



Delegating Consumer Choice to AI: Implications for Product Evaluation and Willingness to Pay

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Abstract

From a marketing perspective, the use of AI to optimise management processes is already a common part of business practice. However, the integration of AI into consumer decision-making processes remains unexplored, particularly regarding customer responses to delegated choice. The main research question was: what is the impact of delegating consumer choice on product perception and customer willingness to pay? The study assumes that the perceived value of AI-supported decision-making varies across purchasing situations and product categories. The hypotheses were tested using the SPSS software interface, employing statistical tests suitable for ordinal and repeated-measures data analysis. The input data was drawn from a questionnaire survey conducted between January and March 2026 on a sample of 420 respondents belonging to Generation Z in the Czech Republic. The results of the research indicate that delegating consumer choice to AI is generally perceived positively by consumers, particularly in the context of tangible products. The findings further show that the effectiveness of AI-based delegated decision-making depends on the type of purchase situation. Willingness to pay more for products recommended by AI differs across product categories and is significantly higher in cases characterised by a rational approach to decision-making and higher investment intensity. These results suggest that the perceived value of AI-supported decision-making is context-dependent, which has important implications for the application of AI in algorithmic recommendation marketing.

Keywords

AI, Buying Behaviour, Buying Decision-Making, AI-Supported Decision-Making, Consumer

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I. Introduction

The growing role of data and digitalisation in e-commerce environments further strengthens the importance of AI-supported mechanisms in shaping customer purchasing behaviour and perceived value (Klimek and Funta, 2021). AI is significantly reshaping business and marketing management, particularly in customer-facing processes where the effectiveness of AI integration depends on customer acceptance and the specific characteristics of products, markets, and purchasing situations (Hadady-Lukacs, 2024; Dvoulety et al., 2025). As customers increasingly delegate purchasing decisions to external sources, including AI algorithms, it becomes essential to examine how this shift influences the perceived value of decision-making and customers' willingness to accept AI-supported choices. The aim of this paper is to identify the value of delegating choice to AI in the purchasing decision-making process and to analyse how this value differs depending on the type of purchasing situation. Customers' willingness to pay more for AI-recommended products was used as an indicator of the perceived value of delegated choice. Such an approach may improve the effectiveness of AI implementation in marketing practice. This research addresses a gap in the understanding of the context in which customers delegate their decision-making to AI, and the differences in how this process is evaluated across different types of purchasing situations. The study contributes to current research by integrating decision-making rationality and investment intensity into a unified analytical framework explaining the contextual acceptance of AI-supported choice delegation. This paper expands current knowledge regarding the use of AI in marketing by shifting the focus from examining the determinants of willingness to pay to analysing the context in which customers delegate their decision-making to AI. The study also provides implications for marketing management practice across representative product categories.

II. Literature Review

In the case of AI, the value is not derived from the product itself, but it has the potential to enhance the quality of the customer experience associated with the product as well as with the process of acquiring it (Xie, 2026). It is precisely because of this characteristic that businesses utilise AI algorithms in the context of mechanisms for delegating customer choice (Vartiak and Das, 2025). In terms of the benefits identified at the level of customer utility it delivers in this application context, these primarily involve time savings and the elimination of customer risk. On the other hand, in terms of the cost component contributing to perceived value, customer concerns about the loss of decision-making autonomy and fears of privacy breaches are prominent. Husairi and Rossi (2024) note that, from a value perspective, it is not only the outcome that is relevant to customers but also the control over the decision-making process. Different combinations of the perceived benefits and costs of AI create varying levels of customer value and willingness to pay across purchasing situations, yet existing research remains fragmented across specific product categories and isolated sources of value, lacking an integrated analytical perspective.

The extent to which AI is involved in decision-making depends on the customer's level of technological literacy, past purchasing experience, and the compatibility of the benefits

of AI with the customer's attitudinal frameworks. A key role is played by the aspect of time-saving and support for decision quality, given the volume of information fed into the supporting algorithms. The effectiveness of AI-supported decision-making therefore depends on the specific purchasing context (Schaap et al., 2025). Recent research highlights that customer acceptance of AI-generated recommendations increasingly depends on perceived transparency, explainability, and trust in algorithmic systems (Li et al., 2025). The willingness to pay for AI-generated value remains an active research topic. It is conducted on two basic levels, namely: 1) the primary level, where AI directly represents a source of subjectively perceived value (Li et al., 2025), and 2) the secondary level, where AI creates another source of subjectively perceived value (Cheng et al., 2025). Nguyen et al. (2026) examined the significance of AI chatbots as a traditional tool for supporting purchasing decisions in the image-building process within destination marketing under the specific conditions of the Vietnamese market. Xu et al. (2026) note that, in terms of willingness to pay for the involvement of AI in the purchasing decision-making process, customers' sense of joy and the quality of the user experience have a positive influence. According to them, a lack of trust in AI and perceived user discomfort have a negative impact on willingness to pay. Their findings are crucial for further research in that they refute the assumption that willingness to pay for AI is based on its rational benefits (time savings, informed choice, etc.). On the contrary, the value orientation associated with willingness to pay shifts to the emotional level. This assumption stems from research conducted by Islami et al. (2025), who examined the role of AI in value-oriented marketing strategies. Based on this summary of the current state of knowledge, research assumption RA 1 was formulated.

RA 1: Delegating choice to AI is perceived as valuable, which is reflected in the willingness to pay for products recommended by AI.

Huholt and Szech (2026) note that once a delegated customer decision has moral implications, AI loses its value and relevance to the customer as a support tool. These findings point towards the need for comparative research of the subjectively perceived value of AI in the context of tangible and intangible products. Voyer et al. (2025) argue that customers perceive AI as valuable only when they retain a sense of decision autonomy and view their choices as freely made based on comprehensive information rather than AI-preselected options. The need for separate research of AI in supporting purchasing decisions in the services sector is also emphasised by Nguyen and Phan (2026). They focus on the willingness to use chatbots for booking hotel services. They identify perceived risks associated with the use of AI as a significant factor.

However, such a categorisation approach is incomplete from the perspective of practical application. Broadly speaking, it describes the possibilities for incorporating AI into supporting purchasing decision-making mechanisms. However, this approach does not sufficiently capture other product-specific characteristics that have already been identified as relevant in scope of the purchasing decision-making process. These relate primarily to the rationality of the purchase and its investment intensity. In current literature, investment intensity is beginning to emerge not only as an objective category but also as a subjective

factor. Separate attention is thus paid to the specifics of how selected phenomena are perceived by the category of so-called affluent customers (Shao et al., 2018).

In terms of the informative value of the results and their practical applicability, a combination of approaches based on distinguishing between the rationality of the customer's choice and the investment intensity of the purchase is appropriate. Specifically, this involves the following four categories of purchasing situations:

1. the customer is involved in the selection and the product is a significant investment,
2. the customer is involved in the selection, but the product is not a significant investment,
3. the customer is not involved in the selection, but the product is a significant investment,
4. the customer is not involved in the selection and the product is not a significant investment.

The first two categories mentioned are characterised by the dominance of rational arguments in the purchasing decision-making process. The latter two categories are characterised by the dominance of emotional arguments in the purchasing decision-making process. Hu et al. (2025) examined selected aspects of AI use in marketing through the distinction between rational and emotional purchasing decision-making. However, their research focused primarily on the specifics of spontaneous purchasing decisions based on rational arguments. They found that AI-generated recommendations lead not only to impulsive purchases with a strong emotional component, but also to rational, although unplanned, purchasing decisions. Song and Lin (2024) suggest that it is also possible to assume that customers prefer AI in situations where there is an objective, rational basis for the decision and where emotions and subjectivity do not play a significant role.

Current research lacks an integrated perspective on investment-intensive versus investment-not-intensive purchasing situations in the context of AI-supported decision-making. Although some studies focus on luxury products or specific product categories, these approaches are limited by sector-specific and regional conditions and cannot fully explain investment intensity, as the perception of luxury is not determined solely by price.

Based on this summary of the current state of knowledge, research assumption RA 2 was formulated.

RA 2: Willingness to pay for the option of delegating choice to AI in the purchasing decision-making process varies across types of purchasing situations.

III. Methodology

The study represents a partial output of broader research examining perceptions of AI integration into purchasing and decision-making processes. From a methodological perspective, a questionnaire survey was used for the study. It was conducted using a CAWI design between January and March 2026 on a sample of 420 Generation Z respondents in the Czech Republic. Respondents were selected using a quota sampling method to ensure basic demographic representativeness in terms of gender and age within the generation under study. The sample also contains characteristics of a non-probability

convenience-based online sample, which should be considered when interpreting the generalisability of the findings. Participation in the survey was voluntary and anonymous, and respondents provided informed consent before completing the questionnaire. The questionnaire included items assessing attitudes towards AI and willingness to pay in the context of delegated customer choice, both in general and across individual products representing different purchasing situations:

- * a robot vacuum cleaner for rational decision-making and a significant investment (1),
- * a cleaning product for rational decision-making and a non-significant investment (2),
- * luxury goods for emotional decision-making and a significant investment (3),
- * chocolate for emotional decision-making and a non-significant investment (4).

The measurement of willingness to pay more for a product recommended by AI was carried out using an ordinal scale. For descriptive purposes, ordinal categories were transformed into interval midpoint values (0–25 scale). Inferential analyses relied on rank-based non-parametric procedures. The scale expressed the degree of accepted price premium (ranging from “no, never” to “yes, more than 20%”). It was interpreted as an indicator of the subjectively perceived value of delegating the choice to AI. To address the identified research gap and reflect the current state of knowledge in the field, the following hypotheses were formulated based on the research assumptions:

- H1: Delegating choice to AI in the purchasing decision-making process is perceived as valuable, which is reflected in the willingness to pay more for products recommended by AI.
- H2: Customers’ willingness to pay more for products recommended by AI differs statistically significantly across different product types.
- H3: Customers’ willingness to pay more for products recommended by AI is higher in rational purchasing situations than in emotional purchasing situations.
- H4: Customers’ willingness to pay more for products recommended by AI is higher for investment-significant products than for investment-insignificant products.

The hypotheses were tested using SPSS statistical software, applying statistical methods suitable for the analysis of ordinal data and repeated measures. The statistical methods reflected the descriptive and comparative nature of the research and focused on identifying differences in willingness to pay across purchasing situations. Non-parametric tests suitable for ordinal data were applied, ensuring robust results without requiring a normal distribution of the data (Garbarova and Vartiak, 2022). Differences in willingness to pay between individual product categories were tested using the Friedman test. In the case of statistically significant results, subsequent pairwise comparisons were carried out using the Wilcoxon test.

The Friedman test represents a non-parametric alternative to analysis of variance for repeated measures (Fig. 1).

$$x^2 = \frac{12}{nk(k+1)} \sum_{j=1}^k R_j^2 - 3n(k+1) \quad (1)$$

where x^2 is an approximation of the chi-square distribution; n is the number of respondents; k is the number of groups being compared; and R_j are the sums of ranks for the individual groups.

The Wilcoxon signed-rank test was subsequently used for paired comparisons (Fig. 2) (Zhang et al., 2026).

$$W = \sum R_i \quad (2)$$

where R_i is the rank of the absolute differences between the compared values. The value W is transformed into a standardised Z-statistic to enable testing for statistical significance. Individual product categories were aggregated into two basic analytical dimensions: rational vs. emotional purchasing situations and investment-significant vs. investment-in-significant products. The interpretation of the results of the statistical tests was carried out on the basis of a comparison of the values of the test statistics and the level of statistical significance ($\alpha = 0,05$ for all tests).

IV. Results and Discussion

H1: Delegating the choice to AI in the purchasing decision-making process is perceived as valuable, which is reflected in the willingness to pay more for products recommended by AI.

Hypothesis H1 was assessed using descriptive rather than inferential statistics, as the aim was to evaluate the existence of perceived value in delegating choice to AI rather than differences between groups. Delegated choice was operationalised through willingness to pay more for AI-recommended products, measured by average willingness-to-pay values across product categories. Positive non-zero values were interpreted as indicators of perceived value. The results of applying this approach are presented in Table 1.

Table 1: Descriptive statistics of willingness to pay in selected product categories for H1

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Standard Deviation
WTP1_robot vacuum cleaner	420	.00	25.00	3.8750	5.86486
WTP2_cleaning product	420	.00	25.00	3.0952	5.78063
WTP3_luxury goods	420	.00	25.00	3.2024	5.98183
WTP4_chocolate	420	.00	25.00	3.3631	6.41976
Valid N (listwise)	420				

Source: Computed by the authors

As shown in Table 1, the willingness to pay for products recommended by AI ranges from 3.10 to 3.88 points on the ordinal scale used (0–25, ranging from “no, never” to “yes, more than 20%” so that the value is always the midpoint of the interval). This suggests that the price premium is acceptable to customers across all product categories. The highest level of willingness to pay was found for robotic vacuum cleaners (3.8750). Conversely,

the lowest level of willingness to pay was found for cleaning products (3.0952). In all the product categories examined, the values are positive. This suggests that customers perceive delegated choice as a source of subjectively perceived value; however, the relatively low willingness-to-pay values indicate that the perceived benefits of AI-supported decision-making remain limited. Thus, hypothesis H1 can be considered descriptively supported using basic descriptive statistical tools. However, it is also necessary to note that the absolute level of willingness to pay remains relatively low, which points to a limited scope of perceived value.

H2: Customers' willingness to pay more for products recommended by AI differs statistically significantly across different product types.

For the purposes of conducting the Friedman test, the categories of the ordinal scale were coded with values whilst maintaining their natural order (0–4 for values ranging from “no, never” to “yes, more than 20%”). The results of the Friedman test are shown in Table 2.

Table 2: Test statistics of the Friedman Test for H2

Test Statistics	
N	420
Chi-Square	34.214
df	3
Asympt. Sig.	.000

Source: Computed by the authors

Since the Friedman test demonstrated the existence of statistically significant differences between the individual product categories ($\chi^2 = 34.214$; $df = 3$; $p < 0.001$), it can be concluded that hypothesis H2 has been confirmed. The Friedman test indicated a very small effect size (Kendall's $W = 0.03$), suggesting limited practical significance despite the statistically significant differences between product categories. Based on the ranking of means (Table 3), customers show the highest willingness to pay for a product recommended by AI in the case of a robot vacuum cleaner (mean rank = 2.69). The lowest willingness to pay was identified for cleaning products (mean rank = 2.41).

Table 3: Ranks of the Friedman Test for H2

Ranks	
	Mean Rank
WTP1	2.69
WTP2	2.41
WTP3	2.46
WTP4	2.45

Source: Computed by the authors

Given the statistically significant results of the Friedman test, subsequent pairwise comparisons were carried out using the Wilcoxon test (Rayner and Livingston, 2023). In this

case, however, it was necessary to apply the Bonferroni correction ($\alpha = 0.008$). The test results are shown in Table 4.

Table 4: Pairwise comparisons (Wilcoxon test with Bonferroni correction)

	Z	Asymp. Sig. (2-tailed)	Significant
WTP1 vs. WTP2	-5.363 ^b	.000	yes
WTP1 vs. WTP3	-4.523 ^b	.000	yes
WTP1 vs. WTP4	-5.031 ^b	.000	yes
WTP2 vs. WTP3	-.078 ^c	.937	no
WTP2 vs. WTP4	-.040 ^c	.968	no
WTP3 vs. WTP4	-.494 ^c	.621	no

b. Based on negative ranks

c. Based on positive ranks

Source: Computed by the authors

From Table 4, it is clear, that statistically significant differences are evident only between the robot vacuum cleaner and the other representative products. As no statistically significant differences were identified among the other products, it is possible to assume that the willingness to pay for AI-generated recommendations is linked to products representing rationally based and investment-significant purchasing decisions.

H3: Customers' willingness to pay more for products recommended by AI is higher in rational purchasing situations than in emotional purchasing situations.

Hypothesis H3 was tested using the Wilcoxon signed-rank test (Table 5). This test demonstrated the existence of statistically significant differences between rational and emotional purchasing situations ($Z = -2.927$; $p = 0.003$). The effect size for the difference between rational and emotional purchasing situations was small to moderate ($r = 0.23$), indicating limited but meaningful practical significance. A higher willingness among customers to pay more for products recommended by AI was identified in rational purchasing situations, thereby confirming Hypothesis H3. Thus, it can be concluded that customers perceive AI-generated recommendations as a source of value with a higher degree of response in terms of willingness to pay in the case of rationally oriented purchasing situations.

Table 5: Test statistics of the Wilcoxon Test for H3

Test Statistics^a	
	emotional – rational
Z	-2.927 ^b
Asymp. Sig. (2-tailed)	.003

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks

Source: Computed by the authors

The rank analysis (Table 6) also revealed that willingness to pay was higher in 95 cases for rational products, whilst for emotional products it was higher in 66 cases. This finding confirms the importance of rational decision-making as a determinant of the acceptance of AI recommendations. On the other hand, the high number of tied values (259) suggests that the differences between these categories are not significant for all respondents.

Table 6: Ranks of the Wilcoxon Test for H3

Ranks				
		N	Mean Rank	Sum of Ranks
emotional – rational	Negative Ranks	95 ^a	86.22	8191.00
	Positive Ranks	66 ^b	73.48	4850.00
	Ties	259 ^c		
	Total	420		

a. *emotional < rational*

b. *emotional > rational*

c. *emotional = rational*

Source: Computed by the authors

H4: Customers' willingness to pay more for products recommended by AI is higher for investment-significant products than for investment-insignificant products.

Hypothesis H4 was tested using the Wilcoxon signed-rank test (Table 7). This test revealed the existence of statistically significant differences between investment-significant and investment-insignificant products ($Z = -3.496$; $p < 0.001$). The effect size for the difference between investment-significant and investment-insignificant purchasing situations was small to moderate ($r = 0.27$), suggesting limited practical significance despite the statistically significant difference. For investment-significant products, a higher willingness among customers to pay more for products recommended by AI was found. Hypothesis H4 was therefore confirmed. Based on this result, it can be concluded that in situations where a purchase is investment-significant and the decision-making process has a greater impact on their satisfaction, customers are more willing to accept recommendations from AI.

Table 7: Test statistics of the Wilcoxon Test for H4

Test Statistics ^a	
	low_investment – investment_intensive
Z	-3.496 ^b
Asymp. Sig. (2-tailed)	.000

a. *Wilcoxon Signed Ranks Test*

b. *Based on positive ranks*

Source: Computed by the authors

The rank analysis (Table 8) also revealed that willingness to pay was higher in 106 cases for investment-intensive products, whilst for low-investment products this was the case in 58 instances. This finding confirms the significance of investment intensity as a determinant of the acceptance of AI recommendations. On the other hand, the high number of tied values (256) suggests that the differences between these categories are not significant for all respondents.

Table 8: Ranks of the Wilcoxon Test for H4

Ranks				
		N	Mean Rank	Sum of Ranks
low_investment – investment_intensive	Negative Ranks	106 ^a	83.20	8819.00
	Positive Ranks	58 ^b	81.22	4711.00
	Ties	256 ^c		
	Total	420		

a. low_investment < investment_intensive

b. low_investment > investment_intensive

c. low_investment = investment_intensive

Source: Computed by the authors

The research confirmed that delegating the choice to AI represents a source of subjectively perceived value. This is reflected in the willingness to pay more for products recommended by AI. This is consistent with the findings of Li et al. (2025) and Cheng et al. (2025) in their research. They found that customers are willing to pay for AI-related value. The research results suggest that the perceived value of AI-supported choice delegation is context-dependent and varies across purchasing situations. The differences identified between individual product categories in this area expand the current state of knowledge regarding the delegation of choice to AI. Unlike previous studies, which examined individual AI tools or individual product categories in isolation (Nguyen et al., 2026), the approach adopted here creates an analytical framework for comparing the specifics of individual purchasing situations. Our findings partly contradict previous studies emphasising customers’ willingness to pay for AI-generated recommendations in emotionally driven purchasing situations (Xu et al., 2026; Islami et al., 2025). On the other hand, however, they support the research conducted by Song and Lin (2024). This research highlights the importance of rational arguments even in purchasing situations that are seemingly spontaneous. At the same time, it confirms the importance of investment intensity as a factor influencing customers’ willingness to accept choice delegation. It can be concluded that customers’ willingness to delegate choice to AI in situations where the purchase is investment-intensive can be interpreted as the customer’s effort to minimise the risk of making the wrong decision. This interpretation is consistent with existing knowledge regarding the perception of risk and value in the purchasing decision-making process (Husairi and Rossi, 2024). At the same time, it contributes to the discussion on the need to examine the investment intensity of a purchase as a separate analytical factor. This study

contributes to the literature by demonstrating the relationship between decision-making rationality and investment intensity, which create a specific context for the willingness to delegate choice to AI. At the same time, the relatively small effect sizes suggest that purchasing context alone cannot fully explain customers' acceptance of AI-supported choice delegation and that additional psychological, cultural, and technological factors are likely to influence these mechanisms. As such an integrated perspective has been absent to date, with attention focused on the isolated examination of individual factors, it can be concluded that the research contributes to a better understanding of the mechanisms that determine the adoption of AI in purchasing decisions.

The findings suggest that the implementation of AI-based recommendation mechanisms should reflect the specific characteristics of the purchasing situation rather than be applied universally. AI-supported choice appears to be most effective in rational and investment-intensive purchasing situations, whereas in emotionally driven or low-investment purchases, AI should serve primarily as a supporting marketing tool without significantly limiting customers' perceived decision autonomy. The findings should be interpreted with regard to the generational and regional specificity of the sample, which limits their generalisability to other market contexts. In addition, the relatively low effect sizes and high number of tied responses indicate that the identified differences are not universally shared among all customers. Future research should therefore apply intergenerational and intercultural comparisons and examine additional representative product categories as well as psychological determinants of AI acceptance in order to verify whether customers respond primarily to the purchasing situation itself or to the specific product category.

V. Conclusion

The aim of this paper was to identify the value of delegating choice to AI in the purchasing decision-making process and to analyse how this value varies depending on the type of purchasing situation. The findings demonstrated that delegating customer choice to AI represents a source of value subjectively perceived by customers, which is reflected in their willingness to pay for a product recommended by AI. It was also found that the perceived value of AI-supported choice delegation is context-dependent and varies across purchasing situations. Significant differences were identified across purchasing situations differing in decision-making rationality and investment intensity. These differences were subsequently explained by the characteristics of the purchasing situation, confirming that rationality and investment intensity are key determinants of the acceptance of delegating the decision to AI. The highest perceived value of delegated choice was found in the case of a rationally based and investment-intensive purchasing decision represented by a robot vacuum cleaner. This paper contributes to the literature by providing an integrated perspective on the factors determining the subjectively perceived value of AI in the purchasing decision-making process. This study integrates decision-making rationality and investment intensity into a unified perspective on AI-supported purchasing decisions. The findings suggest that the effectiveness of AI recommendation tools depends on the purchasing context, particularly in rational and investment-intensive situations, where customers perceive greater value in delegated choice. From a managerial perspective, the findings suggest that firms should

avoid universal implementation of AI-based recommendation systems and instead adapt delegated-choice mechanisms to the characteristics of specific purchasing situations and customers' perceived decision risk.

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