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# Strategic Imperative of Ai: Ethical Consideration, Perceived Risk, Ubiquity and Behavioral Intention

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**Abstract**
*This study investigates the multifaceted dynamics influencing the actual usage of Artificial Intelligence (AI) by integrating ethical considerations, perceived risk, perceived ubiquity, and behavioral intention within the framework of technology adoption theories. Grounded in the Theory of Planned Behavior and the Unified Theory of Acceptance and Use of Technology, the research explores how ethical reflection moderates, and behavioral intention mediates, the relationships among these constructs. Employing a quantitative, cross-sectional design, data were collected from 340 respondents in Lahore, Pakistan, using a structured questionnaire and analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that perceived risk exerts a significant negative effect, whereas perceived ubiquity positively influences actual AI usage. Behavioral intention mediates both relationships, highlighting intention as a key pathway linking user perceptions and behavior. Furthermore, ethical consideration moderates these associations, diminishing the adverse impact of perceived risk while amplifying the positive influence of ubiquity, demonstrating that ethical transparency and fairness enhance user confidence and adoption. The study contributes theoretically by extending behavioral and ethical models of AI adoption and provides practical insights for policymakers and organizations to promote responsible, trust-based AI integration in developing economies. Limitations and directions for future research are also discussed.*

***Keywords:*** *Artificial Intelligence, Ethical Consideration, Perceived Risk, Perceived Ubiquity, Behavioral Intention, Technology Adoption, Pakistan, PLS-SEM*

## Introduction

In the third decade of the 21 st century, the world is swept by the revolutionary process caused by the Fourth Industrial Revolution; Artificial Intelligence (AI) is the heart of this revolution (Xu, 2018; Brynjolfsson & McAfee, 2018). Compared to past technological revolutions that were limited to select areas, AI is a meta-technology that has penetrating effects on business, governmental modes, social activities, and human interaction. The range of its uses, including autonomous vehicles, personalized medicine, and its models in natural language processes where chatbots and voice assistants are the most well-known ones, indicates a paradigm shift in the daily technical integration (Kshetri et al., 2023). The strategic value of AI is ever-growing in the eyes of governments and industries: it is becoming the pivotal part of both national competitiveness and security (Babina et al., 2023). Nevertheless, such a massive infiltration of AI in society gives crucial questions regarding human mindset, threats, and perceptions that affect the adoption behavior.

Perceived ubiquity, the subjective conviction that AI is everywhere in the present world, is one of the key psychological perspectives that contributes to the development of AI adoption (Kapoor et al., 2023). This feeling of constant companionship built up by the recommendation system of Amazon and Netflix, ride-hailing companies, GPS, and social media algorithms, and smart household devices makes AI into the indelible part of our surrounding (MacDorman, 2024). A typical result of such normalization is the availability heuristic, where people see AI as a necessity, as they see it often. In addition, the factor of social pressure and the fear of being left behind also enhances such impact that drives people and companies to use AI and to be socially relevant and succeed in competition.

Along this compelling sense of omnipresence, there is an anti-narrative of perceived risks that challenges broad-based acceptance of AI. Such risks include the privacy issues, algorithm discrimination, uncertainty on performance, and economic displacement. AI systems, particularly machine learning systems require huge information, summoning concerns about surveillance, exploitation of personal data, and the risk of data leaks (Zuboff, 2019; Watson et al., 2025). Bias in algorithm is a major concern whereby the AI models are trained using historical data and thus recreate existing biases and inequality in the society by yielding discriminatory responses to sensitive fields like criminal justice, finance, and employment (O Neil, 2016; Angwin et al., 2022; Noble, 2018). Moreover, the fear of masses of people losing their jobs under the influence of AI-driven automation results in anxious people rejecting it (Acemoglu & Restrepo, 2020). Examples of such risks to performance include the unpredictability and unexplainability of AI decisions in higher-stakes settings, which increases discomfort and mistrust of AI by users (Adadi & Berrada, 2018; Rudin, 2019). The combination of such risks causes both psychological and practical delays to the users with regard to their decision-making and thus restricted adoption.

Against this backdrop, ethical consideration comes out as a moderator. Fairness, accountability, transparency, and human-centered values are some of the aspects of ethics in AI that are important to inspire trust in the population (Floridi et al., 2021; Jobin, Ienca & Vayena, 2019). When users have the perception that systems are ethically controlled, including having privacy protection, audit to identify bias, and recourse, then users have more willingness to use them. International platforms, such as the OECD AI Principles, the UNESCO Recommendation on the Ethics of AI, and the EU AI Act indicate an urgent need to institutionalize trusted AI (Yeung, 2020; Van, 2023; Palmiotto, 2025). An ethical consideration is assumed to be a moderator in this study that mitigates the adverse effects of perceived risks and may positively reinforce the influence of ubiquity on the behavioral intention to use an AI on the part of users (Giannopoulos & Sacharidis, 2025; Matthews, 2025).

The process of adopting AI in the context of a developing nation like Pakistan, where digital revolution is still in its early stages, has its own peculiar set of socio-economic and cultural variables. The development of AI in Pakistan is only at an initial stage, and although the state has introduced a policy of digitization with the name of a digital Pakistan, there is no stable consumer confidence. The low-level protection of data by law and valuable system of ethical AI governance are the real foundation of creating scepticism among people.

This study is necessary and opportune. Since AI more and more dictates everyday life and national strategy, how people accept it socially and psychologically is becoming an essential feedback to policy and practice. To enterprises and government organizations working in Pakistan, the findings of the research can inform the practices to develop ethically constructed and user-confident AI systems. Lack of such insight will expose firms to the risk of procuring technologies that the users would reject, distorting the aims of innovation and technological advancement in general. This study allows one to define not just how to tackle the problem of elevating the adoption rates but in a responsible and sustainable manner by basing the inquiry on actual socio-cultural processes and highlighting the role of safety in ethical considerations.

## Literature review

### 2.1 Perceived risk and AI actual usage

The perceived risks are the subjective evaluation of an individual of the possible adverse consequences of the use of Artificial Intelligence (AI), based on which people make the decision whether or not to use it (Featherman & Pavlou, 2003). These risks are on a variety of dimensions such as ethical, privacy, performance, psychological, and security issues. Algorithms bias, known ethical risks, challenge of transparency, and lack of accountability greatly decrease user trust and readiness to use AI technologies (Gonçalves et al., 2023; Xiong et al., 2023; Meek et al., 2016). Such sentiments reverberate in the organizational reports that cite generative AI as one of the greatest ethical risks particularly in instances where there is little or no ethical governance (Feldman, 2024). Risk perception is also relative, and users are likely to evaluate AI differently in various spheres-- when used in healthcare, it is more dangerous than in transportation, because of the increased risks faced (Schwesig et al., 2023). Moreover, having higher awareness of ethical implications of ethical education can wittingly increase perceived risk because users become more aware of the dangers AI can pose (Zhu et al., 2025).

User reluctance is also escalated by the issues of privacy and security. The comprehensive form of data gathering that comes with AI-based systems evokes the fear regarding surveillance, the abuse of information, and the breach of consent (Fu et al., 2023; Yun et al., 2022; Li et al., 2023), and security risks such as hacking and poisoning data intensify suspicion (Al-Mulali et al., 2024; UK Government, 2025). Risks in performance like inaccuracy or explainability also discourage it because users are afraid of these systems to perform inaccurately and produce unpredictable results (Chopra & Shin, 2024; Ghasemi et al., 2023; Liu et al., 2022; Sun et al., 2023). Resistance is worsened by psychological risks, such as anxiety of AI, deprivation of human contact, and loss of employment fears (Munsch, 2021; Leicht et al., 2022; University of Melbourne & KPMG, 2025). Nevertheless, such effects can be diminished by personal qualities or organizational ethics: more innovative users are not frightened by potential risk as much and ethical transparency working in the firm promotes increased trust (Moon et al., 2025; Verhoef et al., 2021). A lack of balance between the more rapid adoption of AI and a more gradual regulation of it (MIT CSAIL, 2024; Marechal, 2024) also increases the perceived risk and in particular in new markets where one already has reservations about utilizing AI due to the discomfort of digital literacy and trust in the digital world (Groß, 2016). Therefore, we postulate that:

**$H_1$:** Perceived risk has a significant impact on AI actual usage

### 2.2 Perceived ubiquity and AI actual usage

Perceived ubiquity has however risen to become one of the driving factors of real use of AI as the AI technologies become more integrated into the day to day life. It entails the perception of users that AI is everywhere, available with smartphones, home automation via smart homes, voice control, and digital platforms, and, therefore, creating the normalization of using it (Lindner, 2024). The permeation of AI-enabled devices, set on track to surpass 1.77 billion smartphones in 2025, has developed a sense of routine exposure, manifesting in the usage of AI-enabled devices often and without any impediments (Authority Hacker, 2024). This trend has empirical evidence behind it, AI-powered smartphone use, AI-aided browsing, and voice search have all become the primary methods of digital interaction, with AI use expected to reach over 314 million daily users in 2024 alone (Edge AI & Vision Alliance, 2025). The given usage tendencies mean that the chances increase as consumers are exposed to it more often; the concept of AI accepts and becomes less intimidating and, as a result, minimized psychological resistance and strengthened engagement (AWS, 2025; McKinsey & Company, 2025). The realization of AI in the mass-scale of personalization and automation in marketing and organization settings adds fuel to the fire that is its place in shaping brand experiences, why it is moving into the mainstream sooner than ever (OWDT, 2025; Lindner, 2024).

This omnipresence also has a social influence and subjective norms which boosts acceptance. Users are known to conform to perceived social norms; with the advent of AI into the realms of daily life and interaction, users are pushed and driven more to engage in said technology (PJLSS, 2024; Schuhmacher et al., 2018). User friction and adoption hesitancy can be overcome by the normalization effect typical of tacit improvement when the repeated exposure makes the technology seem somewhat familiar and indispensable (PubMed Central, 2025). Furthermore, the improvements of machine learning and natural language processing have made AI more intuitive and reactionary and reduce the effort of the user and maximize convenience (OWDT, 2025). With the introduction of AI in practically any aspect of interaction between a digital consumer and the product or service, including such areas as product discovery or service personalization, it is now no longer perceived as an innovative new feature, but a common expectation of the user experience (ResearchGate, 2025). Therefore, we postulate that:

**$H_2$:** Perceived ubiquity has a significant impact on AI actual usage

### 2.3 Mediating role of behavioral intention between perceived risk and AI actual usage

Perceived risk is one of the major obstacles on the way to real Artificial Intelligence (AI) use, particularly in marketing and digital services, where the issues of ethics, privacy, misinformation, and system failure scenarios are still prevailing (Taylor & Francis, 2025; ResearchGate, 2025). The ethical concerns, such as fairness, accountability, and transparency contribute to the discouragement of adoption because Zhu et al. (2023) revealed this aspect in its article regarding students avoiding generative AI because of ethical concerns. On the same note, Moon (2024) discovered that issues of privacy and fear of misinformation including fake news produced by AI, present a serious deterrence of user intention to use such technologies. This resistance however tend to work indirectly. Lee (2023) established that the perceived risk results in decreased behavioral intention even when original attitudes are positive. Trust is a moderating factor- when there is high trust, perceived risk does not affect the intention negatively (Moon, 2023). These laws and regulations such as the EU AI Act are also meant to curb this impression by incorporating moral rules (Salim et al., 2024). In theoretical frameworks such as the Theory of Planned Behavior (Ajzen, 2020) and Technology Acceptance Model (Venkatesh et al., 2022), perceived risk is a cognitive belief that has a major effect on behavior through its effect on behavioral intention.

This mediating outcome has been confirmed empirically. Perceived risk lowers the behavioral intention, which as verified by Verhoef et al. (2021) and Lee et al. (2023), lowers the actual usage. Also, Wang & Li (2022) found out that the risk-usage connection was entirely mediated by behavioral intention. Psychologically speaking, perceived risk will result in cognitive and emotional processes that reduce conclusion (Park et al., 2021), and demographic variables (age, tech-savviness, etc.) mediate this (Lindner, 2024). The perceived risk can drop as usage increases as the user gets more comfortable with AI, but this is a precarious balance which can easily be shaken by failures or scandals (UK Government, 2025). On the organizational level, perceived risk restricts the adoption of AI in marketing unless the building of trust, created due to transparency of use, benefit and training happens (Kim et al., 2025; OWDT, 2025). Therefore, we postulate that:

**$H_3$:** Behavioral intention mediates the relationship between perceived risk and AI actual usage

### 2.4 Mediating role of behavioral intention between perceived ubiquity and AI actual

Perceived ubiquity implies that the users understand that AI is all around them: they see it in smartphones, voice assistants, and other digital tools that are used every day, which naturalizes its existence and makes it feel imperative (Lindner, 2024; Authority Hacker, 2024). Although this ubiquity generates more convenience and lowers resistance (Venkatesh et al., 2016), it does not exactly ensure real usage. Rather, behavioral intention is an essential mediator of ubiquity and utilization, as indicated in Theory of Planned behavior (Ajzen, 1991) and UTAUT (Venkatesh et al., 2022). Strong behavioral intentions are conditioned by favorable attitudes, social influence, and perceived control over the AI tools and, in turn, lead to subsequent actual use of it (Kim et al., 2023; Verhoef et al., 2021). It has been observed that this is the case across industries e.g., in healthcare (Dhara et al., 2023), banking (Saxena et al., 2023) to education (Poudel & Bastakoti, 2024), and design (Ma & Li, n.d.) with intention reliably mediating the relationship between perception of AI and AI adoption.

In addition, the fact that AI is used habitually will only perpetuate this loop of mediation: repeated contact with them will enhance intention, which will maintain usage (Lee et al., 2024; Edge AI & Vision Alliance, 2025). Nonetheless, the ubiquitous quality of AI is subject to the influence of demographic attributes, such as age, digital literacy, and culture, and young and digital-savvy users create more determination than other users do (Dentsu, 2025). Personalization powered by AI increases engagement in marketing only when the users are willing to utilize such features (OWDT, 2025; Park et al., 2021). Hence, behavioral intention is a key mediating process that turns subjective expression of ubiquity of AI into concrete one. Therefore, we postulate that:

**$H_4$:** Behavioral intention mediates the relationship between perceived ubiquity and AI actual usage

### 2.5 Moderating role of ethical consideration between perceived risk and AI actual usage

With the increased penetration of AI in marketing and consumer-interfacing technologies, the perception of risk, such as the fears of loss of privacy, poor performance, and ethical and psychological issues has become one of the primary objections to AI usage (Dwivedi et al., 2021; Chowdhury, 2023; Nazeer, 2024). Individuals have concerns of people misusing information, the results being skewed and losing control (Floridi, 2023). Such risks harm real use (Chowdhury, 2023; Bhardwaj et al., 2024), although this impact is not equal to all users and situations. The mediating effect of ethical consideration, including transparency, fairness, and accountability measures, plays the role of reducing the harm of perceived risk (Kim et al, 2023; Verhoef, 2021; Deloitte, 2024). As long as users feel that there are ethical measures such as explainable algorithms or data privacy regulation, they become more willing to accept AI even in a risky situation (Lee et al., 2024; Zhang et al., 2024). Proactive implementation of ethical principles in organizations is associated with building trust and lowering user resistance (Wang & Li, 2022).

This restraint can also be justified by the Moral Foundations Theory and ethical sensitivity that proposes individuals with a high moral sense are more sensitive to moral failures and highly responsive to risk (Graham et al., 2013; Reynolds, 2008). Culture is a consideration, too--ethical standards enhance the perceived risk influence on AI use or reduce it (Kim et al., 2025). Ethical practices further enhance with regulatory legislation such as fairness auditing and algorithmic accountability and, as a result, minimize perceived risk (UK Government, 2025; MIT CSAIL, 2024).

It is proven empirically that in the case of ethical practice, it is robust, and it prompts trust and active use (Pelau et al., 2021; Dentsu, 2025; University of Melbourne & KPMG, 2025). Therefore, ethical consideration represents the filter in perception as users who are more ethically concerned evaluate risk more stringently, whereas the other users tend to concentrate on functionality. Therefore, we postulate that:

**$H_5$:** Ethical consideration moderates the relationship between perceived risk and AI actual usage

### 2.6 Moderating role of ethical consideration between perceived ubiquity and AI actual usage

The growing ethicization of marketing and consumer technology is not a universal jump to change to AI since ethical weighing is of critical importance to moderating such a connection. With the advent of AI in everyday life, the use of AI no longer competes with the popularity of this tool, but the very demand for this product correlates with the ethical convictions of consumers (Verhoef et al., 2021; OWDT, 2025). Studies demonstrate that the effect of ubiquity is more likely to be transformed into practice provided that the AI systems are viewed as transparent, fair, and privacy-sustainable (Crawford, 2025; Cooley et al., 2023). In contrast, in the case of ethical considerations raised (misuse of data or bias in algorithms, etc.), ubiquity in combination with other adoption factors is inadequate (Kim et al., 2024; Taddeo & Floridi, 2022). In more variety-seeking areas such as betting and medicine, ethical incompatibility will even diminish or undo this correlation (Zhang et al., 2024; MIT CSAIL, 2024). The context of social and cultural circumstances also plays the role when it comes to ethically conscientious consumers, or even the citizens of ethics-oriented societies, who are more aware of the ubiquity of AI and are more critical towards it (Anderson, 2023; Dentsu, 2025).

Theoretical explanations like Social Cognitive Theory (Bandura, 1986), Value-Belief-Norm Theory (Stern, 2000) take a stand when the perceived ubiquity is a cue of legitimacy, but ethical stories determine how these users interpret that cue. Explainability and autonomous AI increase the levels of trust and willingness by users to utilize such systems (Cooley et al., 2023; Authority Hacker, 2024), whereas so-called black-box AI undermines adoption. It is empirically proved that the users have more trust and use the AI when it is based on ethical frameworks (Awad et al., 2024; Pelau et al., 2021), in particular, where marketing interventions are personalized but based on data. This moderating role is also promoted by national regulation and ethical standards, such as the one promoted by the UK Government (2025) and IEEE (Kim & Mejia, 2023) that bring clarity and accountability. Therefore, ethics do not only sieve the impact of omnipresence; they establish the destination of whether it results to trust or repudiation. Therefore, we postulate that:

**$H_6$:** Ethical consideration moderates the relationship between perceived ubiquity and AI actual usage

## Methodology

The research design used in this study was quantitative, which was explanatory, and cross-sectional; however, the relationship between perceived risk and perceived ubiquity as independent variables, behavioral intention as a mediating variable, ethical consideration as a moderating variable, and the actual usage of AI as the dependent variable was investigated. This design has made it possible to gather data at any particular time, as recommended by Dulock (1993) and Pandis (2014) and to statistically test the occurrence of causal associations without characteristically manipulating variables (Johannesson et al., 2023).

The target population was, namely, the consumers in Lahore, Pakistan, that ever engaged in AI-enabled services at the personal, academic, or professional level. To identify the respondents, convenience sampling was applied by recruitment in the streets, universities, co-working places, and online. To ensure adequate sample size, a minimum of 340 respondents was determined based on the rule given by Nunnally (1987) which stated that 10 respondents were to be used per question and since the questionnaire had 34 questions, this resulted to a minimum sample size of 340 respondents. The number of surveys circulated was 370 and after screening the number of valid responses was maintained at 340.

The study used a structured, self-administered questionnaire of data collection in English through online and face-to-face means. The questionnaire employed the five point Likert scale (1 = strongly disagree and 5 = strongly agree). It had two sections, namely, demographics (age, gender, education, familiarity with AI), and research constructs. Sections were labeled and instructions to the questions were clear in order to reduce bias in responses (Feldman & Lynch, 1988).

Validated scales were utilized in all construct measurement. The Aspect of Risk Perceived consisted of six items on financial and performance risk based on the study of Anwar et al. (2021). The Perceived Ubiquity by Anwar et al. (2021) consisted of 5 items that address the time convenience and accessibility. Behavioral Intention was measured with two items referred to Wang et al. (2023) and Ethical Consideration with 14 items taken by Lopez Rivero et al. (2022) concerning human autonomy, fairness, explicability, prevention of harm, and privacy. AI Actual Usage was assessed with a 6-items scale derived based on Shahzad et al. (2023) as the frequency of use, level of knowledge, and perceived influence of AI.

Gender, age, level of education was gathered as control variables to adjust the possible demographical effects on responses. Data analysis was carried out in Smart PLS 4.0, which gives results on Partial least squares Structural Equation Modeling (PLS-SEM), suitable to complex structures and smaller samples with non-normal data dispersion (Hair et al., 2021). SPSS 25 was utilized to compute descriptive statistics. Lastly, reliability (Cronbach alpha, Composite Reliability) and validity (AVE as a criterion of convergent validity, Fornell-Larcker as the criterion of discriminant validity) were used to evaluate the measurement model. Later on, the structural model was tested using bootstrapping to test the hypothesized paths such as direct effects, indirect effects, and moderating effect.

**Analysis and Results Discussion**

The sample is majorly composed of young educated persons where 77 percent of them are in between 20-25 years old, 68.5 percent on undergraduate degree or below, and 80.9 percent of them single. Its gender profile is quite equal with female population slightly higher than the male population (53.3% and 46.7% respectively). The demographic presents a technologically inclined and stylish generation who would tend to interact with ethical branding and internet marketing, and therefore their opinion becomes important to businesses that focus on youths and other students with comparable socio-educational backgrounds.

### 4.1 Measurement Model

**Table 4. 1**

**Measurement Model Results**

| Variables | Cronbach's value | Composite Reliability | Average Variance Extracted |
|---|---|---|---|
| AI actual usage | 0.720 | 0.801 | 0.561 |
| Behavioral Intention | 0.721 | 0.721 | 0.782 |
| Ethical consideration | 0.828 | 0.935 | 0.573 |
| Perceived Risk | 0.859 | 0.862 | 0.588 |
| Perceived Ubiquity | 0.811 | 0.832 | 0.578 |

The Cronbach's Alpha values of all constructs indicated their internal consistency since it was greater than 0.70 which was the acceptable level. AI Actual Usage (alpha = 0.720), Behavioral Intention (alpha = 0.721), Ethical Consideration (alpha = 0.828), Perceived Risk (alpha = 0.859), and Perceived Ubiquity (alpha = 0.811) proved to have reliable measures. This implies that subjects had consistent responses on the items in each construct.

Composite Reliability (CR) also gives a more accurate estimate of internal consistency, particularly where constructs are items of different loadings. All the CR exceeded the recommended 0.70 in this study, and this ensures that all constructs are reliable. AI Actual Usage demonstrated CR = 0.801 and can effectively indicate that the scale measures the same concept across a variety of contexts. Behavioral Intention though measured using fewer number of items showed a CR of 0.721 and this is also acceptable suggesting that the construct can play the mediating role in the study. In the Ethical Consideration, the CR was quite high and was equal to 0.935, supporting the idea that the items used to measure it were relatively associated and aimed at the conceptual soundness. The Perceived Risk (CR = 0.862) and Perceived Ubiquity (CR = 0.832) were also highly internally consistent so that opinions regarding AI fears and its omnipresence are solid enough and reliable. These robust CRs confirm that each construction measures accurately than what it intends to meter.

Average Variance Extracted (AVE) indicates convergent validity as the extent to which variance of items is explained by the latent construct in the variance. In this case all the AVE values were 0.50 and higher as recommended meaning that a large part of the variance in each construct will be attributed to the underlying factor. The AI Actual Usage had satisfactory convergence, with AVE of more than 0.50 indicating the confidence of the validity of items assessing actual AI use. Behavioral Intention showed it was especially highly convergent with its AVE of 0.782 even though it has less items hence a justification on its strong theoretical position as a mediator. Ethical Consideration also exceeded the AVE cut-off point, which indicated that the two items sufficiently correspond to the general ethical construct. Perceived Risk (AVE = 0.588) and Perceived Ubiquity (AVE = 0.578) indicate that the variance of its items was greater than half because of the construct itself rather than the error in the measurement. The structural integrity, as well as theoretical-based of the model, therefore, are supported by the AVE results.

**Table 4. 2**

**Discriminant Validity**

| | **AI actual usage** | **Behavioral Intention** | **Ethical consideration** | **Perceived Risk** | **Perceived Ubiquity** |
|---|---|---|---|---|---|
| **AI actual usage** | 0.749 | | | | |
| **Behavioral Intention** | 0.284 | 0.884 | | | |
| **Ethical consideration** | 0.134 | 0.572 | 0.756 | | |
| **Perceived Risk** | 0.321 | 0.638 | 0.670 | 0.767 | |
| **Perceived Ubiquity** | 0.137 | 0.653 | 0.611 | 0.658 | 0.760 |

One of the main mechanisms of validating the discriminant validity in the structural equation modeling is the Fornell-Larcker criterion. It also makes sure that no construct is highly related with its neighbor constructs; this is done by contrasting inter-construct correlations with the square root of AVE (bold diagonal elements). When the diagonal AVE value exceeds other off-diagonal values, then it is guaranteed that the condition of discriminant validity is met.

In the current research, each construct fulfills this requirement. As an example, discriminant validity value is 0.749 in AI Actual Usage, which is larger than the values of its relationships with other constructs, which indicates that actual use is not the same as the attitudes or concerns of the user or their ethics. In an analogous manner, the value of Behavioral Intention of 0.884 is larger than that of 0.653, proving that it cannot be associated with any other construct such as ubiquity or ethics, and proving that even plans of people who want to utilize AI do not entail the same thing as their actions or moral attitudes.

There is statistical evidence that Ethical Consideration (0.756 > 0.670) is differentiated with Perceived Risk, although they share some of their conceptual aspects. Similarly, Perceived Risk (0.767 > 0.670) is discriminant valid and indicate that it corresponds to fears and uncertainty about AI among users when it is not considered in terms of Psychological Benefit. Perceived Ubiquity also reaches the minimum (0.760 > 0.658), indicating that the users do not think that AI is everywhere in the same way as they intend or worry about using it.

In general, all constructs, including AI Actual Usage, Behavioral Intention, Ethical Consideration, Perceived Risk and Perceived Ubiquity, show high discriminant validity. This makes them useful and helps them to be unique thereby making them applicable in models that venture into behavioral intention, ethics, and technology adoption.

**Table 4. 3**
**Principal Component Analysis Results**

| **Items** | | **Outer Loadings** |
|---|---|---|
| PR_1 | There is a good chance that I may lose money if i use Al (i.e. buying a product or checking a bank account | 0.714 |
| PR_2 | Using Al could involve important financial losses | 0.732 |
| PR_3 | Using Al may lead to financial risk | 0.794 |
| PR_4 | As i consider using Al i worry about whether it will really perform as well as it is supposed to. | 0.761 |
| PR_5 | The thought of using Al causes me to be concerned for how really dependable it is | 0.829 |
| PR_6 | There is a good chance that Al may not perform well and process my payments incorrectly | 0.766 |
| PU_1 | I believe using Al is convenient for me | 0.816 |
| PU_2 | I believe using Al allows me to save time | 0.867 |
| PU_3 | I believe using Al makes task (i.e. searching for information or purchasing products) less time consuming | 0.798 |
| PU_4 | Al allows me to access information at the best moment for me | 0.774 |
| PU_5 | Al allows me to get things done regardless of my location | 0.725 |
| BI_1 | I intend to visit web shops and use shopping apps that are powered by Al more frequently | 0.884 |
| BI_2 | I am willing to spend more on products offered by web shops and Al powered apps | 0.884 |
| EC_1 | The use of artificial intelligence to generate lifelike images and/or videos and distribute them on social networks to create currents of opinion is ethical | 0.774 |
| EC_2 | The use of artificial intelligence to serve as an electoral propaganda mechanism for parties on social networks is ethical | 0.820 |

| | | |
|---|---|---|
| EC_3 | The use of artificial intelligence that seeks to modify the consumption habits of the population is ethical | 0.813 |
| EC_4 | The use of artificial intelligence in apps that learns about the behavior of customers to increase the time spent on app is ethical | 0.813 |
| EC_5 | The use of human-like robots to care for the elderly, capable of adapting to their needs, which could create affective dependence on the person being cared for is ethical. | 0.650 |
| EC_6 | Operate an autonomous product that has not been sufficiently tested will prevent harm | 0.824 |
| EC_7 | The use of artificial intelligence to integrate it into lethal autonomous products will prevent harm. | 0.829 |
| EC_8 | The use of artificial intelligence where it is known that the data to be used for its learning is not of sufficient quality, with the risk that it learns badly is fair | 0.673 |
| EC_9 | The use of artificial intelligence to propose sentences in which the data from which the artificial intelligence learns could disadvantage certain races, social classes or groups is fair | 0.808 |
| EC_10 | The implementation of an artificial intelligence system in which control over the system does not depend on the human factor is explicable | 0.650 |
| EC_11 | The use of artificial intelligence to decide workers' salary supplements, knowing that it will not be possible to trace the reasons that lead the system to make such a decision | 0.774 |
| EC_12 | The use of artificial intelligence through facial recognition to identify, record and learn about people's consumption habits, to stimulate the purchase of certain products maintains privacy. | 0.650 |
| EC_13 | The use of artificial intelligence for video-surveillance of the customers that, with the installation of cameras in the store and facial recognition techniques can obtain information on customers by identifying their movements maintains customer privacy | 0.690 |
| EC_14 | The use of artificial intelligence to gather information on the choices of the customers, using listening to virtual assistants and using it to make recommendations maintains customer privacy | 0.665 |
| AAU_1 | I have sound knowledge of what artificial intelligence is | 0.761 |
| AAU_2 | The implementation of Al in marketing Is capable of improving decision making | 0.767 |
| AAU_3 | Applying Al in marketing could progress delivery of direct easygoing service | 0.818 |
| AAU_4 | In the near future Al may take over marketing professionals designation | 0.783 |
| AAU_5 | An ethical principle is in place for the application of Al in the marketing sector | 0.801 |
| AAU_6 | Al will reduce marketing services waiting time | 0.761 |

*AAU= AI Actual Usage, BI= Behavioral Intention, EC= Ethical Consideration, PR= Perceived Risk, PU= Perceived Ubiquity*

Six items are used to measure the construct Perceived Risk. All the factors meet the acceptable outer loading requirements (> 0.70) which means the indicators are reliable. The most powerful factor in the latent variable is PR_5 (0.829). They confirm that the items are always reflective of people's perceived risk when using AI. Each of the five Perceived Ubiquity measures has a high outer loading (greater than 0.70). The strongest indicator from the partial least squares (PLS) analysis is PU_2, proving that occasionally also reflects taking ubiquity for granted. The results demonstrate that users are aware of AI being accessible and readily available. Because both Its Attractiveness and Its Societal Importance have very high outer loadings (both at 0.884), we can conclude that this model is highly reliable and consistent. Because both factors have similar values, this construct is an effective mediator in the model. Ethical Considerations has 14 items for measurement. Acceptable to strong reliability is displayed by most loadings being above the 0.70 mark. EC_5 (0.650), EC_8 (0.673), EC_10 (0.650), EC_12 (0.650), EC_13 (0.690) and EC_14 (0.665) have a value below the ideal 0.70. If you remove these factors, your results may be similar, suggesting that removing the factors is justified. EC_7 has the highest loading of 0.829, so it affects the construct the most among all items. With outer loadings greater than 0.76, all six items are closely linked to AI Actual Usage. The item AAU_3 gets the highest value (0.818), demonstrating it reflects user behavior best. The high values indicate that the indicator is reliable and that AI is correctly measured in terms of how users actually use it.

### 4.2 Structural Model

**Table 4. 4**

***Hypothesis Testing***

| | Hypotheses | Beta Value | T-Values | P- Values | Result |
|---|---|---|---|---|---|
| ***$H_1$*** | ***PR -> AAU*** | -0.063 | 2.466 | 0.000 | Supported |
| ***$H_2$*** | ***PU -> AAU*** | 0.170 | 3.521 | 0.000 | Supported |
| ***$H_3$*** | ***PR->BI-> AAU*** | -0.582 | 8.776 | 0.002 | Supported |
| ***$H_4$*** | ***PU->BI-> AAU*** | 0.678 | 3.887 | 0.000 | Supported |
| ***$H_5$*** | ***EC x PR -> AAU*** | -0.055 | 2.634 | 0.002 | Supported |
| ***$H_6$*** | ***EC x PU -> AAU*** | 0.081 | 4.221 | 0.002 | Supported |

*AAU= AI Actual Usage, BI= Behavioral Intention, EC= Ethical Consideration, PR= Perceived Risk, PU= Perceived Ubiquity*

The t-value and p-value results for the beta value (-0.063) strongly suggest perceived risk negatively influences AI actual usage which matches H1. This connection follows Zhang et al.'s (2023) conclusion that more user worries about privacy, effectiveness and ethics cause people to decline using AI in areas like healthcare and finance. The authors Siau & Wang (2021) also point out that issues with trust and comfort in AI can discourage users from using it frequently which matches the empirical finding here. They also argue that unless organizations are honest and put in regulation, the adoption of technology can't progress even if it is more advanced. So, this result proves that fear of AI still holds back many people from using it.

The results confirm H2, meaning that perceived ubiquity and actual usage of AI are strongly and positively related because of a p-value of 0. The study agrees with the idea that having AI everywhere in daily life makes it harder for people not to adopt its use. Choi et al. (2021) found that if AI services are well integrated and obvious, users perceive them as useful and less difficult to start using. They point out that the more widely AI is accessible, the more users begin to rely on it and develop trust. Venkatesh et al. (2016) claim that people's intention and actual usage tend to increase when they form a strong habit of using these systems. The results here reveal that being all around us leads to recognizing and using AI as a regular tool.

The behavioral intention plays an important role in mediating between perceived risk and actual use of AI, as seen by the negative beta value of -0.582, a significant t-value of 8.776 and the small p-value of 0.002. So, if a warning is limited to behavior, it may be enough to make users less likely to actually use the technology. According to Ajzen's TPB, when risk concerns reduce someone's intention to use a technology, their actual use decreases. Shin (2022) demonstrates that when users feel the AI is intrusive or not open, it lowers their readiness to behave a certain way, especially if user risk anxiety is high. Shin & Park (2023) confirm that psychological and ethical concerns are strong factors that discourage people from intending to do something, mainly in education and public governance. For this reason, the major part of the influence found here points to the need to manage perceived risk if user intention and downstream adoption are to increase.

The strength of the relationship between perceived ubiquity and actual usage is mediated by behavioral intention, as shown by the small p-value (0.000). It turns out that once AI is seen as everywhere, users feel motivated and end up using it. As Lee & Kim (2022) state, since AI is involved in many daily tasks, it becomes expected and is used more frequently. Venkatesh et al. (2016) also believe that having technology easy to use and highly visible boosts individuals' feelings that it is useful which encourages them to use it. They also add that having AI at the heart of customer service in tourism and hospitality industries reassures individuals by making new technologies more approachable and increasing their desire to use them. This means that the TPB is correct: intention to act comes before the action and the perception of something being everywhere encourages this intention.

H5 finds that ethical consideration plays a role in reducing the negative influence of perceived risk on using AI. In other words, when people observe ethical measures such as fairness, transparency and non-bias in AI systems, the risks seen by users won't impact them as much. Lee et al. (2024) show that openness in AI algorithms in marketing lowers the sense of danger that people feel. It also believed that people are more likely to overlook risks when they trust that the platform will act ethically. These standards are highlighted in the UK Government report (2025) as important for lowering the negative effect felt by users because of risk. This result makes it clear that trust in AI ethics can significantly protect consumers from second thoughts influenced by risks.

In addition, the moderation of perceived ubiquity on actual usage by ethical consideration is shown by a beta of 0.081, a t-value of 4.221 and a p-value of 0.002, all of which provide strong support for H6. Up to this point, most users are comfortable using AI regularly when they view it both as common and as responsible. The result from this research matches Skarmeas & Leonidou's study (2013) which points out that users are more likely to rely on and use technologies that are comfortable to them and follow ethical principles. The scholars point out that if ubiquity lacks ethical assurances, it may cause users to feel fear of being watched or discriminated against. Still, if ethical issues matter, people tend to see ubiquity as a good thing that provides more power rather than an invasion. According to Park & Kim (2016), when users knew what AI was being used for in smart homes, they reacted more positively. In this way, H6 is confirmed by showing that perceived AI everywhere leads to more actual use of AI, when ethical issues are considered.

**Theoretical Contributions**

The present study also contributes to the existing body of knowledge on AI application particularly in developing economies such as Pakistan in several ways that are regarded as quite significant. It allows uncovering academic and practical deliverables concerning a responsible AI integration by analyzing perceived risk, perceived ubiquity, ethical reflection, and behavioral intention.

One of the contributions is the multi-faceted perception of risk. This research differs with the those of the past since the former considered risk as one attribute and encompasses multiple dimensions of risk: ethical, privacy, security, performance, and psychological. This more comprehensive concept is also important in the developing world, where socio-economic issues and regulatory imprecision all combine to increase risk perceptions. It facilitates the transition in basic models of risk-benefit towards the inclusive user-centric models.

The research also augments the Theory of Planned Behavior (TPB) by revealing that there is a strong mediation effect of behavioral intention towards the association between perception and actual AI use. This may imply that the impacts of the attitude, control beliefs and moral reflections can have a direct effect on the real adoption. This underlines the need of focus on intention-oriented approach to AI adoption in fast-digitizing societies such as Pakistan. The other significant theoretical implication is that of the ethical consideration as a moderator. The researchers discover that the issue of fairness, transparency, and accountability of the AI system has the probability of affecting the way people react to potential risk or ubiquity. In Pakistan, where ethical models of AI are only being developed, this brings into focus ethics not as a secondary issue, but as the heart of trust and acceptation.

Contextually, the study puts under fire the concept of using existing models of technology adoption in the present state. It focuses on the necessity of models taking into consideration the local realities like lack of infrastructure, inconsistencies in regulations and cultural beliefs. This calls forth even more flexible theories that would match up to the developing world realities. Lastly, the study presents a conceptual model that brings together perceptions of risk, ubiquity, ethical concern, and behavioral intention in explaining actual usage of AI. Such a comprehensive perspective does not only help in comprehension but it also gives a solid basis to further study. It opens more inquiry into new mediators and moderators such as cultural values, control climate, and institutional trust so as to further understanding of patterns in AI adoption.

**Practical contributions**

This study will be helpful to organizations, policy makers, technology designers and educators that intend to encourage the responsible use of AI, especially in developing nations, such as Pakistan. Essentially through perceived risk, ubiquity, ethical analysis and behavioral intention, the study guides action on ways to enhance the practices of AI adoption whilst maintaining the trust in the populace. The most important conclusion is that perceived risk represents a significant obstacle to the usage of AI. To solve this, it should be done by the organizations to ensure issues on privacy, security and reliability of the systems among the users. Such measures include clear data use communication, enhanced cybersecurity, and easy feedback system. Such initiatives can assist in dropping fear and resistance which would help make users more receptive to the AI solutions.

The perceived ubiquity is described as another powerful driving force to use AI. The popularity of AI in everyday life due to the use of smartphones, in education, in the service of the population helps to achieve more acceptance. To improve the awareness and exposure to AI, policymakers need to create more campaigns, digital literacy courses and incorporate AI to other sectors in need of such technology such as the health care and education spheres. Another mediator that is essential is behavioral intention. Although risk has been minimized or ubiquity has acquired value, the real use will rely on the willingness of the user. Thus, it is necessary to implement training programs and pilot demonstration of the possibility of solving real problems with the help of AI. These programs will enhance user belief and that they are in control and turn intent to action.

The most significant aspect perhaps is the focus on ethics. Instead of becoming suspicious of the AI, the user is more inclined to use it provided that he or she can find it fair, transparent, and accountable. The appropriation of ethics in the process should be undertaken by companies and the government in several ways, including regular audits, explainability aspects, and the making of ethical claims in the open. Actual ethical position makes one be trusted and less doubtful.

Finally, the locally-based insights can be achieved in the study as the study is focused on Pakistan. It highlights the importance of AI approaches that address the infrastructure disparities, cultural principles and regulating issues. Government, industry, and the academic sectors should integrate efforts to make sure that the development of AI serves national interests and the people.

**Limitations**

- Although this research can be considered important in providing the understanding of factors that shape the adoption of AI, a number of limitations must also be considered. To begin with, the sample is demographically and geographically restricted to include the young educated members of urban Pakistan primarily. Being exposed to digital technologies more, their attitude towards AI must be more positive than in rural or aged people. Consequently, the results might not be generalized completely to represent the cultural and socio-economic diverse Pakistan. In future research, a more diverse sample of different age bracket, education, and rural areas should be utilized.
- Second, the research model is rather complete but other factors that might have been important are not included like social influence, cultural norms, organizational support or prior digital experience. It does not also take into account such demographic moderators as age or occupation. The incorporation of these variables into further models may give the researchers a more extensive and agile insight into the behavior of adopting AI.
- Third, the research has taken a cross-sectional design collecting data on one point in time. This restricts the interpretations of causal explanations and does not permit an observation of how perceptions or behaviors change. The long-term effects of perceptions of risk, ubiquity and ethics on real AI usage may be better monitored using a longitudinal study or an experimental research design.
- Fourthly, use of self-reports leads to the risk of bias and this varies widely including exaggeration or socially acceptable answers. In future studies self-reports should be integrated with objective data such as real usage data or tracking behaviors to increase validity and reliability.
- Fifth, the adherence measurement scale in ethical consideration might require some touch up. Although existing scales were transplanted, the notion of the AI ethics is currently undergoing development, especially in developing nations, such as Pakistan, where cultural values might affect the perception of ethics. General local development and context-sensitive forms of instruments may increase the level of accuracy in future researches.

- Finally, the research involved only one statistical analysis technique. Although it is proper, using more or mixed methods, i.e. using other structural models or using qualitative, might enhance the results and make them more applicable.

**Future research directions**

Based on the results and limitations of the current research, some of the areas in which there can be future research on the topic with potential to add to our knowledge of AI adoption, especially in developing nations such as Pakistan.

- The further studies are expected to widen the geographic and demographic perspective to country and rural, as well as less than educated, populations. The inclusion of those with rural backgrounds, different provinces, age, and education levels would increase the generalizability of the results and show how social-economic and cultural environment conditions the adoption of AI.
- Additional research should also examine other influential variables which are not included in the current study. Evidence can be more elaborated by some factors, including social influence, organizational support, digital literacy, anxiety about technology, and previous exposure to AI. Considering the Pakistan culture and religious diversity, the local values and norms should also be considered moving forward to influence the AI perceptions.
- The study of moderating and meditating variables would add depth on the present findings. Other responses to AI might be differing on the basis of demographics, such as age, gender and socio-economic status. How behavioral intentions contribute to actual AI use can be discussed through the mediators of trust, perceived usefulness, or habit.
- The nature of this study is cross-sectional, and thus, longitudinal or experimental designs should be applied in the future. The methodologies allow monitoring changes over time and evaluating long-term effects of exposure to AI, as well as the outcomes of such interventions as AI literacy programs or ethical transparency efforts.
- Also, accuracy could be improved by integrating the self-reported data with objective data (such as usage log, behavioral analytics or observation data). Interviews or focus groups as mixed-method approaches can retrieve further user motivation or context-specific information which is not reflected in the answers on a survey.
- Industry-related research is also necessary. Not all types of risk and ethical consideration are the same and may be dependent on one area of practice as opposed to another (i.e. in healthcare, finance or education). Adapting AI implementation to the particular industries may ensure that they are the ones to solve any specific issues and facilitate safe implementation.
- Finally, with the initial steps of AI policies being implemented in Pakistan, potential research in the area must include the effects of regulations and ethical frameworks on people, behavior, and adoption rates. A comparison of the effectiveness of changes in the policy and self-regulation of the industry can serve as evidence-based points toward the creation of a stable AI environment.
- In general, future studies need to be more diverse, longitudinal, and contextual, and assistance of responsible and sustainable integration of AI within the acquisition can be relevant in any developing country, such as Pakistan.

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