan. Pakistan's hospitality sector is suffering a significant technological revolution with the prospect of AI to expand operations and guest experiences. However, adoption remains slow. Despite the strong framework of the UTAUT model, the hospitality industry in Pakistan confronts difficulties using AI because there is a dearth of research on this field's application. The lack of research on the connection between behavioral intention and AI adoption in Pakistan's hospitality sector impedes the creation of practical solutions. To discourse this study gap, this research study pursues to explore the relationship of the UTAUT model on the adoption of the hospitality sector of Pakistan, with the main focus on the mediating effect of Behavioral Intention. The objective of the study is to provide important insights into successful techniques for integrating AI technology in Pakistan's hospitality sector for policymakers, industry professionals, and researchers. That's why we explore this study in the hospitality sector in Pakistan.

1.2 Research Objective:

This research study aims to investigate how Behavioral Intentions mediate the relationship between the UTUAT construct and the adoption of AI in the Hospitality sector of Pakistan.

1. To determine the impact of performance expectancy on Behavioral Intentions to use AI hospitality sector of Pakistan.
2. To determine Effort Expectancy's impact on Behavioral Intentions to use AI in the hospitality sector of Pakistan.

3. To determine the impact of Social Influence on Behavioral Intentions to use AI in the hospitality sector of Pakistan.
4. To determine the impact of perceived privacy risk on Behavioral Intentions to use AI in the hospitality sector of Pakistan.
5. To determine the impact of Facilitating Conditions on Behavioral Intentions to use AI in the hospitality sector of Pakistan.
6. To determine the impact of Behavioral intention on adopting of AI in the hospitality sector of Pakistan.

1.3 Significance of the Study:

The significance of reconnoitering the application of the UTUAT model (Unified Theory of Acceptance and Use of Technology) in adopting the AI inside Pakistan hospitality sector can be exaggerated. For those involved in the industry, legislators, scholars, and the economy as a whole, this study is extremely significant. This research study investigates the different variables impacting the adoption of AI and provides helpful information that can be unplanned choices in the hospitality sector through the use of the UTUAT model. This model is used for organizations to boost our operational function in the organizations or increase our operational efficiency, stand out in jam-packed markets, and organization provide the best customer experience, it's authoritative to understand the aspects that boost and encumber the adoption of AI. Furthermore, the policymakers and lawmakers gain benefit from this research study by developing different supportive and additional policies and regulation structures that encourage novelty and technological development by helping understand the unique opportunities and different problems related to AI adoption. In the field of academic circles, the current research study expands our theoretical knowledge of how we adopted technology in various situations and unbolts new opportunities for investigations. In the end, this research study concludes that the division of economic growth, advanced industry development, and put the hospitality sector of Pakistan at the forefront of technological novelty.

2. Literature Review:

2.1 AI in the hospitality industry

Advancements in artificial intelligence, robots, and big data are facilitating the rapid growth of the hotel industry (Reis, Melão, Salvadorinho, Soares, & Rosete, 2020). These advancements are giving rise to the rapid development of the hotel sector. As a result of the incorporation of artificial intelligence and digital technology into systems for revenue management, property management, and customer relationship management (Vinnakota et al., 2022), the hotel industry has been able to combine major performance measures. It is essential to have a deeper understanding of how artificial intelligence technology may impact customer pleasure, loyalty, and service quality via the outcomes that are associated with personnel. There is a major contribution that artificial intelligence services make to the total service quality in the hotel industry. This contribution is made via the quality of personnel service. According to Cai et al. (2024), these contributions are defined by staff involvement, productivity, and the quality of the service provided. In addition, innovations in robotics, artificial intelligence, and improved digital communication are having an impact on all business sectors, including the hotel industry. According to Mingotto and Tamma (2021), organizations make use of cutting-edge trimming and cognitive technologies to optimize operations, save expenses, increase customer happiness, and even propose new ones. Furthermore, the use of robots and artificial intelligence might assist in the reduction of errors caused by humans and allow the development of future projections. Robotics and artificial intelligence services can analyze large volumes of data, which may subsequently be translated into insightful business insights(Almaida et al., 2024). Moreover, hotels are in a better position to supply their customers with first-rate services since they have a better understanding of business. Artificial intelligence (AI) makes company customers happy by enabling them to recognize and maximize potential future sales chances (Kumar, Sharma, & Dutot, 2023). This provides a competitive advantage for businesses. Indeed, artificial intelligence has a significant amount of importance in the hospitality sector. According to Hasni, Farah, and Adeel (2021), Pakistan's hotel business has seen a significant expansion in recent years as a result of the growing number of tourists and corporate travelers. However, the hospitality industry is facing several issues, including a decrease in productivity and an increase in operating expenses (Ali, Jan, Khan, Shakoor, & Mahmood, 2022). The use of robotics and artificial intelligence might potentially be of assistance in resolving some of the issues that have been brought up, as well as in enhancing the efficacy and efficiency of hotel operations. Even though they are still in their infancy, robots and artificial intelligence are already being used in hotels in Pakistan(Ijaz, Chawla, Shahzad, & Watto, 2022). According to A. Iqbal, Shaikh, Saleem, Farooqi, and Usman (2023), there is a paucity of studies on the elements that influence the adoption and resistance to this technology.

2.2 Performance Expectancy (PE) and Behavior Intention to Use AI

According to Venkatesh et al. (2003) on page 447, "the degree to which an individual believes that utilizing the system will enable them to improve their job performance" is known as performance expectancy (PE). Researchers observed that field people from humanitarian groups think AI will help with disaster response. "Pe" is the expression. According to Kovács and Spens (2007), humanitarian groups must overcome a variety of challenges to minimize harm to society and the environment during a chaotic disaster. Several studies undertaken in the hotel industry have proven how important AI is in addressing these issues and improving relief efforts(Asdullah & Watto, 2023). AI fosters coordination across businesses, boosting the efficacy of humanitarian activities. AI facilitates disaster management and mitigation. Positive views among field personnel about the use of AI to enhance performance may encourage its adoption. Industrial AI is a cutting-edge technology, thus conservative organizations should weigh its benefits before using it. We think that for these enterprises to use AI, they must have a recognized "functional value" based on their industrial characteristics. Consumers understand the practical advantages of employing alternative technologies to complete jobs. Based on economic utility theory, the functional value construct breaks through consumers' economic rationalism to allow for a cost-performance trade-off (Shrestha, Ben-Menahem, & Von Krogh, 2019). AI services have a higher perceived functional value because of their evident functional, utilitarian, and physical qualities. Functional value may be defined as the combination of greater performance, decreased operational costs, increased safety, and satisfied customers. In conservative organizations, industrial AI adoption is assumed to be motivated by functional value. Users of conservative industrial AI assess technology-specific criteria such as effort expectancy and performance to calculate functional value. According to Venkatesh et al. (2003), the UTAUT assesses technology adoption based on performance and effort expectancy. Performance expectancy refers to a service or technology's capacity to meet objectives and provide benefits (Gursoy, Chi, Lu, & Nunkoo, 2019). The word "performance expectancy" in this study refers to industrial AI's capacity to improve complex operations, reduce costs, create greater employee collaboration, and so on. This improves worker safety and provides company advantages. Oyewole (2018) defines performance expectancy as efficacy, relative advantage, work fit, intrinsic and extrinsic motivation, and expectations for industrial AI results. Thus, perceived performance expectancy boosts functional value and usefulness. Thus, the following idea is proposed:

H1. There is a significant association amongst performance expectancy (PE) and the Behavioral Intentions to use AI.

2.3 Effort expectancy (EE) and Behavior Intention to Use AI

The level of effort required or the ease of use might affect the behavioral purpose. EE is defined as "the degree of ease associated with IT usage in the supply chain" by (Venkatesh et al., 2003) in the year 2003. The unified Theory of Acceptance and Use of Technology among middle-level managers in humanitarian organizations is described by EE based on this research. According to studies, EE is connected to the amount of technology that consumers consume. In most cases, the goals of middle-level managers are contingent upon the amount of complexity of the system as well as the user's level of expertise. To put it another way, the degree to which the technology is compatible with the skill level and knowledge of local emergency management will determine whether or not they decide to employ it (Prasanna & Huggins, 2016). For operations to be carried out in an efficient and timely manner, the necessary skills are needed. Last but not least, the practices of operational sustainability could affect work performance. Individuals believe that the system is user-friendly since it requires them to exert less effort to complete their tasks. When local emergency management specialists in impoverished nations find that an information technology system is easy to use, suitable for their needs, and convenient, the probability that they will accept the system increases. The effort that is anticipated is here. A product's functional value is defined by the TCV as the extent to which it can carry out activities in a more effective manner. The usability or comprehensibility of an artificial intelligence product is determined by the functional relevance of the product itself among experts working in the sector. According to the UTAUT, the usability of technological products is defined as "effort expectancy." (Venkatesh et al., 2003) mean when they say that effort expectancy is "the degree to which a new technological product or service is user-friendly" Several studies have shown a connection between the anticipated amount of work and the value of the output. It is important to keep in mind that the operational obligations of conservative firms are difficult, time-consuming, and risky (Khan, Hameed, Khan, Khan, & Khan, 2022). Industrial artificial intelligence integration may result in operational disruptions, quality changes, delays in project completion, and increased risks. This is because learning involves time and effort. Since this is the case, apparent effort When it comes to establishing whether a functional value is strong or weak, anticipation is the most important factor to consider. Consequently, we come up with the consequent theory.

H2. There is a significant association among Effort Expectancy (EE) and Behavioral Intentions to use AI.

2.4 Social influence (SI) and Behavior Intention to Use AI

Venkatesh et al. (2003) define social impact (SI) as the process of understanding and considering the perspectives of others on the implementation of a new system. In the field of social psychology, ideas provide insights into how society might impact behavior. Bandura and Walters (1977) social learning theory posits that dependable relationships play a crucial role in the transmission of information via communication. The conflict elaboration theory of social impact (CETSI) was first proposed by (Mugny, Butera, Sanchez Mazas, & Pérez, 1995). This concept explores the impact of an individual's decision to either adopt or reject an innovation on their social connections within their community. (Mugny et al., 1995) social effect theory posits that compliance is the primary and essential outcome. If you want a favorable response from a group or person, you may use the use of influence. Internalization refers to the cognitive process by which an individual recognizes and accepts the validity of other individuals' perspectives. Identification is the cognitive process by which individuals see themselves as possessing the characteristics and qualities associated with a certain group. In the context of our discussion, influence refers to the change in viewpoint that occurs as a consequence of an external stimulus (Mugny et al., 1995). Theories such as the TRA, TBP, TAM, and UTAUT concur that the social consequences of technology determine an individual's behavioral intention toward its adoption and usage. Venkatesh et al. (2003) define "social impact" as the individual use of technology. The concept of social influence suggests that individuals may employ technology to enhance their social standing, even if they do not personally like it. Several empirical studies on the acceptability of information technology have consistently shown that users' behavioral intentions are significantly impacted by social factors. In contrast, other research failed to uncover significant evidence (Purwanto & Loisa, 2020). The influence of social factors on the adoption of GB technology has been rather overlooked. Rifat, Nisha, Iqbal, and Suviitawat (2016) conducted studies that demonstrate a favorable social impact. According to a study conducted by J. Iqbal, Kousar, and Ul Hameed (2018), the social impact did not accurately predict consumers' adoption of GB technology. This study demonstrates the credibility of the viewpoints of individuals about the use of information technology, specifically from the perspective of a middle-level manager in a humanitarian organization. According to Comfort (2005), effective disaster response managers are those who have experience, respect, and trust for each other. They also can complement and criticize each other's acts during practice. This enables them to operate accurately in managing disasters. To provide victims additional assistance, they must collaborate. This demonstrates that the viewpoints of colleagues have an impact on the use of information technology by professionals in the field during crisis response. Multiple research Chaouali, Yahia, Charfeddine, and Triki (2016) indicate that the prevalence of information technology use is higher when individuals get approval from their friends and family. The success is contingent upon the commitment of both the top management of the organization and the colleagues with whom you are interacting. The foundation of anything is established by societal norms, perspectives, and individual needs. The following theory is proposed:

H3. There is a significant association between Social Influence (SI) and the Behavioral Intentions to use AI.

2.5 Facilitating conditions (FC) and Behavior Intention to Use AI

The term "facilitating conditions" is defined under the UTAUT paradigm as the technological resources that are necessary to make a technology accessible to consumers, as stated by (Venkatesh et al., 2003) An individual's trust in their capacity to manage their behavior is what the UTAUT considers to be Facilitating conditions, as stated by (Venkatesh & Bala, 2008). On the other hand, Venkatesh, Thong, and Xu (2012) discovered that enabling JIMA 14,10 2478 conditions had a direct influence on behavioral intention. This is in contrast to the findings of the first UTAUT. According to H. Wang, Tao, Yu, and Qu (2020), facilitating conditions are indicative of a readiness to adopt a variety of technologies. According to a study of tests conducted by GB technology, acquiring information about the behavior of customers' intentions involves the use of optimum settings (M. Iqbal, Nisha, Rifat, & Panda, 2018). A lack of consumer evidence exists in the United Arab Emirates, a country located in the Middle East that has distinctive social and economic structures. This is the case even though favorable facilitating conditions have a significant role in the adoption patterns of global technology. Customers of a hotel are more likely to have favorable opinions when they have easy access to smart gadgets and the internet, are aware of how to use GB technology, and receive expert guidance and help. As stated by Venkatesh et al. (2003) on page 453, "the extent to which an individual is convinced that an organizational and technical infrastructure is in place to facilitate the system's use" is that which is referred to as the facilitating conditions (FC) at this moment in time. Computing requires a significant amount of infrastructure, expertise, and resources. Therefore, end users are more likely to adopt information technology when they have access to additional resources such as technical expertise, training, and organizational support. Specifically, Kabra, Ramesh, Akhtar, and Dash (2017) provide theoretical evidence for the role of FC. Middle-level managers from humanitarian organizations are the ones who decide the FC for this study. Their decision is based on how much support they have for the use of information technology for humanitarian reasons. Therefore, the following theory is proposed:

H4. There is a significant association among Facilitating Conditions (FC) and the Behavioral Intentions to use AI.

2.6 Perceived Privacy Risk and Behavior Intention to Use AI

The uncertainty regarding the negative effects of using AI technology is called perceived AI risk. According to Udo, Bagchi, and Kirs (2010) perceived privacy risk is linked to loss and includes privacy, financial, emotional, and technological issues. Customers' perceived certainty that an information system shares their personal information is called perceived privacy risk (Lee, Kang, & Lee, 2022). Privacy is avoiding unwanted intrusions such as eavesdropping, security vulnerability exploitation, and user identity theft (E. S.-T. Wang & Lin, 2017). VAs' privacy and security problems restrict their use and acceptability (Saura, Ribeiro-Soriano, & Palacios-Marqués, 2021). VAs must collect sensitive data to operate, raising security worries and limiting their use Pizzi and Scarpi (2020) examined how privacy concerns affect consumer behavior in various situations. These results suggest privacy concerns may hinder (Nepomuceno, Laroche, & Richard, 2014). This study focuses on technological risks since people may perceive AI faults or delays while making decisions, which might hurt corporate performance. Managers worry that AI deployment will lead to improper organizational decisions and serious issues (Cao, Zheng, & Ni, 2022). AI's capacity may cause organizations to make bad decisions, lowering their competitiveness (Rana & Arora, 2022). AI services need expertise and skill, and technology-phobic customers may not use them (Chen & Atkin, 2021). Disabled customers who struggle to utilize AI services may leave companies. Sometimes artificial intelligence systems discriminate. Technological factors Organizational Elements Environmental concerns may hurt consumers and businesses. AI adoption performance may suffer when organizations perceive a higher risk associated with AI adoption and are unwilling to spend the required resources to ensure its successful implementation. Therefore, we suggest:

H5. There is a significant association among perceived privacy risk (PPR) and behavioral intentions to use AI.

2.7 Behavior Intention and Adoption of Artificial Intelligence (AI).

According to Venkatesh et al. (2012), applications for artificial intelligence are either accepted or rejected based on how effective they are, how much effort they are predicted to need, and how much money they will cost. Performance anticipation is a significant predictor of technology adoption, according to (Venkatesh et al., 2003). This holds in both voluntary and coercive settings. Industrial artificial intelligence will be more acceptable if it satisfies the standards for functional and conditional value, which will have the effect of raising the expectations for its performance. However, while dealing with conservative organizations, it is necessary to consider the anticipated amount of work on the functional value and the ability of individuals to learn AI-based processes. Therefore, a high functional and conditional value is looking for a bigger effort expectancy to achieve its goals. According to Thompson, Higgins, and Howell (1991), while using complicated artificial intelligence software that needs a large amount of cognitive work to grasp, one can have negative sensations throughout the effort expectancy assessment process. Given that the unfavorable view will continue to exist, low effort expectancy may be a barrier to the adoption of artificial intelligence applications. This will create dissonance in the process of industrial AI acceptance. It was in 1962 that Festinger first introduced the notion of cognitive dissonance. According to this theory, "a person's assessment of an object that is inconsistent with their existing beliefs causes cognitive dissonance, which leads to discomfort." According to Gursoy et al. (2019), higher performance expectancy has the potential to alleviate the detrimental implications of low effort expectancy, provided that the values in question are both functional and conditional. According to Rahi, Othman Mansour, Alghizzawi, and Alnaser (2019), positive acceptance is impacted by performance expectancy, which may be defined as the assumption that a conservative industry would deliver services that are effective, reliable, and consistent in addition to being rich in advantages. Following these theoretical arguments, we propose the following hypothesis.

H6. There is a significant association among Behavioral Intention and the adoption of AI.

3. Methodology:

3.1 Data Set: The main objective of the study is to evaluate the uses of the UTAUT model in the behavioral intentions and adoption of AI how in the Hospitality sector of Pakistan. Regression analysis is a method used in quantitative research designs to determine how one variable affects another (Waqas Ahmad Watto, Monium, Qurban, & Ali, 2020). Testing the study's hypotheses allowed for the assessment of the relationship's direction and intensity. The questionnaire was used for the data collection method. Data gathered from hotels and restaurants that's operates in Lahore city, Punjab Pakistan.

3.2 Research Approach:

This research study is based on a quantitative study like a questionnaire approach to systematically observe the factors that influence the adoption of AI in Pakistan's hospitality industry. The main objective of the study is to evaluate the uses of the UTAUT model in the adoption of AI and we use the questionnaire method for this task. Statistical techniques applied to the analysis of quantitative data obtained from surveys. To compile respondents' demographic details and opinions about UTAUT constructs, descriptive statistics including means, frequencies, and standard deviations calculated. The desire to adopt AI (dependent variable) and UTAUT constructs (independent variables) was compared using multiple regression analysis. The relative significance of each UTAUT component in predicting AI adoption behavior is ascertained with the use of this analysis.

To investigate the mediating function of behavioral intention in the connection between AI adoptions, this investigation shed light on the fundamental processes by which AI adoption behavior is influenced by UTAUT constructs.

3.3 Research Design:

In order to balance economy and procedure with relevance to the research aims, research design entails organizing parameters for data collection and analysis (Fahlevi et al., 2024). It acts as a manual for compiling, assessing, and deciphering data and information (Waqas Ahamd Watto, Khan, Monium, & Abubakar, 2019). Therefore, it suggests a methodical approach with specific procedures that enable researchers to verify the hypothesis and accomplish the goals of the study, as well as ensure that relevant and useful data is acquired and contributes to the effectiveness of the research.

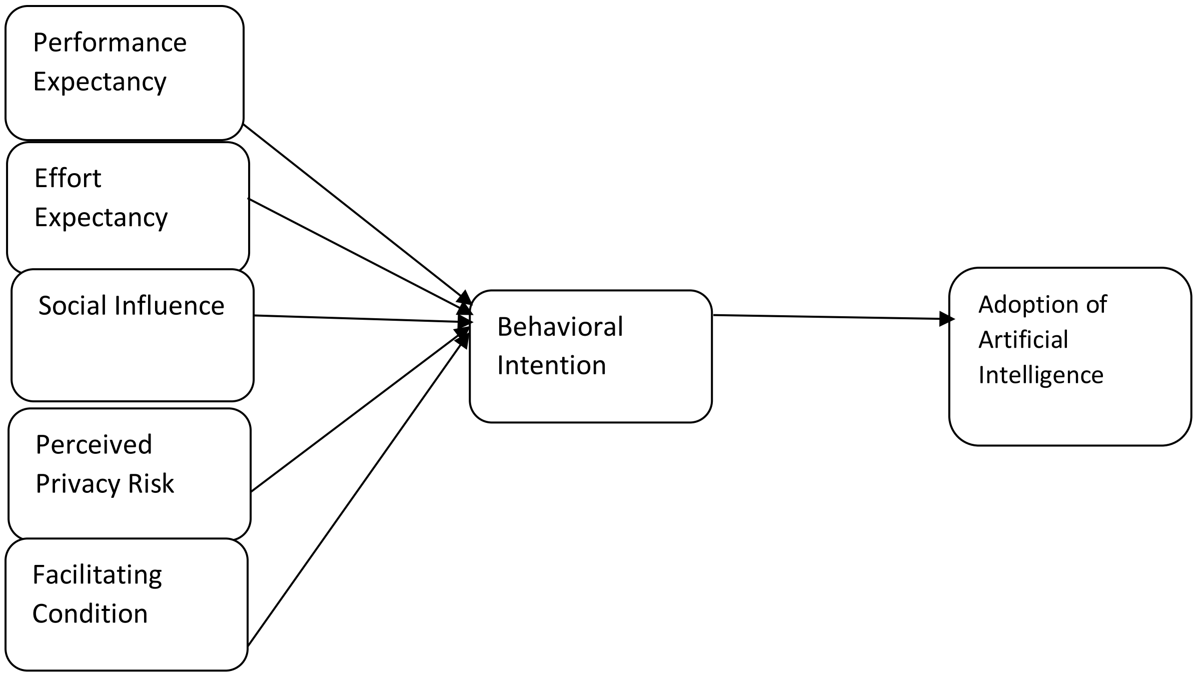
3.4 Descriptive Study:

Descriptive research was used as the research methodology for this study. This kind of analysis avoids asking "why" something happens and instead concentrates on describing the characteristics of the population or problem being studied (Xiang, Shaikh, Tunio, Watto, & Lyu, 2022). Its significance stems from the notion that problems may be solved and procedures improved by observation, analysis, and description. As a result, surveys are used to collect vast amounts of data by sending out questionnaires send be a huge number of respondents in the hospitality sector of Pakistan, data gathered from hotels and restaurants that operate in Lahore city, Punjab Pakistan, and data analysis done using the Smart PLS software.

3.5 Data Collection Method (Primary Data):

The collection of primary data is the main objective of this research. Akram, Li, Anser, Irfan, and Watto (2023) define primary data as unpublished data that was gathered straight from a source and hasn't been tampered with. For this reason, several methods are employed to gather and organize primary data for a particular objective. According to Almeida, primary data has higher validity than secondary data because it has not been altered by humans, making it more dependable and trustworthy. These characteristics are essential for some research approaches where the data must be specific to the problem and not available from published sources (Hussain et al., 2022). The main technique of gathering data for this study used surveys. The UTAUT model constructs, “Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions” serve as the foundation for a structured questionnaire that is tailored to the specifics of AI adoption in Pakistan's hotel industry. Likert-scale items incorporated into the questionnaire to gauge respondents' opinions of each concept. A pilot research with a small sample of hotel industry experts carried out to confirm the validity and reliability of the questionnaire. The pilot study's feedback help the questionnaire's essential revisions. Primary data for this research collected through a questionnaire from hotels and restaurants that operates in Lahore city, Punjab Pakistan.

Theoretical Model:



4. Results and Analysis

4.1 Constructs Reliability

This study evaluated data using SmartPLS 4.1.0.6 and identified statistical and conceptual framework assumptions. PLS-SEM is employed in empirical research of pro-environmental behavior (Waqas Ahamd Watto et al., 2019). Measurement method evaluation. PLS-SEM analysis begins with measurement model evaluation to determine construct reliability and validity. Thus, the construct's discriminant validity, convergence, and reliability were assessed. Table 1 shows the measuring model scales for performance expectancy, effort expectancy, societal effect, enabling conditions, perceived privacy risk, behavioral intention, and AI feature adoption. Table 1 illustrates item loading, composite reliability (CR), and average variance extraction for the construct. Hair, Sarstedt, and Ringle (2019) need the indicator loading to be at least 0.50, and all factor loadings meet this condition. Hair, Sarstedt, et al. (2019) suggested 0.7 composite reliability. All reflective structures surpassed 0.7 composite dependability. This makes structures reliable.

Table 1

Constructs	Items	Standard loadings	CA	CR	AVE
Performance expectancy	PE1	0.807	0.734	0.833	0.557
	PE2	0.807			
	PE3	0.745			
	PE4	0.609			
Effort expectancy	EE1	0.803	0.714	0.791	0.589
	EE2	0.667			
	EE3	0.687			

	EE4	0.632			
Social influence	SI1	0.828	0.797	0.880	0.710
	SI2	0.853			
	SI3	0.847			
Facilitating conditions	FC1	0.894	0.891	0.924	0.753
	FC2	0.868			
	FC3	0.856			
	FC4	0.853			
Perceived privacy risk	PSE1	0.818	0.748	0.841	0.669
	PSE2	0.722			
	PSE3	0.763			
	PSE4	0.710			
Behavioral intention	BI1	0.615	0.775	0.825	0.716
	BI2	0.844			
	BI3	0.869			
Adoption of AI	AI1	0.788	0.803	0.858	0.649
	AI2	0.799			
	AI3	0.739			
	AI4	0.632			
	AI5	0.733			

4.2 Discriminant Validity

The components' discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT). Table 3 shows that all HTMT values were below 0.85, proving the components' discriminant validity (Xin, Bin Dost, Akram, & Watto, 2022). Discriminant validity measures an item's capacity to distinguish variables. The square root of AVE must exceed the latent variable correlation to prove discriminant validity (Hair, Risher, Sarstedt, & Ringle, 2019). Table 1 reveals that all component square root AVE values were more relevant than inter-construct correlations. Furthermore, the latent variable correlation should not exceed 0.9 (Waqas Ahmad Watto et al., 2020). The highest inter-item correlation is 0.873 between ADI and BI. This proves the measurement model's discriminant validity. Methodology of (Fornell & Larcker, 1981): To validate CR scores, factor loadings were examined. Items with loadings below 0.70 were eliminated as per protocol. All loadings exceeded 0.70, as indicated in Table 2 and Figure 2. Convergent validity was indicated by an AVE value of 0.50 (Hair, Risher, et al., 2019).

Fornell and Larcker (1981) Table 2

	PE	EE	SI	FC	PPR	BI	ADI
PE	0.813						
EE	0.612	0.648					
SI	0.624	0.561	0.660				
FC	0.740	0.639	0.621	0.733			
PPR	0.871	0.793	0.621	0.765	0.799		
BI	0.776	0.691	0.728	0.749	0.693	0.786	
ADI	0.785	0.725	0.629	0.639	0.741	0.743	0.804

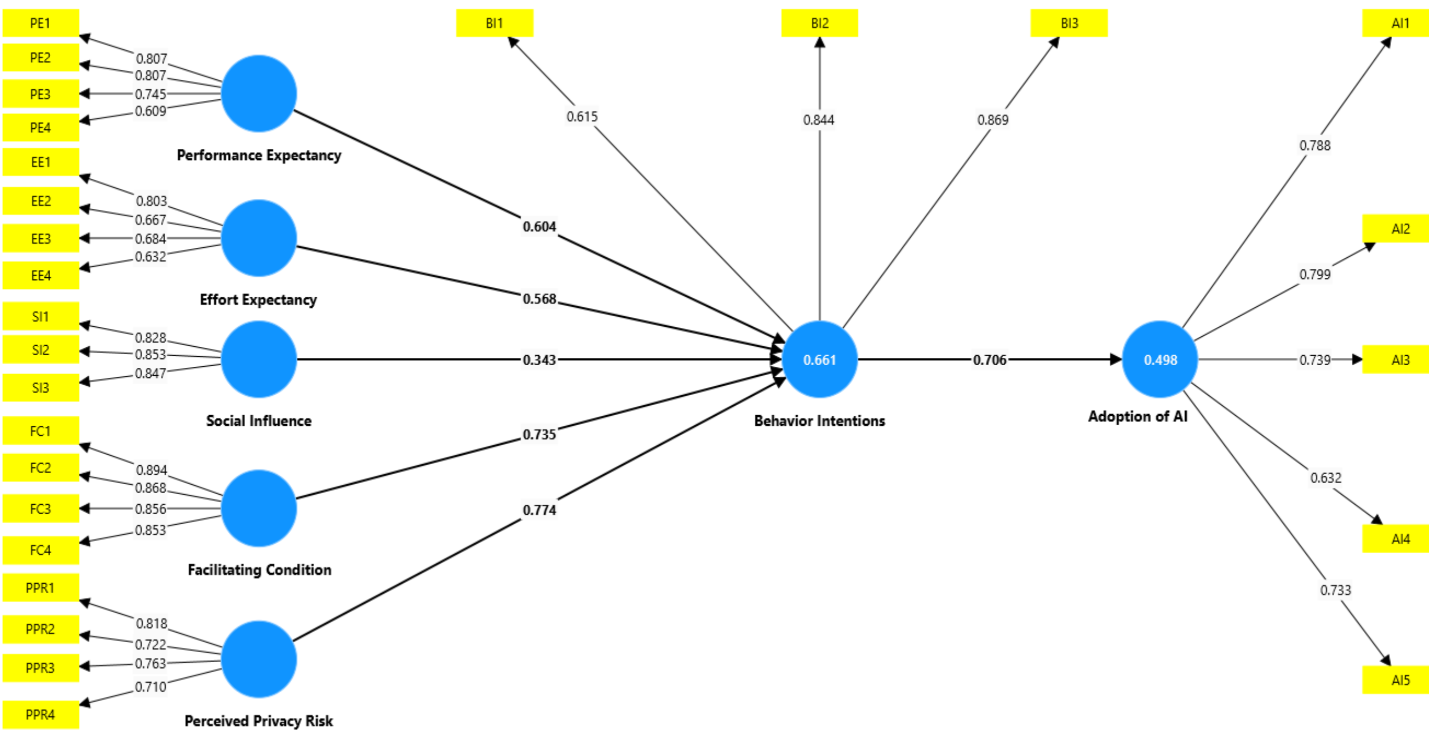
Note: Square values of the AVEs are shown in the diagonal.
Source: ourselves using SMART-PLS Software.

<u>Heterotrait-monotrait ratio (HTMT) – Matrix</u>

Table 3

	PE	EE	SI	FC	PPR	BI	ADI
PE							
EE	0.642						
SI	0.674	0.582					
FC	0.650	0.601	0.599				
PPR	0.770	0.694	0.671	0.765			
BI	0.734	0.603	0.711	0.698	0.693		
ADI	0.779	0.720	0.745	0.718	0.681	0.712	

PE = Performance Expectancy; EE =Effort Expectancy; SI = Social Influence; FC = Facilitating Condition; PPR = Perceived Privacy Risk; BI = Behavior Intentions; ADI = Adoption of AI.
Source: ourselves using SMART-PLS and SPSS Software



R-Square and Factor Loadings

<u>4.3 Output of Variance Inflation Factor Test and Cross loadings:</u>

Table 4

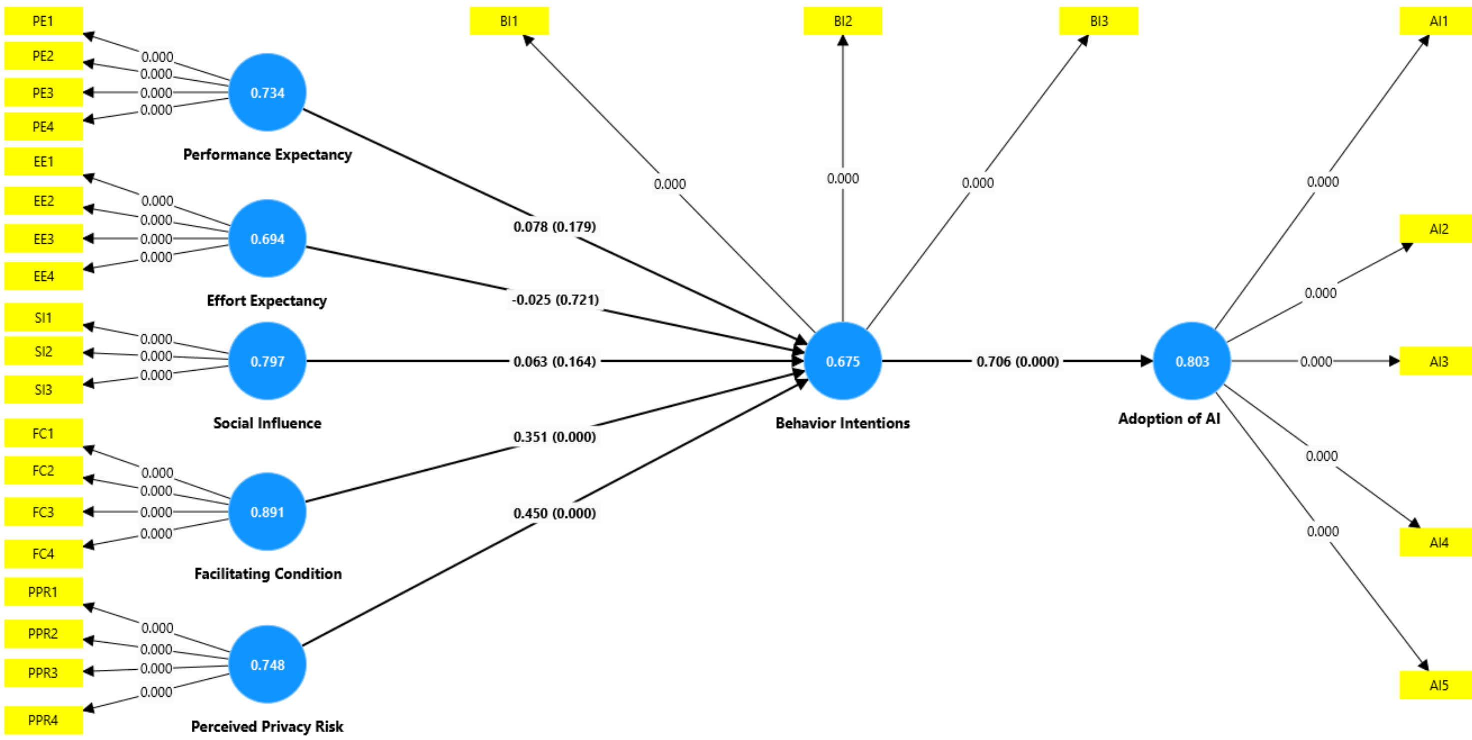
	VIF	PE	EE	SI	FC	PPR	BI	ADI
PE1	1.960	**0.807**	0.323	0.195	0.425	0.403	0.404	0.362
PE2	1.990	**0.807**	0.445	0.322	0.467	0.429	0.411	0.403
PE3	1.879	**0.745**	0.331	0.293	0.382	0.328	0.378	0.345
PE4	1.076	**0.609**	0.350	0.278	0.424	0.763	0.539	0.506

EE1	1.118	0.502	**0.803**	0.246	0.456	0.450	0.502	0.263
EE2	1.478	0.219	**0.667**	0.207	0.286	0.294	0.258	0.204
EE3	1.594	0.250	**0.684**	0.217	0.264	0.333	0.264	0.224
EE4	1.346	0.270	**0.632**	0.404	0.223	0.265	0.269	0.369
SI1	1.622	0.292	0.246	**0.828**	0.202	0.270	0.286	0.402
SI2	1.677	0.366	0.411	**0.853**	0.331	0.386	0.314	0.364
SI3	1.833	0.275	0.252	**0.847**	0.209	0.199	0.263	0.331
FC1	3.022	0.537	0.537	0.258	**0.894**	0.642	0.666	0.633
FC2	2.700	0.511	0.543	0.200	**0.868**	0.638	0.633	0.605
FC3	2.349	0.502	0.803	0.246	**0.856**	0.650	0.602	0.563
FC4	2.265	0.466	0.613	0.328	**0.853**	0.679	0.650	0.606
PPR1	1.690	0.507	0.591	0.240	0.278	**0.818**	0.281	0.258
PPR2	1.506	0.414	0.501	0.239	0.595	**0.722**	0.581	0.512
PPR3	1.798	0.309	0.350	0.278	0.424	**0.763**	0.539	0.506
PPR4	1.682	0.376	0.408	0.298	0.415	**0.710**	0.317	0.415
BI1	1.107	0.271	0.382	0.223	0.411	0.301	**0.615**	0.439
BI2	1.800	0.321	0.236	0.298	0.226	0.185	**0.844**	0.280
BI3	1.840	0.132	0.210	0.281	0.266	0.341	**0.869**	0.325
AI1	1.821	0.299	0.295	0.294	0.496	0.425	0.372	**0.788**
AI2	1.898	0.152	0.170	0.230	0.432	0.364	0.334	**0.799**
AI3	2.180	0.214	0.143	0.418	0.224	0.287	0.394	**0.739**
AI4	1.644	0.272	0.298	0.300	0.295	0.288	0.270	**0.632**
AI5	2.090	0.303	0.346	0.373	0.389	0.376	0.312	**0.733**

Source: ourselves using SMART-PLS

4.4 Hypothesis Testing

Figure 2 demonstrates the model's 0.675–0.803 predictive potential. Performance expectancy accounts for 0.502 of behavioral intention variation. Behavioral intention varies by 0.490 when effort expectancy is included. Results suggest social factors affect behavioral intention variance by 0.389. Enabling variables vary behavioral intention by 0.412. Depending on perceived privacy risk, behavioral intention varies by 0.391. In AI adoption, behavioral intention varies by 0.345.In Table 5, H1: Performance expectancy has no significant positive effect on behavioral intention (B = 0.408, t-value = 0.078) and H2: Effort expectancy has no significant negative effect (B = -0.141, t-value = -0.025).H3: Social impact favorably influences behavioral intention, although not significantly (B = -0.008, t-value = 0.063).H4: Facilitating conditions significantly improve behavioral intention (B = 0.170, t-value = 0.351).H5: Perceived privacy risk positively affects behavioral intentions.H6: Behavioral intention boosts AI adoption significantly.



Path Coefficient and P Values

Table 5

Guidelines	B	*T* –value	*P* –value	Decision
H1: Performance expectancy → Behavioral intention	0.408	0.078	0.179	Unsupported
H2: Effort expectancy → Behavioral intention	−0.141	-0.025	0.721	Unsupported
H3: Social influence → Behavioral intention	−0.008	0.063	0.164	Unsupported
H4: Facilitating conditions → Behavioral intention	0.170	0.351	***	Supported
H8: Perceived privacy risk → Behavioral intention	0.324	0.450	***	Supported
H9: Behavioral intention → Adoption of AI	0.291	0.706	***	Supported

Measurement correlation-values: ***$p < 0.001$.

5. Discussion

Performance expectancy, effort expectancy, facilitating conditions, social influence, perceived privacy risk, behavioral intention and adoption of AI are examined in this study. In today's social media climate, managers know that AI in supply chains may improve hospitality sectors.

Performance expectancy has not significantly impacted AI usage of behavior intention. Managers are hesitant to utilize AI, according to statistics. This suggests they know AI’s benefits but haven't used them. Due to the company's weak AI infrastructure and training. Managers think AI can boost productivity and efficiency. Some managers' views on AI reflect their concerns about its use. Since they didn't experience AI's benefits throughout training, they struggled to adjust. This discovery is within. It seems that effort expectancy and AI usage of behavior Intention are not linked. User-friendliness is vital in humanitarian organizations' AI systems (Cao et al., 2022). Due to its apparent complexity, AI adoption may cause anxiety and reluctance. User-friendly interfaces, professional support, and training are also needed to increase AI adoption. This may lessen opposition and accelerate AI adoption. The social impact-AI adoption behavioral intention relationship is statistically not significantly linked. One possibility is that upper management doesn't see AI as a key to boosting hospitality company performance. Thus, larger commercial enterprises must encourage smaller hospitality organizations to utilize AI. This may assist large and small hospitality businesses. Profitable companies are updating their AI systems to compete. AI adoption has been lower in humanitarian supply chains. Higher management may not commit because they see it as a wasteful administrative expense. It seems that organizational policy has to change. To adopt technology, companies may need to engage their employees. The premise is that the more someone utilizes information technology, the more likely they are to experiment with and accept it, which helps both the individual and the firm. This underlined the need for professional and competent commercial sector workers who can help organizations succeed by integrating AI. Behavioral intention to utilize AI adoption is positively correlated with FC in humanitarian organizations. Pakistani humanitarian workers follow standard assistance operations, which may explain this. This implies they don't realize how technical and infrastructural resources affect AI adoption. The research suggests that facilitation conditions have a significant impact on behavior intention to use AI when performance expectancy, and effort expectancy components are not significant (Cai et al., 2024; Venkatesh et al., 2003). facilitation conditions affect actual usage, and behavioral intention (Chaouali et al., 2016).

5.1 Conclusions and implications

After the COVID-19 outbreak, AI usage grew in numerous regions. Since the global health crisis, there have been few studies on the factors that affect AI device adoption. This model is designed to address that vacuum. A novel method has been developed to quantify user intention for AI applications and acceptance in Pakistani hotels. The theory and analytic framework now include additional filters to analyze performance expectancy, effort expectancy, social impact, perceived privacy risk, and facilitating conditions in Pakistan's hotel industry's AI adoption. Theoretical contribution and data analysis shed new light on personal innovation as a seminal variable for an integrated framework, with a focus on the interdependence of technology use and its context, limited to Pakistan, considering the expanded use of AI in these diverse hotel industries has huge growth potential. The above factors depend on technical advancement, technology proficiency, and user evaluations of new apps (Ali et al., 2022). The research foreshadows the innovative function of the hotel industry in a Pakistani demographic by concentrating on the application of AI in the hotel sector during the worldwide pandemic and in a health-regulated environment. Another factor is how technological advances affect privacy and security. As AI improves, knowing if these technologies make life easier while protecting privacy is crucial to understanding AI usage. An integrated framework that incorporates behavioral intention concepts elevates performance expectancy. This concept, developed by Arzubiaga, Kotlar, De Massis, Maseda, and

Iturralde (2018) provides a consistent framework for variable-based analysis. System designers and business developers in Vas need personal inventiveness. AI utilization, feature prospecting, process optimization, and customer retrofit are measured by this filter (Arzubiaga et al., 2018)). This survey told us that a customer-centric approach, user attention, and dependability and minimal risk are essential to launching new features and improvements with a high adoption rate. The results will help system designers and AI-using hotels in Pakistan. When compared to aligned variables, the data will reveal the most crucial user design components.

5.2 Limitations

Despite the achievement of our objectives, the current research has limitations. Due to the limited availability and application of demographic data to the hotel industry in Lahore, Pakistan, it is critical to use caution when interpreting the first results. Using a cross-sectional method, the same criteria for the ten parts of the user's purpose may be universally applied to different geographical regions. Cross-sectional research is a tool for analyzing the changing perspectives of survey respondents and themes across time. This kind of research may also be conducted. This approach is built on variables that offer a consistent set of criteria for data gathered during a certain period. The present study's results show that performance expectancy does not favorable impact on behavior intention to use AI, but perceived privacy risk does favourable impact on behavior intention to use AI. While these components are not novel in terms of analyzing consumers' adoption of technical devices and smart technology, the context has prompted academics to pursue new pathways for investigating AI adoption. It may be required to incorporate other features, such as ergonomics, in the range of variables and constructions. This might help alleviate any inherent biases associated with physical characteristics and their influence on mental processes. From a technological standpoint, this integration would add another layer of human-like features to the process, since these characteristics are often associated with non-human beings. The act of depicting an animal in a human-like form is known as anthropomorphism. This method strengthens the foundation for assessing a subjective process, resulting in increased trust, happiness, and security among users. Exploring potential development areas may provide new insights into the link between intention and usage. Furthermore, it would be good to include other moderating variables in the research, such as gender, age, experience, and expected outcomes/needs from usage.

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