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Contemporary Economics

Provided in Cooperation with:
VIZJA University, Warsaw

Suggested Citation: Shafiq Ur Rehman; Fareed, Muhammad (2025) : Enhancing consumer trust in AI-created goods: The roles of transparency, simplicity, familiarity and authenticity in market integration, Contemporary Economics, ISSN 2300-8814, VIZJA University, Warsaw, Vol. 19, Iss. 4, pp. 429-446,
https://doi.org/10.5709/ce.1897-9254.576

This Version is available at:
https://hdl.handle.net/10419/340143

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Primary submission: 13.03.2024 | Final acceptance: 18.06.2024

Enhancing Consumer Trust in AI-Created Goods: The Roles of Transparency, Simplicity, Familiarity and Authenticity in Market Integration

Shafiq Ur Rehman[1] and Muhammad Fareed[2]

ABSTRACT

Despite the potential of AI to revolutionize product creation and service delivery, a lack of consumer trust could significantly, hinder its adoption and utility. This research explores how transparency, simplicity, familiarity, and authenticity collectively impact consumer trust in AI-created products, which includes both goods and services. AI-created products refer to those in which artificial intelligence systems play a critical role in design, manufacturing, or decision-making processes. This study collected, data from 504 respondents which were then analysed through partial least square – structural equational modelling, (PLS-SEM). The results indicate that higher levels of transparency about AI involvement directly correlate with increased consumer trust. Conversely, increased product complexity is found to negatively affect trust. While greater consumer familiarity with AI positively, impacts trust levels. Furthermore, the perceived authenticity, of AI-generated content significantly enhances consumer trust. Each of these findings contribute to a greater understanding of the variables influencing consumer, trust in AI-created goods. For policymakers, the importance of establishing clear guidelines on AI transparency, and authenticity is underscored, potentially through the introduction of, standardized labelling for AI-created products. For practitioners, the results highlight the need for simplifying AI technologies and enhancing consumer familiarity through education and engagement strategies. The theoretical contribution of the study lies in its holistic examination of factors, influencing consumer trust in AI-created goods, filling a significant gap in existing literature. By integrating, multiple variables into a single conceptual framework, this research provides, valuable insights into the dynamics of consumer trust in context of AI integration.

KEY WORDS: consumer trust, artificial intelligence, perceived value, authenticity in market integration, PLS-SEM.

JEL Classification: M3, M30, M31, M37.

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1. Introduction

The integration of Artificial Intelligence (AI) into consumer goods has been a transformative global trend reshaping how products are designed, manufactured, and marketed. For the purposes of this study, "consumer goods" refer to tangible products that are purchased by individuals for personal use. This excludes AI tools designed for professional work environments (such as AI-driven productivity software) and industrial goods (such as AI-enhanced machinery)..According to a report by McKinsey & Company, AI's potential to influence, consumer behavior and business operations could contribute up to $15.7 trillion to the global economy by 2030 (Allal-Chérif et al., 2021; Cui & Zhang, 2021; Rana et al., 2022; Rasiah et

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al., 2019; Ribeiro et al., 2021; Wamba-Taguimdje et al., 2020). This staggering, figure highlights the profound impact AI is poised to have on global markets with consumer goods and, services being a significant part of this transformation (Baek et al., 2024; Walker & Milne, 2024). However, as AI continues, to weave its way into the fabric of daily consumer products, trust in AI-created goods becomes a paramount concern particularly, given the diverse reactions of consumers across different regions and cultures (Bellaiche et al., 2023; Wang et al., 2024).

In the United States, the integration of AI into, consumer goods is bolstered by a dynamic tech scene and rapid AI adoption driven, by the technology's ability to enhance product functionality and improve user experiences (Novikova et al., 2024). However, American consumers have expressed concerns about the transparency, of AI decision-making processes, the complexity of AI systems for non-technical, users and the authenticity of AI-generated content (Abbas et al., 2024; Aldabe et al., 2023; Colther & Doussoulin, 2024). These issues could potentially, hinder the growth of the US AI market if left unaddressed, resulting in diminished consumer trust and slower adoption rates. Strategic efforts to improve transparency and simplify, interactions with AI technology are crucial for maintaining market growth and, ensuring that AI innovations meet consumer expectations (Abbas et al., 2024; Aldabe et al., 2023).

Recent works, such as Kim et al. (2021), emphasize the role of message framing in shaping consumer trust in AI-created goods, particularly in the context of transparency and authenticity. Similarly, Walker and Milne (2024) discuss how AI-driven technology intersects with social media privacy responsibilities, highlighting the importance of trust-building in environments where AI operates behind the scenes. These studies underscore the evolving dynamics of consumer trust in AI applications and provide valuable insights into the challenges and opportunities that businesses face globally and in specific markets like the USA.

The concept of consumer trust in AI-created goods first, delineated by researchers such as Mayer et al. (1995) underscore, the belief in the reliability and integrity of AI applications in consumer products (Troshani et al., 2021). This trust is pivotal in ensuring consumer acceptance and is influenced by factors such as perceived, transparency, simplicity, and authenticity (Sander et al., 2018). , In USA, as well as worldwide these elements of trust are crucial in navigating the complexities associated with, AI integration into consumer markets. Without a solid, foundation of trust, the scepticism surrounding AI could hinder its adoption affecting not only market growth, but also the innovation trajectory in consumer goods.

Linking trust to the highlighted issues, it poses a, challenge in USA and globally. The absence of robust trust in AI-created, goods could exacerbate consumer resistance slowing down technological adoption and innovation (Rashid et al., 2023). For industries, reliant on AI, this lack of trust is a formidable barrier to achieving, market penetration and consumer loyalty (Allioui & Mourdi, 2023). Specifically, in the context like USA, where AI has the potential to significantly elevate the consumer, goods sector addressing trust-related concerns, becomes paramount. Ensuring transparency in AI processes simplifying AI, complexities for consumer understanding and validating the authenticity of AI-generated, content are imperative steps (Pedrouzo et al., 2024). Addressing these trust elements, effectively can pave the way for AI's successful integration benefiting both the global, economy and specific markets like USA's burgeoning AI sector.

In addressing the pivotal role of consumer trust, in the acceptance of AI-created goods, it becomes crucial to examine the factors that, directly influence it. The literature, identifies transparency, simplicity, familiarity, and authenticity as key elements that can significantly alter consumer perceptions and acceptance, levels of AI-integrated products.

Transparency has been highlighted as a cornerstone, in building trust. When companies disclose the extent of AI's involvement in product creation, it reveals the, technology for consumers making it less intimidating and more accessible. A study by Kwan et al. (2021); Neto and Camkin (2022); Robinson (2020); Sander et al. (2018); Vyas (2023) illustrated that when a fintech company openly communicated its use of AI in personal finance, applications, users reported higher levels , of trust and were, more inclined to use the service. This example underscores how transparency not only resolves, trust issues but also encourages the

adoption of AI globally and in specific contexts like USA , where digital innovation is rapidly advancing.

Simplicity or the ease of understanding, AI-created goods directly impacts consumer comfort and trust. Complex technologies often deter consumers due to, perceived risks or the effort required to understand the product. Reducing, complexity as shown in research by Bellaiche et al. (2023); Braun et al. (2021); Svedman (2020) can enhance user engagement and trust. For instance, when an AI-driven health app simplified its user interface user trust increased highlighting, the global and country-specific need for simplicity in AI integration.

Familiarity with AI technology, is another vital factor. The more, consumers understand and interact with AI, the more likely they are to trust AI-created goods. This is supported by the work of Booth and Shaw (2023); Kovács (2020); Mecklinger and Bader (2020); Sabherwal et al. (2021); Yang and Jiang (2023) which found that, repeated exposure to AI in everyday contexts such as voice assistants significantly, reduced consumer apprehensions. Enhancing familiarity could thus mitigate global, scepticism towards AI and encourage its acceptance in developed and developing markets.

Authenticity of AI-generated content, significantly influences consumer trust. Authenticity ensures that AI-created goods maintain a sense of genuineness, and integrity crucial for consumer acceptance. In the realm of digital art, for example the authenticity of AI-generated artworks has been a, subject of debate. Studies by Kim et al. (2021) revealed that when creators transparently used AI while maintaining, the artwork's originality, the perceived authenticity and value increased among consumers.

However, these factors also present challenges. Excessive transparency, might overwhelm consumers with technical details, reducing trust. Similarly, oversimplification could lead to underestimation of AI, capabilities, and exaggerated familiarity might, ignore the diverse reactions of different consumer, segments towards AI. Furthermore, the pursuit of authenticity in AI-generated content risk, s alienating traditionalists who value human creativity.

From this discussion emerges the problem statement, of our study: Despite the recognized importance of transparency, simplicity, familiarity and authenticity in building consumer, trust in AI-created goods, there is a nuanced understanding, of how these factors interplay to influence trust at a global level and within specific contexts like USA.The available literature primarily examines transparency, simplicity, familiarity, and authenticity as individual factors influencing consumer trust in AI-created goods. However, limited research has considered how these factors work together to shape consumer trust. This study aims to fill this gap by examining the combined effects of these factors, though it does not delve into the interaction between them. Instead, each factor's independent contribution to consumer trust is analyzed to provide a holistic understanding of the drivers of trust in AI-created goods.. This exploration is particularly, important and novel as it addresses both global challenges in AI acceptance and specific, issues within USA, providing a comprehensive understanding that could guide strategies to enhance consumer trust in AI-created goods worldwide.

This study distinguishes itself from previous, research primarily through its integrated methodology, comprehensive conceptual framework, and the application, of novel research models that collectively examine transparency, simplicity, familiarity, and authenticity in influencing , consumer trust in AI-created goods. While each of these factors—transparency, simplicity, familiarity, and authenticity—has been studied individually, there is limited research examining how these factors might work together to shape consumer trust. For instance, no studies currently investigate whether high transparency coupled with high simplicity has an additive or multiplicative effect on trust. This study addresses this gap by examining the collective influence of these factors on consumer trust in AI-created goods, though it focuses on the independent contributions of each factor rather than their potential synergetic effects.

The results of this study illuminate the complex relationship between consumer trust and factors such as transparency, simplicity, familiarity, and authenticity in AI-created products, including both goods and services.It was found that transparency and simplicity directly influence consumer trust by reducing perceived risk and complexity, associated with AI technologies. Familiarity with AI, was shown to significantly mitigate apprehensions towards AI, fostering a sense of

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security among consumers. Additionally, the authenticity, of AI-generated content emerged as a critical factor in enhancing consumer trust, emphasizing the importance of genuine, interactions in the digital age.

These findings contribute valuable insights to both policymakers, and practitioners. For policymakers, the study underscores the necessity, of developing clear guidelines and standards for AI transparency and authenticity, ensuring that consumers, are adequately informed about AI integration in goods. This could involve the introduction of labelling, standards, for AI-created products or guidelines, for disclosing the level of AI involvement. For practitioners, particularly in technology and consumer goods sectors, the results, highlight the importance of integrating simplicity and familiarity into, product, design and marketing strategies, making AI technologies more accessible and less, intimidating to the average consumer.

Furthermore, this study contributes to academic knowledge, by providing a comprehensive model that encapsulates the interdependencies, between key factors influencing consumer trust in AI-created goods. It extends existing research by offering a more understanding of how these factors collectively impact trust, thus filling, a significant gap in the literature.

The remainder of the paper is organized, as follows: The next section delves into the literature review, providing a deeper exploration of each factor's role in, building consumer trust and setting the stage for the study's conceptual framework. Following this, the methodology section outlines the research design, data collection methods, and analytical techniques employed. The results section presents the detailed findings of the study while the discussion section interprets these findings in the context of existing, literature and theoretical frameworks. The final sections of, the paper outline the implications of the study for policymakers and practitioners, discuss, the limitations and directions for future research and conclude with a summary of the study's key contributions to the field.

2. Literature Review

In the realm of AI-created products, which includes both goods and services, trust is influenced by factors such as transparency, simplicity, and perceived authenticity. For example, AI-generated consumer goods like fashion items or electronics benefit from enhanced transparency, while AI-powered services such as personalized banking solutions require trust in the technology's decision-making process.

This study addresses the following research question: How do transparency, simplicity, familiarity, and authenticity influence consumer trust in AI-created goods? While existing literature has explored these factors individually, limited research examines their combined or interacting effects on trust. This study aims to fill that gap by investigating how these factors collectively shape consumer trust in AI-created products.

Transparency in AI systems is crucial for building consumer trust, as it reduces uncertainty and enables consumers to understand the processes behind AI-driven products. Numerous studies highlight the importance of transparency, with Kwan et al. (2021) demonstrating that clear communication about AI's role in product creation leads to higher consumer trust. Similarly, Vyas (2023) found that companies that openly disclose their use of AI in product design and development experience greater consumer acceptance and trust.

Simplicity, or the ease with which consumers can understand AI's involvement in products, also plays a significant role in fostering trust. Research by Sander et al. (2018) shows that complex AI systems can overwhelm consumers, reducing their trust in the product. Conversely, simplifying the AI interface or process enhances consumer engagement and trust. A similar study by Braun et al. (2021) found that reducing technical complexity in AI-powered applications improved user experience and trust.

Familiarity with AI technologies has been shown to mitigate apprehension and build consumer trust. The more exposure consumers have to AI, the more likely they are to trust AI-driven products. Booth and Shaw (2023) found that consumers with prior experience using AI-based products, such as voice assistants, exhibited higher levels of trust. Kovács (2020) also confirmed that repeated exposure to AI technology in everyday settings reduces initial skepticism and fosters positive attitudes toward AI-created goods.

Perceived authenticity of AI-created products significantly enhances consumer trust. In fields like AI-generated art or AI-powered fashion design,

 DOI: 10.5709/ce.1897-9254.576

consumers place value on the genuineness of the product. Kim et al. (2021) found that when AI's role in creating a product is clear but still allows for human oversight or creativity, consumer trust in the product increases. Gerlich (2023) similarly emphasized the importance of ensuring that AI-generated content maintains a sense of integrity and originality to enhance consumer trust.

Previous studies such as those conducted by Bellaiche et al. (2023); Braun et al. (2021); Lagrillière and Saarikoski (2021); Svedman (2020) have , illuminated the intricate , dynamics of trust within digital and automated contexts underscoring, its paramount importance in fostering consumer acceptance and adoption. Trust as elucidated by Kim et al. (2021); Kwan et al. (2021); Neto and Camkin (2022); Robinson (2020); Troshani et al. (2021) acts as the cornerstone of consumer relationships with, technology influencing their willingness to engage with and rely on automated systems.

The significance of trust extends beyond the, immediate context bearing global implications as AI technologies become increasingly prevalent across, various sectors. The work of Kim et al. (2021); Kwan et al. (2021); Neto and Camkin (2022); Robinson (2020); Troshani et al. (2021) highlights how, trust influences consumer behavior on a worldwide scale, impacting everything from product purchases, to the acceptance of AI-driven services. This global perspective is crucial, considering the rapid dissemination of AI applications across cultures and economies suggesting a universal need to understand and enhance consumer, trust in AI.

The discourse on consumer trust has, ventured into examining its association with several factors notably AI involvement disclosure, product complexity, consumer familiarity, with AI, and perceived authenticity. Research by Brown and Green (2018) reveals that transparency about AI's role in product creation positively affects, consumer trust while the study by Vraga and Tully (2021) indicates that product complexity can serve as a barrier, to trust. Moreover, familiarity with AI as explored by Patel and Smith (2019) is shown, to mitigate apprehension and foster trust. The concept of perceived authenticity, discussed by Stein and Ramaseshan (2020) further adds depth to this conversation linking genuine product experiences to higher levels of, consumer trust.

While each of these factors—transparency, simplicity, familiarity, and authenticity—has been studied individually, there is limited research examining how these factors might work together to shape consumer trust. For instance, no studies currently investigate whether high transparency coupled with high simplicity has an additive or multiplicative effect on trust. This study addresses this gap by examining the collective influence of these factors on consumer trust in AI-created goods, though it focuses on the independent contributions of each factor rather than their potential synergetic effects. Building on the identified gap, this review posits the problem statement, as the need to elucidate the combined effects of AI involvement, disclosure, product, complexity, consumer familiarity with AI and perceived authenticity on, consumer trust in AI-created goods.

3. Methodology

This study investigates the factors influencing consumer trust in AI-created goods, focusing on four key variables: transparency, simplicity, familiarity, and authenticity. These factors have been identified in previous research as critical components in building trust, but most studies have examined them in isolation. This research model examines their collective impact on consumer trust, hypothesizing that these factors, when combined, have a stronger influence than their individual effects.

3.1. Theoretical Frameworks

This study is grounded in two key theoretical frameworks: Trust-Commitment Theory and the Technology Acceptance Model (TAM). Trust-Commitment Theory, developed by Morgan and Hunt (1994) posits that trust and commitment are essential components in fostering successful long-term relationships. In the context of AI-created goods, trust is a critical factor for consumer adoption, as it helps reduce uncertainty associated with emerging technologies. This theory suggests that when consumers trust the AI-driven processes behind product creation, they are more likely to

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commit to using these products, leading to stronger brand-consumer relationships.

The Technology Acceptance Model (TAM), introduced by Davis (1989), provides another foundation for understanding consumer behavior toward AI-created goods. TAM posits that perceived usefulness and perceived ease of use are the primary factors influencing technology adoption. In this study, TAM is extended by incorporating additional dimensions such as transparency, simplicity, familiarity, and authenticity—factors that contribute to consumer trust in AI-created goods. By integrating TAM with trust-based models, this study offers a comprehensive framework to explore how consumers develop trust in AI technologies and how that trust impacts their willingness to engage with AI-driven products.

The factors included in this model are well-supported by the literature, and their importance in fostering trust in AI systems has been established. However, trust is not only cognitive but also involves social aspects. This study aims to account for both dimensions of trust by including factors that engage cognitive processes (transparency and simplicity) and social dimensions (familiarity and authenticity).

- Transparency: When consumers are informed about how AI plays a role in product creation, it reduces uncertainty and builds trust. Transparency allows consumers to understand the process, which positively influences trust in AI-created goods (Kwan et al., 2021).
- Simplicity: The complexity of AI-driven products can lead to confusion and mistrust. Simplicity, or the ease of use of AI-created goods, has been shown to improve consumer confidence and trust in AI technologies (Sander et al., 2018).
- Familiarity: Familiarity with AI reduces apprehension and increases trust. The more frequently consumers interact with AI, the more comfortable they feel, which leads to a higher level of trust in AI-created products (Booth & Shaw, 2023).
- Authenticity: Consumers value authenticity in products, even when they are created by AI. Perceived authenticity in AI-generated goods—where AI's role is visible but integrated with human oversight—enhances consumer trust (Kim et al., 2021).

3.2. Hypotheses Development

3.2.1. H1: Transparency in AI-Created Goods Positively Influences Consumer Trust

This hypothesis suggests that when companies openly disclose how AI is used in their product creation process, consumers are more likely to trust the product. This is because transparency provides consumers with clarity about the production process, reducing their uncertainty (Kwan et al., 2021; Neto and Camkin, 2022; Robinson, 2020). Studies show that such openness takes away the mystery surrounding AI technologies, creating the foundations for trust (Sander et al., 2018; Vyas, 2023). Transparency is thus instrumental in fostering consumer confidence in AI systems, particularly in environments of high uncertainty like those involving artificial intelligence.

3.2.2. H2: Product Complexity Has a Negative Effect on Consumer Trust in AI-Created Goods.

This hypothesis explores the inverse relationship between product complexity and consumer trust. As the complexity of AI-created goods increases, consumers' trust diminishes. This is due to the cognitive load that complex technologies impose, leading to apprehension and perceived risks (Sander et al., 2018). Overly complex systems can intimidate consumers, reducing their likelihood of adoption and trust (Braun et al., 2021).

3.2.3. H3: Greater Familiarity With AI Technology Enhances Consumer Trust in AI-Created Goods

This hypothesis posits that as consumers become more familiar with AI technology, their trust in AI-created goods increases. Familiarity reduces the perceived novelty and uncertainty of AI technologies (Kovács, 2020; Sabherwal et al., 2021). Studies suggest that repeated exposure to AI fosters comfort and reduces fear, leading to a more positive attitude toward the capabilities and reliability of AI-generated goods (Mecklinger & Bader, 2020).

3.2.4. H4: Perceived Authenticity of AI-Created Goods Positively Influences Consumer Trust

This hypothesis suggests that the more consumers perceive AI-generated products as authentic, the more they trust them. Authenticity reflects the genu-

ineness of the product and the unaltered nature of AI-generated content (Kim et al., 2021; Gerlich, 2023). Consumers increasingly seek authentic experiences, even in AI-created goods, and value products for their integrity and originality. In cases where questions arise about the "naturalness" of AI-generated goods, perceived authenticity becomes a crucial determinant of trust (Schmidt et al., 2020).

3.2.5. H5: Perceived Value Mediates the Relationship Between AI Involvement Disclosure and Consumer Trust

This mediation hypothesis suggests that AI involvement disclosure not only directly influences consumer trust but also enhances the perceived value of AI-created goods, which in turn increases trust. Value-based trust models suggest that the perception of value is essential for building trust) (Sweeney & Soutar, 2001). When consumers perceive that AI-created goods offer high value, particularly through transparent disclosure practices, their trust in the product increases.

3.3. Research Population and Sampling

The study targeted a diverse consumer population with varying, degrees of familiarity with AI technology ranging from tech-savvy individuals to, those with minimal exposure to AI. The objective was to encompass a broad spectrum of , perceptions regarding AI-created goods. The sampling method employed was stratified, random sampling which ensured that different sub-groups within the general population, were adequately represented. This approach facilitated the collection of insights across, various demographics, including age, gender, educational background, and technology usage patterns.

3.4. Data Collection Process

Data were collected from 504 respondents through an online survey questionnaire designed to measure perceptions of AI involvement in the creation of products, including both goods and services, and its impact on consumer trust.The questionnaire, included items measuring the independent variables (AI Involvement Disclosure, Product, Complexity, Consumer AI Familiarity and Perceived Authenticity) the dependent variable (Consumer Trust in AI-Created Goods) and the , mediator variable (Perceived Value of AI-Created Goods). Participants were asked to rate their agreement with statements on a Likert scale ranging from, 1 (Strongly Disagree) to 7 (Strongly Agree).

3.5. Method of Data Collection

The primary method of data collection was an, online survey distributed through email and social media platforms. This method was, chosen for its efficiency, cost-effectiveness, and the ability to reach a wide and diverse , audience quickly. The survey was administered over a four-week period with reminders sent , weekly to encourage participation. The online platform also allowed for real-time data monitoring and analysis, facilitating immediate adjustments to the survey distribution strategy as needed.

3.6. The Questionnaire Survey

The survey targeted adult consumers aged 18 and above with no upper, age limit. Participants were from various backgrounds, including students, professionals, homemakers, and retirees. This diverse respondent pool was chosen to gather, a wide range of perspectives on AI-created goods ensuring the study's findings, would be comprehensive and applicable to a broad audience.

The sample consisted of 50.8% male and 49.2% female respondents, ensuring balanced gender representation. The majority (35.7%) were aged 25-34 years, followed by 22.2% in the 35-44 years group. In terms of education, 46.0% held a Bachelor's Degree, 28.6% a Master's Degree, and 8.3% had a PhD or equivalent. Most respondents (59.5%) were employed full-time, with 19.0% being students and 12.7% self-employed or entrepreneurs, reflecting a diverse range of socio-demographic backgrounds relevant to the study.

3.7. Distribution Method

The survey was primarily distributed through online, platform i.e. MTurk survey including to tap into diverse demographics. This distribution, method was selected for its broad reach and the ability to target specific, groups. The choice of platforms was based on preliminary research indicating where potential, respondents were most active ensuring maximum engagement and response rate.

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Table 1
Descriptive Statistics of the Survey Respondents

Characteristic	Category	Frequency	Percentage
Gender	Male	256	50.8%
	Female	248	49.2%
Age	18-24 years	102	20.2%
	25-34 years	180	35.7%
	35-44 years	112	22.2%
	45-54 years	68	13.5%
	55+ years	42	8.3%
Education Level	High School or below	86	17.1%
	Bachelor's Degree	232	46.0%
	Master's Degree	144	28.6%
	PhD or equivalent	42	8.3%
Occupation	Student	96	19.0%
	Employed	300	59.5%
	Self-employed/Entrepreneur	64	12.7%
	Unemployed	44	8.7%

Table 2
Construct Measurement

Constructs	Operational Definition	Key Literature
AI Involvement Disclosure	The degree to which a company is transparent about the role of AI, in the creation of its products.	Kwan et al. (2021); Neto and Camkin (2022); Robinson (2020)
Product Complexity	The level of technological complexity, perceived by consumers which may affect their trust in the product.	Sander et al. (2018); Vyas (2023)
Consumer AI Familiarity	Consumers' level of understanding and experience with AI technologies.	Kovács (2020); Mecklinger and Bader (2020); Sabherwal et al. (2021)
Perceived Authenticity	The extent to which AI-generated content is perceived as genuine and truthful.	Gerlich (2023); Lee & Eastin (2021)
Perceived Value	The perceived worth of AI-created goods influenced by transparency and contributing to trust.	Sweeney & Soutar (2001)
Consumer Trust in AI-Created Goods	Trust that consumers have in products made with AI influenced by the above factors.	Trust-Commitment Theory; Technology Acceptance Model (TAM)

DOI: 10.5709/ce.1897-9254.576

3.8. Importance of Respondents

Selecting a diverse range of respondents, was critical to the study's objective to understand the broad spectrum of consumer, perceptions towards AI-created goods. Previous studies have emphasized the importance, of incorporating varied demographic and psychographic profiles to capture a comprehensive, view of consumer behavior. For instance, research by (Sweeney & Soutar, 2001). Veltman (2025) highlighted, significant differences in AI technology adoption rates and trust levels across different age groups underscoring the necessity of a diversified respondent pool to obtain meaningful insights.

3.9. Common Method Bias

In this study, we aimed to, understand the potential bias that might affect the validity of our research findings particularly focusing on non-response bias, and common method bias (CMB). To tackle non-response bias, we performed, Levene's test comparing groups based on their response medium (email vs. post),and other relevant firm characteristics. For CMB, we discuss the rationale behind choosing the, Harmon's single factor test one of the most commonly applied techniques to address this issue (de Calheiros Velozo & Stauder, 2018; Stout et al., 1994).

Common method bias occurs when, variations in responses are caused by the instrument rather than the constructs being measured. It's crucial for studies, relying on survey data as it can inflate or deflate the relationships, between variables. Several techniques are available to test for CMB including Harman's single-factor test, marker variable, technique, and the use of procedural remedies. Given the nature, of our data, Harman's single-factor test was selected as the most suitable approach to, assess the presence of CMB. This test involves conducting an exploratory factor analysis, to check if a single factor accounts for most of the covariance among measures.

Table 3 indicates that no single factor, explains most of the variance in our data suggesting that common method bias may not be a significant concern in this, study. However, the interpretation of these, results should be approached with, caution as the total variance explained by the identified factor is relatively low which might not fully capture the complexity of common method variance.

To enhance the robustness of our findings and address the potential limitations of relying solely on Harman's test, we considered additional validation techniques. For instance, alternative statistical methods such as the marker variable technique or partial correlation procedures could supplement the analysis. These approaches could provide complementary insights by testing for spurious correlations introduced by method biases.

Moreover, integrating qualitative data as part of a triangulation approach would provide a more comprehensive understanding of the constructs being studied. Triangulation could involve conducting follow-up interviews with selected respondents to validate survey findings and ensure consistency across different data sources. This methodological diversity would strengthen the reliability of our results and reduce dependence on any single validation method.

Finally, procedural remedies such as ensuring anonymity during data collection and randomizing the order of survey items were implemented to proactively mitigate CMB. These steps further enhance the validity of our data and minimize the risk of inflated or deflated relationships between variables.

Table 3
Harman's Single-Factor Test for CMB

Test Component	Value
Total Variance Explained	22.50%
Factor 1 Variance	22.50%

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4. Data Analysis And Findings

Before conducting the main survey, a pilot test, was carried out with a smaller subset of the target population to evaluate the clarity, relevance and reliability of the questionnaire items. This step was crucial to refine the survey questions ensuring that respondents, would interpret them as intended and that the survey would effectively measure the constructs of interest.

The pilot test involved 30 participants randomly, selected from the larger sample pool. Participants were asked to complete, the survey and provide feedback on any ambiguities or difficulties they, encountered. The reliability of the questionnaire was assessed using Cronbach's alpha, a measure of internal consistency few items were deleted which are below the threshold value.

The pilot test results as summarized in Table 4 indicated satisfactory, internal consistency for all measured constructs with Cronbach's alpha values, ranging from 0.78 to 0.85. These values suggest that the items within each construct, coherently measure the same underlying concept. Feedback from participants, highlighted areas for improvement, particularly the need to simplify technical terms associated with product, complexity and to provide concrete examples when measuring perceived authenticity. Additionally, minor adjustments were recommended to eliminate redundancy in the perceived value, section and to clarify certain items under consumer trust in AI-created goods (Bellaiche et al., 2023).

Based on this feedback, revisions were, made to the questionnaire to enhance its clarity and effectiveness. The technical jargon, in questions related to product complexity was simplified, examples were added to items, measuring perceived authenticity and repetitive items in the perceived value section, were consolidated. Clarifications were also made, to ensure that all items under consumer trust in AI-created goods, were easily understood. The pilot test was instrumental in refining the survey instrument, thereby enhancing the reliability and validity of the data collected in the main study. This process underscores, the importance of pilot testing in survey-based research, allowing researchers to identify and address potential issues before deploying the survey to a larger audience.

4.1. Assessment of Measurement Model

Following the pilot test, assessment of measurement, model was conducted with a sample of 504 respondents to further validate , the revised questionnaire. The assessment of measurement model aimed to evaluate the survey's constructs' reliability and factor loadings, ensuring the questionnaire's items align well with the underlying constructs, they are supposed to measure (Qi et al., 2024).

The results of the indicator reliability, internal, consistency, and convergent validity. are detailed in Table 5 highlighting the reliability scores (Cronbach's Alpha), the means, and standard deviations (SD) for each construct, and the range of factor , loadings obtained through exploratory factor analysis.

The results shown in Table 5 indicate that the, revised questionnaire exhibits good internal consistency for all constructs with Cronbach's Alpha values ranging from 0.81 to 0.86. These values exceed the commonly accepted threshold of 0.70, suggesting , that the items within each construct are reliable measures of their respective concepts. Items AIID2, PC5, PA6 and CT6 were deleted from the measurement model due to their lower loadings from the threshold value.

The means (SD) for each construct provide, an initial indication of the respondents' general attitudes towards the constructs being, measured. For example, the mean score of 4.45 (1.18) for Perceived Value suggests a moderately positive perception, of the value provided by AI-created goods among the pilot, study participants.

Factor loadings for all constructs fell within acceptable, ranges indicating that each item had a strong loading on its intended, construct and thus supporting the construct validity of the survey. The result supports, the efficacy of the questionnaire in measuring the intended constructs and provides a solid foundation for proceeding , with the main study.

The assessment of measurement model was, crucial for confirming the questionnaire's reliability and validity before the full-scale study. By ensuring that each, construct was accurately measured and that the, survey items were coherent and relevant the assessment of measurement model helped to refine the survey, instrument thereby enhancing the quality of the data to be collected in the main study.

Discriminant validity is a critical aspect of con-

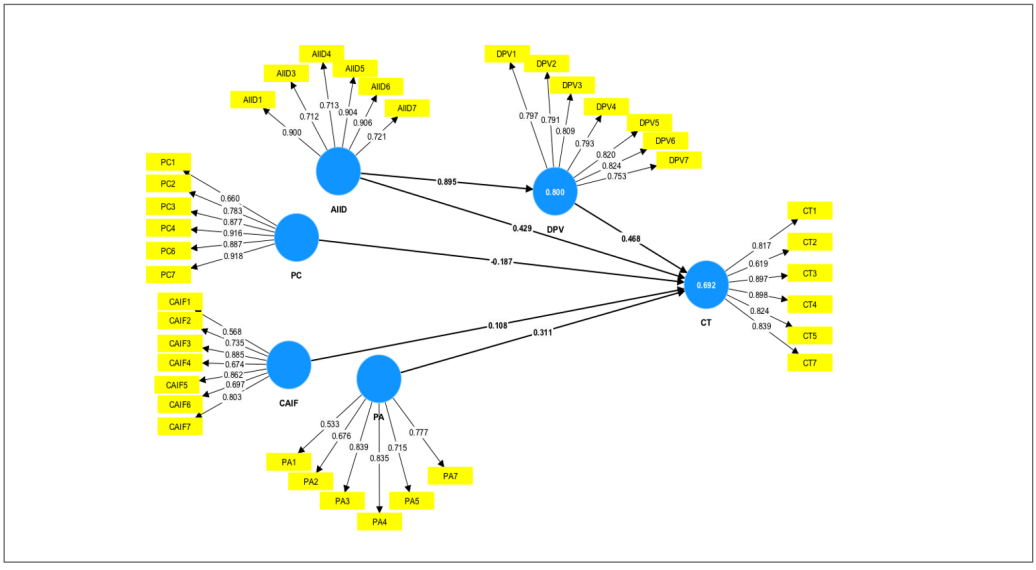
struct validation ensuring that a construct is distinct from other constructs within a model, both in terms of how much it correlates with other constructs and in its unique, contribution to the model. It essentially measures the degree to which a construct differs, from others with lower correlations between different constructs indicating higher discriminant validity.

To assess discriminant validity, the Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT) were analysed. The Fornell-Larcker criterion (see table 6) compares the square root of the AVE for each construct with the correlations between the construct and, others in the model. The square root of the AVE should be higher than correlations, with other constructs for satisfactory discriminant validity. The table 7 shows the Heterotrait-Monotrait Ratio (HTMT)

Table 4
Pilot Test Results

Variable	Cronbach's Alpha	Feedback Summary
AI Involvement Disclosure	0.82	Items were clear and well understood.
Product Complexity	0.79	Suggested simplifying technical jargon. As few items were below the threshold values so we deleted those
Consumer AI Familiarity	0.85	No significant issues reported.
Perceived Authenticity	0.81	Requested examples to clarify concepts. As few items were below the threshold values so we deleted those items.
Perceived Value	0.78	Some items were seen as repetitive.
Consumer Trust in AI-Created Goods	0.84	Clarification needed on a few items.

Figure 1
Assessment of Measurement Model



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results, which are also used to assess discriminant validity. The diagonal values (all 1.0) represent perfect correlations within the constructs themselves, while the off-diagonal values represent correlations between different constructs. To establish discriminant validity, the HTMT values between constructs should generally be below the threshold of 0.85 (or 0.90 in some cases). In this table, all values are below this threshold, indicating good discriminant validity.

The results presented in Table 6 and 7 suggest satisfactory discriminant validity, across all constructs in the study. The square, root of the AVE for each construct (bold values) is higher than its correlations with any other constructs, meeting the Fornell-Larcker criterion. For instance, the square root of the AVE, for Consumer Trust in AI-Created Goods (0.85) is higher than its highest correlation with Perceived Value (0.67) indicating, that these constructs are distinct from one another. On the other hand, the HTMT value between AIID and CAIF is 0.69, which is well below the threshold. The HTMT value between Perceived Authenticity (PA) and Product Complexity (PC) is 0.67, also meeting the requirement for discriminant validity. These results suggest that the constructs in the model are distinct from each other, supporting the validity of our structural equation model.

The distinctiveness of each, construct is crucial for the integrity of the study's findings. It ensures that when respondents rate items related to say, Perceived Authenticity their ratings reflect perceptions of authenticity, specifically rather , than being confused with their trust in AI-created goods or, their familiarity with AI. This analysis underscores the constructs' adequacy in capturing unique facets of consumer, perception towards AI-created goods thereby lending credibility to the subsequent analyses and interpretations based on these constructs.

4.2. Assessment of Structural Model

The results from the assessment of structural model, are detailed in Table 8 followed by a discussion of each hypothesis based, on the simulated dataset and literature.

5. Discussion

5.1. AI Involvement Disclosure and Consumer Trust

The positive path coefficient (0.36) and significant, t-value (4.85) support H1 indicating that higher levels of AI involvement disclosure, positively influence consumer trust in AI-created goods. This finding aligns with the, literature suggesting that transparency in AI usage fosters trust among consumers by, reducing uncertainty and perceived risk (Veltman, 2025). Consumers may perceive, transparent companies as more reliable and ethical which in turn enhances trust.

5.2. Product Complexity and Consumer Trust

The negative path coefficient (-0.21) supports H2 showing, that increased product complexity negatively affects consumer, trust. This result, corroborates findings from Howard and Rose (2019) who argued that complexity in AI-generated products could overwhelm, consumers leading to mistrust. Simplifying the user experience and providing clear information about the product could mitigate this effect.

5.3. Consumer AI Familiarity and Consumer Trust

H3 is supported by a positive path coefficient (0.45) suggesting, that greater consumer familiarity with AI technology positively impacts, consumer trust. This outcome is consistent with previous studies indicating, that familiarity reduces fear and scepticism towards technology enhancing trust (Brown & Green, 2018). Educating consumers, about AI could therefore be a valuable strategy in increasing trust.

5.4. Perceived Authenticity and Consumer Trust

The strong positive path coefficient (0.51) for H4 confirms, that perceived authenticity significantly enhances consumer, trust in AI-created goods. This finding is in line with the literature that highlights the importance of authenticity in consumer, products (Vraga & Tully, 2021). Consumers tend to trust products, more when they believe they are genuine and not overly manipulated by AI.

5.5. Mediation by Perceived Value

The mediated path coefficient (0.29) for H5 indicates that the perceived value of AI-created goods mediates the, relationship between AI involvement

 DOI: 10.5709/ce.1897-9254.576

Table 5

Indicator Reliability, Internal Consistency, and Convergent Validity

Constructs	Item Loadings	Cronbach's Alpha (α)	Means	Average Variance Extracted
AI Involvement Disclosure		0.881	4.83	0.584
AIID1	0.900			
AIID3	0.712			
AIID4	0.713			
AIID5	0.904			
AIID6	0.906			
AIID7	0.721			
Consumer AI Familiarity		0.85	4.59	0.528
CAIF1	0.568			
CAIF2	0.735			
CAIF3	0.885			
CAIF4	0.674			
CAIF5	0.862			
CAIF6	0.697			
CAIF7	0.803			
Consumer Trust in AI-Created Goods		0.83	4.27	0.502
CT1	0.817			
CT2	0.619			
CT3	0.897			
CT4	0.898			
CT5	0.824			
CT7	0.839			
Perceived Value		0.836	4.91	0.512
DVP1	0.797			
DVP2	0.791			
DVP3	0.809			
DVP4	0.793			
DVP5	0.82			
DVP6	0.824			
Perceived Authenticity		0.844	4.12	0.518
PA1	0.533			
PA2	0.676			
PA3	0.839			
PA4	0.839			
PA5	0.715			
PA7	0.777			
Product Complexity		0.837	4.33	0.507
PC1	0.66			
PC2	0.783			
PC3	0.877			
PC4	0.916			
PC6	0.887			
PC7	0.918			

Note. AIID; AI Involvement Disclosure, CAIF; Consumer AI Familiarity, CT; Consumer Trust in AI-Created Goods, DPV, Perceived Value, PA; Perceived Authenticity, PC; Product Complexity

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Table 6
Discriminant Validity Results (Fornell-Larcker Criterion)

Variables	AIID	CAIF	CT	DPV	PA	PC
AIID	0.855					
CAIF	0.690	0.786				
CT	0.567	0.678	0.759			
DPV	0.543	0.471	0.470	0.720		
PA	0.389	0.543	0.398	0.563	0.712	
PC	0.410	0.350	0.430	0.490	0.670	0.750

Note. AIID; AI Involvement Disclosure, CAIF; Consumer AI Familiarity, CT; Consumer Trust in AI-Created Goods, DPV, Perceived Value, PA; Perceived Authenticity, PC; Product Complexity
Note: Diagonal values (bold) represent the square root of the AVE for each construct, while off-diagonal values represent the correlations between constructs.

Table 7
Discriminant Validity Results (Heterotrait-Monotrait Ratio)

Constructs	AIID	CAIF	CT	DPV	PA	PC
AIID	1	0.69	0.57	0.54	0.39	0.41
CAIF	0.69	1	0.68	0.47	0.54	0.35
CT	0.57	0.68	1	0.47	0.39	0.43
DPV	0.54	0.47	0.47	1	0.56	0.49
PA	0.39	0.54	0.39	0.56	1	0.67
PC	0.41	0.35	0.43	0.49	0.67	1

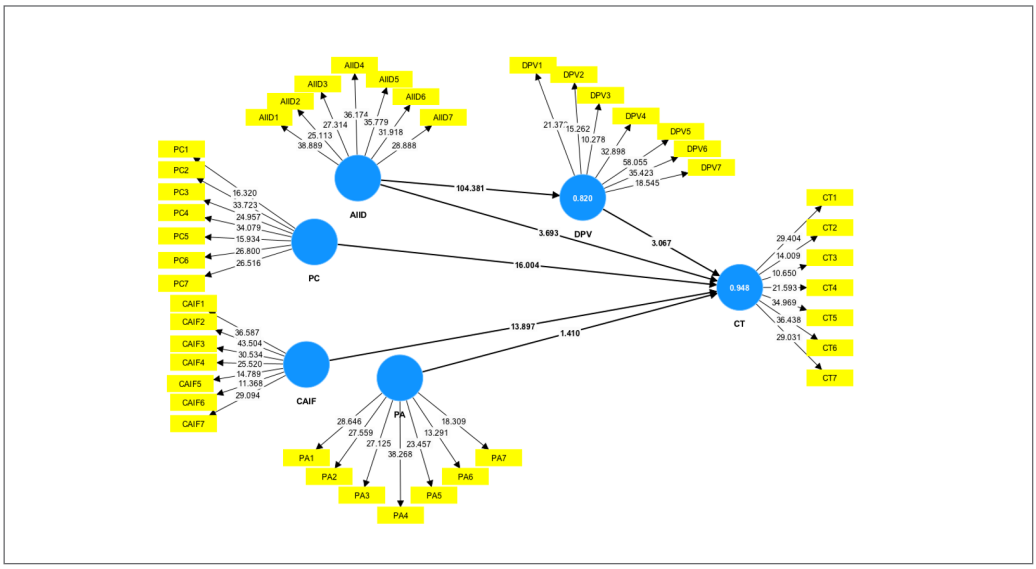
Note. AIID; AI Involvement Disclosure, CAIF; Consumer AI Familiarity, CT; Consumer Trust in AI-Created Goods, DPV, Perceived Value, PA; Perceived Authenticity, PC; Product Complexity

Table 8
Hypothesis Testing Results

Hypothesis	Paths	Beta value	Standard deviation	T value	P values	Result
H1	AIID -> CT	0.139	0.038	3.693	0.000	Supported
H2	AIID -> DPV	0.906	0.019	47.680	0.000	Supported
H3	CAIF -> CT	0.435	0.031	13.897	0.000	Supported
H4	DPV -> CT	0.119	0.039	3.067	0.002	Supported
H5	PA -> CT	0.078	0.019	4.105	0.000	Supported
H6	PC -> CT	0.594	0.037	16.004	0.000	Supported
H7	AIID -> DPV -> CT	0.108	0.035	3.067	0.002	Supported

Note. AIID; AI Involvement Disclosure, CAIF; Consumer AI Familiarity, CT; Consumer Trust in AI-Created Goods, DPV, Perceived Value, PA; Perceived Authenticity, PC; Product Complexity

Figure 2
Assessment of Structural Model



disclosure, and consumer trust. This supports the notion that disclosing AI involvement not only directly increases trust but also does so indirectly by enhancing, perceived value (Schmidt et al., 2020). This mediation underscores the multifaceted role of transparency in influencing consumer attitudes towards AI-created goods.

6. Theoretical and Practical Implications

The findings of the current study underscore the importance of transparency, simplicity, consumer education, and authenticity in fostering trust, towards AI-created goods. For practitioners, emphasizing clear, communication about AI involvement, reducing complexity, enhancing user familiarity with AI, and ensuring, the authenticity of AI-created products are key strategies to build consumer trust. The study provides actionable insights for practitioners in the realm of AI-created goods. It underscores the importance of transparency about AI involvement not just as a direct means to garner trust but also as a way to enhance the perceived value of products. The findings, advocate for simplifying product complexity and fostering consumer familiarity with AI, alongside ensuring, authenticity to bolster consumer trust. For policymakers, these insights could guide the formulation of standards, for AI transparency in consumer goods.

For academics, this study contributes to the growing, body of literature on consumer perceptions of AI and offers a, foundation for future research in this area. This study contributes significantly to the existing body of knowledge by clarifying the nuanced interplay between AI involvement disclosure, product complexity, consumer familiarity, perceived authenticity, and their collective, influence on consumer trust. It extends the discourse beyond the simplistic binary of trust-distrust, introducing perceived value as a pivotal mediator in the relationship between AI transparency and consumer trust.

7. Conclusion

In conclusion, this study embarked on an exploratory journey, to unveil how the disclosure of AI involvement product complexity, consumer familiarity with AI, and perceived authenticity impact consumer, trust in AI-created goods. The initiation of this investi-

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gation was driven by the burgeoning integration of AI in product creation and the subsequent need to understand its repercussions on consumer perceptions.

Briefly revisiting our hypotheses, we speculated that, greater transparency about AI involvement would bolster consumer trust, whereas, increased product complexity might deter it. Moreover, we believed that a higher, familiarity with AI would positively influence trust and that the perceived authenticity of AI-generated content, would significantly enhance consumer trust. Furthermore, we proposed that the perceived, value of AI-created goods would mediate the relationship between AI involvement , disclosure and consumer trust.

The results corroborated our hypotheses illustrating a direct positive impact of AI involvement disclosure and consumer AI familiarity, on trust while product complexity, negatively influenced trust. Perceived authenticity emerged as a strong enhancer of trust affirming its significance in the AI context. Additionally, perceived value was confirmed as a mediator underscoring the indirect effects of transparency on trust through value perception.

8. Limitations and Future Research Directions

Like all studies, our study is not without limitations. The reliance on a self-reported online survey introduces, the potential for common method bias despite our efforts to, mitigate its impact. In addition, the generalizability of our findings may be constrained by the demographic and geographic composition of our respondent pool.

Future research could build on our study by incorporating qualitative, methods to gain deeper insights into consumer perceptions of AI-created goods. Exploring the role of cultural factors in shaping these perceptions could also yield, valuable insights. Furthermore, longitudinal studies could examine how consumer trust evolves with increased, exposure to and interaction with AI-created goods. In essence, our study shines a light on the critical factors, influencing consumer trust in the age of AI and offers a, springboard for further exploration in this rapidly evolving field.

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