Influence of AI Recommendations on Consumer Choices:

Trust as a Moderating Factor

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Abstract

This research focused on how personalized AI recommendations influence customers decision time and product choice, and whether the level of trust in AI moderates this effect. An online experiment was designed where participants (*n* = 207) received either a personalized or generic product advice. The results of this study showed no statistically significant differences in decision time or product choice between the two sample groups. Contrarily, higher levels of trust in AI caused faster decision times. An exploratory analysis revealed that people may prefer generic recommendations that align with their preference. One possible explanation for this could be the greater sense of autonomy in the decision-making process. The results of this study highlight that the personalization of an AI does not automatically mean more effective decisions for users. Also this study highlights the important role of trust and user experience play in how consumers respond to recommendations generated by AI.

Influence of AI Recommendations on Consumer Choices: Trust as a Moderating Factor

Historically, digital platforms such as online stores, social media, and streaming websites, used an approach where they provided the same content to all users, a practice that is described as a ’universal approach’ (Oluwademilade et al., 2024). However, the advancement of digital technologies has evolved online marketing, and customers are constantly confronted with personalized marketing messages and products. The concept of personalization refers to the alignment of products, content, services, and messages with the demands of individual customers or clients (Piller & Tseng, 2003). This customer-oriented marketing strategy allows companies to align their content delivered based on the consumers' individual desires and needs, which results in enhancement of customer engagement and satisfaction (Piller & Tseng, 2003).

With the integration of Artificial Intelligence (AI) companies have the opportunity to rely on algorithms to automate their sales strategies through personalization (Anzén & Ekberg, 2020; Gujar, 2024). AI-driven personalization automatically builds profiles of individuals based on their previous user behavior (Haleem et al., 2022). These profiles are then used to create recommendations that are tailored specifically to individual preferences. Literature suggests that such personalized recommendations can greatly streamline consumers’ decision-making, making it faster and more efficient through targeted suggestions (Becker et al., 2022). However, AI personalization could also complicate decision-making processes. In certain individuals, the AI generated recommendations seemed to lead to feelings of uncertainty and consumers spent additional time re-evaluating recommendations (Kovari, 2024).

To understand the effectiveness of personalized AI on customers’ behavior, the level of trust in AI systems may be a key component. Previous research showed that customers with high levels of trust in AI are generally quicker to accept AI-generated recommendations without needing time for re-evaluation, while those with lower trust spend additional time evaluating the recommendations (Yu & Li, 2022). Furthermore, trust in AI impacts customers' perceptions of an AI system's accuracy and reliability which, in turn, influences their willingness to rely on such systems for future decisions (Tolmeijer et al., 2022). Although the importance of trust in interactions with AI systems is well recognized, its role in the association between AI personalization and decision-making time has yet to be fully explored. Therefore, this research addresses the following central research question: How do AI personalized recommendations influence consumers' decision-making time and product choice as compared to generic AI recommendations, and is this relationship moderated by trust in AI?

Literature Review

Personalization in General: Effects on Consumer Behavior

Personalization has become a powerful tool for companies to align an individual's desires and needs with the objective's nature (Piller & Tseng, 2003). In particular, from the marketing point of view, personalization operates in a way that identifies and recognizes the customers' needs and provides them with a range of alternatives that are well-matched to their needs (Surprenant & Solomon, 1987).

A study by Matz et al. (2017) shows the effectiveness of psychological targeting, which is a specific form of personalization; tailoring persuasive appeals to match with individuals' psychological characteristics increases consumer engagement and the probability of making a purchase. These findings highlight the strong potential of personalization to impact consumer decisions as compared to generic or non-tailored messages. Hirsh et al. (2012) support these findings, demonstrating that persuasive messages become significantly more effective when designed in alignment with personality profiles of users, indicating that personalization based on personality traits enhances consumer engagement, and therefore the effectiveness of marketing communication.

Kumar et al. (2022) also found that personalized experiences increase customers' brand perceptions, boosting overall engagement and loyalty, and Ballı (2024) found that personalized marketing enhances customer satisfaction and therefore strengthens the relationship between customers and brands. Despite substantial evidence on personalization's effectiveness and general effects on consumers, research specifically addressing the role of personalization on product choice and decision time is limited.

AI-Driven Personalization: Shaping Consumer Choices

The use of AI has improved personalization strategies by automating the alignment of recommendations to consumer preferences. Becker et al. (2022) demonstrated that AI-generated suggestions help streamline the consumers' decision-making process by reducing complexity and making choices faster and more efficiently. Their research stated that AI recommendations bring down the cognitive effort used during decision-making processes. This is done by matching the right choice options with personal user preferences which are gathered by AI. In this way consumers find it easier to choose when shopping online, choosing healthcare options, or managing financial issues.

Conversational AI systems nowadays are increasingly used by companies as advanced personalization tools, offering alternatives to the traditional product search methods (Werner et al., 2024). This research provided experimental evidence that conversational AI can discreetly guide consumer choices without their explicit awareness, therewith influencing their product preferences. However, this also raises concerns about the possibility that companies might misuse these tools to nudge consumer behavior in favor of their sales strategies and profits. Baines et al. (2024) found that AI-driven recommendations are efficient but can increase overreliance and decrease users' ability to critically assess and evaluate their decisions. Their results highlight that, when users are presented with AI-generated advice, they often fail to ignore poor suggestions, especially in complex or unfamiliar decision-making contexts.

This indicates that AI systems not only shape the choice of the consumer, but also the way the consumer engages with decision-making processes. Further research found that the time people spend on making decisions, also reflects how much users engage with the decision-making process itself (Tejeda et al., 2022). This suggests that the time people spend on making a decision is not just a measure of speed but also an important indication of cognitive involvement.

Caraban et al. (2019) highlight that personalized persuasive technologies could nudge users' choice behavior effectively, even without recognizing the slight and subtle influences involved in these recommendations. These findings reinforce the ethical concerns stated by Werner et al. (2024) and highlight the importance for further exploration of human-AI interaction models, which are increasingly used by companies to gain profits.

Trust in AI Systems: Moderating Effects on Consumer Behavior

The effect that personalized AI recommendations have on the decision time and product choices of consumers may depend on the level of trust that consumers have in AI. Bach et al. (2022) reviewed several studies and found that the trust in AI consists of the perception of transparency and fairness of the system, how well it fits expectations, and the level of perceived control of users. Their findings suggest that a good foundation for trust depends on both the technical design of the system and how well it supports user needs.

Later research conducted by Frank et al. (2023) found that trust in a company increases the level of users' adaptation of AI services. According to Kovari (2024), the level of trust in AI systems is an important factor in the relationship between personalization and decision-making time. He showed that users who trust AI systems are more likely to make decisions faster and re-evaluate previous options less often. Similarly, Yu and Li (2022) revealed that consumers with high levels of trust in AI systems accept AI-driven recommendations more easily, while consumers with lower trust levels tend to reconsider suggestions generated by AI.

These findings together suggest that trust in AI systems influences how personalization impacts the decision-making process and time. That means that the absence of trust in AI can slow down or even complicate decisions, even though the personalization is originally designed to enhance the efficiency of consumers' decision making processes.

Research Gap and Positioning of the Current Study

Although extensive research demonstrated the benefits of personalization and the role of trust, the role that trust in AI plays when it comes to AI-driven personalization and consumer decision-making time and product choice has not been thoroughly explored. This study explicitly addresses this gap by investigating the influence of AI-driven personalization on consumer decision-making time and product choices and the moderating role of consumers' trust levels in AI systems on these effects. The insights gained will provide valuable theoretical contributions and practical implications, enabling more effective and ethically grounded AI personalization strategies.

Motivation and Contribution

This study is relevant because of the increasing adoption of AI personalization strategies that have been applied to global companies. For example, Spotify uses AI algorithms to analyze users' preferences in music taste and offer personalized playlists based on their previous listening habits (Hofseth, 2023). Netflix uses AI personalized recommendation systems to reduce customer's turnover (Sudhir & Toubia, 2023) by following a filtering algorithm that learns what kind of recommendations each viewer wants by analyzing their viewing history (Khandelwal et al., 2023). While the increase of personalized recommendation strategies used by companies is globally recognized, it is still unsure how personalization affects the speed and quality of customers' decisions.

It seems essential to improve the understanding concerning the way personalization and trust influence how consumers interact with AI recommendations. Therefore, we focus on the decision-making process of customers in an online shopping setting. The findings of our research will contribute to the existing literature and are relevant because they help companies to improve the design of AI systems that are both efficient and also trusted by users.

RQ: *How does AI personalization influence consumers' decision-making time and product choice, and is this relationship moderated by trust in AI?*

Based on the literature, the following hypotheses are proposed:

H1: Personalized AI recommendations will reduce the time users spend on making decisions compared to generic AI recommendations.

H2: Higher trust in AI will lead to faster decision times with personalized AI recommendations, while lower trust in AI will result in similar or slower decision times compared to generic AI recommendations.

H3: Higher trust in AI will lead to a greater likelihood of choosing personalized AI recommendations, while lower trust in AI will result in similar or lower likelihoods of choosing personalized AI compared to generic AI recommendations.

Methods

Research design

In the current study, an experimental design was used to evaluate the effectiveness of AI personalized recommendations on consumers' decision-making time and product choice. Participants were randomized into two groups; an experimental group, which was exposed to personalized AI recommendations, and a control group, which received generic AI recommendations concerning the choice of clothing. Then, both conditions participated in four decision-making-tasks. Also, trust in AI was measured after the intervention tasks to be able to determine whether the difference in decision-making time and product choice was dependent on the level of trust in AI.

Participants

The target population consisted of people aged 18 years or older. So, to participate in the current research, eligible participants had to be at least 18 years old and exhibit a strong command of the English language.

An a priori power analysis for a multiple regression analysis with three predictors was conducted using G*Power (version 3.1.9.7; Faul et al., 2007) to estimate the sample size that is needed to detect effects with an effect size (f^2) of 0.10, a significance level of 0.05 and a power of 95%. The analysis resulted in a required sample size of 176 (See Appendix D).

Procedure

Participants were recruited by means of calls through Tilburg University, as well as posts on social media platforms Instagram, WhatsApp, and LinkedIn. Participants completed a questionnaire on the online platform Qualtrics. After providing consent, participants were engaged in a task where they were asked questions regarding product preferences. They were asked whether they like bright and colourful, or muted and neutral colours in products. Also whether they liked bright and colourful, or muted and neutral colours in products (clothing). And they were asked whether they liked products with visible well-known brand logos, or without recognizable brand logos. Based on the outcome of these questions, personalized preference profiles were identified for each participant. Participants were then randomly assigned to one of two condition groups: Personalized AI condition or Generic AI condition.

Experiment

The experiment consisted of three parts; 1) Gather information on the preferences of the participants; 2) AI recommendation that was either personalized or generic; 3) product choice by participants.

Part I: Participant preferences

To uncover the personal preferences for each participant, they were asked two questions: Which type of products do you prefer?**,** which could be answered with 1) *Bright and colorful products* or 2) *Muted and neutral color products*, and Which type of products do you prefer? With the answers 1) *Products with visible well-known brand logos* and 2) *Products without recognizable brand logos*. Based on the responses to these product preference questions, the participants were placed into one of four different preference groups: (1) Bright and colorful & visible well-known brand logos, (2) Bright and colorful & no recognizable brand logos, (3) Muted and neutral & visible well-known brand logos, or (4) Muted and neutral & no recognizable brand logos.

Part II: AI-recommendation

This part of the experiment was different for the two condition groups.

In the personalized AI condition, participants received recommendations that aligned with their specific product preference that was determined in Part I (see Figure 1). The participants in the Generic AI condition received an at random chosen recommendation from the same set of the four product recommendations.

Figure 1

Personalized advice on product choices

Different advices

1) You like bright, colorful products from popular brands. These products not only stand out, but also come from trusted names. Choosing a well-known brand with bold colors will give you both style and quality.

2) You enjoy colorful and unique products but prefer brands that are not too famous. Smaller or less common brands often have creative and special designs. Picking a colorful product from a smaller brand will help you express your own style.

3) You prefer simple and classic designs from trusted brands. Well-known brands often offer high-quality products that look elegant and timeless. Choosing a product with a soft and calm look from a famous brand will suit your style.

4) You like simple and calm designs and prefer brands that are not too famous. Smaller brands often offer high-quality products with a unique but subtle style. Choosing a product that is simple and different will match your taste.

All the product recommendations used in the experiment were created with ChatGPT. The Prompt that was used to generate the four different recommendations was:

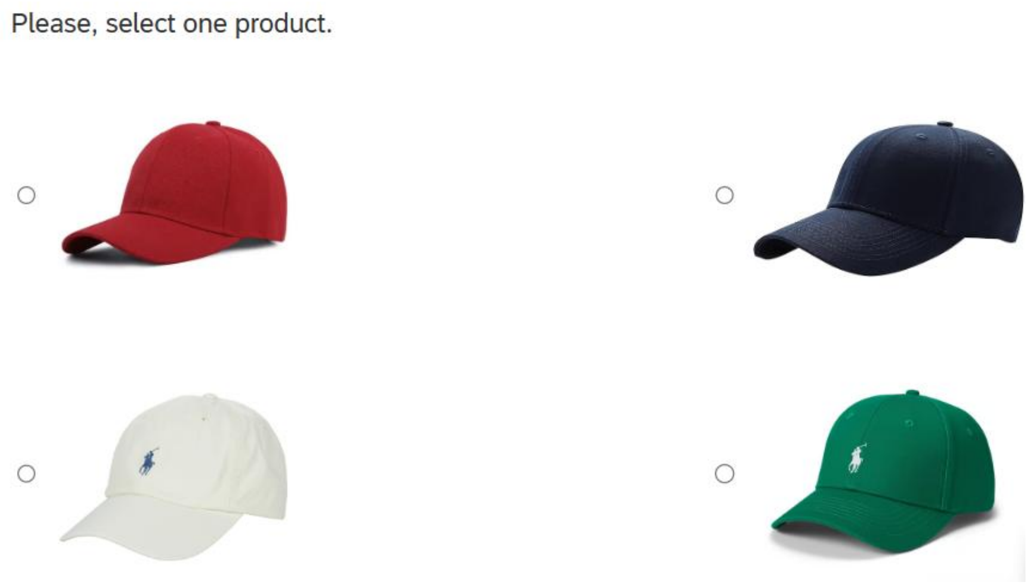
“Generate a brief, personalized piece of style advice for each of the four possible combinations of the following two preferences: (1) whether someone prefers bright and colourful products or muted and neutral ones, and (2) whether they are drawn to well-known branded products or to products without recognizable branding”.

Part III: Product choice.

After the personalized or generic recommendations, participants from both conditions were given a task in which they were asked to choose a product among a set of four alternatives. This task was repeated four times in total using four different product categories: shoes, hoodies, backpacks and caps (See Figure 2 for an example of the product choices that were presented to the participants). During these four tasks, decision time as well as the chosen product were registered in Qualtrics. Decision time was determined by measuring the time between the moment the options were presented to the participant and the moment the participants made their choice between the four alternative products. The study was designed to take around 5 minutes to complete.

Figure 2

Example of product choice options for hats



Materials

After completing the tasks, participants were asked to answer a questionnaire that contained questions on the level of trust in AI systems and personal demographic information.

Trust in AI was assessed using a validated scale based on Körber (2018). The scale included five items such as, ‘’I am confident in the AI systems ability to perform its tasks accurately”, and ‘’I feel the AI systems behave consistently across similar tasks’’. Each of the five items could be answered on a 5-point Likert scale ranging from 1) *strongly disagree* to 5) *strongly agree*. For each participant, an average score of the five items was calculated. The trust in AI-score could range from 1 to 5 with a higher score indicating more trust in AI. The reliability of the 5-item scale measuring trust was determined and showed acceptable internal consistency with a Cronbach’s alpha of .66, and a total score for trust was calculated by averaging the five items. Lastly, several **demographic characteristics** were asked, i.e. age and gender, in the questionnaire.

Based on the outcomes of the experiment, the two dependent variables in the study were calculated. An overall **decision time** was calculated by summing the decision time across all four tasks. The second dependent variable was **product choice.** Product choice was based on the products that were chosen by the participants in the four tasks. If the chosen product for each task aligned with the recommendations, they were given one point and if the product did not align with the recommendations, they received zero points. The product choice variable could therefore range from 0 (no products align with recommendations) to 4 (all products align with recommendations).

Data Analysis

The collected data were analysed using SPSS, version 30. First, data-inspection was used to determine whether participants had completed the questionnaire. Participants who did not complete the full questionnaire were excluded to be able to have a constant sample for each of the analyses. Also, responses with exceptionally fast (+ 3 sd’s from the mean) or extremely slow decision times (-3 sd’s) were determined (Miller, 1991). The extreme response times can point to inattention during the decision task, or technical issues. To determine the impact of the extreme responders on the outcomes of the analyses, the main analyses were performed twice, once with and once without outliers.

In order to test whether the groups in which the participants were randomized were comparable, participant demographics were compared between the groups by means of independent t-test (age) and chi square test (gender). Significant differences between the condition groups may lead to bias arising from the randomization process (*Cochrane Methods 2016*, 2016). In case of differences in age and/or gender between the groups, the relevant variable was added to the main analyses as control variables.

To test the first hypothesis (*H*1), a one-way ANOVA was performed to examine whether personalized AI recommendations help people to make decisions faster compared when receiving generic AI recommendations. F-value, p-value, ηp^2, and 95% confidence intervals are used to determine whether a difference in decision time exists between the two conditions. Bar charts are used to display mean decision times for both conditions.

For the second hypothesis (*H*2), a hierarchical regression analysis was performed to determine whether trust in AI moderates the relationship between AI personalization and decision making time. It was expected that participants with higher trust in AI will make faster decisions when they receive personalized recommendations, compared to participants who receive generic recommendations. If a significant interaction was found, simple slope analysis was performed to determine how decision-making time varies between respondents who reported high levels of trust in AI with respondents who reported low levels of trust in AI. Reported statistics included model fit outcomes (F-value, p-value, R^2 change) and predictor outcomes (beta coefficients, t-values, p-values, and confidence intervals). An interaction plot was included to visualize a significant moderation effect of trust at different levels (-1SD, M, +1SD).

To test our final hypothesis (*H*3), another hierarchical regression analysis was performed for product choice as an independent variable. The reported statistics included similar model fit outcomes and predictor outcomes as the analysis for Hypothesis 2.

Prior to interpreting the results of the analysis, the assumption of the one-way ANOVA (dependent variable is normally distributed per group, no outliers, and homogeneity of variances) and of the regression analysis (residuals are normally distributed, have no outliers/influential points, no multicollinearity, homoscedasticity, and linearity) were tested. Violations of these assumptions are reported as well as measures taken to ensure that the outcomes are interpretable. For all statistical analyses a threshold for significance of $a = 0.05$ is used.

Results

In total, 237 individuals opened the survey, but 30 did not complete all of the questions and were removed from the dataset. Finally, 207 participants remained in the dataset, of which 95 (45.9%) were male and 112 were female. Their average age was 38.8 (*SD* = 16.94) ranging from 18 to 89. Also three respondents showed average decision times that were more than three standard deviations above the average decision time. To test whether the results of the study were sensitive to the influence of these outliers, the main analysis of this study (moderation analysis) was performed twice, once with the outliers and as a sensitivity check once without these three respondents.

The respondents were randomized into two condition groups, a generic AI recommendation group (n = 100) and a personalized AI recommendation (n = 107). To test whether risk of bias arising from the randomization existed, a randomization check was performed of which the results are reported in Appendix E. As no differences between the groups were found when it comes to gender, $\chi^2(1) = 1.87$, $p = .172$, and age, $t(205) = 0.04$, $p = .965$, it was concluded that the randomization has led to two comparable groups when it comes to gender and age. For this reason, gender and age were not included in the main analyses as control variables.

The main variables in the current study are decision time (dv 1), product choice (dv 2), condition (iv) and trust in AI (mod). Table 1 contains the descriptive statistics for the main variables. The average decision-making time across all participants was 8.25 seconds (*SD* = 4.21), with times ranging from 1.19 to 24.70 seconds. On average, participants selected 1.22 (*SD* = 1.16) products that matched the AI's recommendations on a scale range from 0–4. The mean trust in AI score was 3.20 (*SD* = 0.62) on a theoretical 1 to 5 range.

Table 1

Descriptive statistics of the main variables in the study

Variables	*M*	*SD*	*Min*	*Max*
Decision time (s)	8.25	4.21	1.19	24.70
Product choice	1.22	1.16	0.00	4.00
Trust in AI	3.20	0.62	1.40	4.80

The effect of personalized AI recommendations on decision time and product choice

To test the first hypothesis, a one-way ANOVA was performed to compare decision making times between the experimental and control condition. No significant difference in average decision time was found between the personalized recommendations group (M = 8.14, SD = 4.12) and generic recommendations group (M = 8.37, SD = 4.33), $F(1, 205) = 0.16$, p = .688, η^2 = .001. See Figure 1A.

When it comes to the number of products were chosen that aligned with the recommendation, in the generic AI recommendation group the average aligned product choice was 1.25 (SD = 1.22) products, while in the personalized AI recommendation group the average number of aligned products was 1.20 (SD = 1.10; Figure 1B), but the difference was not significant, F(1, 205) = 0.11, p = .739, η^2 = .001.

Figure 1

Average decision time and product choice of the generic AI recommendation and personalized AI recommendation groups

Figure 1A

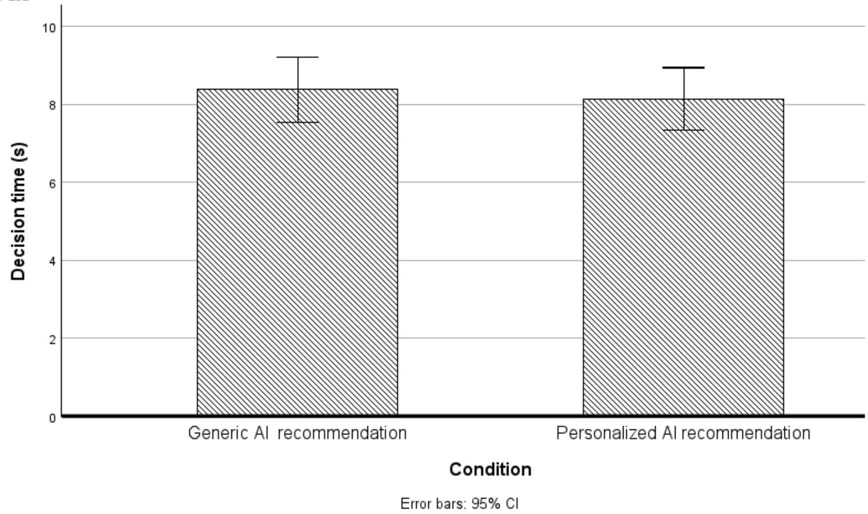
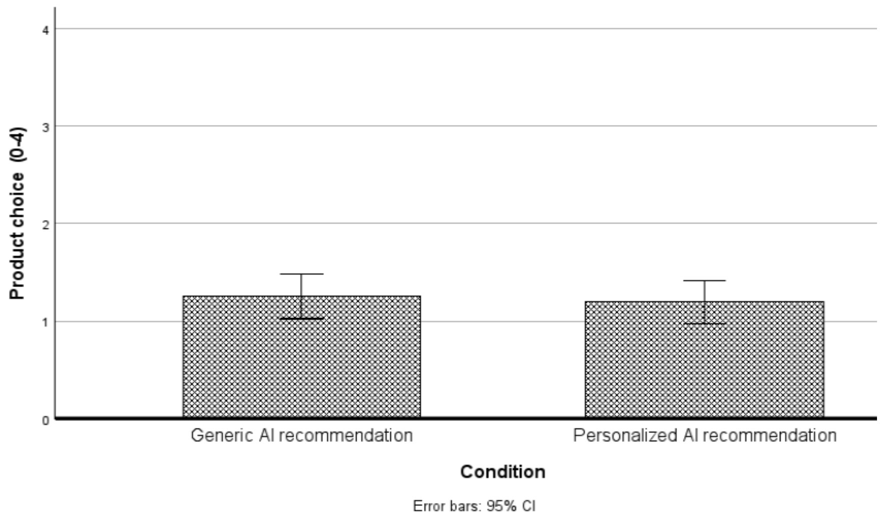


Figure 1B



The moderating effect of trust in AI

To test the moderating effect of trust in AI, a hierarchical regression analysis was performed to test whether trust in AI moderated the relationship between personalization and decision time. The results are reported in the upper part of Table 2. Before interpreting the results of the analysis, the assumptions of the regression were checked. The histogram and P-P plot showed a slight deviation from normality of the residuals with a positive indicating that most individuals needed a short time to decide about the product they chose, while some individuals needed a longer time. However, given the Central Limit Theorem (Field, 2017) which indicates that in case of a large sample (N > 30) normality can be assumed, the outcomes of the regression analysis were not expected to be influenced by the deviation in normality. The scatterplot between residuals and predicted values showed a linear relationship. This study noticed that there may be some heteroscedasticity issues, as the scatterplot showed smaller variances of the residuals when the predicted values were small than with high predicted values. This means that the regression analysis may be better able to predict the decision time of people that are quick to decide than of people who take longer to decide. The maximum Cook's distance of the regression was 0.24, which is lower than the threshold of 1 according to Tabachnick en Fidell (2006), which means there were no extreme influential points (outliers). VIF values of the predictors in the model ranged from 1 to 1.86. This is lower than the threshold of 10 (Field, 2017), and it can be assumed there is no multicollinearity. Although not all assumptions passed the test, it was decided to perform the multiple regression as planned.

The first model, which included the variable condition, was, in line with the outcomes of the one-way ANOVA, not significant, $F(1, 205) = 0.16$, $p = .688$, $R^2 = .001$. Adding the direct effect of trust in AI in the second step significantly improved the model, $F_{change}(1, 204) = 11.06$, $p = .001$, $R^2_{change} = .051$, while adding the interaction between condition and trust in AI did not improve the model, $F_{change}(1, 203) = 2.14$, $p = .145$, $R^2_{change} = .010$. The total model was significant and explained 6.2% of the variance in decision time, $F(3, 203) = 4.48$, $p = .005$, $R^2_{change} = .062$. Regression coefficients showed no significant direct effect of condition ($\beta = –0.02$, $p = .720$) which confirms that there is no significant difference between the two condition groups when it comes to decision time. The direct effect of trust was also not significant ($\beta = –0.14$, $p = .147$). Finally, the interaction term between condition and trust in AI was not significant ($\beta = –0.14$, $p = .145$). This means that trust in AI does not moderate the association between condition and decision time.

Table 2

Results of the hierarchical regression analyses with decision time (top) and product choice (bottom) as dependent variables.

	DV: Decision time											
	Model1				*Model 2*				*Model 3*			
Variables	*b*	*se*	β	*p*	*b*	*se*	β	*p*	*b*	*se*	β	*p*
Intercept	8.37	0.42		< .001	8.36	0.41		< .001	8.36	0.41		< .001
Condition	-0.24	0.59	-.03	.688	-0.21	0.57	-.03	.720	-0.21	0.57	-.02	.720
Trust in AI					-1.55	0.47	-.23	.001	-0.92	0.63	-.14	.147
Condition * trust									-1.37	0.93	-.14	.145
df	1, 205				2, 204				3, 203			
F	0.16				5.62				4.48			
p	.688				.004				.005			
R^2	.001				.052				.062			
R^2_{change}	.001				.051				.010			
	DV: Product choice											
	Model1				*Model 2*				*Model 3*			
Variables	*b*	*se*	β	*p*	*b*	*se*	β	*p*	*b*	*se*	β	*p*
Intercept	1.25	0.12		< .001	1.25	0.12		< .001	1.25	0.12		< .001
Condition	-0.05	0.16	-.02	.739	-0.05	0.16	-.02	.743	-0.05	0.16	-.02	.744
Trust in AI					-0.04	0.13	-.02	.781	-0.06	0.18	-.03	.741
Condition * trust									0.05	0.27	.02	.851
df	1, 205				2, 204				3, 203			
F	0.11				0.09				0.07			
p	.739				.910				.974			
R^2	.001				.001				.001			
R^2_{change}	.001				.000				.000			

Note: Condition 0 = generic AI recommendation, 1 = personalized AI recommendation

A similar hierarchical regression was conducted to explore whether personalization, trust, or their interaction predicted product choice. See the bottom part of Table 3. The residuals were not normally distributed and showed more respondents have lower residuals and fewer respondents have higher residuals. The scatterplot between residuals (y-axis) and predicted values (x-axis) showed linearity and homoscedasticity. Cook's distance was not higher than the threshold of 1 (max = 0.096), and similar to the previous regression VIF scores did not exceed 10.

The overall model was not significant, $F(3, 200) = 0.02$, $p = .997$, $R^2 = .001$. Therefore, none of the individual predictors in the model reached statistical significance: condition ($\beta = -.02$, $p = .891$), trust in AI ($\beta = -.02$, $p = .849$), or the interaction between condition and trust in AI ($\beta = .01$, $p = .882$).

Based on these findings it can be concluded that using personalized AI recommendations do not lead to shorter decision times or product choices that align more with the recommendation than using generic AI recommendations and these differences in condition groups do not depend on the level of trust in AI of the individual.

Sensitivity check

Three respondents had average decision times more than three standard deviations above the average. A sensitivity check was performed by repeating the multiple regression analysis without these three respondents, to check whether the results of the main analyses were sensitive to the influence of these outliers. The results of the hierarchical regression analyses are reported in Appendix E.

There were some slight differences in outcome between the main analysis and the sensitivity check analyses, for example the total model of the hierarchical regression analysis with decision time as a dependent variable was no longer significant in the sensitivity check, $F(3, 200) = 2.29$, $p = .079$, $R^2 = .033$. However, the main conclusions of the analyses remained the same: no differences in decision time ($\beta = -.05$, $p = .506$) or product choice ($\beta = -.02$, $p = .744$) were found between the group receiving personalized AI recommendations and the group generic AI recommendations. Also, the reported level of trust in AI did not moderate this effect for either decision time (β = –.06, p = .495) or product choice (β = –.02, p = .851).

Exploratory analyses.

The set-up of the interventions was such that respondents in the personalized AI recommendation group always received a recommendation that matched their personal preferences. However, in the generic recommendation group, a random recommendation was formulated. This recommendation could match personal preferences by chance. Potentially, the respondents in the generic AI recommendation group who received a recommendation that aligned with their preferences, may have shown a decision time and/or product choice that were more similar to the personalized AI recommendation group than the respondents who received a recommendation that was not aligned to their preferences. To, exploratory, investigate whether the alignment of the recommendation with the preference of the participant plays a role in the outcomes of the experiment, the main analyses were performed again. This time, the generic AI recommendation group was split into two groups: alignment with preference (n = 23) and non-alignment with preference (n = 77). The personalized AI recommendation group remained as is.

In the one-way ANOVA, the omnibus effect was not significant, $F(2, 204) = 0.10$, p = .908, $\eta^2 = .001$, indicating there were no significant difference between the group with personalized AI recommendation (M = 8.13, SD = 4.11), generic AI recommendation group in which the recommendation was not aligned (M = 8.33, SD = 4.33), and the generic AI recommendation group whose recommendations did align with their preferences (M = 8.51, SD = 4.41).

The omnibus effect of the ANOVA with product choice as a dependent variables was also not significant, $F(2, 204) = 0.53$, p = .590, $\eta^2 = .005$. This means that there was no significant difference in average number of products that were chosen according to the recommendations in the generic AI recommendation group that received recommendations that aligned with the preferences (*M* = 1.04, *SD* = 1.30), the group that received personalized AI recommendations (*M* = 1.20, *SD* = 1.10), and the generic AI recommendations that did not align with the personal preferences (*M* = 1.31, *SD* = 1.19).

The results of the hierarchical regression analyses with condition as independent variable and trust in AI as potential moderator and decision time (upper part) and product choice (lower part) as dependent variables are reported in Table 3.

The direct effects of condition on decision time were not significant (respectively aligned (β = .03, *p* = .670) and non-aligned (β = .02, *p* = .813) as compared to the personalized AI recommendation. There was a significant direct effect of trust in AI on decision time (β = –.33, *p* = .001). The interaction effects between trust and aligned recommendation (β = .07, *p* = .394) and between trust and non-aligned recommendation (β = .13, *p* = .172) were not significant.

The hierarchical regression with product choice as a dependent variable, however, did result in a significant interaction effect between trust and aligned generic recommendations (β = .17, *p* = .027). The difference in average product choice between the personalized AI recommendation group and the generic AI recommendation that received recommendations in alignment with their preference increases as trust in AI is higher. This interaction effect is further explained in Figure 2. As can be seen, the number of products that is chosen in line with the recommendation increases as the trust in AI is higher in the generic AI recommendation group that received recommendations in alignment with their preferences. However in the generic not aligned recommendation group, the number of products chosen in accordance with the recommendations decreases as trust in AI is higher. The average number of products that are chosen in alignment with recommendation does not appear to depend on trust in AI in the personalized recommendation condition.

Figure 2

Moderation effect of trust in AI on the association between condition and product choice

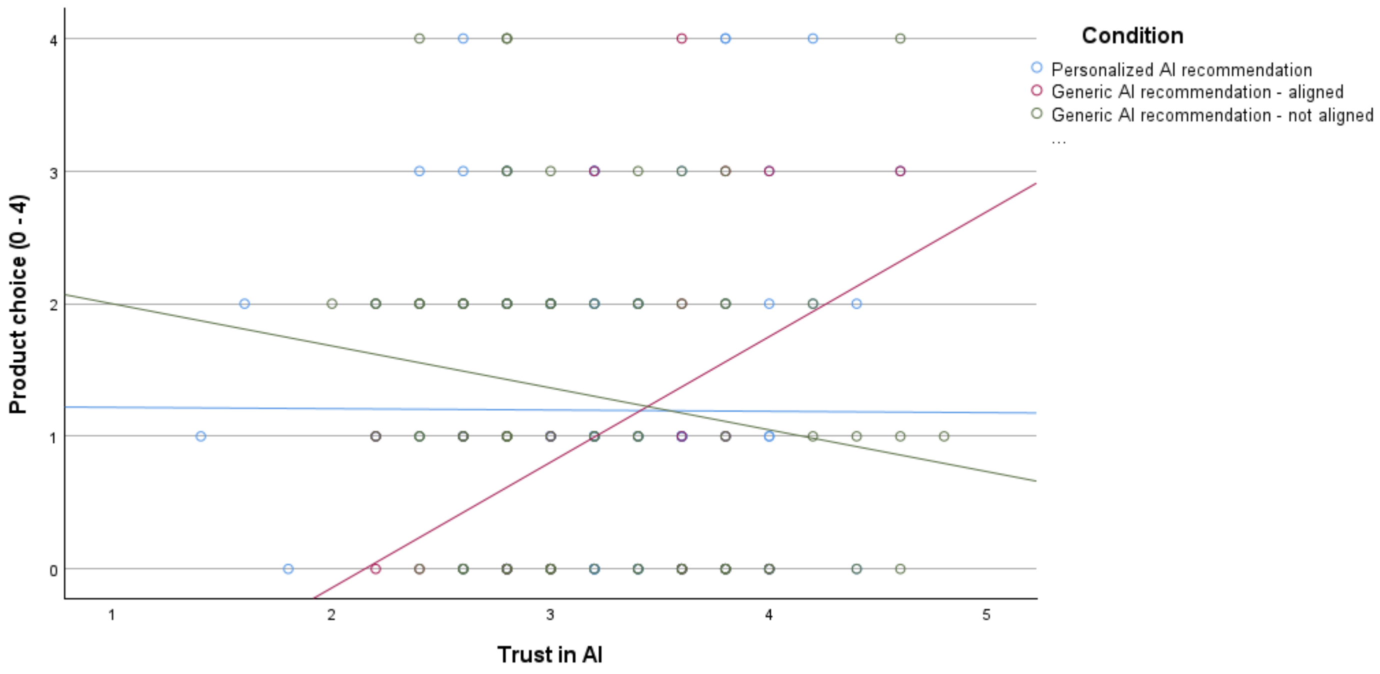


Table 3

Results of the hierarchical regressions with three condition groups

	DV: Decision time											
	Model1				*Model 2*				*Model 3*			
Variables	*b*	*se*	β	*p*	*b*	*se*	β	*p*	*b*	*se*	β	*p*
Intercept	8.14	0.41		< .001	8.15	0.40		< .001	8.16	0.40		< .001
Condition - alignment	0.38	0.97	.03	.700	0.45	0.95	.03	.640	0.41	0.95	.03	.670
Condition - non-alignment	0.20	0.63	.02	.758	0.14	0.62	.02	.828	0.15	0.62	.02	.813
Trust in AI					81.56	0.47	-.23	.001	-2.29	0.69	-.33	.001
Alignment * trust									1.33	1.55	.07	.394
Non-alignment*trust									1.36	1.00	.13	.172
df	2, 204				3, 203				5, 201			
F	0.10				3.76				2.67			
p	.908				.012				.023			
R^2	.001				.053				.062			
R^2_{change}	.001				.052				.010			
	DV: Product choice											
	Model1				*Model 2*				*Model 3*			
Variables	*b*	*se*	β	*p*	*b*	*se*	β	*p*	*b*	*se*	β	*p*
Intercept	1.20	0.11		< .001	1.20	0.11		< .001	1.20	0.11		< .001
Condition -	-0.15	0.27	-.04	.567	-0.15	0.27	-.04	.572	-0.20	0.26	-.06	.440

alignment												
Condition - non-alignment	0.12	0.17	.05	.506	0.11	0.17	.05	.512	0.11	0.17	.04	.536
Trust in AI					-0.03	0.13	-.02	.811	-0.01	0.19	-.01	.959
Alignment * trust									0.96	0.43	.17	.027
Non-alignment*trust									-0.31	0.28	-.11	.268
df	2, 204				3, 203				5, 201			
F	0.53				0.37				1.93			
p	.590				.774				.091			
R^2	.005				.005				.046			
R^2_{change}	.005				.000				.040			

Note: Condition reference is personalized AI recommendation

Discussion

The goal of this study was to examine whether the personalization of AI recommendations influences the decision-making time and product choices of consumers as compared to generic AI recommendations, and whether trust in AI influences these relationships.

Hypothesis 1: Personalization and Decision Outcomes

The findings revealed that personalized AI recommendations lead to comparable decision time and product choices as generic AI recommendations. The first hypothesis (H1) was therefore not supported. These results challenge the commonly assumed direct link between AI personalization and decision-making efficiency. While prior research indicated that personalization facilitates faster decisions (Becker et al., 2022; Haleem et al., 2022), the findings of the current study suggest this effect may not hold in all contexts. Earlier research also found that the effectiveness of personalization may be highly context-dependent (Gorgoglione et al., 2006). For instance, Longoni and Cian (2020) suggest that AI recommendations are more effective on products with utilitarian attributes as compared to hedonic attributes. In the current study, clothing was used as the product type which can be considered both utilitarian, as they have a functional purpose, but also hedonic, as they can appeal to one's sense of fashion or identity. Potentially using a product with more utilitarian attributes would have resulted in larger differences between personalized and generic AI recommendations.

Scherpinski and Lessmann (2021), on the other hand, demonstrated that personalization appears to rely on the level of complexity of the decision-task. Within the framework of purchasing groceries online, where individuals are often faced with a wide range of similar products, personalized recommendations have the potential to ease the process of choosing products (Scherpinski & Lessmann, 2021). In situations with an overwhelming amount of similar options, smart filtering through AI recommendations may decrease customers' mental effort and simplify users' process experience. However, in scenarios where few choices are available, personalization might not add enough value to the recommendation. This may have been the case in the current experiment, in which participants were first asked to voice their own preferences and then to choose between four products. The added value of the recommendations may have been too limited. Hence, this suggests that personalization seems most effective in situations where people are confronted with more complex and time-consuming choices, where there is more similarity among products and more than one product fits their personal preferences. Consequently, future research is proposed to emphasize the extent to which personalization influences decision-making across different types of products or services where different numbers of choices are available. Future theoretical models of AI-driven decision support therefore could reconsider the central role of personalization, and explore under which conditions personalized AI recommendations add more value and under which conditions they don't.

Hypothesis 2: Trust and Decision Time

We found partial support for the second hypothesis (H2); people who reported higher trust in AI tended to make decisions more quickly compared to people who have lower levels of trust in AI. Earlier research supported this finding because they showed that when levels of trust in AI are high people are more likely to follow AI generated advice and spend less time on re-evaluating their decisions. (Yu & Li, 2022; Kovari, 2024). This suggests that trust in AI could diminish the mental hesitations when people make decisions, as well as the cognitive hesitations of individuals. On the other hand the level of trust in AI did not appear to be associated with the product choices people made. This result supports earlier findings that consumers can be hesitant to change their product choices, even if they trust the AI systems providing the recommendations (Husairi & Rossi, 2023). Hesitation of choice is more like among people who feel that AI recommendations are feeling forced and undermines their freedom and autonomy in decision making. This indicates that the level of trust in AI systems could make the decision-making process more easy and reduce cognitive effort, but due to perceived threat of autonomy it does not necessarily cause a behavioral change in consumers.

Hypothesis 3: Trust as a Moderator

Hypothesis three (H3), which expected an increased likelihood of selecting personalized recommendations among users with high trust in AI, could not be supported. There appeared no difference in decision making time nor product choices between personalized and generic AI recommendation regardless of their level of trust in AI. This hypothesis was expected based on research we discussed earlier suggesting that trust in AI enhances the acceptance of AI advice in personalization contexts (Yu & Li, 2022; Kovari, 2024). Although trust in AI appears not to be a moderating factor when it comes to the relation between recommendation type and decision time, more trust in AI is directly associated with faster decision-making. Possibly, when receiving recommendations people make faster decisions, because they spend less time on re-evaluating the possible options, which is in accordance with (Yu & Li, 2022). This research suggests that the reason for this could be that the level of trust in AI itself makes people feel more confident about their choices.

A possible reason for not finding a moderating effect could be due to the categories used in our experiment. For example clothing is something very personal and closely related to identity. Earlier research found that AI recommendations normally work better in everyday products that have a clear purpose (Longoni & Cian, 2020). The categories used in this study are very personal and didn't involve actual purchases with real money, which could have led to participants not feeling much pressure to take it seriously or depend on the AI recommendations they received. Future work could focus on how trust in AI systems works in different decision making contexts. The development of more effective AI systems that feel natural and relevant can be realized in this way.

Exploratory Analysis: Trust and Recommendation Alignment

The finding that a generic recommendation that match with the consumers' preferences, is associated with a higher chance of choosing the product that was recommended to them if they have a high level of trust in AI could indicate that when people are aware of the personalization of the recommendations, it may have caused a lower feeling of autonomy or decreased feeling of naturalness in the decision-process. There may be a greater likelihood that this is the case especially for people who are aware that the recommendations are AI-driven. When a generic recommendation happens to align with the personal preferences, it possibly could feel more spontaneous. Recent research conducted by Van Arum et al. (2025), showed that people are more likely to experience AI advice as natural and less-restrictive when they align with their original intended decision-making style. This is also the case when the recommendations participants received are not personalized. That could explain why those participants were more likely to choose one of the recommended products while also trusting the AI system.

Additional research supported this idea and revealed that users feel reduced in autonomy and motivation when AI advice limits their choices, even when these received suggestions are very accurate (Faas et al., 2024). The findings of their study suggested that too much personalization can make the decision-making process feel more forced and also limit their freedom of choice. The results of this exploratory analysis raise new questions about how trust in AI and the recommendation type interact with one another, and what the influence is of the extent in which users feel in control of their choices. Therefore, future research should focus on the attributes of AI system designs that create a balance in recommendations that both feel helpful and authentic.

Limitations and future directions

The findings of this study provide the literature with valuable insights on the role of AI personalization and the level of trust within decision-making processes. But it's also important for future researchers to address the limitations of this study so they can adjust these in their future work. In this experiment the sample size consisted mostly of students, social media users and people with a LinkedIn profile. This may not fully represent the Dutch population because these participants may likely be higher educated and younger. A reason why this could be a limitation is that it may be possible that the people from our used sample are more aware of the role of AI in advertising compared to people who are not that familiar with such technologies. Future research could increase the generalizability by improving the sample group and including individuals who are less digitally active and from a more diverse educational background.

Another limitation is that the context we used may not correctly represent real purchasing situations people experience in daily life. In real life, people may consider possible choices more thoroughly when their choices may actually lead to spending their money, which makes the decision-making process way more complicated than in this experiment. Brand visibility and colour preferences may also not be all the attributes that are considered by consumers in the complex process as decision-making. Other related factors such as size of clothes, season, price of products and fashion trends were not taken into account. Therefore our experiment operated as a more simplistic view compared to how real life purchase situations look like, which could be a reason that influenced the results of this study. One way to increase the ecological validity of future research is to create real purchase scenarios where people actually can use money, and also include more diverse product categories during the decision-making task.

The limitations of this study provide future researchers with valuable insights and highlight the importance and complexity of contexts in AI personalization. Therefore, this paper could be used as a foundation to develop future experiments regarding AI personalization in purchase situations. Researchers should consider creating experimental purchase settings that are more realistic, with a broader and more representative sample size, and products that are more refined and diverse.

Practical and theoretical implications

The results of this study suggest, from a practical perspective, that enhancing personalization alone may not be sufficient to decrease consumer decision-making time and may even work contra-productive when it comes to people’s product choices. Efforts could be focused towards building more trust-enhancing features in AI systems but also leaving space to consumers to be introduced with new/unknown options. This could be done in, for example, platforms like Amazon or Netflix, that could implement transparent explanations for recommendations, or offer users control over personalization settings. This could possibly lead to increasing confidence and reducing decision fatigue. These future design choices could increase trust in AI, which this study found to be associated with faster decision making. In line with Tolmeijer et al. (2022), this points to the importance of transparency and perceived fairness in increasing user trust and also the system's usability for consumers. Future research could therefore explore which specific design strategies most effectively promote, trust and so reduce consumer hesitation in online digital platforms.

While faster decisions, as presented, are considered a positive aspect, as companies seek to enhance ease and effectiveness of customers’ online shopping experience, the present research suggests that it is relevant to examine closely whether the reduced decision-time should consistently be the ultimate objective. This is due to the fact that while it is apparent that faster decisions can reduce customers' effort, it is important to acknowledge that by making an impulsive decision might also lead to negative outcomes. This statement was confirmed by Inbar et al. (2011), who revealed that among individuals who made an impulsive decision ended up regretting their choice eventually, which may be due to the experienced pressure to make a quick decision. Further research by Linn et al. (2024) showed that individuals who engaged in quick decision-making, were more inclined to rely on intuitive judgments and personal cognitive biases, which resulted in lower levels of satisfaction as the outcomes were less accurate. Thus, it is clear that decision-speed can exhibit both positive and negative outcomes. While the process can be characterized as smoother, it can additionally provide undesirable outcomes leading customers to regret their product choice. It is therefore essential to consider in which cases faster decision making can be helpful, and when it is more beneficial to reduce the pace of the process in order to invest more time in evaluating certain options.

This study contributes to existing literature as a more complete understanding of how AI personalization and trust affect user behaviour in everyday consumer decisions like online shopping. While much of the literature highlights the benefits of personalization, for instance when it comes to the purchase of food products, our findings suggest that these effects may not exist when it comes to the specific product type of clothing. At the same time, higher levels of trust in AI was related to lower decision-making time. This supports the idea that trust in AI may function as a more general factor that helps users feel more confident and therefore reduces the need for extended deliberation such as re-evaluating choices.

Conclusion

Personalization of AI recommendations does not automatically influence people's decision time, nor the choice of product itself. However, the level of trust in AI systems appears to plays a role in decision time after AI recommendations are given. AI in advertising is still developing and there are many factors that should be taken into account. Considering the multifaceted role of AI recommendations in marketing, additional research is needed in order to further develop personalized AI recommendation in a way there exists a healthy balance between helpful personalization, and remaining choice autonomy for customers.

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Appendix A

Informed Consent Form

Study Information

This study examines consumer decision-making processes in online shopping environments. As a participant, you will complete an online survey in which you will answer questions about your product preferences. Following this, you will engage in a decision-making task, where you will select between different products and categories. After completing this task, you will be asked to fill out a brief questionnaire and provide some additional information.

The study will take approximately 5 minutes to complete. The risks associated with participation are no greater than in daily life. The study will be independently reviewed and approved by Tilburg University.

Consent Form

Your participation is voluntary. The collected data will be anonymously stored following Tilburg University and AVG policies. You are able to withdraw at any time, your data then will be deleted. For further privacy concerns, please contact privacy@tilburguniversity.edu.

To participate you must be 18+ and you must be fluent in speaking English. No financial compensation will be provided for participants. For further questions about the study you can reach out to the researcher via f.j.m.vanriel@tilburguniversity.edu.

By participating you confirm that:

You understand the study and your contribution is voluntary.

Your data will be stored anonymously and securely.

You can withdraw your consent anytime.

Your data will be processed for research purposes.

Appendix B

Online survey

Instructions

This study explores product preferences. First, you'll be asked about your personal preferences. Then, you'll receive AI-generated advice before engaging in a product selection task. After completing this process, you'll be asked to answer a few follow-up questions.

Please, answer the following questions regarding your product preferences.

Which type of products do you prefer?

1. Bright and colorful products
2. Muted and neutral color products

Which type of products do you prefer?

1. Products with visible well-known brand logos
2. Products without recognizable brand logos

Now, you will receive AI-generated advice **tailored to your preferences**, built by an advanced algorithm. This advice is designed to help you choose the most suitable products for you in the next task.

OR

Now, you will receive AI-generated advice that is **randomly assigned and not personalized**. This advice is designed to help you choose the most suitable products for you in the next task.

Different advices

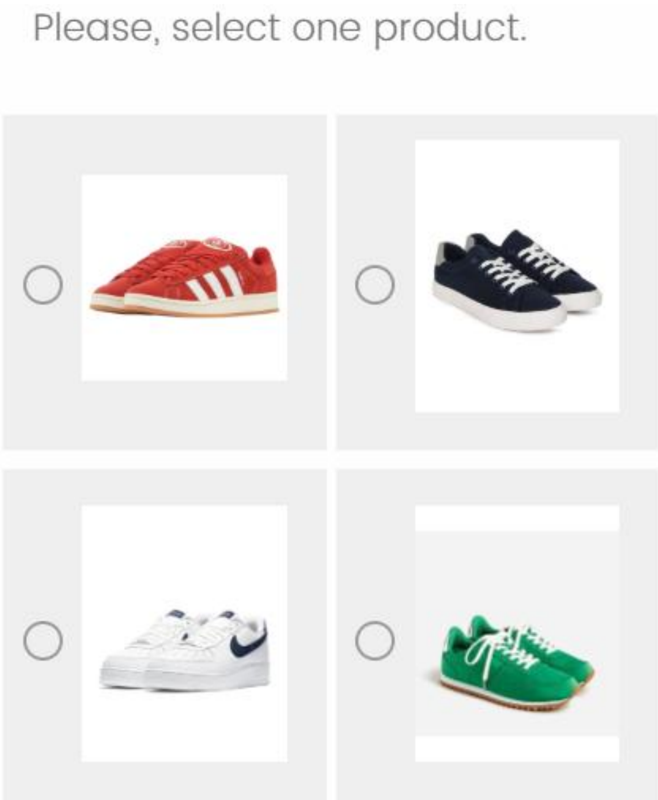
1) You like bright, colorful products from popular brands. These products not only stand out, but also come from trusted names. Choosing a well-known brand with bold colors will give you both style and quality.

2) You enjoy colorful and unique products but prefer brands that are not too famous. Smaller or less common brands often have creative and special designs. Picking a colorful product from a smaller brand will help you express your own style.

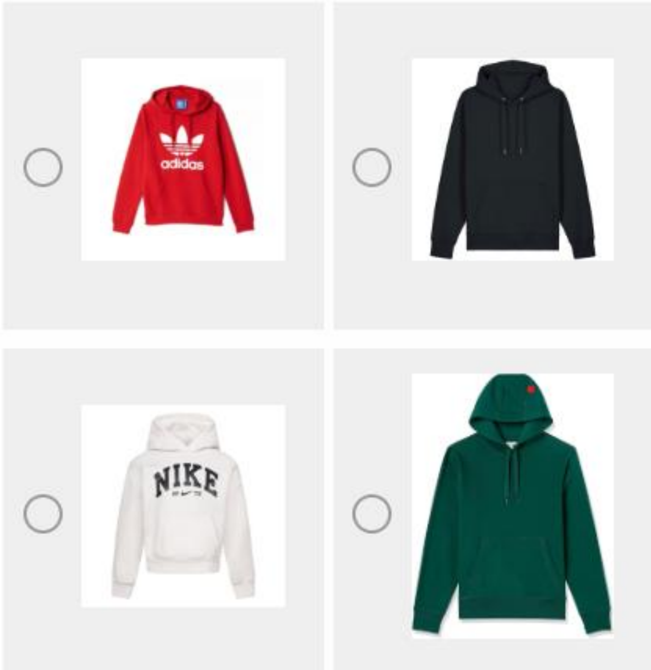
3) You prefer simple and classic designs from trusted brands. Well-known brands often offer high-quality products that look elegant and timeless. Choosing a product with a soft and calm look from a famous brand will suit your style.

4) You like simple and calm designs and prefer brands that are not too famous. Smaller brands often offer high-quality products with a unique but subtle style. Choosing a product that is simple and different will match your taste.

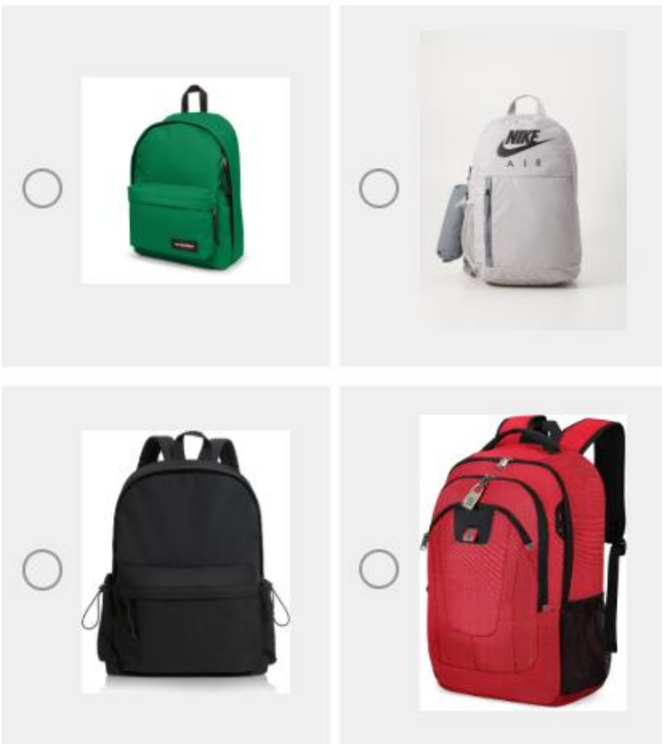
Please, select one product. (4 times)

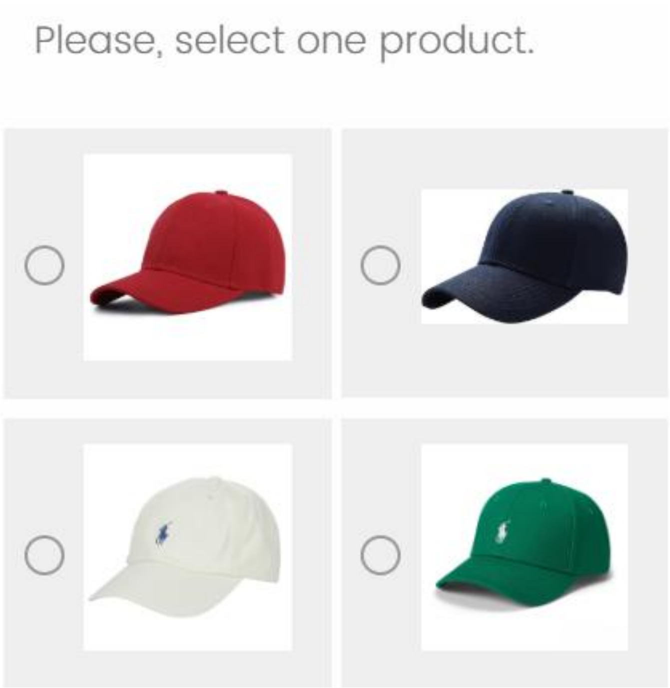


Please, select one product.



Please, select one product.





Please read each of the following statements regarding your trust in AI carefully, and indicate the extent to which you agree or disagree using the scale below:

1 – Strongly Disagree ,

2 – Disagree

3 – Neutral

4 – Agree

5 Strongly Agree

Select the option that best reflects your opinion. There are no right or wrong answers—please respond honestly.

Q32

Please, select the option that best reflects your opinion.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am confident in the AI systems ability to perform its tasks accurately.	○	○	○	○	○
I feel the AI systems behaves consistently across similar tasks.	○	○	○	○	○
I am willing to rely on the AI system's recommendations.	○	○	○	○	○
I understand how AI systems generate recommendations.	○	○	○	○	○
I would trust this AI system in important decisions.	○	○	○	○	○

Which of the following colors do you like the most?

White

Black

Green

Red

What is your gender?

Male

Female

Non-binary

Prefer not to say

What is your age?

…..

Thank you for participating in this study on consumer decision-making in online shopping platforms. Please click the arrow below on the page to complete your response.

In this study, we aimed to examine how consumers make product choices based on AI personalized advice and AI generic advice. By analysing participants' responses, we hope to gain insights into decision-making behaviours that influence online shopping preferences.

If you have any comments or feedback about the survey, please feel free to share them below. Your input helps us improve future research.

Thank you for your participation! Your contribution is greatly appreciated.

If you have any further questions about the study, feel free to contact the researcher at f.j.m.vanriel@tilburguniversity.edu

Appendix C

Different recommendations

1) You like bright, colorful products from popular brands. These products not only stand out, but also come from trusted names. Choosing a well-known brand with bold colors will give you both style and quality.

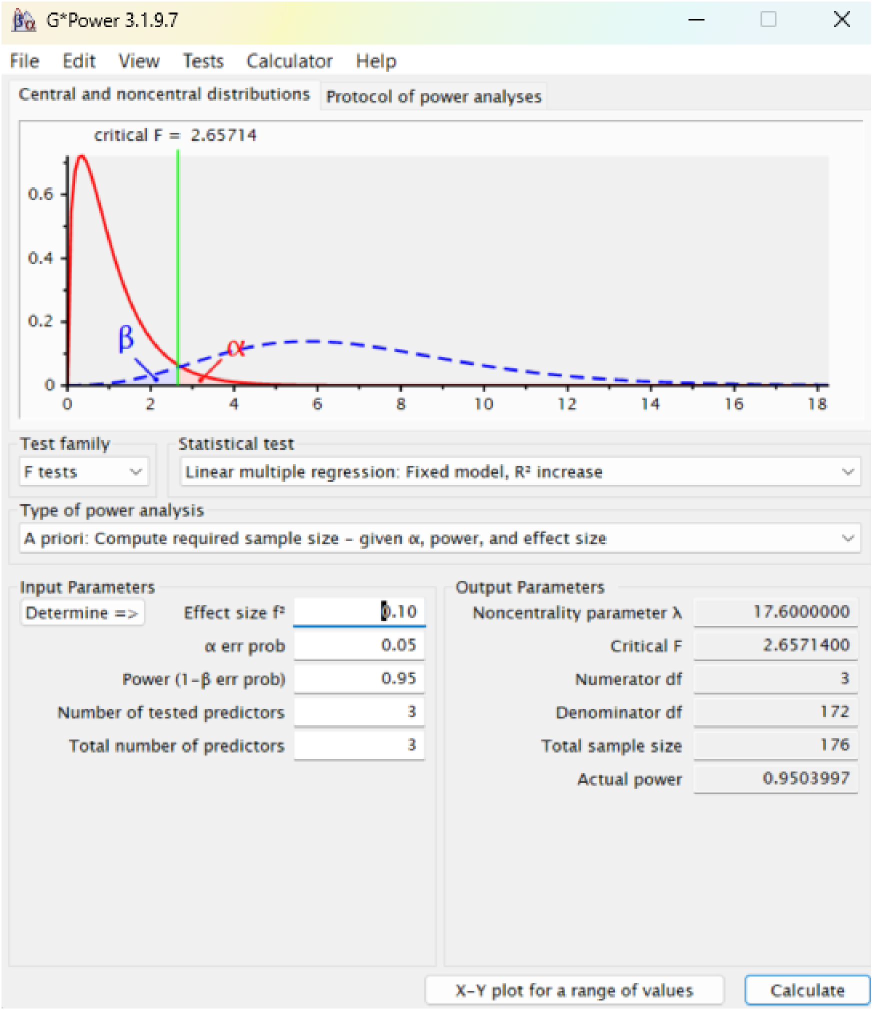
2) You enjoy colorful and unique products but prefer brands that are not too famous. Smaller or less common brands often have creative and special designs. Picking a colorful product from a smaller brand will help you express your own style.

3) You prefer simple and classic designs from trusted brands. Well-known brands often offer high-quality products that look elegant and timeless. Choosing a product with a soft and calm look from a famous brand will suit your style.

4) You like simple and calm designs and prefer brands that are not too famous. Smaller brands often offer high-quality products with a unique but subtle style. Choosing a product that is simple and different will match your taste.

Appendix D

Results power analysis using G*Power (Faul et al., 2007)



Appendix E

Results of the randomization checks

Table 1

Results randomization checks

	Control (n = 100)		Intervention (n = 107)			
Variable	*N*	%	*N*	%	χ^2 (1)	*p*
Gender					1.87	.172
Male	41	41.0	54	50.5		
Female	59	59.0	53	49.5		
	M	*SD*	*M*	*SD*	$t(205)$	*p*
Age	38.87	17.43	38.77	16.54	0.04	.965

Appendix F

Results sensitivity check

	DV: Decision time											
	Model1				*Model 2*				*Model 3*			
Variables	*b*	*se*	β	*p*	*b*	*se*	β	*p*	*b*	*se*	β	*p*
Intercept	8.22	0.38		< .001	8.20	0.38		< .001	8.21	0.38		< .001
Condition	-0.39	0.53	-.05	.464	-0.35	0.53	-.05	.504	-0.35	0.53	-.05	.506
Trust in AI					-1.05	0.43	-.17	.016	-0.79	0.58	-.13	.177
Cond * trust									-0.60	0.88	-.06	.495
df	1, 202				2, 201				3, 200			
F	0.54				3.21				2.29			
p	.464				.042				.079			
R^2	.003				.031				.033			
R^2_{change}	.003				.028				.002			

	DV: Product choice											
	Model1				*Model 2*				*Model 3*			
Variables	*b*	*se*	β	*p*	*b*	*se*	β	*p*	*b*	*se*	β	*p*
Intercept	1.25	0.12		< .001	1.25	0.12		< .001	1.25	0.12		< .001
Condition	-0.05	0.16	-.02	.739	-0.05	0.16	-.02	.743	-0.05	0.16	-.02	.744
Trust in AI					-0.04	0.13	-.02	.781	-0.06	0.18	-.03	.741
Cond * trust									0.05	0.27	.02	.851
df	1, 202				2, 201				3, 200			
F	0.02				0.02				0.02			

p	.890	.983	.997
R^2	.000	.000	.000
R^2_{change}	.000	.000	.000

Note: Condition 0 = generic AI recommendation, 1 = personalized AI recommendation