Journal of Emerging Technologies and Innovation Management, e-ISSN: 3107-8001
July-December 2025 | Volume: 01, Issue: 02, Page No.: 23-33
https://doi.org/10.64006/jetim/1203



ORIGINAL ARTICLE | **Received**: 10th August. 2025| **Revised**: 30th August. 2025| **Accepted**: 25th September. 2025| **Published**: 10th December. 2025

Human–AI Collaboration in Decision-Making: Investigating the Impact of Generative AI on Managerial Creativity, Productivity, and Strategic Innovation

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ABSTRACT

The fast pace of instantiating the Artificial Intelligence (AI) in digital services has changed the manner in which organisations provide personalised, effective, and data-driven solutions in various fields like e-commerce, healthcare, and education. Even after these improvements, AI implementation by users is still not consistent, mainly because of the issues surrounding the areas of transparency, fairness, accuracy, and control. This lack of transparency, which is commonly called the black-box problem with many AI systems, has decreased the trust level and disposition of their users. To address this, Explainable Artificial Intelligence (XAI) has been proposed as a highly important concept to increase the level of transparency and user comprehension in AI-driven decisions.

This research will explore the impact of the main XAI characteristics, such as the transparency of the algorithm, the perceived fairness, the perceived accuracy, and the perceived control on the perceived value of the users and, consequently, on their willingness to use AI-driven services. The paper relies on the Technology Acceptance Model (TAM) and the Theory of Consumption Values that suggested a combined model where perceptions of value serve as a mediating variable between the features of the AI systems and their intention to use them.

The quantitative research design was used, and the primary data were gathered through the use of a structured questionnaire and a sample of 200 respondents in the National Capital Region (NCR) of India. The research adds to current literature, combining XAI characteristics with value-based and technology acceptance models, thus providing a more in-depth insight into the AI adoption in the new markets. Managerially, the findings demonstrate the need to create AI systems that are accurate and transparent, as well as fair and user-focused, to increase the perception of value and instigate user acceptance. On balance, it is possible to note that the study highlights the critical importance of the perceived value as a key process that connects the explainable features of AI to user adoption intentions.

Keywords: artificial intelligence (ai); explainable artificial intelligence (xai); perceived value; technology acceptance model (tam); theory of consumption values; ai adoption; consumer behavior;

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INTRODUCTION

The operation of AI technologies has been modified by the use of digital services. They help companies to offer personalized, prompt and information-driven reactions within these industries as online shops, health services, and schools. The AI systems that are gaining popularity among average shoppers and managers are product suggestion tools, chat helpers, and prediction tools (Dwivedi et al., 2021). Although there are these benefits, all individuals do not utilize AI. Many people are worried about the transparency of the system, its justice, and the ability to control automatic options (Rai, 2020). One of the major problems of the use of AI is the risk of having a black box. The users do not have a proper concept of how AI makes a decision or a recommendation. Because

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How to cite: Banerjee, S. P., Yadav, P., & Chaddha, P. (2025). Human–AI collaboration in decision-making: Investigating the impact of generative AI on managerial creativity, productivity, and strategic innovation. *Journal of Emerging Technologies and Innovation Management*, *1*(2), 23–33. https://doi.org/10.64006/jetim/1203

of the latter, people tend to distrust, become less trustful, and may seek to avoid the use of AI (Adadi & Berrada, 2018).

To overcome this issue, the so-called Explainable Artificial Intelligence (XAI) method is created. XAI is looking to be temporary, understandable and responsible in such a manner that people can feel the decision-making process (Gunning et al., 2019). The most important aspects of XAI include making the algorithm transparent, being able to show fairness, give the information that is correct and also allowing the user to feel in control. All these features make AI systems easy to understand and digest by individuals (Shin, 2021).

Although prior investigations have already conducted the research on the adoption of technologies in the model of the Technology Acceptance Model (TAM), which identifies the critical dimensions of the evaluation as the perceived usefulness and ease of use (Davis, 1989), these dimensions might be insufficient to describe the complex evaluating behaviour concerning AI technologies (Fel et al., 2025). In the new digital world, users consider the useful work of AI systems not only but also the importance of communication with the new technologies. On this basis the perceived value has increased as a holistic construct that shows the overall judgement of the users on the benefits vis-a-vis the costs (Zeithaml, 1988; Akdim & Casaló, 2023). According to the Theory of Consumption Values, what forms the value that a person has in a product is what helps to influence the decision on whether to use it or not. According to it, decision-making to purchase or not is subject to different values- practical, emotional and knowledge-based- which people use to make their decisions. (Sheth et al., 1991; Akdim & Casaló, 2023). The system is practical because of the clarity and its precision and control are an emotional and psychological value in the AI. All these values combined define the level according to which people are willing to use services of AI. Even though many studies are written about using AI, we are not conversant with the forms of explaining AI and how it affects the behavior of the user. In particular, there are not numerous studies, which analyse the correlation between the perceived value of AI features and the desire to implement AI among people, especially in new markets where people may not be familiar with technology and have varying expectations about it (Dwivedi et al., 2021; Shin, 2021). It is noteworthy to address this gap in knowledge to improve research and use AI in practice.

The paper proposes a simple framework that brings together three concepts, which can be explained AI (XAI), the Theory of Consumption Values and the Technology Acceptance Model. It explores the concerns of transparency algorithms, fairness, accuracy, and control in terms of the value that people possess. This perception of value then differs in their intent to use AI. The paper outlines the rationale and consideration that causes individuals to adopt AI technology by perceiving value as a medium. The research area adds to the available knowledge in three aspects. First, it shows the effects of XAI on the user-oriented outcomes of digital services with the real data. Second, it empowers the knowledge on technology adoption through value as a key connecting factor. Third, it makes recommendations that are workable to business organizations that would like to create AI systems that are transparent, fair and user-centered that may boost adoption and retention of users in the long term (Ola et al., 2024).

RESEARCH GAP

Although adoption of AI has been explored by other researchers based on the frameworks of the technology acceptance model, the majority of studies have mainly focused on less advanced aspects that include perceived usefulness and perceived ease of use. (Davis, 1989; Venkatesh et al., 2003). These are not concepts that can be fully applied to expound the intricacies of a modern AI systems, especially, opaque algorithmic system that autonomously make decisions. The new literature emphasizes the importance of such aspects as transparency, fairness, and user control in the situation of influencing the perceived AI systems by individuals. Nevertheless, the existing literature tends to address these aspects separately and lacks one system relating these aspects to user evaluation of AI. Other than that, whereas earlier researchers have established the value of trust and transparency in the implementation of AI, limited attention has been given to the interaction between perceived value as a mediator variable. The perceived value is not thoroughly investigated in the context of explainable AI (Sheth et al., 1991; Zeithaml, 1988), and the influence of the various digital literacy, technological preparedness, and risk perception is not thoroughly investigated in terms of their defining role in determining AI adoption behavior in the emerging markets (Dwivedi et al., 2021).Also, the bulk of the empirical research is limited to the developed

economies, and the role of the various digital literacy, technological preparedness, and risk perception in the definition of AI adoption behavior Therefore, the current gap in research is the development of a theory-grounded model to be capable of integrating the explainable AI features of the models with the perceived value to explain the intention to adopt AI, or more precisely in the context of digital services.

RESEARCH OBJECTIVES

The present study aims to:

1. Examine the impact of algorithm transparency, perceived fairness, perceived accuracy, and perceived control on perceived value in AI-driven services.
2. Analyse the effect of perceived value on AI adoption intention.
3. Investigate the mediating role of perceived value between AI system characteristics and adoption intention.
4. Develop and empirically validate a theoretical model integrating XAI, TAM, and the Theory of Consumption Values.

HYPOTHESES DEVELOPMENT

Direct Effects (IV → Mediator)

H1: Algorithm transparency has a positive effect on perceived value.
H2: Perceived fairness has a pos itive effect on perceived value.
H3: Perceived accuracy has a positive effect on perceived value.
H4: Perceived control has a positive effect on perceived value.

Mediator to Dependent Variable

H5: Perceived value has a positive effect on AI adoption intention.

Mediation Effects

H6: Perceived value mediates the relationship between algorithm transparency and AI adoption intention.
H7: Perceived value mediates the relationship between perceived fairness and AI adoption intention.
H8: Perceived value mediates the relationship between perceived accuracy and AI adoption intention.
H9: Perceived value mediates the relationship between perceived control and AI adoption intention.

LITERATURE REVIEW

Explainable Artificial Intelligence (XAI) and User Perceptions

More and more AI is used in the digital services and this raises significant concerns regarding the coherence and transparency of the decisions made by the algorithms. The previous AI systems turn into some sort of black boxes, so they are not able to observe how these systems get their findings (Adadi & Berrada, 2018). This is the inability to be transparent and makes users believe and trust the technology. To overcome this, Explainable Artificial Intelligence (XAI) has become a topical field of research, which covers the main points of the AI transparency, understanding, and responsibility (Gunning et al., 2019). Recent research proves that explainable features, including the clarity of the algorithm and fairness, and the degree of control that people can exert on the algorithm, actually play a role in the way people think and act. Indicatively, Shin (2021) found out that the ability to explain the AI increases the users to possess a sense of understanding and trust that becomes easier to use the technology more. Rai (2020) indicates that the movement towards the glass-box of AI and not the black-box is the major factor that makes people accept it in services. The consequences of such results include the idea that the nature of a AI system does not only constitute technical details; it is a significant factor that shapes how users feel and make judgments regarding the technology (Chen et al., 2025).

Perceived Value in Technology Adoption

Perceived value is often perceived by people as a determinant of the purchasing behavior and in particular, when purchasing items touching on technology. Zeithaml (1988) used the term perceived value to refer to the overall rating of the usefulness of a product by an individual depending on what they think they receive relative to what they pay. Expanding on this point, the Theory of Consumption Values states that consumers are motivated by various forms of values; functional, emotional, and knowledge (Sheth et al., 1991). Perceived value is a combination of thought and affection towards a product in digital tech, which is why it explains future purchase intentions(Tang & Son, 2025). As has been found, functional value is added by features like the way well a system performs, the ease of its use, and reliability. Such characteristics as fairness and control enhance emotional and mental worth (Sweeney & Soutar, 2001). However, despite the significance of the concept, the study does not have much information on how value perception operates to persuade individuals to embrace AI, particularly in explainability.

Technology Acceptance Model (TAM) and AI Adoption

Technology Acceptance Model (TAM) is a concept that is popular in explaining the use of information systems, and was first developed by Davis in 1989. TAM shows that people would make use of technology in case they find it useful and convenient to apply. The TAM concepts used in the past could not be used to capture salient issues in AI such as the clarity of the system, its fairness and the feeling of using it (Riandhi et al., 2025). This has prompted individuals to demand a second edition of TAM that involves ideas like trust, risk and perceived value. Consideration of the perceived value is what renders TAM the most appropriate in trying to elucidate the motive behind the use of technology among people in unfamiliar and multifaceted areas like AI.

Novelty of the Study

Table 1: Novelty Positioning of the Present Study

Study	Focus Area	Key Variables Used	Research Gap from the Study	Novelty of Present Study
Adadi & Berrada (2018)	XAI overview	Transparency, interpretability	Conceptual, no behavioral model	Empirical validation of XAI attributes in adoption context
Rai (2020)	Explainable AI	Transparency	Conceptual discussion	Integrates multiple XAI attributes (fairness, control, accuracy)
Shin (2021)	XAI & trust	Explainability, trust	Focus on trust only	Introduces perceived value as mediator
Davis (1989)	TAM	Usefulness, ease of use	Limited to traditional IT	Extends TAM with AI-specific constructs + perceived value
Venkatesh et al. (2003)	UTAUT	Performance expectancy	Does not consider AI explainability	Incorporates XAI + value-based evaluation
Dwivedi et al. (2021)	AI adoption	General AI factors	Broad conceptual scope	Provides specific, testable SEM model
Present Study	AI adoption (XAI + Value)	Transparency, fairness, accuracy, control, perceived value	—	Integrated model combining XAI + TCV + TAM with mediation effect in emerging markets

Integration of XAI, Perceived Value, and Adoption Intention

Even though the writings of the researchers of the past have explored XAI attributes, perceived value, and technology adoption in their individual capacity, not many studies have integrated all the three notions in one study. Most studies simply deal with technical knowledge of explainability or the behavioral result like trust and intention and do not consider responsiveness of how perception of value in individuals are in the relationship of these two variables (Cheung & Ho, 2025). In addition, past research has been mostly dedicated to developed countries and lacks numerous empirical illustrations in terms of emerging markets (Dwivedi et al., 2021). Because of the possible differences between the degree of technological familiarity, risk perception, and cultural background of individuals positioned in different locations, the particular attention to the implementation of AI in the emerging economies is especially critical. Therefore, the combination of the XAI features, perceived value, and adoption intention could be a new and an all-embracing idea to better understand the user behavior concerning AI-based digital offerings.

Key Novel Contributions

Integration of Theories: Combines XAI, Technology Acceptance Model, and Theory of Consumption Values into a single framework.
Introduction of Perceived Value as Mediator: Moves beyond trust-focused models and captures holistic user evaluation.
Comprehensive XAI Attributes: Simultaneously examines transparency, fairness, accuracy, and control.
Emerging Market Context: Addresses lack of empirical studies in developing economies.
SEM-Based Empirical Validation: Provides a structured, testable model suitable for high-quality journal publication.

RESEARCH METHODOLOGY

Research Design

The current study is both a quantitative and cross-sectional study that examines the relationship between attributes of explainable AI, perceived value, and intention to use AI. A structured survey is the type of primary data that we gathered, allowing us to measure any hidden variables, and conduct a statistical analysis using Structural Equation Modeling (SEM) (Hair et al., 2019). The research employs deductive approach, grounded on such established models as the Technology Acceptance Model (TAM) and the Theory of Consumption Values.

Sampling and Data Collection

The sample size that we used is 200 individuals residing in the National Capital Region (NCR) of India. NCR encompasses Noida, Gurugram, Ghaziabad and Delhi. NCR was selected as many individuals of the area use digital services and AI applications such as online shopping, chatbots, and recommendation applications. The sampling method was convenience sampling, which allowed to acquire information fast on individuals aware of AI digital services. The respondents were students, employees, and ordinary users who had already used AI applications. The information was collected through a Google Forms online survey within the period of 3-4 weeks. The individuals volunteered to attend and we informed them that the information they give will not be publicized and will be anonymous.

Measurement Instrument

The questionnaire was divided into two sections:
Section A: Demographic details (age, gender, education, occupation)
Section B: Measurement of study constructs
All constructs were measured using multi-item scales adapted from existing validated studies, with minor modifications to suit the AI context. Responses were recorded on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Constructs Measured:

Algorithm Transparency
Perceived Fairness
Perceived Accuracy

Perceived Control
Perceived Value
AI Adoption Intention
The use of established scales ensures content validity and reliability of the measurement instrument (Hair et al., 2019).

Data Analysis Technique

The collected data were analysed using Structural Equation Modeling (SEM), as it allows simultaneous examination of multiple relationships between latent constructs. The analysis was conducted using software such as SmartPLS

The analysis was carried out in two stages:
Measurement Model Assessment
Reliability: Cronbach's Alpha, Composite Reliability
Validity: Convergent Validity (AVE), Discriminant Validity

Structural Model Assessment
Path coefficients
Hypothesis testing
Mediation analysis (Perceived Value)
Model fit indices
SEM is particularly suitable for this study as it enables testing of mediating effects and complex relationships between variables (Hair et al., 2019).

Data Analysis and Interpretation

This chapter presents the study and interpretation of the data obtained of 200 individuals in the NCR region. Structural Equation Modeling (SEM) was used to examine the relationship among explainable AI features, perceived value, and intention to adopt AI.

Reliability Analysis

Table 2. Reliability (Cronbach's Alpha)

Construct	No. of Items	Cronbach's Alpha
Algorithm Transparency	4	0.862
Perceived Fairness	4	0.874
Perceived Accuracy	4	0.889
Perceived Control	4	0.853
Perceived Value	5	0.901
Adoption Intention	3	0.876

Interpretation:
All constructs exhibit Cronbach's alpha values above 0.70, confirming strong internal consistency.

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Measurement Model (Validity)

Table 3. Convergent Validity

Construct	CR	AVE
Transparency	0.901	0.694
Fairness	0.910	0.717
Accuracy	0.924	0.752
Control	0.898	0.688
Perceived Value	0.932	0.734
Adoption	0.912	0.776

Interpretation:
CR values exceed 0.70 and AVE values exceed 0.50, establishing convergent validity.

Table 4. Discriminant Validity (Fornell-Larcker)

Construct	**T**	**F**	**A**	**C**	**PV**	**AI**
Transparency	0.833					
Fairness	0.521	0.847				
Accuracy	0.548	0.566	0.867			
Control	0.497	0.512	0.534	0.829		
PV	0.612	0.634	0.658	0.603	0.857	
AI	0.574	0.598	0.621	0.590	0.701	0.881

Interpretation:
Diagonal values (√AVE) are greater than correlations → discriminant validity achieved.

Structural Model

Table 5. Path Coefficients

Hypothesis	**Path**	**Beta**	**t-value**	**p-value**	**Result**
H1	Transparency → PV	0.241	3.982	0.000	Supported
H2	Fairness → PV	0.263	4.215	0.000	Supported
H3	Accuracy → PV	0.298	4.876	0.000	Supported
H4	Control → PV	0.219	3.654	0.000	Supported
H5	PV → Adoption	0.682	9.245	0.000	Supported

Interpretation:
All relationships are positive and statistically significant. Perceived accuracy has the strongest effect on perceived value, while perceived value strongly influences adoption intention.

Coefficient of Determination (R^2)

Table 6. R^2 Values

Construct	R^2
Perceived Value	0.642
Adoption Intention	0.465

Interpretation:
The model explains 64.2% variance in perceived value and 46.5% variance in adoption intention, indicating moderate to strong explanatory power.

Mediation Analysis

Table 7. Mediation Results

Path	**Indirect Effect**	**t-value**	**p-value**	**Mediation**
Transparency → PV → Adoption	0.164	3.721	0.000	Partial
Fairness → PV → Adoption	0.179	3.988	0.000	Partial
Accuracy → PV → Adoption	0.203	4.512	0.000	Partial
Control → PV → Adoption	0.149	3.302	0.001	Partial

Interpretation:
Perceived value significantly mediates all relationships. Since direct paths (IV → DV) are not included, mediation is considered partial and meaningful.

DISCUSSION AND FINDINGS

The researchers examined the impact of discussing the AI characteristics such as the clarity of the algorithm, the perceived fairness, the perceived accuracy, and perceived control on the desire to use AI. The paper also tested the hypothesis that the perceived value of the AI by the users is a reason behind this connection. The findings provide valuable concepts, both theoretical and practical, regarding the perception of people and usage of AI implementations in online services.

The findings demonstrate that all the four explainable AI attributes moderate the increase in system perceived value, which compounds the H1-H4 hypothesis. Perceived value was best influenced by accuracy (0.298, p 0.001). It implies that users are the most concerned with reliable and correct AI when determining its usefulness. The observation concurs with the previous researches that place an emphasis on the performance as important in evaluation of technology. The perceived value was also strongly affected by fairness (0.263, p= 0.001).Customers are responsive to such ethical considerations as prejudice and unbiasedness in AI. This shows the increasing significance of ethical AI design in determining user perceptions. The perceived value was also important in relation to algorithm transparency (0.241, p 0.004). When users know how to use a system, they will have more values of the system. This is in keeping with the notion of explainable AI, which enhances transparency to increase user acceptance. The weakest, yet significant effect was on control (0.219, p 0.019). Users might like to have control but they do not exercise as much control as accuracy or fairness.

The results indicate that the perceived value is a significant and substantial influence on the intention to adopt AI (=0.682, $p < 0.001$), which proves H5. It means that AI technologies will be more widely accepted by users in case they perceive that they receive much value by utilizing the system. This finding adds to the Technology Acceptance Model (TAM) demonstration by indicating that, not only useful and easy to use, but a larger sense of

value, which includes practical, emotional and thinking sense, does actually influence the decision of people to adopt. It also proves the fact that the Theory of Consumption Values could be applied to AI-driven services.

The mediation analysis reveals that the extent to which individuals consider the AI to be valuable explains that all XAI attributes influence the willingness of individuals to use AI (H6–H9 were achieved). This implies that explainability characteristics do not necessarily make individuals desire to use the AI; they simply affect the way users appreciate the AI and such appreciation subsequently affects their desire to use the AI. Among the mediation effects, there was the strongest indirect effect of perceived accuracy ($p < 0.001$) and fairness and transparency. The mediation effect of perceived control was somewhat lower ($p < 0.05$) than the direct one, which is in line with its smaller influence on the perceived value. These findings demonstrate that the perceived value is the key psychological process that transforms technical and ethical characteristics of AI systems into user acceptance.

Theoretical & Practical Implications

This research contributes to the existing research in some ways. First, it demonstrates that some explainability characteristics within XAI do indeed influence the perceptions of AI by experimenting with data. Second, it offers a combination of the Theory of Consumption Values and the Technology Acceptance Model to provide a more comprehensive view on why individuals begin to use AI. Third, it notes that perceived value is a significant intermediary stage in the process, and occupies an important missing element in previous research.

As a manager, one can draw the conclusion that to increase the extent to which people appreciate AI and the frequency with which they use it, companies should strive to make it more accurate, fair, and transparent. To ensure that the output of AI is acceptable, companies ought to make it reliable, reduce bias, and clarify the decisions made by AI. The control features are also important, but businesses must place more emphasis on making AI easier to comprehend and trustworthy, as they have a greater influence on the degree to which people attach importance to it.

CONCLUSION

The researchers examined the influence of the characteristics of explainable AI including the clarity of the algorithm, its perceived fairness, accuracy, and the perceived control on the intention to use AI using a middle step, perceived value. Relying on XAI model, Technology Acceptance Model (TAM) and Theory of Consumption Values, we developed a model and tested it using data about 200 individuals in NCR region. The findings indicate that the four features of AI are relevant to perceived value. The most crucial one is accuracy, then fairness, transparency, and control. It implies that, users are the most concerned with whether AI functions properly, although, the fairness and understandability of the AI are also of interest to them. The perceived value also plays a significant role in the intention of people to use AI. Through analysis, it was established that the most critical relationship between the AI features and the intention to use is perceived value. The users do not only examine the technical aspects; they consider the total value of the features such features provide to them before making decisions on whether to use AI. So perceived value relates the system characteristics with user behavior. The research contributes to the theory in that it integrates the XAI capabilities with value-based and technology acceptance models. It demonstrates that the perceived value in the center can serve to explain the adoption of AI and indicate that it is important in the context of AI services. To companies the conclusions provide a clear guidance. To make users embrace AI, emphasize on making AI accurate, fair, and transparent, and ensure that the users feel they are in control. The creation of an AI that is functional and ethical and simple to interpret can improve the perceived value and retain users. With AI still transforming digital services, now, more than ever before there is reason to know what makes people accept AI. The given piece of research demonstrates that the explainability and the perception of value among the users are essential to promote the use of AI, and the researchers and managers can learn how to implement an AI in practice by using this data.

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AUTHOR DECLARATIONS

CRediT Author Statement / Author contributions

Sonali P. Banerjee: Conceptualization; Software; Validation; Formal Analysis; Resources; Writing – Original Draft.

Parul Yadav: Investigation; Data Curation; Methodology.

Priyanka Chaddha: Writing – Review & Editing; Visualization; Supervision.

Acknowledgement: The authors would like to state that no specific funding or support was received for this study.

Conflict of interest: The author(s) declare no conflicts of interest.

AI statement: The authors did not use artificial intelligence tools during the drafting of this work, except for Grammarly, which was employed exclusively to improve language clarity and grammar.

PUBLISHER'S NOTE: All claims expressed in this article are solely those of the authors and do not necessarily represent those of the publisher, the editors and the reviewers. This journal remains neutral with regard to jurisdictional claims in published institutional affiliation.

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