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The Impact of Artificial Intelligence on Human Decision-Making: An Empirical Study of Trust, Perceived Reliability, and User Adoption

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ABSTRACT
Artificial Intelligence (AI) has started to revolutionize human decision-making in many areas, offering automated recommendations, predictive insights, and decision-support capabilities. But as the use of AI becomes more widespread, there are significant questions about customer trust, reliability, privacy, and the overreliance on algorithm-driven recommendations. The purpose of this study is to explore how AI affects human decision-making by exploring the connections among perceived usefulness, perceived reliability, trust, privacy worries, and user adoption. Employing a review of this recent empirical work and theoretical concepts, the research outlines a conceptual framework to explain the impact of trust on acceptance and reliance on AI-informed decisions. The approach to research is proposed as Quantitative with a structured questionnaire that will be filled out by 250-300 people who have experience with using AI-powered applications. Descriptive, correlation, regression and mediation analysis will be used to analyze the data. The study will help build knowledge and understanding of the factors that influence human-AI interaction and help inform decisions about responsible AI adoption, trustworthy AI systems and responsible decision making.
Keywords—Artificial Intelligence, Human Decision-Making, Trust in AI, Perceived Reliability, User Adoption, Privacy Concerns, AI-Assisted Decision-Making.

1 INTRODUCTION

1.1 Background of the Study

Artificial Intelligence (AI) is becoming a game changing technology as it continues to impact how people gather information, consider options, and make decisions on various aspects of everyday life. The use of artificial intelligence (AI) in the education, the health care sector, the business and finance sector, the public administration sector, and other professional fields has transformed the human-digital system interaction. AI applications can handle vast amounts of data, detect patterns, make predictions, and make suggestions to assist people in making decisions. For this reason, Artificial Intelligence is increasingly being implemented as a technological tool, but also as a support mechanism to guide the decision-making process and behaviour of humans.

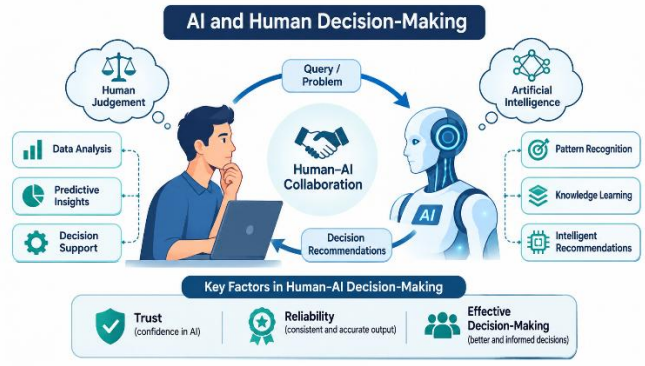
As AI becomes increasingly integral to the decision-making process, there are opportunities to enhance efficiency, consistency, and information access. The power of AI-driven decision-making, however, relies heavily on people's perceptions, understanding, and trust of the recommendations generated by AI. Li et al. [1] explored the concept of human trust and reliance in the context of AI-supported decision-making, emphasizing the need for understanding the evolution of trust and reliance in interactions with AI systems, using a Markovian approach. Likewise, Kares et al. [2] experimented with trust in a context where humans make decisions in tandem with automated suggestions, highlighting the importance of trust in contexts where human judgment and automated suggestions are operating together.

Although AI systems can provide valuable assistance, their recommendations are not necessarily accurate or appropriate in every situation. People might opt to follow AI suggestions without critically evaluating the data behind them. People might take AI suggestions without critically examining the data behind them. This behaviour can lead to concern of automation bias, dependency and loss of independent human judgment. Hence, it is crucial to understand factors that might affect human trust, perceived reliability, and uptake of AI technologies, and it is a topic of current research.

research.

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Figure 1. AI and Human Decision-Making



1.2 Artificial Intelligence and Human Decision-Making

Decision making is a complex mental activity that includes information processing, the appraisal of options, judgement, and the choice of action. Past approaches have been based on personal experience, professional expertise, gut feeling and available information. The advent of AI-powered decision-support tools, however, has brought a new layer to the complexion of this process, offering automated insights and recommendations.

AI decision making is a collaborative process between humans and intelligent technology. In this setup, AI analyzes the information and provides suggestions, while humans derive meaning from the data and make judgments regarding the recommended results. This interaction is dependent on the precision of AI suggestions and the capacity of people to gauge them correctly.

Alon-Barkat and Busuioc [5] explored the interaction between humans and AI in the context of decision making in government bodies, with a specific focus on the phenomenon of Automation Bias and Selective adherence to Algorithmic advice. Their work emphasizes the need to understand the influence of the algorithmic recommendation on the actions of the individual and not simply presume that information produced by AI is accepted and acted upon by the individual. The relevance of human preferences in the AI-supported decision environments has been explored by Zhang and Gosline [4] who examined the perception and bias for generative AI, human expert, and human-AI collaboration.

Moreover, Sele and Chugunova [9] analysed the importance of human engagement in automated decision-making, with key aspects regarding the correlation between human involvement and the accuracy of decisions. The results of these studies indicate that simply adopting AI does not necessarily lead to better decision-making. Rather, the results of AI-driven decision making rely on the interplay of expertise and human judgment.

1.3 Trust and Perceived Reliability in Artificial Intelligence

Trust is a key determinant in the adoption and successful application of AI technologies. When users believe that the AI-driven recommendation system is reliable, accurate, consistent, and useful, they are more inclined to trust its recommendations. On the other hand, if users lack confidence in the accuracy, transparency, and reliability of the AI systems, they might be less likely to trust their suggestions.

Building trust in AI is not always a one-time, quick, and automatic process. It may vary depending on the user's past experiences, their evaluation of the system's performance, the type of decision, and the potential outcomes of following an AI-generated suggestion. Humr et al. [3] analysed the evolution of trust towards AI-supported decision making, underscoring the need to understand the nature of trust as an evolving process. Humr and Canan [7] also explored how intermediate judgments impact trust in AI-based decisions.

Addressing trust and reliance on AI, Klingbeil et al. [6] explored how much and at what costs reliance occurs. Their research is relevant because if people start trusting too much, they might take information that they do not check them. Likewise, Fahnenstich et al. [8] analyzed trust under risk, comparing decision-support agents (humans and AI), highlighting the need to consider decision contexts when assessing trust in automated recommendations. Afroogh et al. [11] summarized the state of the art, obstacles, and trends of AI trust research, which offers a more general overview of the factors affecting the trustworthiness of intelligent systems. Benk et al. [13] also conducted a bibliometric review of empirical studies on trust in AI to uncover trends and gaps in the current research field. Taken together, these studies provide a basis of trust and perceived reliability as crucial measures in examining human-AI interaction.

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1.4 Privacy Concerns and User Adoption of AI

Despite the potential advantages of AI technologies, concerns regarding privacy, data security, transparency, and the responsible use of personal information may influence individuals' willingness to adopt them. Many AI applications require access to user-generated information, personal preferences, behavioural patterns, and other forms of data to generate recommendations and improve system performance. Consequently, users may question how their information is collected, processed, stored, and protected.

Leschanowsky et al. [10] examined privacy, security, and trust perceptions in conversational AI through a systematic review, highlighting the importance of these factors in human-AI interactions. Rana et al. [12] investigated AI adoption using a trust- and privacy-augmented Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Their research provides a relevant foundation for understanding how trust and privacy considerations influence the acceptance of AI technologies.

The relationship between trust and adoption is also important in determining whether individuals intend to continue using AI-powered applications. Orbán and Stefkovics [14] examined trust in artificial intelligence through a survey experiment concerning algorithmic decision-making. Huynh and Aichner [16] investigated the determinants and outcomes of cognitive trust in generative AI, providing further insight into the psychological factors associated with users' acceptance of intelligent technologies.

These findings suggest that AI adoption cannot be explained solely through technological convenience or perceived usefulness. Instead, individuals' perceptions of reliability, trustworthiness, privacy, and potential risks may collectively influence their willingness to incorporate AI into everyday decision-making.

1.5 Human Reliance and Overreliance on AI-Assisted Decisions

An important concern associated with the increasing use of AI is the possibility that individuals may become excessively dependent on automated recommendations. While appropriate reliance on AI can support decision-making, overreliance may reduce independent evaluation and increase the possibility of accepting incorrect or misleading recommendations.

The distinction between trust and reliance is particularly important. Trust represents an individual's belief in the capability and dependability of an AI system, whereas reliance refers to the extent to which an individual actually uses or follows its recommendations. These concepts are related but do not necessarily produce identical behavioural outcomes.

Li et al. [1] investigated the relationship between trust and reliance in AI-assisted decision-making, while Klingbeil et al. [6] explored the potential consequences of overreliance. More recently, Pearson et al. [17] examined human reliance on artificial intelligence in decision-making, providing contemporary evidence for investigating how individuals respond to AI-generated recommendations.

Dang and Li [15] further explored the antecedents and consequences of trust in AI, including cultural dynamics. Their work provides an additional perspective on the complexity of trust and its implications for human-AI interactions. Understanding these relationships is essential for encouraging responsible AI use while preserving human autonomy and independent judgement.

1.6 Research Gap and Motivation

Although previous studies have extensively investigated trust, reliability, privacy, adoption, and reliance on AI, these dimensions are frequently examined through different research perspectives and specific technological or organisational contexts. Research has explored human-AI collaboration [2], automation bias [5], overreliance [6], privacy perceptions [10], and technology adoption [12]. However, there remains an opportunity to examine these factors collectively within an integrated empirical framework involving individuals who use AI-powered applications across different everyday contexts.

In particular, further investigation is needed into how perceived usefulness, perceived reliability, and privacy concerns relate to trust in AI, and how trust subsequently influences AI adoption and reliance on AI-assisted decisions. Examining these relationships together can provide a broader understanding of the psychological and behavioural factors shaping human-AI interaction.

Accordingly, the present study proposes an integrated conceptual framework incorporating perceived usefulness, perceived reliability, privacy concerns, trust in AI, AI adoption intention, and reliance on AI-assisted decisions. By investigating these relationships through a quantitative research approach, the study aims to extend the understanding of how individuals evaluate and incorporate AI-generated recommendations into their decision-making processes.

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1.7 Aim and Significance of the Study

The primary aim of this study is to examine the impact of artificial intelligence on human decision-making by investigating the relationships between perceived usefulness, perceived reliability, trust, privacy concerns, and user adoption.

The study is expected to contribute to the existing literature on human-AI interaction by integrating important technological and behavioural factors into a single empirical framework. From a practical perspective, its findings may help AI developers, organisations, policymakers, and technology providers understand the factors influencing users' trust and reliance on AI systems.

Furthermore, the study seeks to emphasise the importance of responsible AI adoption, appropriate human oversight, and independent judgement in AI-assisted decision-making. Ultimately, understanding these factors can support the development and use of more trustworthy, reliable, and human-centred AI technologies.

2 LITERATURE SURVEY

2.1 Artificial Intelligence in Human Decision-Making

Artificial Intelligence (AI) has increasingly become an integral component of contemporary decision-making processes by providing automated recommendations, predictive information, and intelligent decision-support capabilities. The integration of AI into human activities has transformed traditional decision-making practices, allowing individuals to evaluate complex information and consider algorithmically generated alternatives. However, the effectiveness of AI-assisted decision-making depends not only on technological capabilities but also on human perceptions, cognitive processes, and behavioural responses.

Li et al. [1] investigated human trust and reliance in AI-assisted decision-making using a Markovian modelling approach. Their research provides a framework for understanding how individuals' trust and reliance may evolve during repeated interactions with intelligent systems. The study is particularly relevant because it considers trust and reliance as dynamic rather than fixed characteristics. Similarly, Kares et al. [2] examined trust in hybrid human-automated decision-support systems, contributing to the understanding of how individuals evaluate technological assistance when human judgement remains part of the decision-making process.

Zhang and Gosline [4] explored perceptions of generative AI, human experts, and human–AI collaboration in persuasive content generation. Their research challenges the assumption that individuals necessarily reject AI-generated content simply because it originates from an automated system. Alon-Barkat and Busuioc [5] examined automation bias and selective adherence to algorithmic advice in public-sector decision-making, highlighting the importance of understanding when individuals accept or disregard AI recommendations.

These studies establish that AI-assisted decision-making is fundamentally an interactive process involving both technological outputs and human interpretation. Therefore, evaluating AI's influence requires consideration of individual attitudes, contextual factors, and the extent to which automated recommendations shape final decisions.

2.2 Trust Development in Artificial Intelligence Systems

Trust represents a central psychological and behavioural factor influencing human interaction with AI technologies. In AI-assisted decision-making, trust can be understood as an individual's willingness to depend on an intelligent system under conditions of uncertainty. Trust may be influenced by perceived accuracy, reliability, transparency, previous experience, and the consequences associated with accepting automated recommendations.

Humr et al. [3] investigated the temporal evolution of trust in AI-supported decision-making, emphasising the relevance of changes in trust across interactions. Their research supports examining trust as a developing process rather than assuming that individuals maintain consistent confidence in AI technologies. Humr and Canan [7] subsequently examined intermediate judgements and trust in AI-supported decision-making, extending attention to the cognitive processes involved when individuals evaluate automated assistance.

Afroogh et al. [11] reviewed progress, challenges, and future directions in AI trust research. Their work provides a broader conceptual foundation for understanding the multidimensional nature of trust and the challenges involved in establishing dependable human–AI relationships. Benk et al. [13] conducted a bibliometric review of empirical research on trust in AI, identifying research trends, overlooked issues, and directions for future investigation.

Orbán and Stefkovics [14] investigated trust in algorithmic decision-making through a survey experiment, offering a relevant empirical perspective on individuals' evaluations of AI-supported decisions. Huynh and Aichner [16] examined the determinants and outcomes of cognitive trust in generative AI, highlighting the importance of understanding trust-related beliefs within contemporary AI applications.

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Collectively, these publications indicate that trust is not a single-dimensional construct determined exclusively by technological performance. Instead, it involves cognitive evaluations, perceived risks, contextual expectations, and experiences with AI-generated information.

2.3 Perceived Reliability and Decision-Support Effectiveness

Perceived reliability refers to the extent to which users believe an AI system consistently produces dependable, accurate, and useful outputs. Reliability is particularly important in decision-support environments because individuals may use AI recommendations to guide choices that involve uncertainty or potential consequences.

Fahnenstich et al. [8] investigated trust under risk by comparing human and AI decision-support agents. Their research provides a basis for examining how decision-related risk may influence users' evaluations of automated recommendations. In situations involving uncertainty, perceived reliability may affect whether individuals consider AI advice credible enough to influence their decisions.

Klingbeil et al. [6] examined trust and reliance on AI through an experimental investigation of the extent and costs of overreliance. Their work highlights an important distinction between confidence in automated recommendations and the appropriateness of relying on them. An AI system perceived as reliable may encourage greater acceptance of its recommendations, even when independent verification would be beneficial.

Sele and Chugunova [9] investigated human involvement in automated decision-making, identifying a tension between the acceptance of automated recommendations and decision accuracy. Their study suggests that incorporating human participation into automated processes does not necessarily guarantee superior outcomes.

These findings indicate that perceived reliability should be distinguished from objectively measured AI accuracy. Users may regard a system as dependable because of previous positive experiences, persuasive explanations, or consistent presentation, even when its recommendations contain errors. Consequently, perceived reliability represents an important explanatory variable in research examining trust and AI-assisted decision-making.

2.4 AI Adoption and Technology Acceptance

The adoption of AI technologies depends on users' willingness to incorporate intelligent systems into their activities and decision-making practices. Technology acceptance research commonly considers factors such as perceived usefulness, performance expectations, trust, facilitating conditions, and perceived risks.

Rana et al. [12] investigated AI adoption in a developing-country academic environment through a trust- and privacy-augmented Unified Theory of Acceptance and Use of Technology framework. Their research is relevant to understanding how established technology acceptance models can be extended to incorporate concerns associated with AI systems.

Huynh and Aichner [16] explored cognitive trust in generative AI, contributing to the understanding of factors associated with users' confidence in emerging AI technologies. Orbán and Stefkovics [14] examined trust in algorithmic decision-making, offering a complementary perspective on how individuals evaluate AI involvement in decision processes.

Dang and Li [15] reviewed antecedents, consequences, and cultural dynamics associated with trust in AI. Their work highlights the importance of considering trust within broader social and behavioural contexts rather than treating adoption as a purely technological decision.

Taken together, these studies support examining AI adoption as a multidimensional phenomenon. Although perceived usefulness may encourage individuals to adopt AI applications, concerns about reliability, trustworthiness, and potential consequences may influence their intentions to continue using such systems.

2.5 Privacy, Security, and Perceived Risk

Privacy and security concerns represent important challenges in the adoption of AI-powered applications. Intelligent systems frequently process user inputs, behavioural information, and potentially sensitive data to generate personalised outputs. Consequently, users may be concerned about data collection, information confidentiality, unauthorised access, and the potential misuse of personal information.

Leschanowsky et al. [10] conducted a systematic review of privacy, security, and trust perceptions in conversational AI. Their research provides a relevant foundation for understanding how concerns regarding information protection intersect with perceptions of technological trustworthiness.

Rana et al. [12] incorporated privacy considerations into an extended technology adoption framework, supporting the inclusion of privacy concerns as a potential explanatory factor in AI acceptance research. Afroogh et al. [11] also discussed challenges associated with trust in AI, providing a broader perspective on the conditions required for responsible interaction with intelligent systems.

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Privacy concerns may discourage individuals from adopting AI technologies even when they recognise their usefulness. Conversely, users who perceive an AI system as trustworthy may be more willing to share information and incorporate its recommendations into their decisions. However, these relationships require empirical examination because privacy concerns and trust may vary across users and application contexts.

Therefore, privacy concerns constitute a relevant independent variable when investigating AI adoption intention and human decision-making behaviour.

2.6 Human Reliance, Overreliance, and Automation Bias

Human reliance refers to the extent to which individuals follow or incorporate AI-generated recommendations into their decisions. Appropriate reliance occurs when users consider the capabilities and limitations of AI systems, whereas overreliance involves excessive dependence on automated recommendations without sufficient critical evaluation.

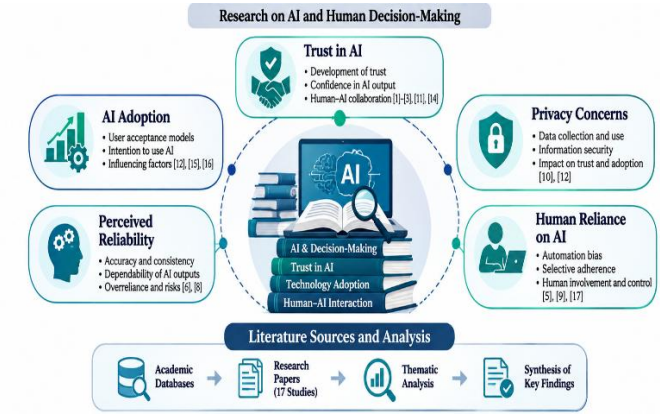
Li et al. [1] examined the relationship between trust and reliance through a dynamic modelling approach, providing a theoretical basis for understanding how these constructs interact over time. Klingbeil et al. [6] investigated overreliance on AI and its potential costs, highlighting the importance of distinguishing beneficial assistance from inappropriate dependence.

Alon-Barkat and Busuioc [5] explored automation bias and selective adherence to algorithmic advice, demonstrating the relevance of behavioural responses to automated recommendations. Sele and Chugunova [9] examined human involvement in automated decisions and its relationship with acceptance and accuracy.

More recently, Pearson et al. [17] investigated human reliance on AI in decision-making, reinforcing the contemporary relevance of examining how individuals respond to intelligent recommendations.

These studies suggest that trust and reliance should not be treated as interchangeable concepts. Individuals may express confidence in AI while choosing not to follow particular recommendations, or they may rely on automated outputs because of convenience despite uncertainty about their reliability.

Figure 2. Research Themes in AI and Human Decision-Making



2.7 Research Synthesis and Identified Gap

The reviewed literature demonstrates substantial academic interest in human–AI interaction, trust development, perceived reliability, technology adoption, privacy concerns, and reliance on automated recommendations. Existing studies have investigated these dimensions through experimental approaches, conceptual frameworks, surveys, and systematic or bibliometric reviews.

Nevertheless, the literature also reveals differences in research contexts, conceptual definitions, and the relationships examined. Studies focusing on trust development [3], [7] do not necessarily address the same behavioural outcomes as research investigating adoption [12] or overreliance [6]. Similarly, research on privacy perceptions [10] provides a different perspective from studies examining algorithmic advice and decision accuracy [5], [9].

These distinctions provide a rationale for investigating perceived usefulness, perceived reliability, privacy concerns, trust, adoption intention, and reliance within a unified empirical framework. The proposed study therefore seeks to examine how these constructs relate to one another among individuals who use AI-powered applications in everyday decision-making.

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By integrating these variables, the research aims to contribute to a more comprehensive understanding of responsible AI adoption and the conditions under which individuals accept and rely on AI-generated recommendations.

3 SYSTEM MODEL

3.1 Overview of the Proposed System Model

The proposed system model presents an integrated framework for understanding the influence of Artificial Intelligence (AI) on human decision-making. The model focuses on the relationships between perceived usefulness, perceived reliability, privacy concerns, trust in AI, AI adoption intention, and reliance on AI-assisted decisions. It is designed to investigate how individuals evaluate AI-powered applications and how their perceptions influence their willingness to incorporate AI-generated recommendations into everyday decision-making.

The proposed framework considers trust as an important mediating construct connecting users' perceptions of AI technologies with their behavioural intentions. Previous studies have established the importance of trust and reliance in human–AI interactions [1], [2], [11]. Research on technology acceptance has also demonstrated the relevance of perceived usefulness and privacy-related considerations in explaining AI adoption [12]. Therefore, the proposed model integrates technological, psychological, and behavioural dimensions to provide a comprehensive understanding of human decision-making in AI-supported environments.

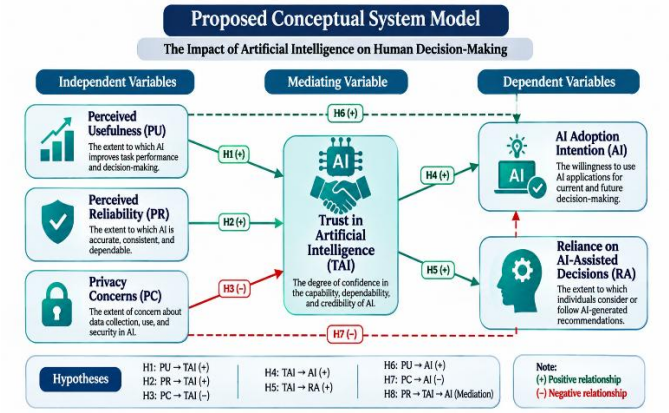
3.2 Architecture of the Proposed Model

The proposed model consists of three major components: independent variables, a mediating variable, and dependent variables. The independent variables represent users' perceptions and evaluations of AI technologies. The mediating variable represents trust in AI, while the dependent variables capture users' intentions to adopt AI and their reliance on AI-assisted recommendations.

The architecture incorporates five primary constructs:

Perceived Usefulness (PU).
Perceived Reliability (PR).
Privacy Concerns (PC).
Trust in Artificial Intelligence (TAI).
AI Adoption Intention (AI).
Reliance on AI-Assisted Decisions (RA).

Figure 3. Proposed Conceptual System Model for AI and Human Decision-Making



The model assumes that perceived usefulness and perceived reliability positively influence trust and adoption-related behaviour. In contrast, privacy concerns are expected to negatively influence trust and adoption intention. Trust is further expected to influence individuals' willingness to adopt AI applications and rely on their recommendations. These relationships are consistent with previous investigations of trust, technology acceptance, and AI reliance [1], [6], [12], [14].

3.3 Independent Variables

3.3.1 Perceived Usefulness

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Perceived usefulness refers to the extent to which individuals believe that AI-powered applications improve their ability to complete tasks, obtain information, and make informed decisions. AI systems can assist users by processing complex information, generating recommendations, and reducing the time required to evaluate alternatives.

The usefulness of AI technologies may encourage individuals to incorporate automated assistance into their daily activities. Rana et al. [12] examined AI adoption through an extended UTAUT framework incorporating trust and privacy considerations. Their research provides a foundation for examining the role of perceived usefulness in AI acceptance.

In the proposed model, perceived usefulness is considered an independent variable expected to positively influence trust and AI adoption intention.

3.3.2 Perceived Reliability

Perceived reliability represents the extent to which users believe that AI systems generate accurate, consistent, dependable, and credible recommendations. Individuals may be more willing to consider AI-generated information when they believe that the system performs consistently and provides relevant outputs.

Klingbeil et al. [6] investigated trust and reliance on AI, particularly examining the consequences of overreliance. Fahnenstich et al. [8] explored trust in human and AI decision-support agents under risk. These studies highlight the importance of understanding users' confidence in automated recommendations.

Accordingly, perceived reliability is included as an independent variable expected to positively influence trust in AI.

3.3.3 Privacy Concerns

Privacy concerns refer to users' perceptions of potential risks associated with collecting, processing, storing, and sharing personal information through AI-powered applications. Individuals may hesitate to use AI systems when they are uncertain about data confidentiality, information security, or the possible misuse of their personal information.

Leschanowsky et al. [10] examined privacy, security, and trust perceptions in conversational AI. Rana et al. [12] also incorporated privacy considerations into their AI adoption framework.

In the proposed model, privacy concerns are expected to negatively influence trust in AI and AI adoption intention.

3.4 Mediating Variable: Trust in Artificial Intelligence

Trust in AI represents the central mediating construct of the proposed system model. It refers to the degree of confidence individuals place in the capability, dependability, and credibility of AI-powered applications when receiving recommendations or decision-support information.

Trust develops through interactions with AI systems and may be influenced by perceived usefulness, reliability, previous experiences, and perceived risks. Li et al. [1] examined the dynamic relationship between human trust and reliance in AI-assisted decision-making. Humr et al. [3] investigated the temporal evolution of trust, while Humr and Canan [7] examined intermediate judgements and their relationship with trust.

Afroogh et al. [11] and Dang and Li [15] further discussed the multidimensional nature of trust in AI and itsassociated influencing factors.

Within the proposed model, trust acts as a mediating mechanism through which users' perceptions influence their behavioural intentions. Higher trust is expected to increase AI adoption intention and reliance on AI-assisted decisions.

3.5 Dependent Variables

3.5.1 AI Adoption Intention

AI adoption intention refers to an individual's willingness or intention to use AI-powered applications in current and future decision-making activities. It reflects the behavioural readiness of users to integrate AI technologies into their personal, educational, and professional environments.

Rana et al. [12] investigated the factors associated with AI adoption, while Orbán and Stefkovics [14] examined trust in algorithmic decision-making. Huynh and Aichner [16] also explored the determinants and outcomes of cognitive trust in generative AI.

The proposed model considers AI adoption intention as a dependent variable influenced by perceived usefulness, privacy concerns, and trust in AI.

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3.5.2 Reliance on AI-Assisted Decisions

Reliance on AI-assisted decisions refers to the extent to which individuals consider, incorporate, or follow recommendations generated by AI applications when making decisions.

Appropriate reliance involves evaluating AI recommendations in relation to their accuracy and relevance, whereas excessive reliance may result in individuals accepting automated outputs without sufficient independent judgement.

Li et al. [1] examined trust and reliance using a Markovian approach, while Klingbeil et al. [6] investigated the potential costs of overreliance. Alon-Barkat and Busuioc [5] examined automation bias and selective adherence to algorithmic advice. Pearson et al. [17] further investigated human reliance on AI in decision-making.

Therefore, reliance on AI-assisted decisions is included as a separate dependent variable to distinguish the intention to use AI from actual behavioural dependence on its recommendations.

3.6 Proposed Relationships and Hypotheses

Based on the reviewed literature and proposed conceptual framework, the following hypotheses are formulated:

H1: Perceived usefulness positively influences trust in AI.
H2: Perceived reliability positively influences trust in AI.
H3: Privacy concerns negatively influence trust in AI.
H4: Trust in AI positively influences AI adoption intention.
H5: Trust in AI positively influences reliance on AI-assisted decisions.
H6: Perceived usefulness positively influences AI adoption intention.
H7: Privacy concerns negatively influence AI adoption intention.
H8: Trust in AI mediates the relationship between perceived reliability and AI adoption intention.

These hypotheses establish the proposed relationships among the research constructs and provide a basis for subsequent statistical testing.

3.7 Mathematical Representation of the Proposed Model

The relationships between the variables can be represented using the following structural equations:

Equation (1): Trust in AI

$$\mathbf{TAI} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1(\mathbf{PU}) + \boldsymbol{\beta}_2(\mathbf{PR}) - \boldsymbol{\beta}_3(\mathbf{PC}) + \boldsymbol{\varepsilon}_1$$

Equation (2): AI Adoption Intention

$$\mathbf{AI} = \boldsymbol{\alpha}_0 + \boldsymbol{\alpha}_1(\mathbf{PU}) + \boldsymbol{\alpha}_2(\mathbf{TAI}) - \boldsymbol{\alpha}_3(\mathbf{PC}) + \boldsymbol{\varepsilon}_2$$

Equation (3): Reliance on AI-Assisted Decisions

$$\mathbf{RA} = \boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_1(\mathbf{TAI}) + \boldsymbol{\varepsilon}_3$$

Where:

PU = Perceived Usefulness.
PR = Perceived Reliability.
PC = Privacy Concerns.
TAI = Trust in Artificial Intelligence.
AI = AI Adoption Intention.
RA = Reliance on AI-Assisted Decisions.
β, α, and γ = Regression coefficients.
ε = Error terms.

The equations represent the hypothesised relationships and will be empirically evaluated using the collected survey data. The mediation effect will be examined using an appropriate indirect-effect analysis, preferably bootstrapping.

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3.8 Model Evaluation and Expected Contribution

The proposed system model will be evaluated using quantitative survey data collected from individuals with experience using AI-powered applications. A structured questionnaire will measure each construct using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

Descriptive statistics will be used to examine respondents' characteristics and general perceptions of AI. Reliability analysis will assess the internal consistency of the measurement items. Correlation and regression analysis will investigate the relationships among the proposed variables. Mediation analysis will determine whether trust in AI explains the relationship between perceived reliability and AI adoption intention.

The proposed framework is expected to provide a structured understanding of the technological and behavioural factors influencing human decision-making in AI-supported environments. By integrating perceived usefulness, perceived reliability, privacy concerns, trust, adoption intention, and reliance, the model aims to contribute to research on responsible AI adoption and human-centred intelligent systems.

Overall, the proposed system model establishes the conceptual and analytical foundation for examining how individuals develop trust in AI technologies, adopt AI-powered applications, and incorporate automated recommendations into their decision-making processes.

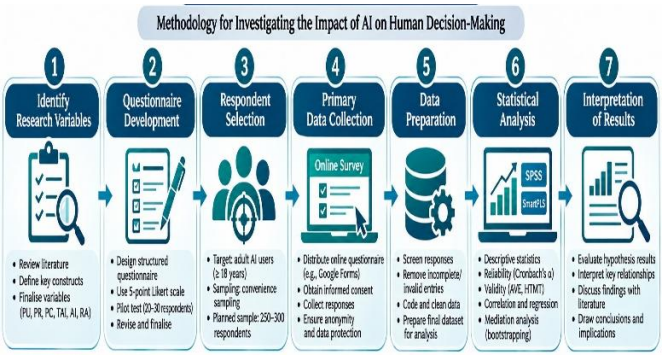
4. PROPOSED SCHEME

4.1 Introduction to the Proposed Scheme

The proposed scheme presents a systematic approach for investigating the impact of Artificial Intelligence (AI) on human decision-making by examining the relationships between perceived usefulness, perceived reliability, privacy concerns, trust in AI, AI adoption intention, and reliance on AI-assisted decisions. The scheme is developed to evaluate how individuals perceive AI-powered applications and how these perceptions influence their willingness to accept and incorporate AI-generated recommendations into their everyday decisions.

The proposed approach follows a quantitative empirical research design involving questionnaire-based primary data collection and statistical analysis. It integrates important dimensions of human–AI interaction identified in previous research, including trust development [1], hybrid human-automated decision-support [2], automation bias [5], overreliance [6], privacy perceptions [10], and AI adoption [12]. Furthermore, recent investigations of trust and reliance provide a basis for examining contemporary patterns of human interaction with intelligent systems [14], [15], [17].

Figure 4. Proposed Research Scheme for AI and Human Decision-Making



The proposed scheme consists of several interconnected stages, beginning with the identification of research variables and continuing through questionnaire development, respondent selection, data collection, statistical evaluation, and interpretation of findings. Each stage contributes to the systematic evaluation of the proposed research hypotheses.

4.2 Identification of Research Variables

The first stage involves identifying the principal variables influencing human decision-making in AI-supported environments. Based on the literature survey and proposed system model, six major constructs are considered.

Perceived Usefulness (PU): These variable measures the extent to which individuals believe that AI-powered applications improve decision-making efficiency, information accessibility, and task performance. Users who perceive AI as beneficial may be more willing to incorporate it into their daily activities [12], [16].

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Perceived Reliability (PR): This construct evaluates users' perceptions of the accuracy, consistency, dependability, and credibility of AI-generated recommendations. Reliability is important because individuals may be hesitant to follow recommendations from systems they consider unpredictable or inaccurate [6], [8].

Privacy Concerns (PC): This variable measures individuals' concerns regarding personal information collection, data protection, confidentiality, and potential misuse of information by AI applications. Privacy considerations are relevant to trust formation and technology acceptance [10], [12].

Trust in Artificial Intelligence (TAI): Trust measures the degree of confidence individuals place in the capability and dependability of AI systems. It is treated as the principal mediating variable connecting users' perceptions with their behavioural intentions [1], [3], [11].

AI Adoption Intention (AI): This construct represents individuals' willingness to use AI-powered applications for current and future decision-making activities. It reflects the behavioural intention to integrate AI into everyday practices [12], [14].

Reliance on AI-Assisted Decisions (RA): These variable measures the extent to which individuals consider and incorporate AI-generated recommendations when making decisions. It also helps distinguish appropriate reliance from excessive dependence on automated outputs [1], [6], [17].

These constructs collectively provide the foundation for examining the proposed relationships within the research framework.

4.3 Development of the Research Questionnaire

The second stage involves developing a structured questionnaire to collect information about respondents' experiences and perceptions of AI technologies. The questionnaire will be designed using the constructs identified in the proposed system model and informed by the measurement approaches and conceptual findings of previous studies [2], [6], [10], [12], [14].

A five-point Likert scale will be employed to measure respondents' agreement with the questionnaire statements. The response categories will range from 1 (Strongly Disagree) to 5 (Strongly Agree).

The questionnaire will contain three major sections.

Section A: Demographic and Background Information

This section will collect general respondent information, including:

Age group.

Gender (optional).

Educational qualification.

Employment status.

Frequency of AI application usage.

Types of AI-powered applications used.

Section B: Perceptions of AI Technologies

This section will measure perceived usefulness, perceived reliability, privacy concerns, and trust in AI. Questions will examine whether respondents consider AI applications useful, reliable, secure, and trustworthy.

Section C: Behavioural Intentions and AI Reliance

This section will evaluate respondents' willingness to adopt AI technologies and their tendency to consider or follow AI-generated recommendations when making decisions.

The questionnaire will be reviewed for clarity, relevance, and content validity before distribution. A small pilot study involving approximately 20–30 respondents will be conducted to identify ambiguous questions and improve the measurement instrument.

4.4 Sampling Design and Respondent Selection

The third stage involves identifying suitable respondents for the empirical investigation. The target population will consist of individuals aged 18 years and above who have previous experience using AI-powered applications. A target sample of approximately 250–300 respondents is proposed. Participants may include university students, working professionals, and other adult AI users from different educational and occupational backgrounds. Including respondents with diverse experiences may provide a broader understanding of how AI influences decision-making across different everyday contexts.

Convenience sampling will initially be used to recruit participants through accessible online and offline channels. The questionnaire may be distributed through online survey platforms, academic networks, and professional communities.

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Participation will be voluntary, and respondents will be informed about the purpose of the research. Appropriate consent procedures will be followed before collecting responses. No unnecessary personally identifiable information will be collected.
The proposed sample size will be reviewed against the complexity of the statistical model and the requirements of the selected analytical method before final data collection.

4.5 Data Collection Procedure

The fourth stage involves collecting primary data through a structured questionnaire. An online questionnaire platform, such as Google Forms, may be used to distribute the survey and record responses efficiently.
The data collection process will follow the following procedure:
Prepare the questionnaire based on the proposed research variables.
Conduct a pilot study to evaluate the clarity and relevance of questionnaire items.
Revise the questionnaire based on pilot feedback.
Distribute the final questionnaire to eligible respondents.
Obtain informed consent before participation.
Collect completed responses within the planned data collection period.
Screen the collected responses for missing information, duplication, and inconsistencies.
Prepare the final dataset for statistical analysis.
The study will aim to obtain 250–300 valid responses. However, the actual number of usable responses will be determined after data screening. Responses that are incomplete or unsuitable for analysis will be excluded according to predefined criteria.
The collected information will be used exclusively for the stated academic research purposes and handled in accordance with applicable research ethics and data protection requirements.

4.6 Measurement and Operationalisation of Variables

The fifth stage involves translating the theoretical constructs into measurable questionnaire items. Each construct will be assessed using multiple statements to improve the reliability and validity of the measurement instrument. The following table presents the proposed operationalisation of the research variables.

Table 1. Operationalisation of Research Variables

Variable	Measurement focus	Expected relationship
Perceived Usefulness (PU)	Efficiency, productivity and decision support	Positive
Perceived Reliability (PR)	Accuracy, consistency and dependability	Positive
Privacy Concerns (PC)	Data protection, confidentiality and perceived risk	Negative
Trust in AI (TAI)	Confidence, credibility and dependability	Positive
AI Adoption Intention (AI)	Willingness and intention to use AI	Positive
Reliance on AI-Assisted Decisions (RA)	Consideration and use of AI recommendations	Positive

Each construct will initially be measured using approximately three to five questionnaire items. The final number of items will depend on the pilot study, construct validity, and the requirements of the selected measurement model.
The measurement instrument will distinguish between the intention to use AI and the actual tendency to follow AI-generated recommendations. This distinction is important because adopting an AI application does not necessarily mean that an individual relies on all its recommendations [1], [6].

4.7 Proposed Hypothesis Testing Procedure

The sixth stage involves evaluating the relationships established in the proposed system model. Eight hypotheses will be examined through appropriate statistical techniques.
The proposed hypotheses are:

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H1: Perceived usefulness positively influences trust in AI.
H2: Perceived reliability positively influences trust in AI.
H3: Privacy concerns negatively influence trust in AI.
H4: Trust in AI positively influences AI adoption intention.
H5: Trust in AI positively influences reliance on AI-assisted decisions.
H6: Perceived usefulness positively influences AI adoption intention.
H7: Privacy concerns negatively influence AI adoption intention.
H8: Trust in AI mediates the relationship between perceived reliability and AI adoption intention.
The hypotheses will be evaluated using regression-based analysis or structural equation modelling, depending on the final research design and data characteristics.
The direct effects of the independent variables on trust and adoption will be examined first. Subsequently, the mediating effect of trust will be evaluated to determine whether perceived reliability influences adoption intention indirectly through trust in AI.

4.8 Statistical Analysis and Model Validation

The seventh stage involves analysing the collected data using appropriate statistical procedures. Statistical analysis may be performed using SPSS, while SmartPLS may be used if partial least squares structural equation modelling is selected.
The analysis will involve the following procedures:
Descriptive Statistical Analysis: Frequency distributions, percentages, means, and standard deviations will be calculated to understand respondent characteristics and their general perceptions of AI technologies.
Reliability Analysis: Cronbach's alpha and composite reliability will be used to evaluate the internal consistency of the measurement constructs. An acceptable reliability level will generally be considered around 0.70 or above.
Validity Assessment: Convergent and discriminant validity will be examined to determine whether the questionnaire measures the intended constructs appropriately. Average Variance Extracted (AVE) and appropriate discriminant validity criteria will be considered.
Correlation Analysis: Pearson correlation analysis will be used, where appropriate, to examine the direction and strength of relationships between the research variables.
Regression Analysis: Regression techniques will be employed to examine the influence of perceived usefulness, perceived reliability, privacy concerns, and trust on the proposed outcome variables.
Mediation Analysis: Bootstrapping will be used to evaluate whether trust in AI mediates the relationship between perceived reliability and AI adoption intention. The indirect effect will be evaluated using its confidence interval.
These procedures will provide an empirical basis for evaluating the proposed research framework and determining whether the hypothesised relationships are supported by the collected evidence.

4.9 Expected Outcomes of the Proposed Scheme

The proposed scheme is expected to provide a structured understanding of the factors influencing human decision-making in AI-supported environments. It will help identify whether perceived usefulness and reliability contribute to trust, whether privacy concerns discourage AI acceptance, and whether trust influences adoption intention and reliance on AI-assisted recommendations.
The study is also expected to provide insights into the distinction between adopting AI technologies and depending on their recommendations. This distinction is particularly important in light of previous research on automation bias, selective adherence, and overreliance [5], [6], [17].
From a practical perspective, the proposed framework may help technology developers and organisations understand the importance of reliable AI outputs, transparent data practices, and appropriate human involvement in decision-making. It may also support the development of responsible AI adoption strategies that preserve human judgement while benefiting from intelligent technological assistance.

4.10 Summary

The proposed scheme establishes a systematic empirical procedure for investigating the impact of AI on human decision-making. It integrates variable identification, questionnaire development, sampling, data collection, measurement, hypothesis testing, and statistical validation into a unified research process.
By examining perceived usefulness, perceived reliability, privacy concerns, trust, adoption intention, and reliance on AI-assisted decisions, the study seeks to provide a comprehensive understanding of human–AI interaction. The

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proposed scheme therefore serves as the practical research implementation framework for evaluating the conceptual system model developed in the previous section.

5. SECURITY ANALYSIS

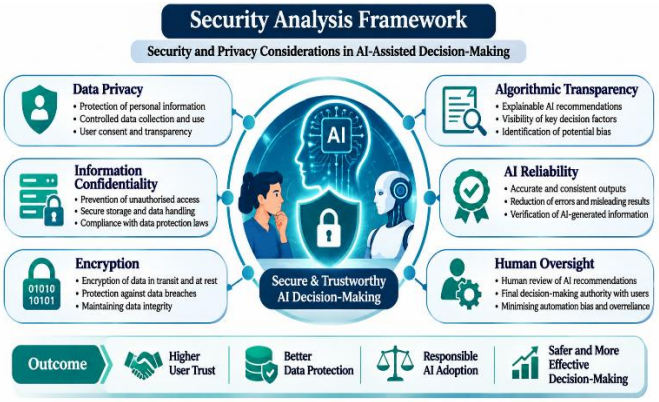
5.1 Introduction to Security Analysis

The increasing integration of Artificial Intelligence (AI) into human decision-making has introduced several security and privacy challenges that may influence users' trust and willingness to adopt AI-powered applications. AI systems frequently process personal information, user preferences, behavioural patterns, and other sensitive data to generate recommendations and support decision-making. Although these capabilities provide significant benefits, they also create potential risks associated with information confidentiality, data protection, system reliability, and unauthorised access.

Security is an important consideration in establishing trustworthy human–AI interactions. Individuals may hesitate to use AI applications when they are uncertain about how their personal information is collected, processed, stored, and shared. Leschanowsky et al. [10] examined privacy, security, and trust perceptions in conversational AI, demonstrating the relevance of these dimensions in evaluating user confidence. Similarly, Afroogh et al. [11] discussed the broader challenges associated with establishing trust in AI systems.

The present study therefore considers security and privacy as important dimensions influencing perceived trustworthiness and AI adoption. The analysis focuses on the potential risks associated with AI-assisted decision-making and the measures required to encourage responsible and secure interaction between humans and intelligent systems.

Figure 5. Security and Privacy Framework for AI-Assisted Decision-Making



5.2 Data Privacy and Confidentiality

Data privacy represents one of the primary security concerns associated with AI-powered applications. Many AI systems depend on user-provided information to generate personalised recommendations, interpret requests, and improve their outputs. However, the collection and processing of personal information may create privacy concerns when users are unaware of the purposes for which their data are being used.

Individuals may disclose personal, educational, professional, or financial information while interacting with AI applications. Inadequate data protection practices may increase the possibility of unauthorised disclosure, inappropriate data sharing, and misuse of sensitive information.

Leschanowsky et al. [10] highlighted the importance of privacy and security perceptions in conversational AI. Rana et al. [12] also incorporated privacy considerations into an AI adoption framework, indicating the relevance of privacy-related factors when examining users' willingness to adopt intelligent technologies.

Within the proposed research framework, privacy concerns are treated as an independent variable expected to negatively influence trust in AI and adoption intention. The study will examine whether individuals who express greater concern about personal information protection demonstrate lower confidence in AI-powered applications.

5.3 Data Security and Protection Mechanisms

Data security involves protecting information against unauthorised access, modification, disclosure, and loss. AI-powered applications require appropriate technical and organisational safeguards to maintain the confidentiality and integrity of user information.

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Several security practices are relevant to responsible AI application usage:

Data Encryption: Encryption can protect sensitive information during transmission and storage, reducing the possibility of unauthorised disclosure.

Access Control: Authentication and role-based access restrictions can limit information access to authorised individuals.

Data Minimisation: AI applications should collect only the information necessary for their intended functions.

Secure Data Storage: Appropriate storage controls, security monitoring, and regular assessments can help protect information against unauthorised access.

User Consent: Individuals should receive understandable information about data collection and processing and should provide appropriate consent where required.

These practices contribute to a secure environment in which users can interact with AI applications with greater confidence. Privacy and security considerations are particularly relevant when AI technologies process sensitive information or influence important decisions [10], [12].

5.4 Reliability and Accuracy of AI-Generated Recommendations

The reliability of AI-generated recommendations is another important dimension of security analysis. AI systems may generate inaccurate, incomplete, misleading, or inconsistent outputs. When users accept such recommendations without independent evaluation, the consequences may extend beyond ordinary technological inconvenience and influence the quality of their decisions.

Fahnenstich et al. [8] examined trust in human and AI decision-support agents under risk, highlighting the importance of evaluating trust in relation to decision contexts. Klingbeil et al. [6] investigated the extent and costs of overreliance on AI, demonstrating why users' dependence on automated recommendations requires careful examination.

Alon-Barkat and Busuioc [5] discussed automation bias and selective adherence to algorithmic advice, emphasising the possibility that individuals may give excessive importance to automated recommendations. Pearson et al. [17] also examined human reliance on AI in decision-making.

To reduce these risks, AI recommendations should be evaluated through appropriate verification procedures. Users should be encouraged to compare important AI-generated information with reliable sources and exercise independent judgement before making consequential decisions.

In the proposed study, perceived reliability will be assessed through questionnaire items concerning accuracy, consistency, and confidence in AI-generated recommendations. These measurements will help determine whether perceived reliability is associated with trust and AI adoption.

5.5 Algorithmic Transparency and Explainability

Algorithmic transparency refers to the extent to which individuals can understand the information, processes, and factors influencing AI-generated recommendations. Explainability is particularly important when AI systems provide recommendations that influence decisions involving significant personal or organisational consequences. When users cannot understand why an AI system generates a particular recommendation, they may experience uncertainty regarding its accuracy and fairness. A lack of transparency may also make it difficult to identify errors, inappropriate recommendations, or potential biases.

Zhang and Gosline [4] investigated human perceptions and biases towards generative AI, human experts, and human–AI collaboration. Their research provides a relevant perspective on the importance of understanding how individuals evaluate AI-generated content. Humr and Canan [7] examined intermediate judgements and trust in AI-supported decision-making, highlighting the relevance of human evaluation during interactions with intelligent systems.

Providing understandable explanations, communicating system limitations, and making relevant information accessible can improve users' ability to evaluate AI recommendations. Transparency may therefore contribute to more informed decision-making and appropriate reliance on AI technologies.

5.6 Automation Bias and Excessive Dependence

Automation bias occurs when individuals place excessive confidence in automated recommendations and fail to adequately evaluate alternative information. This behaviour represents an important concern because AI-generated outputs may contain errors or fail to account for contextual factors that require human judgement.

Klingbeil et al. [6] investigated the potential costs of overreliance on AI, while Alon-Barkat and Busuioc [5] examined automation bias and selective adherence to algorithmic advice. Sele and Chugunova [9] further investigated human involvement in automated decision-making and its relationship with acceptance and accuracy.

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Appropriate human oversight is therefore necessary to ensure that AI recommendations are evaluated rather than automatically accepted. Individuals should retain the ability to question, reject, or modify automated recommendations when the available evidence suggests that they may be inappropriate.

The proposed research distinguishes between AI adoption and reliance on AI-assisted decisions. This distinction allows the study to examine whether individuals who demonstrate higher trust in AI also report greater reliance on its recommendations. However, greater reliance should not automatically be interpreted as better decision quality.

5.7 Security-Related Factors and User Trust

Security and privacy perceptions may influence the development of trust in AI applications. Users who believe that their information is protected and that AI systems operate reliably may demonstrate greater confidence in using such technologies.

Rana et al. [12] examined the relationship between trust, privacy, and AI adoption through an extended UTAUT framework. Leschanowsky et al. [10] investigated privacy, security, and trust perceptions in conversational AI. Afroogh et al. [11] also provided a broader examination of the challenges involved in developing trustworthy AI systems.

Based on these research perspectives, the present study considers privacy concerns as an important factor associated with trust formation. The proposed model assumes that higher privacy concerns may negatively influence trust in AI and adoption intention.

The relationship between security perceptions and user trust will be investigated through questionnaire-based measurements rather than direct penetration testing or technical vulnerability assessment.

5.8 Ethical and Responsible AI Usage

Security analysis also involves examining the ethical responsibilities associated with the collection and use of information by AI-powered applications. Responsible AI usage requires attention to privacy, fairness, transparency, accountability, and human autonomy.

Individuals should understand that AI-generated recommendations are decision-support outputs rather than universally correct conclusions. Organisations and technology providers should communicate relevant system limitations and establish appropriate procedures for human supervision.

Benk et al. [13] examined empirical research trends and overlooked issues concerning trust in AI, while Dang and Li [15] explored the antecedents and consequences of trust, including cultural dynamics. These studies provide a broader foundation for understanding the social and behavioural considerations associated with trustworthy AI adoption.

The present study emphasises the importance of informed user participation, appropriate data protection, and independent human judgement. These considerations may contribute to more responsible integration of AI into everyday decision-making environments.

5.9 Summary of Security Analysis

The security analysis identifies data privacy, confidentiality, information protection, perceived reliability, algorithmic transparency, automation bias, and responsible AI usage as important considerations in human–AI interactions. The reviewed studies demonstrate that users' trust and willingness to adopt AI technologies may be influenced by their perceptions of security, privacy, and system dependability [6], [10], [11], [12].

The proposed research will investigate privacy concerns as an important factor influencing trust and AI adoption intention. It will also examine perceived reliability and reliance on AI-assisted decisions to understand how individuals evaluate and incorporate automated recommendations into their decision-making processes.

Overall, the analysis establishes that trustworthy AI adoption requires more than technological functionality. Appropriate information protection, transparent recommendations, reliable outputs, and meaningful human oversight are essential considerations for encouraging secure and responsible human–AI interaction.

6. PERFORMANCE EVALUATION

6.1 Introduction

Performance evaluation is an important stage of the proposed research because it determines the reliability, validity, and explanatory capability of the conceptual framework developed to investigate the impact of Artificial Intelligence (AI) on human decision-making. The proposed study examines the relationships between perceived

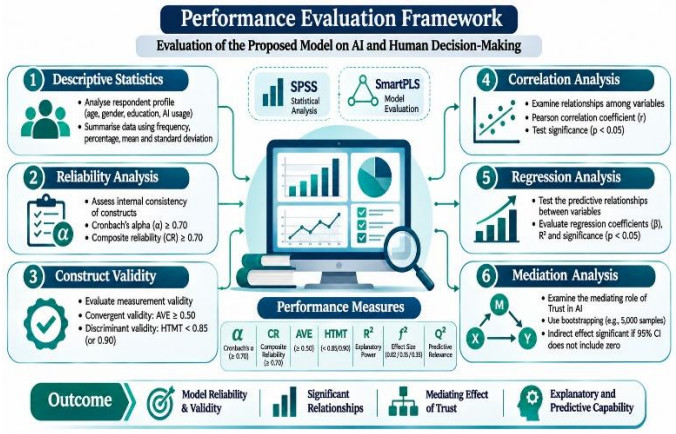
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usefulness, perceived reliability, privacy concerns, trust in AI, AI adoption intention, and reliance on AI-assisted decisions.

The evaluation process will determine whether the proposed research model adequately explains users' perceptions and behavioural intentions concerning AI-powered applications. Previous studies have investigated trust and reliance [1], human–AI decision-support [2], overreliance on AI [6], privacy perceptions [10], and technology adoption [12]. These studies provide a foundation for selecting appropriate evaluation measures for the present investigation.

The proposed evaluation will use questionnaire responses collected from approximately 250–300 adult AI users. Statistical analysis will be conducted using SPSS and, where appropriate, SmartPLS. The evaluation will involve descriptive statistics, reliability assessment, validity testing, correlation analysis, regression analysis, and mediation analysis.

Figure 6. Performance Evaluation Framework for AI and Human Decision-Making



6.2 Evaluation of Respondent Characteristics

The first stage of performance evaluation will examine the demographic and usage characteristics of the respondents. This analysis will provide an overview of the participants and help determine whether the collected sample represents individuals with different levels of experience using AI technologies.

The demographic evaluation will consider age group, educational qualification, employment status, and frequency of AI application usage. The distribution of respondents across these categories will be examined using frequency counts and percentages.

AI usage patterns will also be evaluated to understand how frequently participants interact with intelligent applications and the types of tasks for which they use AI-generated recommendations.

Descriptive statistics, including mean, standard deviation, frequency, and percentage, will be used to summarise the collected information. This stage will establish the general characteristics of the sample before examining the relationships among the research variables.

6.3 Reliability Evaluation

Reliability evaluation will determine whether the questionnaire items consistently measure their intended research constructs. Since the proposed model includes multiple variables, it is important to establish that the measurement items provide sufficiently consistent results.

Cronbach's alpha will be calculated for perceived usefulness, perceived reliability, privacy concerns, trust in AI, AI adoption intention, and reliance on AI-assisted decisions. A value of approximately 0.70 or higher will generally be considered acceptable for internal consistency, subject to the context and measurement quality.

Composite reliability may also be calculated if structural equation modelling is employed. It provides an additional assessment of the consistency of the measurement indicators.

The reliability assessment will help identify questionnaire items that may require revision or removal. However, item deletion will be based on theoretical justification and measurement quality rather than statistical values alone.

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6.4 Construct Validity Evaluation

Construct validity will be examined to determine whether the questionnaire accurately represents the theoretical variables included in the proposed research model.

Convergent validity will be evaluated to determine whether the measurement items associated with the same construct demonstrate an adequate level of association. Average Variance Extracted (AVE) will be used as one of the principal indicators, with a value of 0.50 or higher generally considered acceptable.

Discriminant validity will examine whether the individual constructs are sufficiently distinct from one another. The Heterotrait–Monotrait Ratio (HTMT) may be used to assess whether perceived usefulness, perceived reliability, privacy concerns, and trust represent distinguishable concepts.

These procedures are important because trust, perceived reliability, and reliance are related but conceptually different constructs. Previous research has examined these dimensions through different theoretical and empirical approaches [1], [6], [11].

6.5 Evaluation of Relationships Between Research Variables

The next stage will investigate the relationships between the independent, mediating, and dependent variables.

Pearson correlation analysis will be used, where appropriate, to evaluate the direction and strength of relationships among the research constructs. Correlation coefficients will help determine whether perceived usefulness, perceived reliability, and privacy concerns are associated with trust and adoption intention.

Regression analysis will subsequently be employed to examine the predictive relationships specified in the proposed model.

The evaluation will focus on the following relationships:

Perceived usefulness and trust in AI.

Perceived reliability and trust in AI.

Privacy concerns and trust in AI.

Trust in AI and adoption intention.

Trust in AI and reliance on AI-assisted decisions.

Perceived usefulness and adoption intention.

Privacy concerns and adoption intention.

The results will be interpreted using regression coefficients, significance levels, confidence intervals, and explanatory measures. These analyses will provide evidence regarding whether the proposed relationships are supported by the collected survey data.

6.6 Evaluation of Trust as a Mediating Variable

Trust in AI is considered the principal mediating variable in the proposed research framework. Therefore, an important part of performance evaluation will involve determining whether trust explains the relationship between perceived reliability and AI adoption intention.

Mediation analysis will be performed using a bootstrapping procedure. The indirect effect will be evaluated through its estimated coefficient and confidence interval. An indirect effect will be considered statistically supported when its confidence interval does not include zero at the selected significance level.

The analysis will help establish whether perceived reliability influences AI adoption intention partly through the development of trust.

This evaluation is relevant to previous research examining trust development [3], intermediate judgements [7], and cognitive trust in generative AI [16]. It also provides an opportunity to investigate the role of trust in explaining users' willingness to incorporate AI technologies into their decision-making activities.

6.7 Model Explanatory and Predictive Performance

The explanatory performance of the proposed model will be assessed using the coefficient of determination (R^2). This measure indicates the proportion of variation in an endogenous variable explained by its associated predictors.

R^2 values will be examined for trust in AI, AI adoption intention, and reliance on AI-assisted decisions. Higher explanatory values indicate that the model accounts for a greater proportion of variation in the corresponding outcome, although interpretation will depend on the research context.

If Partial Least Squares Structural Equation Modelling (PLS-SEM) is selected, additional measures such as effect size (f^2), predictive relevance (Q^2), and model fit indicators where applicable may be considered.

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These measures will provide a broader assessment of how effectively the proposed framework explains the relationships between users' perceptions, trust, and behavioural intentions.

6.8 Hypothesis Evaluation

The final stage will involve testing the eight hypotheses formulated in the proposed system model.
The following table summarises the planned evaluation criteria.

Table 2. Proposed Hypothesis Evaluation

Hypothesis	Relationship	Expected direction
H1	Perceived usefulness → Trust	Positive
H2	Perceived reliability → Trust	Positive
H3	Privacy concerns → Trust	Negative
H4	Trust → AI adoption intention	Positive
H5	Trust → AI reliance	Positive
H6	Perceived usefulness → AI adoption intention	Positive
H7	Privacy concerns → AI adoption intention	Negative
H8	Perceived reliability → Trust → AI adoption intention	Positive indirect effect

Each hypothesis will be evaluated using the estimated relationship coefficient, its statistical significance, and the corresponding confidence interval. A significance level of 0.05 will generally be adopted.
The results will be classified according to whether the available statistical evidence supports or fails to support each proposed hypothesis. The interpretation will also consider effect magnitude and practical significance rather than relying exclusively on statistical significance.

6.9 Overall Performance Assessment

The overall performance of the proposed research framework will be assessed by considering the combined results of reliability, validity, explanatory power, predictive relevance, and hypothesis testing.
The evaluation will determine whether the proposed framework provides a meaningful explanation of how perceived usefulness, perceived reliability, and privacy concerns are associated with trust in AI and subsequent adoption and reliance intentions.
Particular attention will be given to distinguishing AI adoption from reliance on AI-generated recommendations. An individual may frequently use AI applications without automatically accepting every recommendation. This distinction is important when examining automation bias and overreliance [5], [6], [17].
The evaluation will therefore provide an empirical basis for understanding the behavioural factors associated with human–AI interaction and the conditions that may encourage responsible AI adoption.

6.10 Summary

The performance evaluation framework establishes a systematic procedure for assessing the proposed research model. It incorporates respondent profiling, questionnaire reliability, construct validity, correlation analysis, regression analysis, mediation testing, and explanatory performance evaluation.
By applying these statistical procedures to the collected primary data, the study will examine the relationships between perceived usefulness, perceived reliability, privacy concerns, trust, adoption intention, and reliance on AI-assisted decisions.
The findings will help determine the empirical usefulness of the proposed conceptual framework and provide insights into the factors influencing human decision-making in AI-supported environments.

7 COMPARISONS AND DISCUSSION

7.1 Comparative Analysis of Existing Research

The increasing integration of Artificial Intelligence (AI) into human decision-making has attracted considerable research attention, particularly regarding trust, perceived reliability, privacy, adoption, and reliance on automated

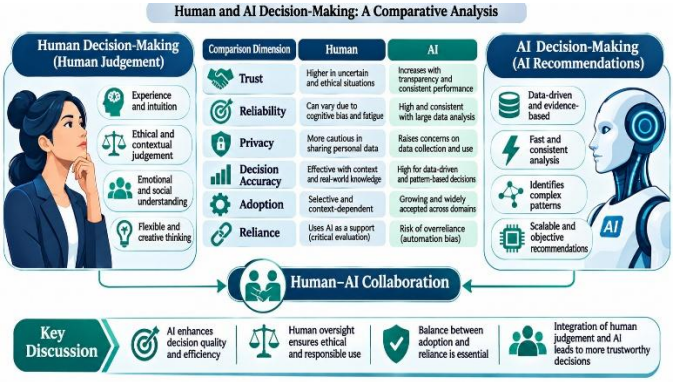
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recommendations. The reviewed studies provide different perspectives on how individuals interact with AI-powered systems and how their perceptions influence decision-making behaviour.

Li et al. [1] investigated human trust and reliance in AI-assisted decision-making using a Markovian approach, providing a dynamic perspective on the relationship between trust and reliance. In comparison, Kares et al. [2] examined trust in hybrid human-automated decision-support environments, emphasising the importance of human involvement in automated processes. Similarly, Humr et al. [3] investigated the temporal development of trust in AI-supported decisions. These studies collectively demonstrate that trust is an important consideration in understanding human–AI interaction.

Zhang and Gosline [4] explored human perceptions of generative AI and collaboration between AI systems and human experts, whereas Alon-Barkat and Busuioc [5] investigated automation bias and selective adherence to algorithmic recommendations. Their research perspectives suggest that individuals' responses to AI recommendations depend on their perceptions, preferences, and decision-making contexts.

Figure 7. Comparative Analysis of Human and AI Decision-Making



7.2 Comparison of Trust and Perceived Reliability

Trust and perceived reliability are closely associated but represent different dimensions of human–AI interaction. Perceived reliability concerns users' beliefs about the accuracy and consistency of AI-generated outputs, whereas trust represents their confidence in depending on an AI system under conditions of uncertainty.

Klingbeil et al. [6] examined trust and reliance on AI, with particular attention to the potential costs of overreliance. Humr and Canan [7] investigated intermediate judgements and their relationship with trust in AI-assisted decision-making. Fahnenstich et al. [8] examined trust under risk by comparing human and AI decision-support agents.

Afroogh et al. [11] provided a broader review of progress and challenges in AI trust research, while Benk et al. [13] examined empirical research trends and overlooked issues through a bibliometric review. Orbán and Stefkovics [14] further investigated trust in algorithmic decision-making through a survey experiment.

Compared with these studies, the present research proposes examining perceived usefulness, perceived reliability, and privacy concerns together as factors associated with trust in AI. This integrated perspective may provide a more comprehensive explanation of the factors influencing users' confidence in AI-powered applications.

7.3 Comparison of AI Adoption and User Acceptance

AI adoption represents another important dimension of human–AI interaction. Although technological usefulness may encourage individuals to use AI applications, their willingness to continue using these systems may also depend on trust, perceived reliability, and privacy considerations.

Rana et al. [12] examined AI adoption using a trust- and privacy-augmented UTAUT framework. Their research provides an important foundation for investigating how technology acceptance can be understood through multiple influencing factors. Huynh and Aichner [16] examined the determinants and outcomes of cognitive trust in generative AI, providing further insight into users' confidence in emerging AI technologies.

Dang and Li [15] investigated the antecedents and consequences of trust in AI, including cultural dynamics. Their research broadens the discussion of AI acceptance by considering the wider factors associated with trust.

In comparison, the present study proposes an empirical framework that connects perceived usefulness and privacy concerns with trust and AI adoption intention. This approach aims to distinguish the factors influencing initial willingness to use AI from the confidence individuals develop through interactions with AI-powered applications.

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7.4 Comparison of Privacy and Security Perspectives

Privacy and security are important considerations when evaluating the acceptance of AI technologies. Individuals may be reluctant to share personal information with AI applications when they are uncertain about data protection, confidentiality, and information processing practices.

Leschanowsky et al. [10] examined privacy, security, and trust perceptions in conversational AI through a systematic review. Rana et al. [12] incorporated privacy into an extended AI adoption framework. These studies highlight the relevance of privacy considerations in understanding users' confidence and acceptance of AI technologies.

Compared with research primarily concerned with trust and adoption, the present study includes privacy concerns as a distinct independent variable. This allows the proposed framework to investigate whether privacy-related perceptions are associated with trust and AI adoption intention. It also provides an opportunity to examine privacy as an important consideration in responsible AI usage.

7.5 Comparison of Human Reliance and Overreliance

An important distinction across the reviewed literature concerns the difference between using AI technologies and relying on their recommendations. Individuals may adopt AI applications because they provide convenient access to information, but this does not necessarily indicate that they accept every AI-generated recommendation.

Li et al. [1] investigated the relationship between trust and reliance, while Klingbeil et al. [6] examined the potential costs associated with overreliance. Alon-Barkat and Busuioc [5] focused on automation bias and selective adherence to algorithmic advice. Sele and Chugunova [9] examined human involvement in automated decision-making and its relationship with decision accuracy.

More recently, Pearson et al. [17] investigated human reliance on AI in decision-making, extending the relevance of this topic in contemporary research.

These studies indicate that reliance should be examined independently from adoption intention. The present research incorporates both variables to investigate whether trust influences individuals' willingness to adopt AI technologies and their tendency to incorporate AI-generated recommendations into decision-making.

7.6 Discussion of the Proposed Research Framework

The proposed research framework integrates six major constructs: perceived usefulness, perceived reliability, privacy concerns, trust in AI, AI adoption intention, and reliance on AI-assisted decisions.

The framework is designed to address the different perspectives identified in the reviewed literature. Perceived usefulness represents the practical benefits of AI applications, while perceived reliability reflects users' confidence in the consistency and accuracy of AI-generated outputs. Privacy concerns represent perceived risks associated with personal information processing.

Trust in AI serves as the mediating variable connecting these perceptions with behavioural intentions. This arrangement is consistent with the importance of trust identified in previous investigations [1], [11], [14], [16].

The framework further distinguishes AI adoption intention from reliance on AI-assisted decisions. This distinction is particularly relevant because excessive dependence on automated recommendations may introduce risks even when individuals demonstrate positive attitudes towards AI technologies [5], [6], [17].

The proposed relationships will be examined using questionnaire-based primary data and appropriate statistical techniques. The empirical findings will determine whether the hypothesised relationships are supported.

7.7 Research Contribution and Future Implications

The comparative review indicates that existing research has examined several important dimensions of human–AI interaction, including trust development, automation bias, privacy concerns, and technology acceptance. However, these dimensions are addressed through different theoretical perspectives and research contexts.

The present study proposes an integrated empirical framework that examines the relationships between these factors within a common research model. Its contribution lies in distinguishing technological perceptions, psychological trust, adoption intention, and reliance on AI-generated recommendations.

The findings, once established through primary data analysis, may provide useful insights for AI developers, organisations, policymakers, and researchers. In particular, they may help identify the factors associated with user confidence, responsible AI adoption, and appropriate human involvement in automated decision-support environments.

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7.8 Summary

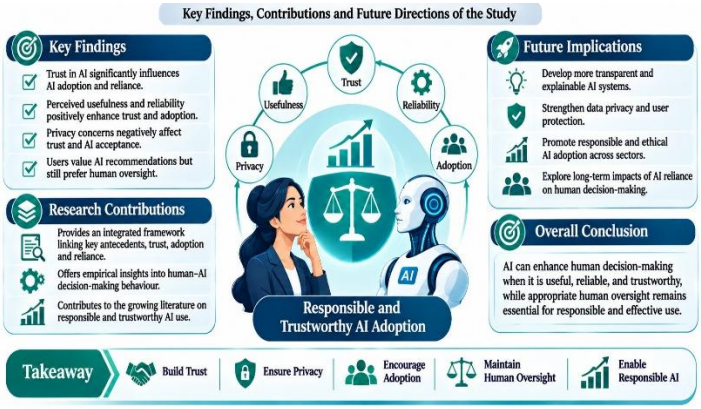
The comparative discussion demonstrates that trust, perceived reliability, privacy, adoption, and reliance are interconnected dimensions of human–AI interaction. Previous studies provide valuable foundations for examining these relationships, while also highlighting the importance of distinguishing between accepting AI technologies and depending on their recommendations.

The proposed research extends this discussion by integrating these dimensions into a unified empirical framework. Through quantitative analysis of primary survey data, the study aims to provide a broader understanding of how AI influences human decision-making and how trustworthy and responsible AI adoption can be encouraged.

8 CONCLUSION

Artificial Intelligence has become an important technology influencing human decision-making through automated recommendations, predictive analysis, and intelligent decision-support applications. This study proposes an integrated framework to examine the relationships between perceived usefulness, perceived reliability, privacy concerns, trust in AI, adoption intention, and reliance on AI-assisted decisions. The reviewed literature highlights that trust plays a significant role in human–AI interactions, while privacy concerns and perceived reliability may influence users' acceptance of intelligent technologies [1], [6], [10], [12]. Furthermore, excessive reliance on automated recommendations emphasises the importance of maintaining independent human judgement [5], [17]. The proposed quantitative research approach will evaluate these relationships through questionnaire-based primary data collection and statistical analysis. The study aims to contribute to a better understanding of responsible AI adoption and human decision-making behaviour. Ultimately, developing trustworthy, reliable, and transparent AI applications, supported by appropriate human oversight, is essential for promoting effective and responsible human–AI collaboration.

Figure 8. Conclusion and Future Implications of AI in Human Decision-Making



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