DOI:10.17951/h.2025.59.5.155-175

ANNALES
UNIVERSITATIS MARIAE CURIE-SKŁODOWSKA
LUBLIN – POLONIA

VOL. LIX, 5 SECTIO H 2025

MIROSŁAW WÓJCIK

miroslaw.wojcik@pw.edu.pl
Warsaw University of Technology. Faculty of Management
Plac Politechniki 1, 00-661 Warszawa, Poland
ORCID ID: https://orcid.org/0000-0003-1167-7036

The Impact of AI-Driven Product Creation on Customer Value Perception: A Preliminary Study

Keywords: artificial intelligence; customer value perception; desired customer value; AI value paradox

JEL: O33; M31; D12

How to quote this paper: Wójcik, M. (2025). The Impact of AI-Driven Product Creation on Customer Value Perception: A Preliminary Study. *Annales Universitatis Mariae Curie-Skłodowska, sectio H – Oeconomia*, *59*(5), 155–175.

Abstract

Theoretical background: Individual assessments and customer preferences play a crucial role in determining the subjective perception of the value of a product or service. A prime example is the emotions experienced by customers when evaluating modern technologies, their concerns about these technologies and, consequently, their attitudes toward products or services produced using them. The perception of technology and the awareness of its use in the product creation process can lead to the depersonalization of a company and a decrease in the perceived value of its products, even if they possess competitive attributes such as quality and price.

Purpose of the article: This study aims to determine how knowledge about the use of intelligent technologies in the production of goods or services influences the personal beliefs of potential customers regarding the value assessment of such products and services compared to their human-made counterparts.

Research methods: A pilot study was conducted using a computer-assisted web interview (CAWI) questionnaire administered through the Biostat research panel. The sample consisted of a non-randomly selected nationwide group of respondents (n = 386). For statistical analysis, non-parametric methods such as the Chi-square test, Kruskal–Wallis test, and Dunn's *post-hoc* test were employed.

Main findings: Knowledge about the use of artificial intelligence (AI) in creating a product or service influences the customer's value assessment of that product. Demographic variables do not play a significant role in this process; however, most respondents believe that the use of AI in creating a product or service negatively impacts its perceived value. Furthermore, the majority of customers would choose a product created by a human over one produced using intelligent technology, solely based on the awareness that AI was involved in its production.

Introduction

Although the concept of artificial intelligence (AI) is not new, in recent years, due to, among other factors, the dynamic development of generative technologies and their widespread adoption, this topic has gained significant popularity. AI has become a symbol of the technological challenges faced by organizations worldwide across virtually every sector (Davenport & Ronanki, 2018). Researchers emphasize the broad potential of intelligent technologies to improve the efficiency of processes encompassing almost every area of business operations. This belief underpins the conviction that the implementation of these modern technologies will translate into added value for business activities, expressed, for example, through variables such as cost reduction and efficiency improvement (Alsheibani et al., 2020). The promise of benefits from technological advancement drives the steady growth of investments in developing and implementing these solutions.

According to the study *The State of AI in Early 2024* conducted by McKinsey & Company (2025), half of the respondents stated that their organizations have adopted AI in at least two business functions, up from less than a third of respondents in 2023. In many industries, organizations are equally likely to invest more than 5% of their digital budgets in generative AI as they are in non-generative, analytical AI solutions. However, in most industries, a larger share of respondents reports that their organizations spend more than 20% on analytical AI compared to generative AI. Looking ahead, most respondents (67%) expect their organizations to invest more in AI over the next three years. A study conducted by *MIT Sloan Management Review* found that over 80% of organizations view AI as a strategic opportunity, and almost 85% see it as a means to achieve competitive advantage (Ransbotham et al., 2017).

Despite the growing interest in intelligent technologies and their implementations, organizations encounter difficulties in achieving the intended goals of their AI investments (Fountaine et al., 2019). Despite increasing investments in developing these technologies, the results achieved do not meet the expected outcomes (Makarius et al., 2020) while simultaneously defining new barriers and challenges in the practical application of AI (Duan et al., 2019). Among the most significant challenges are difficulties in integrating knowledge from different domains, the multitude of required data sources (Mikalef & Gupta, 2021), integration of solutions with existing IT systems and organizational processes (Davenport & Ronanki, 2018), as well as social factors, such as concerns from employees and consumers. Facilitating and inhibiting factors can be categorized into three main groups: technological, organizational, and environmental (Enholm et al., 2022). To unlock the potential of AI technologies, organizations must learn to overcome these difficulties and understand how these technologies can generate added value. Despite the varied reasons underlying the limited success of AI in enterprises, contemporary research in this field primarily focuses on the technological aspects of AI implementation, somewhat marginalizing the identification of organizational (Alsheibani et al., 2020) and social challenges associated with its utilization. This generates research gaps (Dwivedi et al., 2021), leading to a lack of holistic understanding of the mechanisms by which intelligent technologies create value.

Fragmentary knowledge regarding the mechanisms of customer value creation related to their perception of products and services produced with the involvement of AI is one of the barriers preventing a complete understanding of the reasons behind unsatisfactory outcomes in the implementation processes of intelligent technologies. This study aims to determine how knowledge about the use of intelligent technologies in producing goods or services affects the personal beliefs of potential customers in assessing the value of such products and services compared to their human-made counterparts.

As previously mentioned, customer value is a complex construct. It encompasses objective factors stemming from the physical characteristics of a given product or service and those of competing products and services, as well as subjective factors arising from personal beliefs, experiences, trust, and customer openness. In the case of products created with AI involvement, the value evaluation seems even more complex. How consumers understand and accept intelligent technologies is not fully explored. Openness to or rejection of these technologies, driven by various factors, may significantly influence value assessment.

In this context, an important issue is the need to establish the relationship between trust and acceptance of AI technology in the process of product and service creation and the physical characteristics of these products, such as quality and innovation, in the process of making purchasing decisions or value assessment. These physical factors may play a significant role in the concept of customer value, and their importance in the context of AI perception may lead to the conclusion that, in this domain (products created by AI), customer decisions are not subject to rational evaluation but are based on subjective assessment and perception of the technology employed.

Literature review

The concept of customer value was first introduced into economics by Peter Drucker in 1954. According to Drucker (1994), value is created by the attributes of the product and the producer, such as price, durability, reliability, and reputation. Over the years, this definition has evolved, with various authors proposing their own interpretations and emphasizing different aspects of the concept. Some researchers have focused on the difference between the cost of acquiring and using a good and the sum of the benefits derived from it (Anderson et al., 1993; Gale, 1994; Monroe, 1990; Szymura-Tyc, 2005; Zeithaml, 1988), while others have concentrated on the relativistic nature of customer value, pointing to personal and situational preferences (Holbrook, 1999; Woodruff, 1997). Butz and Goodstein (1996) draw attention to the emotional aspect of value, defining it as the emotional bond between the customer and the producer that arises after using the product and discovering additional value in it.

This diversity of definitions highlights the complexity and multidimensionality of the concept of customer value. Despite differences in interpretations, a common element is the aspect of personal preference in a given place and time. Customer value is thus the result of a subjective assessment in which the customer compares the benefits received with the costs incurred, both financial and non-financial. Customer value should not be equated solely with price; rather, it should be viewed as a comprehensive concept that links the outcomes of business activities with customers' willingness to accept a certain price level for the product offering and to engage in transactions. Several models of customer value creation exist, including the value chain, the value shop, and the value network (Falencikowski, 2017).

The value chain model proposed by Porter (1985) identifies two types of activities common to all enterprises. Primary activities encompass the process from acquiring materials to delivering finished products to customers, while support activities include procurement, technology development, human resource management, and infrastructure. Both types of activities generate a margin, which is the difference between the value created and the cost of creating that value.

In the linear value chain concept proposed by Slywotzky et al. (2000), it is emphasized that the starting point must be customer priorities, followed by distribution channels, product offering, costs, and finally, resources and core competencies. This approach excludes support activities, allowing for the identification of values that are important to the customer.

Another concept that emphasizes the role of the customer in the value-creation process is the value shop, introduced by Stabell and Fjeldstad (1998) which focuses on understanding the problem affecting the customer, implying collaboration to determine optimal, feasible solutions.

In the value network concept, as defined by Stabell and Fjeldstad (1998), the value generation process is based on intermediation between customers. As highlighted by the authors, the essence of generating customer value lies in facilitating exchanges between these customers. Existing definitions of customer value and models can be divided into two categories (Graf & Maas, 2008). The first pertains to value perceived from the enterprise's perspective, while the second focuses on the customer's perspective. From the viewpoint of perceived customer value (PCV), value is conceptualized as a trade-off between benefits and sacrifices, emphasizing specific performance characteristics of products and services. In this concept, assessing a product or service's potential value is conducted without the customer's involvement, focusing on objective attributes such as price, quality, availability, or functionality. If the balance of benefits and costs of these attributes is favorable compared to those of other market participants, the product is deemed to offer the greatest value, and customers are expected to choose it. However, customers sometimes opt for products with inferior attributes, which can be explained by the desired customer value (DCV) concept. According to this approach, customer value is subjective and may encompass many elements. DCV focuses on abstract value dimensions or consequences arising from specific performance characteristics, defining value from the customer's perspective and emphasizing the subjective nature of their assessment and the extent to which the product enables them to achieve their goals and desires.

Kotler et al. point out that in an environment of low trust, product or service offerings encompass a range of functional, emotional, and spiritual values (Kotler et al., 2010). While the use of AI in manufacturing and service delivery processes enhances the functional dimension, particularly in terms of price, flexibility, personalization options, delivery time, it is less evident in the emotional and spiritual dimensions. Here, the reputation factor, as highlighted by Drucker, becomes significant. According to Webster's Dictionary, reputation refers to the overall quality or character perceived or judged by the public. Customer value is thus created not only objectively, based on measurable physical characteristics, but also by subjective factors. This is confirmed by numerous studies emphasizing the importance of preferences (Łada, 2011; Woodruff, 1997), reputation (Dobiegała-Korona, 2006; Drucker, 1994), and the ability to meet emotional needs (Cagan & Vogel, 2002). Contextual factors, such as current trends (Łada & Ziarkowski, 2017) or the customer's previous experiences (Dobiegała-Korona et al., 2004), are also significant.

Building on the DCV concept, which emphasizes the subjective nature of value assessment (Graf & Maas, 2008), this study introduces the concept of the "technology provenance effect" in customer value perception. In the context of AI-created products, customer value assessment incorporates an additional evaluative layer beyond the traditional trade-off between benefits and sacrifices: the psychological response to the awareness of AI involvement in the creation process itself. This awareness creates what is termed the AI value paradox. While AI may enhance objective product attributes (functionality, efficiency, personalization), the knowledge of AI involvement may simultaneously diminish subjective value perception through reduced trust, concerns about authenticity, and depersonalization effects (Gashenko et al., 2020). Unlike traditional value frameworks that assume customers primarily evaluate "what" they receive, this framework suggests that in AI-created products, customers also evaluate "who" (or "what") created it, introducing a symbolic dimension to value assessment. Thus, customer value in this context represents the integrated assessment of what the product delivers (functional value), how it makes the customer feel (emotional value), and what it represents in terms of human versus artificial creation (symbolic value).

Given the complexity of subjective evaluation factors, it is essential to understand how customers prioritize different product attributes. Does the customer's evaluation prioritize price, physical attributes, or other subjectively important features (Mahajan, 2020)? Research on the role of AI in creating customer value indicates that objectively important features stemming from intelligent solutions such as personalization and improvements in virtually every element of the value chain (Wodecki, 2018) do not always translate directly into purchasing decisions and, consequently, into the results achieved by enterprises. Lipowski (2015) suggesting that customers evaluate offers through multiple dimensions beyond functional benefits. This observation aligns with the notion that in technology-mediated contexts, subjective value assessment may override objective product attributes, particularly when customers prioritize psychological factors such as autonomy and control over pure economic considerations. This raises a pertinent question: Does the involvement of intelligent technologies in creating a product or service affect the preference for choosing that product?

In studies on AI and its perception by people, particular attention is paid to the aspect of trust, which, alongside money, information, image, and loyalty, influences the subjective evaluation of value by the customer. Dobiegała-Korona (2010) states, "the higher the value of these streams for the enterprise, the higher the value for the customer, which in turn translates into higher enterprise value and value for other stakeholders" (p. 22). Trust is also addressed in the context of the customer-enterprise relationship, where it is believed that in everyday practice, trust generates more value than any management concept (Zupok, 2018). Haghkan et al. (2020) emphasize trust's positive and significant role in building customer loyalty, leading to repeat purchasing decisions. In the research report *Technology in the Service of Society: Will Poles Become a 5.0 Society?* (Digital Poland, 2023), it was indicated that one-third of respondents are willing to trust AI or share information with it. Conversely, an equal number of people distrust AI and would not share their data with algorithms. Given such a significant polarization of opinions, it is worth asking whether trust in technology influences the perception of products and services created with AI.

Considering the emotional and spiritual factors mentioned by Kotler et al. (2010), the values and beliefs held by customers may also be significant in identifying customer value. According to the theory of anthropomorphism, AI intentionally designed to resemble humans can fundamentally influence interest in a product or service and customer engagement. However, existing research results are not conclusive. On the one hand, the positive role of anthropomorphized products and services is highlighted (Aggarwal & McGill, 2007). Anthropomorphism increases customers' comfort and trust in the product (Longoni et al., 2019); on the other hand, some studies demonstrate opposite effects (Garvey et al., 2023). Garvey et al. attribute this to differences in individual perceptions of AI and anthropomorphized technology. Individual beliefs and openness to intelligent technologies can, therefore, influence the relationship between the customer and AI. Beliefs, which are a complex aggregate of personality factors, can shape attitudes of acceptance or rejection toward new technologies, fundamentally affecting the perception of products created by AI. Gashenko et al. (2020) hypothesized that technologies lead to the depersonalization of a company and reduce the value of its products, even though the product or service may exhibit competitive parameters such as quality and price.

Research methods

The research aims to determine how knowledge about the use of intelligent technologies in producing goods or services influences the personal beliefs of potential customers regarding the value assessment of such products and services compared to their human-made counterparts.

The study schema (Figure 1) can be illustrated using five knowledge-derived elements that may influence how customers perceive the value of products created by AI.

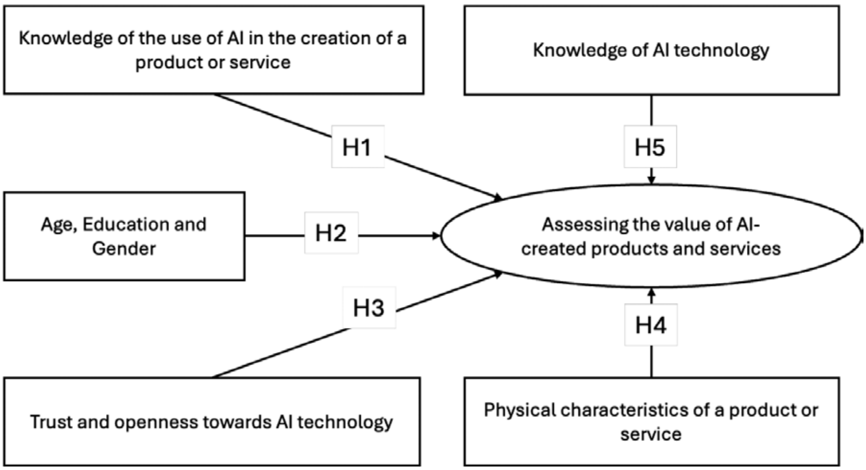

Figure 1. Study schema

Source: Author's own study.

The research schema presented in Figure 1 illustrates five hypotheses formulated based on the defined research objective and literature review:

H1. Awareness that a product or service has been created using AI influences the perceived value of that product or service.

H2. The perception of the value of products and services created using AI does not differ significantly based on age, gender, or education level.

H3. The value assessment of AI products differs significantly depending on the level of trust and openness toward these products compared to human-made products.

H4. The declaration of purchase of AI products differs significantly depending on the assessment of the quality and innovation of these products.

H5. The perceived value of AI products is higher among individuals who declare familiarity with AI topics.

These hypotheses operationalize the technology provenance effect by examining how awareness of AI involvement (H1) interacts with psychological factors such as trust and openness (H3), cognitive factors such as AI knowledge (H5), and product-related factors such as quality and innovation (H4) to influence value assessment and purchase intentions. Demographic variables (H2) serve as control factors to verify whether the observed effects are universal across different population segments or vary by age, gender, or education. This integrated framework allows for testing whether knowledge about the production method becomes an independent dimension of customer value assessment, potentially overriding objective product attributes.

The pilot study was conducted using a CAWI (computer-assisted web interview) survey questionnaire administered through the Biostat research panel. The research sample consisted of a non-randomly selected nationwide group of respondents ($n = 386$) recruited through convenience sampling from the panel's active members. Participants were invited to complete the survey based on their availability and willingness to participate, without applying probability-based selection methods or demographic quotas. The study was conducted on August 9, 2024.

The questionnaire used in the study consisted of a demographic section and the main section. The demographic section included questions about gender, age, education, place of residence, and employment status. The main section of the questionnaire was divided into three parts. In the first part, respondents were asked to self-assess their level of knowledge about AI, to express their views on the relationship between the use of AI in creating a product and the value of that product or service and indicate their preferences between a product or service created by AI or by a human. The second part focused on respondents' attitudes toward products and services created by AI, particularly their level of trust, openness, and overall attitude toward such products and services. The third part included questions about evaluating the characteristics and attributes of products and services created by AI, including their quality, innovativeness, and value.

A 5-point Likert scale was used in the questionnaire, arranged as follows: *strongly agree*, *somewhat agree*, *somewhat disagree*, *strongly disagree*, and *unsure*. The *unsure* option was placed at the end to reduce the number of non-committal responses. Experimental research conducted by the Strategic Analysis Department of the Warsaw University of Technology (Dział Analiz Strategicznych PW, 2023) shows that placing a non-committal option in the middle of the scale significantly increases the number of respondents selecting it. The availability of both a non-committal and a neutral option significantly increases the selection of these options, leading to a higher number of uninterpretable responses. However, respondents should be able to choose a neutral response when they do not have a formed opinion on the subject.

For this study, the *unsure* option was provided but placed at the end of the scale. For subsequent analyses, it was recoded to the middle position.

The consistency of the questionnaire was verified using Cronbach's alpha test (Table 1), which confirmed the internal consistency of the questionnaire for the second and third groups of questions, indicating values of 0.78 and 0.79, respectively. For the first part of the questionnaire, Cronbach's alpha coefficient was not calculated because the questions in this section addressed unrelated topics, making calculating this coefficient unnecessary.

Table 1. Results of Cronbach's alpha test for the survey questionnaire groups

Group	Quantity	Sum variance	Sum total variance	Cronbach's alpha
1	3	3.650297619	7.619832251	0.78
2	3	3.761728896	7.910579004	0.79

Source: Author's own study.

Nunnally's (1978) book is frequently cited as a primary reference for determining appropriate reliability coefficients. However, his recommendations suggest varying criteria depending on the objective or stage of the research, which challenges a one-size-fits-all approach. Despite this, a reliability criterion of 0.7 is commonly applied across different types of studies, whether in exploratory research, applied research, or scale development. Nunnally originally proposed the 0.7 threshold specifically for the early stages of research, but most studies published in academic journals do not fall into this category. For most empirical studies, Nunnally's recommended criterion of 0.8 for applied research is more appropriate (Lance et al., 2006). His recommended level did not imply a strict cutoff point. If a criterion is interpreted as a cutoff point, it is important whether or not it is met, but it is less important how much it exceeds or falls short of the threshold. When Nunnally referred to the criterion of 0.8, he did not mean it should be strictly 0.8. If the reliability value is near 0.8 (e.g. 0.78), it can be considered that his recommendation has been met (Cho, 2020).

Given that the questionnaire was constructed using a Likert scale and the distribution of responses deviated from normality, as confirmed by the Shapiro–Wilk test, non-parametric methods were employed in the statistical analysis, including the Chi-square test, Kruskal–Wallis test, and Dunn's *post-hoc* test for pairwise comparisons.

Results and discussion

Among the respondents, women predominated, constituting 63% of the sample. Higher education was declared by 57% of participants, secondary education by 35%, and the remaining 8% had primary or vocational education. Regarding place of residence, 82% of respondents indicated that they lived in a city, while 18% lived in rural areas. Among the participants who declared living in a city, the largest group (25%)

came from the largest urban centers with over 500,000 inhabitants. The remaining city dwellers were distributed as follows: 22% from urban centers with 150,000 to 500,000 inhabitants, 16% from cities with 50,000 to 150,000 inhabitants, and 19% from towns with fewer than 50,000 inhabitants.

In terms of the age of the respondents, a generational variable was used (EY Polska, 2025) to categorize participants into the Baby Boomers (Generation BB), X, Y, and Z cohorts. The BB group included individuals born between 1946 and 1964, Generation X included those born between 1965 and 1980, Generation Y those born between 1981 and 1996, and Generation Z those born between 1995 and 2012. The respondents were predominantly from Generation Y (45%), followed by Generation Z (26%), Generation X (21%), and Baby Boomers (8%).

The non-random nature of the sample has several implications for interpreting the study's findings. The convenience sampling approach may result in self-selection bias, as individuals participating in online research panels may systematically differ from the general population in terms of digital engagement and technological curiosity, potentially affecting the observed attitudes toward AI-created products.

Additionally, the overrepresentation of women, highly educated individuals, younger generations, and urban residents limits the generalizability of findings to the broader consumer population. These demographic characteristics may be associated with specific patterns of technology adoption and AI perception that do not reflect the views of underrepresented groups, particularly older consumers, those with lower educational attainment, and rural residents.

Given these limitations, the results should be interpreted as preliminary insights into customer value perception of AI-created products rather than definitive population-level estimates. The findings are most applicable to digitally engaged, urban, and relatively young consumer segments, while caution should be exercised when extrapolating to other demographic groups or the general population.

The first case analyzed is the impact of knowledge about the use of AI in the product or service creation process on customers' perception of the value of that product or service. To this end, a statistical analysis was conducted on the responses to the Question: "To what extent do you agree with the statement: Awareness that a product was created using artificial intelligence influences my assessment of its value?"

It was determined that 58% of respondents answered positively, selecting either *strongly agree* or *somewhat agree*, 22% responded negatively, choosing either *strongly disagree* or *somewhat disagree*, and 20% were unable to decide.

First, it was verified whether the distribution of responses was close to a normal distribution. For this purpose, the Shapiro–Wilk normality test was conducted.

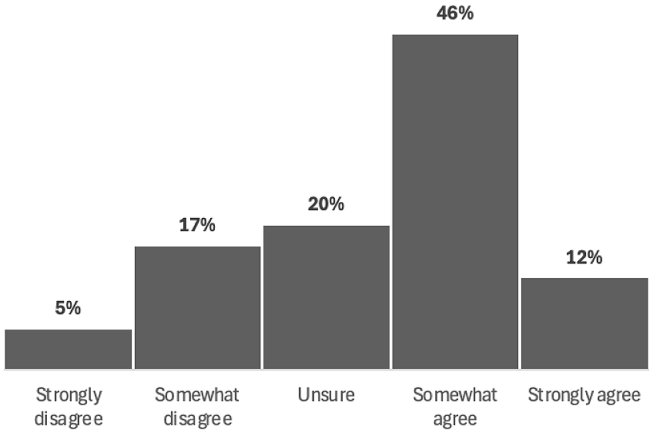

Figure 2. Distribution of responses to the question: "To what extent do you agree with the statement: Awareness that a product was created using artificial intelligence influences my assessment of its value?"

Source: Author's own study.

Table 2. Results of the Shapiro–Wilk test for the distribution of responses to the question: "To what extent do you agree with the statement: Awareness that a product was created using artificial intelligence influences my assessment of its value?"

Question	Shapiro–Wilk test (*W*)	*p*
Knowing that a product was created using artificial intelligence affects my assessment of its value	0.870	< .001

Source: Author's own study.

The Shapiro–Wilk test ($W = 0.870$, $p < 0.001$) confirmed deviation from normality, justifying the use of the non-parametric Chi-square test.

Table 3. Results of the Chi-Square test for the distribution of responses to the question: "To what extent do you agree with the statement: Awareness that a product was created using artificial intelligence influences my assessment of its value?"

Question	Test χ^2	*df*	*p*
How much do you agree with the statement: Knowing that a product was created using artificial intelligence affects my assessment of its value?	183.506	4	< .001

Source: Author's own study.

The achieved Chi-square statistic value $\chi^2 = 183.51$ and *p*-value < 0.001 indicate a strong statistical difference between the observed respondents' answers and the expected uniform distribution. This means there are significant differences between the observed and expected frequencies, suggesting that the distribution in the studied sample is not uniform.

Table 4. Descriptive statistics for the distribution of responses to the question: "To what extent do you agree with the statement: Awareness that a product was created using artificial intelligence influences my assessment of its value?"

Measure	Value
Valid	385.000
Missing Data	0.000
Mean	3.431
Standard Deviation	1.078
Skewness	-0.585
Standard Error of Skewness	0.124
Kurtosis	-0.444
Standard Error of Kurtosis	0.248
25th Percentile	3.000
50th Percentile (Median)	4.000
75th Percentile	4.000

Source: Author's own study.

The rejection of the null hypothesis, which states that the distribution of responses is uniform, does not directly support the research hypothesis H1. (Awareness that a product or service was created using AI influences the perceived value of that product or service.) The result merely suggests that the respondents' opinions are not uniformly distributed, indicating a certain tendency in the responses, which may suggest that the fact that AI was used in producing a given product or service influences its value assessment. To support the research hypothesis H1, a distribution analysis of the responses was conducted, including descriptive statistics such as mean, standard deviation, skewness, and kurtosis (Table 4) and the percentage distribution of responses for each category (Figure 2). Analysis of the response distribution revealed negative skewness (-0.585), with 58% of respondents agreeing that AI involvement affects their value assessment. Therefore, Hypothesis H1 was supported. To determine whether the responses to this Question differ significantly among groups of respondents divided by gender, age, and education level, the Kruskal–Wallis test was conducted. This non-parametric test does not require a normality assumption in the sample distribution.

Table 5. Kruskal–Wallis test results for responses to the question: "To what extent do you agree with the statement: Awareness that a product was created using artificial intelligence influences my assessment of its value?" by Gender, Age, and Education

Variable	Kruskal–Wallis test	*df*	*p*
Gender	0.321	1	0.571
Generation	5.873	3	0.118
Education	0.625	2	0.731

Source: Author's own study.

The analysis conducted, and the *p*-values obtained ($p > 0.05$) for each of the examined cases (Table 5) indicate no significant differences in the distribution of responses across the analyzed groups. Therefore, there are no grounds for rejecting

Hypothesis H2: The perception of the value of products and services created using AI does not differ significantly depending on age, gender, and education.

In the case of responses to the question: "To what extent do you agree with the statement: If given the choice between the same product created by a human and by artificial intelligence, I would choose the one created by artificial intelligence?" in the context of respondents' evaluations regarding trust, openness, and attitude, the Kruskal–Wallis test yielded a value of 121.357 with $p < 0.001$ (Table 6).

Table 6. Kruskal–Wallis test results for responses to the question: "To what extent do you agree with the statement: If given the choice between the same product created by a human and by artificial intelligence, I would choose the one created by artificial intelligence?" by different levels of declared trust in AI products

Question	Kruskal–Wallis test	*df*	*p*
How much do you agree with the statement: I have a higher level of trust in products created by artificial intelligence compared to those created by humans?	175.181	4	< .001

Source: Author's own study.

The analysis conducted, and the *p*-values obtained ($p < 0.05$) for each of the examined cases indicate significant differences in the distribution of responses across the studied groups. However, similar to the case of analysis of variance, a statistically significant Kruskal–Wallis test result only indicates that at least one group differs from another. Therefore, to determine which specific groups differ from each other, a *post-hoc* Dunn's test should be used.

Table 7. Dunn's *post-hoc* comparisons – "To what extent do you agree with the statement: I have a higher level of trust in products created by AI compared to those created by humans?"

Comparison	*z*	*Wi*	*Wj*	*rrb*	*p*	*pbonf*	*pholm*
Strongly Disagree – Somewhat Disagree	-4.944	104.356	173.110	0.454	< .001	< .001	< .001
Strongly Disagree – Unsure	-7.731	104.356	240.475	0.711	< .001	< .001	< .001
Strongly Disagree – Somewhat Agree	-11.736	104.356	307.806	0.889	< .001	< .001	< .001
Strongly Disagree – Strongly Agree	-7.194	104.356	307.000	0.817	< .001	< .001	< .001
Somewhat Disagree – Unsure	-4.064	173.110	240.475	0.463	< .001	< .001	< .001
Somewhat Disagree – Somewhat Agree	-8.270	173.110	307.806	0.759	< .001	< .001	< .001
Somewhat Disagree – Strongly Agree	-4.862	173.110	307.000	0.666	< .001	< .001	< .001
Unsure – Somewhat Agree	-3.445	240.475	307.806	0.566	< .001	0.006	0.002
Unsure – Strongly Agree	-2.249	240.475	307.000	0.548	0.024	0.245	0.049
Somewhat Agree – Strongly Agree	0.027	307.806	307.000	0.257	0.978	1.000	0.978

Source: Author's own study.

Based on the conducted test, it was shown that significant differences exist in each of the examined pairs except for the pair *somewhat agree – strongly agree* (Table 7). This indicates that respondents who provided positive responses to the question about trust in AI-created products responded similarly to the question: "To what extent do you agree with the statement: If given a choice between the same product created by a human and by artificial intelligence, I would choose the one created by artificial intelligence?” At the same time, they responded differently than all other respondents, which consequently supports Hypothesis H3: The assessment of the value of AI products differs significantly depending on the level of trust and openness towards these products compared to those created by humans.

For the responses to the question: “To what extent do you agree with the statement: If given the choice between the same product created by a human and by artificial intelligence, I would choose the one created by artificial intelligence?” in the context of respondents’ evaluations of innovation, quality, and value, the Kruskal–Wallis test yielded a value of 126.916 with $p < 0.001$ (Table 8).

Table 8. Kruskal–Wallis test results for responses to the question: “To what extent do you agree with the statement: If given the choice between the same product created by a human and by artificial intelligence, I would choose the one created by artificial intelligence?” by Aggregated Quality, Innovation, and Value Assessment Index

Question	Kruskal-Wallis test	*df*	*p*
Given the choice between the same human-made product and artificial intelligence, would I choose the one created by artificial intelligence?	126.916	2	< .001

Source: Author’s own study.

The obtained p-value < 0.05 for the conducted test (Table 8) indicates a significant difference in the distribution of responses across the examined groups. However, similar to the previously discussed case, a *post-hoc* Dunn’s test was conducted to determine which specific groups differ from each other.

Table 9. Dunn’s *post-hoc* comparisons – “To what extent do you agree with the statement: If given a choice between the same product created by a human and by artificial intelligence, I would choose the one created by artificial intelligence?” by Aggregated Quality, Innovation, and Value Assessment Index

Comparison	*z*	*Wi*	*Wj*	*rrb*	*p*	*pbonf*	*pholm*
Negative Assessment – Unsure	-3.958	145.635	211.490	0.389	< .001	< .001	< .001
Negative Assessment – Positive Assessment	-11.188	145.635	287.319	0.713	< .001	< .001	< .001
Unsure – Positive Assessment	-4.135	211.490	287.319	0.496	< .001	< .001	< .001

Source: Author’s own study.

The conducted test (Table 9) indicates that significant differences exist in each examined pair. Therefore, the way respondents answered the question: “If given a choice between the same product created by a human and by artificial intelligence, I would choose the one created by artificial intelligence,” varied depending on whether their aggregated assessment of the product’s quality, innovation, and value was negative, neutral, or positive.

Table 10. Descriptive statistics for responses to the question: "To what extent do you agree with the statement: If given a choice between the same product created by a human and by artificial intelligence, I would choose the one created by artificial intelligence?"

Index	*N*	Median	Std. Dev.	Std. Error	Coefficient of Variation
Low Assessment	229	2	0.809	0.053	0.416
Unsure	51	3	0.900	0.126	0.350
High Assessment	105	4	1.057	0.103	0.302

Source: Author's own study.

This is also reflected in the descriptive statistics (Table 10). Groups differ in their median responses: respondents who rate the quality, innovation, and value of AI-created products negatively also prefer human-made products, while those who evaluate these factors positively tend to prefer AI-created products.

The results of the statistical analysis, therefore, do not allow for the rejection of Hypothesis H4: The preference for AI-created products over human-made products differs significantly depending on the level of assessment of the quality and innovation of these products.

In response to the question, "To what extent do you agree with the statement: I am well-versed in issues related to the concept of artificial intelligence?," 67% of respondents answered *strongly agree* or *somewhat agree*, 24% responded *strongly disagree* or *somewhat disagree*, and 9% were unsure. To determine whether the level of familiarity with AI concepts influences the perceived value of AI-created products, the Kruskal–Wallis test was conducted.

Table 11. Kruskal–Wallis test results for responses to the question: "To what extent do you agree with the statement: The value of a product created by artificial intelligence is greater compared to a product created by a human?" in the context of knowledge related to the concept of artificial intelligence

Question	Kruskal–Wallis test	*df*	*p*
I am well aware of the concept of artificial intelligence	8.124	2	0.017

Source: Author's own study.

The test results (Table 11) indicate that the responses in the examined groups differ statistically ($p < 0.05$). Dunn's test was used to determine which groups these differences occur in.

Table 12. Dunn's *post-hoc* Comparisons – "To what extent do you agree with the statement: The value of a product created by artificial intelligence is greater compared to a product created by a human?" in the context of knowledge related to the concept of artificial intelligence

Comparison	*z*	*Wi*	*Wj*	*rrb*	*p*	*pbonf*	*pholm*
Strongly Disagree – Somewhat Disagree	-0.324	155.889	168.018	0.067	0.746	1.000	1.000
Strongly Disagree – Unsure	-0.772	155.889	186.671	0.181	0.440	1.000	1.000
Strongly Disagree – Somewhat Agree	-0.775	155.889	184.032	0.147	0.438	1.000	1.000
Strongly Disagree – Strongly Agree	-3.251	155.889	281.265	0.625	0.001	0.011	0.008
Somewhat Disagree – Unsure	-0.869	168.018	186.671	0.110	0.385	1.000	1.000

Comparison	*z*	*Wi*	*Wj*	*rrb*	*p*	*pbonf*	*pholm*
Somewhat Disagree – Somewhat Agree	-1.160	168.018	184.032	0.083	0.246	1.000	1.000
Somewhat Disagree – Strongly Agree	-5.981	168.018	281.265	0.581	< .001	< .001	< .001
Unsure – Somewhat Agree	0.135	186.671	184.032	0.017	0.892	1.000	1.000
Unsure – Strongly Agree	-4.040	186.671	281.265	0.528	< .001	< .001	< .001
Somewhat Agree – Strongly Agree	-5.828	184.032	281.265	0.503	< .001	< .001	< .001

Source: Author's own study.

Based on Dunn's test, statistically significant response distributions occur in cases where respondents declare a strong familiarity with AI concepts. The *p*-value for these cases was less than 0.05 (Table 12).

Table 13. Descriptive statistics for responses to the question: "To what extent do you agree with the statement: The value of a product created by artificial intelligence is greater compared to a product created by a human?" in the context of knowledge related to the concept of artificial intelligence

AI knowledge self-assessment	*N*	Median	Std. Dev.	Std. Error	Coefficient of Variation
Strongly Disagree	9	2	0.782	0.261	0.414
Somewhat Disagree	84	2	0.864	0.094	0.427
Unsure	35	2	0.901	0.152	0.410
Somewhat Agree	206	2	1.075	0.075	0.481
Strongly Agree	51	4	1.405	0.197	0.400

Source: Author's own study.

The analysis of medians in the studied groups (Table 13) indicates that respondents who declare a very good understanding of AI-related topics evaluate the value of AI-created products higher than that of similar human-made products. In other cases, this evaluation is negative. Therefore, the statistical analysis results do not allow for the complete rejection of Hypothesis H5: The perceived value of AI products is higher among individuals who declare familiarity with AI concepts.

As a result of the study, Hypothesis H2, which posits that factors such as age, gender, or education influence the perception of AI-created products and services, was rejected. The distribution of responses and the basic statistics were similar in all the examined groups, making it impossible to identify significant differences. The lack of demographic differences (H2) may reflect the increasing heterogeneity within generational cohorts. Lipowski (2017) demonstrates that even within Generation Y there are substantial differences in technology adoption, suggesting that age groups are too internally diverse to serve as reliable predictors of AI product value assessment. The factor that appears to have the greatest influence on the evaluation of AI-created products and services is the level of trust in AI products. In the groups declaring the highest positive levels of trust, respondents simultaneously expressed a preference for choosing such products and services. Similarly, when considering the aggregated evaluation of AI technology's quality, innovation, and value, respondents who rated these aspects higher also declared a greater willingness to choose AI-created products over human-made ones.

Although the indicated relationships are clear, it should be noted that the number of respondents declaring a high level of trust in AI products, as well as those positively assessing their quality, innovation, and value, remains in the minority, accounting for 20% and 27% of the sample, respectively. The percentage of respondents expressing positive feelings toward AI-created products and services was 56%, but only 20% declared greater trust in these products. At the same time, the percentage of respondents who considered AI-created products to be of higher quality was 24%, 42% were more modern, and only 19% were more valuable. In response to the question "To what extent do you agree with the statement: If given the choice between the same product created by a human and by AI, I would choose the one created by artificial intelligence?" 19% of respondents answered *strongly agree* or *somewhat agree*, 56% *strongly disagree* or *somewhat disagree*, and 25% were unsure.

Although the majority of respondents expressed generally positive attitudes toward intelligent technologies and their application in the creation of products and services, and although the perception of such solutions as innovative was strongly dominant, these views did not translate into decisions related to the potential choice of AI-created products. Rakowska (2022), drawing on research on workplace robotization, notes that reactions to AI are marked by emotional ambivalence: despite expected benefits, robotization is often associated with negative feelings and resistance. A similar pattern emerges in the present study. Declared openness toward AI does not correspond with actual or hypothetical purchasing decisions, in which products created by humans are preferred.

This divergence between declared attitudes and behavioral intentions is further reflected in a noticeable level of distrust toward AI-generated products. Interestingly, this lack of trust does not correlate with their positive perception or openness to such products and services. The Spearman correlation coefficient in the studied sample was 0.41 and 0.47, respectively. The inconsistency, expressed through openness and a positive attitude alongside a lack of trust and a clear preference for human-made products, is thought-provoking.

Conclusions

Respondents' awareness of AI involvement in the creation of a given product or service influences their value assessment of that product. This evaluation is independent of the demographic characteristics of the respondents but differs among those participants who declare a strong familiarity with AI-related topics. Physical attributes of the product or service, such as modernity, quality, or value, play a role in the decision-making process when choosing between a product created by a human and its AI-created counterpart. However, the percentage of respondents who associate AI products with higher quality, modernity, or value remains a clear minority. Similarly, trust and a positive attitude toward AI-created products play a significant role. Although various market studies indicate that the level of trust Poles have in intelligent technologies exceeds 50%, only 20% of respondents indicate greater trust in AI-created products when directly compared to human-made products.

Most respondents prefer human-made products, perceiving them as higher in quality, value, and trustworthiness. The lack of correlation between the declared level of trust and openness to AI technologies, along with a positive attitude toward them, may suggest that emotional or spiritual factors, as indicated by Kotler et al. (2010) such as beliefs, perceptions of technology, perceived threats, or cultural influences play a key role in the value assessment process and remain largely ambiguous. On the one hand, there is fear and resulting distrust; on the other hand, there are declarations of openness and positive attitudes toward these technologies.

This study contributes to customer value theory by demonstrating that, in AI-created product production methods, transparency introduces a new dimension of value assessment. The technology provenance effect operates independently of, and sometimes contrary to, objective product quality, suggesting that traditional value frameworks (e.g. PCV, DCV) require extension to account for technology-mediated production contexts. The identified AI value paradox has significant implications for understanding why AI implementations often fail to achieve their expected outcomes (Fountaine et al., 2019; Makarius et al., 2020). Organizations may focus on enhancing functional attributes through AI, inadvertently diminishing emotional and symbolic value, which can result in customer rejection despite objective product improvements.

These findings suggest that research on AI implementation outcomes should address not only technical aspects (Alsheibani et al., 2020) but also intangible factors shaping recipient attitudes. Key questions emerge: To what extent do intangible factors limit implementation effectiveness? What are the sources of lower trust in AI-created products? Does fear of labor market changes affect product perception? From a practical perspective, organizations must consider whether their AI implementation processes adequately analyze sources of subjective evaluations, include proper communication strategies to counteract stereotype-based assessments, and ensure adequate human and intangible resources for successful adoption.

This preliminary study has several important limitations. First, the non-randomly selected sample from the Biostat research panel may not be fully representative of the broader consumer population, potentially introducing selection bias related to digital literacy and technological awareness. Second, reliance on self-reported AI knowledge (67% claimed familiarity) may be subject to bias, as individuals often overestimate or underestimate their actual understanding. This discrepancy between perceived and actual knowledge could influence the observed relationships between AI familiarity and value assessment. Third, the study does not distinguish between industries, product types, or AI application contexts, making it difficult to assess whether results apply to specific market sectors. Consumer perceptions may vary significantly depending on whether AI is used in creative products (such as art and music), functional products (like household appliances), or services (including customer support and financial advice), and a generalized approach may mask important sector-specific patterns.

These limitations suggest several promising research directions. First, studies should explore the mechanisms underlying distrust toward AI-created products. While trust plays a significant role in value assessment, the sources of this distrust remain unclear, whether stemming from fears of job displacement, perceived loss of human creativity, or skepticism about AI capabilities. Second, sector-specific studies are needed to understand how value perception varies across industries and product categories, revealing whether negative bias toward AI-created products is universal or context-dependent. Third, the technology provenance effect introduced here represents a novel construct requiring substantial development. While this research demonstrates that AI awareness influences value perception, the underlying mechanisms, boundary conditions, and temporal dynamics remain unexplored. Future research should investigate the cognitive pathways that mediate the relationship between AI awareness and value judgments, the circumstances under which AI enhances rather than diminishes perceived value, and how these perceptions evolve as AI becomes increasingly ubiquitous. Given the study's preliminary nature, a substantial opportunity exists for developing a comprehensive theoretical framework that integrates technology provenance effects into customer value theory. The three-dimensional value model and AI value paradox provide conceptual foundations, but significant work remains to understand why objective product improvements through AI often fail to translate into subjective value gains.

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