ERASMUS UNIVERSITY ROTTERDAM

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Bachelor Thesis Economics and Business Economics

Exploring the Viability of AI-Produced Art in the Clothing Industry: A Study on Dutch Consumers.

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Abstract

The development and popularity of Artificial Intelligence (AI) has increased drastically over the last years. Multiple studies have been done on the acceptance and interest in AI with contradictory results. The scarcity of research on art produced by AI in combination with clothing on consumer behaviour has led to this study. Based on a self-collected sample of 436 participants the analyses were made on 3 different consumer behaviour factors, the information search process, consideration of alternative brands and willingness to pay. The results show that in-store purchases and social media purchases increase the chance of a consumer falling into a higher category of interest in clothing containing AI produced art. Males have a higher willingness to pay for clothing containing AI produced art. Respondents living in the western parts of the Netherlands have a higher willingness to pay for clothing containing AI produced art, compared to the other regions.

Contents

1. Introduction:

Artificial Intelligence (AI), “the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages”. (Duckett, 2006) Over the last couple of years the development of AI and the interest for AI has increased drastically. With humanity questioning the applications of AI and AI making some aspects of human life much easier, this raises the following question: What possibilities will AI open up for mankind? Art, for example, is a task that has been performed by humans for generations. This paper wonders if AI produced art opens up doorways for entrepreneurs to benefit from these developments. AI that produces art already exists. Currently the biggest companies that produce art in such manner are OpenArt and MidJourney. One possible application for AI produced art could be to combine art with clothing design. This could give consumers the possibility to send a prompt to the AI telling the AI what kind of clothes they are looking for, the AI could then produce a prototype that matches the consumers prompt. This paper wonders if such application of AI is desired by the Dutch consumers. By researching this matter entrepreneurs will have extra information on whether it is beneficial to enter this new market. In this way a whole new market of clothing with AI produced art could be established. The research on the demand for customizable clothing based on AI in the Netherlands could open up a whole new market for consumers as well. In the future consumers might want to decide what they want rather than pick from an assortment of pre-determined clothing. This paper wonders if the Dutch consumers are ready for AI-produced art in clothes. The main goal of this paper will be to analyse the consumer behaviour of Dutch consumers on AI-produced art in clothes.

Initial research question:

> To what extent is there demand for clothing containing AI produced art for adults in the Netherlands?

2. Literature Review

This literature review examines the integration and acceptance of artificial intelligence (AI) in various industries, particularly the clothing and fashion industry. The review covers twelve papers which are relevant to the essence of this paper.

Consumer behaviour in the clothing industry

Jones & Hayes (2002) present a regression model that explains consumer spending on clothing in the UK from 1987 to 2000, using changes in income and price as predictors. They have analysed price elasticities of multiple variables which resulted in the conclusion that over time clothing has shifted from being a necessity to being a luxury good. They also conclude that the rise in price elasticity of the clothing industry validates the increase in discounts, because price cuts as a motivation to purchase work more efficiently when the elasticity is higher.

Gouvea et al. (2018) research the influence of brand, quality and price on the willingness to pay. They use conjoint analysis to analyse whether there is a significant difference between brands that associate themselves with a cause or high valued apparel brands on the purchase intentions of consumers. The research revealed that quality is more important than the brand type.

Ong et al. (2021) analyse the factors influencing the purchasing behaviour of Filipinos towards clothing during the COVID-19 pandemic, highlighting the significant effects of marketing mix and COVID-19-related factors. According to their research family and friends have the highest impact on purchase decisions in the clothing industry. This could be explained by friends and family expect that people have new clothing apparel once in a while. Their analysis also concludes that the brand image, endorsement, sales/promos and social media advertisements have influence on the promotion of clothing apparel. Furthermore, the sales personnel have great effect on customers purchase decisions. Additionally, maintenance of stock, availability, merchandise displays and store or website designs have high impact on customer’s purchasing decisions.

AI Acceptance and Adoption

Gursoy et al. (2019) develop and empirically test a theoretical model of AI device use acceptance (AIDUA) to understand customers' willingness to accept AI device use in service encounters. The study highlights a three-step acceptance generation process and emphasizes the role of social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, and emotion in AI device acceptance.

Sohn et al. (2020) compare various technology acceptance models, such as TAM, TPB, UTAUT, and VAM, to determine which model best explains consumer acceptance of AI-based intelligent products. The study finds that the Value-based Adoption Model (VAM) performed best in modeling user acceptance, with enjoyment being the most influential factor, followed by subjective norms. (Sohn, Sung, Koo, & Kwon, 2020)

Upadhyay et al. (2022) aim to determine the entrepreneur's intention to accept AI and advance the domain of digital entrepreneurship. The study reveals that performance expectancy, openness, social influence, hedonic motivations, and generativity have a positive impact on entrepreneurs' AI acceptance intentions. Affordance indirectly affects AI acceptance intention through attitude, while inconvenience has a negative relationship and uncertainty has a positive relationship with AI acceptance intention. (Upadhyay, Upadhyay, & Dwivedi, 2022)

Artificial Intelligence and Art acceptance

Chamberlain et al. (2018) investigate the public's response to visual art created by humans and computers, specifically examining biases and prejudices against computer-generated art. The study found that observers generally exhibited a bias against computer-generated art when compared to human-created art. However, this bias was reversed when observers witnessed robotic artists creating the artwork, as it allowed them to attribute anthropomorphic characteristics to the computer programs.

The findings of Mullin et al. (2018) reveals an explicit prejudice against computer-generated art, which is largely driven by observers' beliefs about the capabilities of computer algorithms in producing art. The study suggests that these prejudices can be overridden when observers perceive anthropomorphic characteristics in computer programs, which has implications for the future of artistic AI and the way AI-generated art is perceived and valued in society.

Hong & Curran (2019) examine people's perception of AI-generated artwork and how presumed knowledge of the artist's identity (Human vs. AI) affects evaluations of art. The study finds that AI-created and human-created artworks are not judged to be equivalent in artistic value, but knowing a piece was created by AI did not significantly influence evaluations unless participants held a schema that AI cannot create art.

Artificial Intelligence in the Fashion and Clothing Industry:

Sohn & Kwon (2020) explore consumers' evaluations of product consumption values, purchase intentions, and willingness to pay for fashion products designed using generative adversarial networks (GANs). The study finds that functional, social, and epistemic consumption values positively affect willingness to pay for GAN-generated products, which is higher than for non-GAN-generated products. Moreover, evaluations are highest when GAN technology is used but not disclosed.

Yan & Chiou (2020) focus on digital customization in the Chinese clothing industry, constructing dimensions of customer value based on the development of the industry under digital technology. The study establishes four dimensions of customer value: authenticity value, social value, aesthetic value, and utility value, and reveals that Chinese consumers' value demands for apparel customization have shifted toward perceptible authenticity values.

Chrysopoulos & Bilalis (2021) investigate the application of AI in a Greek clothing manufacturing company to improve product design and support decision-making in the sample room. The proposed research explores AI's potential in transforming the product design field, utilizing machine learning techniques for grouping and combining similar products, extracting meaningful attributes from images through computer vision, and reinforcing learning systems based on user preferences.

Relevance of this paper based on the literature review

According to the research of Chamberlain et al. (2018) there is a bias against computer-generated art. Adding to that, Sohn & Kwon (2020) conclude that the evaluation on AI produced fashion products is significantly more positive when the consumer is not aware that the fashion product is produced by AI. While on the other hand, the research of Hong & Curran (2019) shows that the judgement of humans on whether an artwork is produced by an AI or by a human is not valued artistically equivalent, but their results show that there was no significant difference in evaluations of the artworks. These papers show different results considering the bias of consumers towards AI produced art which this paper will try to give an answer to within the Dutch consumer market.

Existing research has not yet thoroughly analysed the impact of AI-produced art on specific consumer behaviours in the clothing industry. This paper aims to address this gap by examining key consumer behaviours, such as the information search process, the consideration of alternative brands and purchasing decisions. (Kotler & Keller, 2012) Consequently, the following final research question and sub-questions have been established.

Final Research question:

What is the implication of AI produced art in clothing on the consumer behaviour of Dutch consumers?

Sub-questions:

1. Which factors influence consumer behaviour in the clothing industry?
2. What are the effects of AI-produced art in clothing on the information search process of consumers?
3. What is the effect of AI-produced art in clothing on consumer consideration of alternative brands?
4. What is the effect of AI-produced art in clothing on the willingness to pay?

3. Research methodology

This study uses desk research and quantitative research to analyse the effect of AI-produced art on consumer behaviour within the fashion industry. This method was chosen to compare the results against different studies mentioned, since the papers mentioned in the literature review have quantitative research as their main research methodology. The analyses will be conducted with SPSS 28.

A survey will be designed to gather data from the participants. The aim of the survey is to assess consumers' information search processes, their consideration of alternative brands and their likelihood to purchase clothing featuring AI-produced art. The survey questions will use a Likert scale if necessary from 1 (strongly disagree) to 5 (strongly agree).

Stratified random sampling will be used to ensure that the sample is as representative as possible to citizens of the Netherlands. The strata is defined into 4 groups based on the region that the participant lives in, North, East, South and West. This strata was picked to ensure that the data can be collected within the timeframe of this research and to increase the representativeness of the data compared to simple random sampling. Moreover this will make it possible to analyse each stratum individually to see which area is most beneficial for promotion of clothing containing AI-produced art. The regions are defined by the 12 different provinces of the Netherlands. North is Groningen, Friesland and Drenthe. East is Overijssel and Gelderland. South is Noord-Brabant, Limburg and Zeeland. West is Utrecht, Noord-Holland, Zuid-Holland and Flevoland. The proportion of each strata based on the total population of the Netherlands will be maintained to ensure representativeness of the data. Data will be collected in person at random locations. For instance to collect data in the North a random city in the North will be picked and data will be collected proportionate to the total population of the North.

The sample size is determined with the following formula:

$$n = \frac{Z^2 \times \ \sigma \ \times (1 - \sigma)}{(CI)^2}$$

N is the sample size, Z is the z-score of the confidence level, σ is the standard deviation and CI is the confidence interval.

The sample size is determined on a 95% confidence level, a standard deviation of 0.5 and 5% margin of error resulting in 384.16, thus the minimum sample size for this research is n = 385.

10% of Dutch citizens live in the North, 19% live in the East, 48% live in the West and 23% live in the South (CBS, 2023). This results in the following sample sizes respectively; 38, 72, 186 and 90.

For sub-question 1, desk research will be conducted to establish an understanding of the key factors that influence consumer behaviour in the clothing industry. During the survey making process, the established understanding is important to increase the relevance of the survey questions. In the analyses of this research, this basic understanding is essential for interpreting the responses to the survey questions.

For sub-question 2, the survey questions will be centred around the information search process. The participants will be presented with a list of potential information sources, based on the findings for sub-question 1. Participants will be asked to rate the importance of each source on a 5-point Likert scale as mentioned before. The participants perceived knowledge of AI-produced art in clothing will be collected and their general interest in AI-produced art in clothing will be measured. These findings will be analysed in a multiple linear regression analysis, with interest in buying clothes with AI-produced art (dependent variable) based on the perceived knowledge of AI, interest in AI, importance of different information sources and multiple demographic variables (independent variables). The following demographic variables will be used: age, gender, education level, employment status, range of monthly family income and region the participant lives.

To answer sub-question 3, multiple linear regression analysis will be used as well. The survey question that will assist in answering this sub-question will ask the participants whether they would consider buying from a different brand if their favourite brand offered AI-produced art on their clothing. This factor will be the dependent variable, while perceived knowledge of AI, interest in AI, interest in AI-produced art in clothing and multiple demographic variables will be the independent variable. The same demographic variables will be used as in sub-question 2.

For both sub-question 2 and 3, the assumptions of multiple linear regression will be tested to check if all variables can be used in the multiple linear regression. The following assumptions will each be tested: Linearity, normality, homoscedasticity and absence of multicollinearity.

For sub-question 4, conjoint value analysis will be conducted. The following attributes will be tested: brand, quality, price and whether the art on the clothing is produced by AI. These attributes will have 3 different results based on the findings for sub-question 1. Brand will be categorized as ‘well-known’, ‘emerging’ and ‘unknown’, while the AI-art attribute will be ‘AI-produced’, ‘Human-produced’ and ‘undisclosed’. This results in $81(3^4)$ potential product profiles. To manage the amount of potential product profiles, their complexity and reduce respondent burden, a fractional factorial design will be used. This will be calculated by SPSS 28 to ensure that the profiles which are shown to the respondents are sufficient and manageable, without compromising the validity of the analysis.

3.1. Results sub-question 1:

According to the research of Ong et al. (2021) there are multiple variables that have high influence on the purchase decisions of consumers. For sub-question 2, the most important information search processes from their research was taken into consideration for the survey questions. The information search processes with the highest influence on the consumers purchase decisions in their research were: store design, website design, social media, family, friends and sales personnel. These aspects will be inquired to the participants of the survey to test whether this research gives similar results and to increase the validity of the multiple linear regression analysis.

To increase the relevance of the survey questions required to answer sub-question 3, the brand aspects have been analysed. In the research of Ong et al. (2021) they mention that brand image has relatively high positive influence on purchase intention. According to Chamberlain et al. (2018) and Sohn & Kwon (2020) the knowledge of AI involvement decreases the valuation of fashion products. While on the other hand Hong & Curran (2019) find no significant difference in consumers valuations of knowing about AI involvement in fashion products. Thus, if these 3 statements are combined, would the knowledge of AI-involvement in fashion products decrease the brand image? And could this result in consumers switching to other brands? These findings will be combined into questions for the survey. In this way the effect of AI-involvement on consideration of alternative brands will be tested.

For the last sub-question 4, the most relevant attributes will be tested in the conjoint value analysis. According to the research of Gouvea et al. (2018), the brand types are differentiated by a well-known apparel brand, a social cause brand and no brand. They established this by showing the participants a t-shirt with no print, a social cause print and an apparel brand print. Worldwide the highest valued apparel brand is Nike. Their logo will be used in the questionnaire (Brown, 2022). According to Dutch consumers the most sustainable apparel brand is MUD Jeans. Their logo will be used in the questionnaire (SB Insights, 2023). Just in case a participant is not aware about the sustainability goals of MUD Jeans, their goals will be added before the conjoint analysis part to make sure that the participants are well informed and to reduce the misclassification bias. Gouvea et al. (2018) used price and quality levels of high, average and low to avoid numerical measures. The reason they chose these price and quality levels is, because the population of interest was heterogeneous in multiple characteristics and they wanted to avoid different interpretations for each participant. In this paper the population of interest is also heterogeneous in multiple characteristics for each participant thus this paper will use the same price and quality levels. The AI categorizations are, “AI-produced”, ‘Human-produced’ and ‘Undisclosed’, these 3 categories have been picked, because earlier research has found different outcomes of consumer valuations for knowledge of AI involvement. (Chamberlain, Mullin, Scheerlinck, & Wagemans, 2018) (Sohn & Kwon, 2020) (Hong & Curran, 2019) In this way, the results for the Dutch consumer market can also be analysed to add extra information to this matter.

4. Data collection

A survey was made for data collection. To ensure that respondents felt safe when filling in the survey, we used the Erasmus University version of Qualtrics in which respondents would see the name of Erasmus University when filling in the questionnaire. The survey consisted of 28 questions, of which the first 6 questions were demographics, questions 7 – 15 were questions related to the information search process, questions 16 and 17 asked the participants their perceived knowledge and interest in AI, question 18 related to their interest in clothing containing AI produced art, question 19 was meant to measure the chance at which a respondent would switch to another brand if their favourite brand would sell clothing with AI produced art, and questions 20 – 29 were designed to answer the conjoint analysis. For the conjoint analysis part, SPSS 28 was used to design the fractional factorial computation. Afterwards, the result of that computation was used to design tables which would show the participants all of the 9 different cards in a random order and ask them if they could give the combination of attributes a rating based on whether they would purchase that specific card. The demographic variables which are used in the survey are, age, gender, highest achieved education, current working status, family monthly income and region. The questions 7-18 were designed on a 5-point Likert scale.

The data collection method was planned with the stratified sampling in mind. To ensure that data can be collected in the corresponding regions, a list was created per region. In those regions, the municipalities were sorted from most populated to least populated. A dice was rolled to pick municipalities from which the data was collected.

After that, the proportions per region were taken into consideration to justify the amount of municipalities which would join the randomized selection. For every 10%, 1 municipality will be randomly picked within a list of 5 municipalities. For example, the North needed to have a proportion of 10%, thus the top 5 most populated municipalities are listed and one of them is picked randomly. The East had a proportion of 19%, thus 2 municipalities were randomly pick from the top 10 most populated municipalities. The following municipalities were visited for data collection: North = Assen, East = Nijmegen and Enschede, West = Utrecht, Dordrecht, Amstelveen, Haarlemmermeer and Zoetermeer, South = 's Hertogenbosch and Helmond.

The municipalities were visited during a period of 9 days and the most populated areas were actively searched for to increase the chance of finding people which are willing to fill in the survey. This was to ensure that the minimum required amount of respondents per municipality would be reached and that it would not be necessary to visit the same municipality twice. This was done because some of the rolled municipalities were very far away which meant that half of the day was lost on travelling, Assen and Enschede were the farthest away and took the most time to collect data from.

At the location small papers with a QR-code were given out which would send the participants to the Qualtrics website where they could fill in the survey. During the distribution of the survey the research intentions and reasons were explained to the participants. On the first day, the observations were made that people sitting on terraces were very willing to fill in a survey. This might be explained by the sunny weather and that people might not be in a rush to leave. These observations have dictated the survey distribution for the other municipalities, to save time during the data collection process.

This does introduce the sampling bias, which states that the survey distribution method is not fully randomized when at the municipalities, because the most populated areas are visited and people which are sitting on a terrace are mainly asked to fill in the survey. Using a QR-code meant that some older people could not access the survey link, which resulted in a channel bias. During the data collection, one participant stated that she did not fully understand the questioning of question 20-28. This could be the reason why many missing values were observed in this part of the survey.

5. Data cleaning

The data was split into 2 parts, the first part was used to analyse the second and third sub-question (Survey questions 7 – 19), the second part was used to analyse the last sub-question (Survey questions 20 – 28) and the sub-questions which held the demographic variables were used for both parts. The analyses and data cleaning was divided into 2 parts, because the amount of missing values in the second part was relatively high. If both parts were cleaned simultaneously the first part would have had less data, compared to splitting the data cleaning into 2 parts. The research methodologies for both parts are different, which backs up the decision of splitting the 2 parts.

Total number of observations is 448, this also includes the preview questionnaires sent out to solve any overlooked issues. 12 preview questionnaires were filled in which mainly resulted in changes in question structure. The preview observations will not be used for the analysis, because the participants mainly looked at improvements for the survey. 436 observations were made after the preview questionnaire. These observations were cleaned up before analysis.

5.1. Survey questions 1 – 19.

The decision was made to delete respondents which did not complete the survey and answered with the same answer multiple times, this could be explained by ERB. ERB refers to the tendency of respondents to systematically use only the extreme points on a scale.

In the survey questions for the demographics, question 5 asked for the monthly household income of the participants, but the question stated that the participants do not have to fill this in if they are not feeling comfortable with that question. This led to 37 missing values, which is 9.1%. This is relatively high which led to the decision to drop question 5 for the analysis. This led to a total sample size of 396.

For the variables which had a low percentage of missing values the mode was used for categorical variables and mean value substitutions was used for demographic variables.

Question 4 had 2 missing values and question 6 had 1 missing value. These categorical variables have been replaced by the most frequently observed answer, i.e. the mode.

Mean-value substitution was used for the missing values from questions 6 through 19. This means that the missing values have been replaced with the mean of each question, this method was picked because the maximum amount of missing values per question was 1, which is relatively low compared to the total sample size of 396.

As mentioned in the data collection and the methodology, stratified sampling was used based on the regional proportions of the Netherlands, these proportions were observed from the Dutch population, North 10%, East 19%, West 48%, South 23% (CBS, 2023).

From the 396 observations the following proportions are observed: North 8%, East 25%, West 47%, South 21%. In this case North is underrepresented by 2%, East is overrepresented by 6%, West is underrepresented by 1% and South is underrepresented by 2%. The observations are weighed to properly match the proportions of the Dutch population.

After weighing for the region variable the following proportions of demographics were observed.

For the age variable, 3.1% of the respondents are <18, 34.8% are between 18-24, 25.4% are between 25-34, 10.8% are between 35-44, 12.3% are between 45-54, 7.6% are between 55-64 and 6.1% are older than 65.

Of the participants 47.5% is male and 52.5% is female.

The proportions of the highest obtained education of the respondents are as follows. 1.3% had achieved a highest education which is lower than high school, 22.6% achieved high school, 21.2% achieved MBO, 31.7% achieved HBO and 23.2% achieved WO.

The current work status of the participants were distributed as follows. 47.4% worked full-time, 20.1% part-time, 2.5% unemployed, 2.2% not working, 21.5% student and 6.4% retired.

5.2. Survey questions 1 – 6, 20 – 28.

The total number of observations are 436. The missing values from each question is ranging from 14 – 31. According to Peduzzi Et al. (1996) the minimum sample size for conjoint value analysis is calculated with the following formula:

$$n = \frac{1000c}{qa}$$

c is the maximum number of levels of any attribute, q is the number of questions shown to each respondent, a is the number of alternatives per questions.

According to the fractional factorial computation of SPSS 28 the conjoint value analysis consists of 9 different profiles. Thus, In the case of this questionnaire the values are as follows: $c = 3$, $q = 9$ and $a = 3$. Resulting in a minimum sample size of 111.

Some of the participants gave the 9 different cards the exact same rating, this could be explained by the extreme response bias (ERB). ERB refers to the tendency of respondents to systematically use only the extreme points on a scale. The fact that participants misunderstood questions 20-28 might be a reason that ERB has occurred with some respondents. To reduce the risk of ERB the responses containing only the same value have been deleted for the analysis. Thus, the respondents which had no answers, the same answer for each question or any missing values have been deleted for the questions 20-28 resulting in a total sample size of 317, which is more than 111.

Furthermore, 132 respondents were removed of which, 127 had a reversal and 5 had a modelling correlation below 0.7, these values were removed to improve the quality of the preference model generated for the sample (Gouvea, Homen de Mello Castro, & Vincente, 2018). This resulted in a total sample size of 185, which is still above the threshold of 111. These improvements increased the Kendall's tau correlation from 0.778 to 0.833.

After these modifications the proportions of the regions were observed to match the stratified sampling proportions. 7% of the respondents were from the North, 25.4% from the East, 28.6% from the West and 18.9% from the South.

Stratified sampling was used to improve the representativeness of the data, the stratified proportions are, 10% north, 19% east, 48% west and 23% south. In this case north is underrepresented by 3%, east is overrepresented by 6.4%, west is overrepresented by 0.6% and south is underrepresented by 4.1%. The observations are weighed to properly match the proportions of the Dutch population.

After weighing the region the following proportions of demographics are observed:

For the age variable, 3.6% of the respondents are <18, 37.7% are between 18-24, 26.5% are between 25-34, 13.3% are between 35-44, 10.6% are between 45-54, 5.6% are between 55-64 and 2.9% are older than 65.

Of the participants 42.9% is male and 56.1% is female.

The proportions of the highest obtained education of the respondents are as follows. 1.7% had achieved a highest education which is lower than high school, 22.3% achieved high school, 15.3% achieved MBO, 35.8% achieved HBO and 24.9% achieved WO.

The current work status of the participants were distributed as follows. 45.5% worked full-time, 21.3% part-time, 3.7% unemployed, 3% not working, 23.1% student and 3.4% retired.

The monthly family income of the participants was as follows. 32% has a monthly family income which is lower than 2000, 14% between 2000 and 3000, 13.4% between 3000 and 4000, 9.6% between 4000 and 5000 and 31.2% above 5000.

6. Results

To ensure that the analysis of the results is well structured, the decision was made to also split the results, but this time into 3 parts. Before the 3 parts are explained, the results for sub-question 1 will be summarized. The first part will explain the results for sub-question 2, the second part will explain the results for sub-question 3 and lastly the results of sub-question 4 will be explained.

For sub-question 1, desk research was conducted. The information search processes with the highest influence on the consumers purchase decisions are store design, website design, social media, family, friends and sales personnel. Brand image has a high positive influence on purchase intention (Ong, et al., 2021). According to Chamberlain et al. (2018) and Sohn & Kwon (2020), the knowledge of AI involvement decreases the valuation of fashion products. On the other hand, Hong & Curran (2019) find no significant difference in consumers valuations of knowing about AI involvement in fashion products. Sub-question 1 was answered in the research methodology part, because the answer for this sub-question was required to ensure that the questionnaire was consistent with other research, making it possible to compare results. The full extent of the results for sub-question 1 can be found in the research methodology.

For sub-questions 2 & 3, the assumptions were not met for multiple linear regression analysis, thus the ordinal logistic regression and multinomial logistic regression were used to interpret the collected data.

For these two models, the independent ordinal variables must be used as continuous variables. The assumption will be made that the independent ordinal variables from questions 7-19 have the same intervals between categories. When a Likert scale from 1-4 is used the ordinal variables have to be used as a categorical variable, from 5 and above the ordinal variables can be analysed as continuous variables (Sullivan & Artino Jr, 2013). The survey has only used 5-point Likert-scale, this means that the independent ordinal variables can be used as continuous variables. The further findings of the assumption testing of all 3 models are elaborated in each designated part.

6.1. The information search process of consumers

These results will answer sub-question 2:

> What are the effects of AI-produced art in clothing on the information search process of consumers?

For the analysis of sub-question 2, the multiple linear regression analysis was taken into consideration based on the methodology part discussed before. The assumptions for multiple linear regression analysis have to be met to use this model for analysis.

One of these assumptions is the test of normality, this was tested with the Kolmogorov-Smirnov test of normality. When the Kolmogorov-Smirnov test of normality has a significant value >0.05 the variables are normally distributed. With the data set of this paper, the Kolmogorov-Smirnov test of normality has a significant value of .001<.05 which means that none of the variables are significantly normally distributed, when the Log of the variables is tested the same results occur (Tables 6 and 7 in the Appendix).

This results in the conclusion that multiple linear regression analysis is not the proper method for the collected data.

To analyse the collected data, the ordinal logistic regression analysis was taken into consideration. The ordinal logistic regression has 3 assumptions which have to be met to conduct analysis using this model.

Firstly, the Model Fitting Information has to be significant to make sure that there is a significant difference between the baseline model and the final model. The baseline model is the model without the independent variables and the final model is the model with the independent variables.

Secondly, The Pearson Goodness-of-Fit significance value must be insignificant to make sure that there are no significant differences in the observed data and fitted data.

Finally, The Test of Parallel lines have to be insignificant, because the test of parallel lines states that the location parameters are not the same across the response categories when the significance level is < .05. Which means that if the value is insignificant the chance of falling into a higher category of the dependent variable is different across the independent variables.

With the data collected the first 2 assumptions are met but the Test of Parallel lines has a significant value of .016<.05 which means that the test of proportional odds is violated.

The latter only occurs when the categorical variable ‘Age’ is added to the model. The ‘Age’ variable is skewed towards the lower age category. 60.3% is allocated towards 18-34 years old. The reason for this could be based on the data collection method mentioned before. Thus the decision was made to drop the ‘Age’ variable for the ordinal logistic regression analysis. This results in the following assumption results:

The Model Fitting Information has a significant value of <.001 (Table 9 in the Appendix). Which means that the independent variables of this sample have a significant relationship with the dependent variable.

The Pearson Goodness-of-Fit has a significant value of .992 (Table 10 in the Appendix). Which means that the observed data does not have a significant difference compared to the fitted data.

The Test of Parallel lines has a significant value of .178 (Table 12 in the Appendix). Which means that the test of proportional odds is not violated.

This concludes that the assumptions for ordinal logistic regression analysis are met. This means that the parameter estimates of this ordinal logistic regression can be interpreted. The results are shown in table 2.

The Pseudo R-squared results are Cox and Snell, 0.305, Nagelkerke, 0.323 and McFadden, 0.126, which means that the independent variables in the model improve the prediction on interest in AI clothing by 12.6% to 32.3%, compared to a model where there are no independent variables. Because the R-squared value is below 0.7 the assumption is made that there are more independent variables which have influence on the variance of the dependent variable (Table 1). In this case it means that there are more factors which would have influence on the interest in AI art on clothing.

Table 1. Pseudo R-squared

Cox and Snell	.305
Nagelkerke	.323
McFadden	.126

The table shows the results of the pseudo R-squared tests of the ordinal logistic regression analysis with ‘AI Clothing Interest’ as the dependent variable.

When the parameter estimates are observed from the Ordinal logistic regression, the following observations are made.

For the information search process, the store purchase has a positive estimate which means that, when someone purchases clothes in stores more often there is a higher chance for the person to fall into a higher category of interest in AI clothes ($P = .046 < .05$). The exponential estimate for store purchases is 1.204, which means that the odds of higher interest in AI clothes are 1.204 times greater when someone falls into 1 higher category of store purchases.

People who buy clothes more often through social media ads also have a higher chance on falling into a higher category of interest in AI clothes ($P = .004 < .05$). The exponential estimate for social media ads is 1.336, which means that the odds of higher interest in AI clothes are 1.336 times greater when someone falls into 1 higher category of social media ads.

The other information search processes do not have a significant effect on the interest in AI clothes. Variables are not significant to the .05 significance level, thus those variables cannot be interpreted.

For the AI element, people who are more interested in AI have a higher chance to fall in a higher category of interest in AI clothes ($P = .000 < .05$). The exponential beta for AI interest is 2.452, which means that the odds of higher interest in AI clothes are 2.452 times greater when someone falls into 1 higher category of AI interest.

The self-perceived knowledge in AI does not have a significant effect on the interest in AI clothes.

The element gender was compared with female as the reference. Males do not have a significant difference in interest in AI clothes levels compared to females, because the significance level is $.30 > .05$.

The element work status was compared with ‘not working’ as the reference. The work status’ full-time, part-time, unemployed, retired and student do not have a significant difference in interest in AI clothes compared to ‘not working’ (respectively, .209; .164; .442; .262; .260; $> .05$).

The element highest education level was compared with HBO as the reference. People which have finished WO as their highest education have lower interest in AI clothes compared to HBO. The exponential estimate for WO is 0.442, which means that the odds of higher interest in AI clothes is 0.442 times lower for people with a highest education of WO compared to people with a highest education of HBO ($P = .002 < .05$).

The other education levels, less than high school, high school and MBO, have no significant difference in interest in AI clothes, compared to HBO (respectively, .302; .153; .132 > .05)

The element region was compared with West as the reference. People who live in the East have a lower chance of falling into a higher category of interest in AI clothes, compared to people who live in the West. The exponential estimate is 0.598, which means that the odds of higher interest in AI clothes are 0.598 times lower for people living in the east compared to people living in the west (P = .048 < .05).

People who live in the south also have a lower chance of falling into a higher category of interest in AI clothes, compared to people who live in the west. The exponential estimate is 0.584, which means that the odds of higher interest in AI clothes are 0.584 times lower for people living in the south compared to people living in the West (P = .031 < .05). The region North was not significantly different in their interest of AI clothes compared to the West, because the significance level was .683, which is lower than .05.

Table 2. Parameter estimates

	B	Exp(B)	SE	95% CI		Sig.
				LL	UL	
Dependent						
AICLINT = VL	1.909		0.932	0.083	3.735	0.041
AICLINT = L	3.595		0.944	1.745	5.444	0.000
AICLINT = N	5.621		0.966	3.728	7.514	0.000
AICLINT = H	7.773		1.005	5.803	9.742	0.000
Info search						
SPurchase	0.186	1.204	0.093	0.003	0.370	0.046
SDesign	-0.028	0.972	0.116	-0.255	0.198	0.806
WPurchase	0.126	1.134	0.091	-0.052	0.304	0.166
WDesign	0.150	1.162	0.109	-0.064	0.363	0.169
SMPurchase	0.016	1.016	0.104	-0.188	0.219	0.879
SMAds	0.290	1.336	0.102	0.090	0.490	0.004
FInfluence	-0.067	0.935	0.090	-0.243	0.109	0.455
EAdvice	0.132	1.141	0.113	-0.089	0.353	0.243
EInfluence	0.078	1.081	0.124	-0.165	0.320	0.531
AI						
AIKnowledge	0.035	1.036	0.100	-0.162	0.232	0.727
AIInterest	0.897	2.452	0.120	0.663	1.132	0.000
Gender						
Male	-0.224	0.799	0.216	-0.648	0.200	0.300
Work status						
Full-time	-0.849	0.428	0.676	-2.175	0.476	0.209
Part-time	-0.967	0.380	0.694	-2.327	0.393	0.164

Unemployed	-0.677	0.508	0.881	-2.402	1.049	0.442
Retired	-0.856	0.425	0.762	-2.349	0.638	0.262
Student	-0.792	0.453	0.704	-2.171	0.587	0.260
Education						
<HSchool	-0.911	0.402	0.884	-2.643	0.820	0.302
HSchool	-0.419	0.658	0.293	-0.992	0.155	0.153
MBO	-0.412	0.662	0.273	-0.948	0.124	0.132
WO	-0.817	0.442	0.265	-1.336	-0.298	0.002
Region						
North	-0.138		0.339	-0.802	0.525	0.683
East	-0.514	0.598	0.260	-1.023	-0.004	0.048
South	-0.538	0.584	0.250	-1.027	-0.049	0.031

Table 2 shows the results of the Parameter estimates of the ordinal logistic regression analysis with ‘AI Clothing Interest’ as the dependent variable. ‘AICLINT’ is the dependent variable which corresponds to the stated AI clothing interest of the participants. ‘VL’, ‘L’, ‘N’, ‘H’, ‘VH’ correspond to the stated AI clothing interest of the participants, respectively very low, low, neutral, high and very high. The ‘VH’ interest was used as the reference category. ‘Info search’ corresponds to the information search process variables. The variables have the following meanings: ‘SPurchase’, ‘WPurchase’, ‘SMPurchase’ are the variables which correspond to the stated amount of, respectively store purchases, web purchases and social media purchases. ‘SDesign’ and ‘WDesign’ are the variables which correspond to the influence of, respectively the store design and web design, on the purchase intentions of the respondents. ‘SMAds’ corresponds to the variable which indicates the stated influence of social media advertisements on the purchase intentions of the participants. ‘FInfluence’ and ‘EInfluence’ correspond to the influence of, respectively family and employees, on the purchase intentions of the participants. ‘EAdvice’ corresponds to the effect of advice from the employees on the purchase intentions of the participants. ‘AIKnowledge’ and ‘AIInterest’ correspond, respectively to the perceived knowledge in AI and the interest in AI of the participants. All of the independent ordinal variables were measured on a 5-point Likert scale ranging from ‘VL’ to ‘VH’. The demographic variables used for the table are ‘Gender’, ‘Work status’, ‘Education’ and ‘Region’. For the ‘Gender’ variables, ‘female’ was used as the reference category. For the ‘Work status’ variables, ‘not working’ was used as the reference category. For the ‘Education’ variables, ‘HBO’ was used as the reference category. The ‘<Hschool’ corresponds to a highest education of lower than high school. ‘Hschool’ corresponds to a highest education of high school. ‘MBO’ corresponds to a highest education of ‘secondary vocational education’. ‘HBO’ corresponds to a highest education of ‘higher professional education’. ‘WO’ corresponds to a

highest education of ‘University education’. For the ‘Region’ variables, ‘West’ was used as the reference category. The regions were distributed based on the provinces of the Netherlands. North corresponds to Groningen, Friesland and Drenthe. East corresponds to Overijssel and Gelderland. ‘West’ corresponds to Utrecht, Noord-Holland, Zuid-Holland and Flevoland. South corresponds to Noord-Brabant, Limburg and Zeeland.

6.2. Consumer consideration of alternative brands

These results will answer sub-question 3:

> What is the effect of AI-produced art in clothing on consumer consideration of alternative brands?

For the analysis of sub-question 3 the multiple linear regression analysis was taken into consideration based on the methodology part discussed before. The assumptions for multiple linear regression analysis have to be met to use this model for analysis. 1 of these assumption is the test of normality, this was tested with the Kolmogorov-Smirnov test of normality. The Kolmogorov-Smirnov is significant for all the variables used to answer sub-question 3. This means that the regression test does not meet all of the assumptions for multiple linear regression.

To analyse the collected data the Ordinal logistic regression analysis was taken into consideration. Firstly the assumptions for Ordinal logistic regression are tested.

The Pearson Goodness-of-Fit of the ordinal logistic regression analysis for sub-question 3 is significant, <0.001 (Table 14 in the Appendix). This means that the model does not fit the dataset. Thus ordinal logistic regression analysis is not a valid analysis for the dataset used for sub-question 3, because the assumptions for ordinal logistic regression analysis are not all met.

In this case, the multinomial logistic regression analysis was taken into consideration. The following assumptions have to be met to interpret the parameter estimates: Model Fitting Information needs to have a significant value below .05. The Goodness-of-Fit need to have a significant value above .05.

Model fitting information tests whether there is a significant relationship between the dependent and the independent variables in the final model. The significant value is <.001, which is lower than .05, this means that there is a significant relationship between the dependent and the independent variables (Table 16 in the Appendix).

The Pearson & Deviance goodness-of-fit significance value must be insignificant to make sure that there are no significant differences in the observed data and fitted data. In this case the Pearson significance level is .042 which means that the Pearson goodness-of-fit is 'nearly' insignificant (Table 17 in the Appendix). While the Deviance goodness-of-fit significance level is insignificant, with a significant value of 1.000 > 0.05, which would indicate that there are no significant differences in the observed data and fitted data. With these two significance levels in mind the parameter estimates are still interpreted, because the Pearson significance level is 'nearly' insignificant and the Deviance goodness-of-fit is insignificant.

The Pseudo R-squared results are Cox and Snell, .422, Nagelkere, .447 and McFadden, .189, which means that the independent variables in the model improve the prediction on the decision of choosing another brand by 18.9% to 44.7%, compared to a model where there are no independent variables (table 3). Because the R-squared value is below .7 the assumption is made that there are more independent variables which have influence on the variance of the dependent variable. In this case it means that there are more factors which would have influence on the decision of choosing another brand when the current brand sells AI clothing.

Table 3. Pseudo R-Square

Cox and Snell	.422
Nagelkerke	.447
McFadden	.189

The table shows the results of the Pseudo R-Square tests for the multinomial logistic regression analysis with 'Other Brand' as the dependent variable.

The table of parameter estimates is shown in table 4. The parameter estimates are analysed from top to bottom. First of all the comparison between very low (VL) chance of switching to another brand and high (H) chance of switching to another brand were analysed.

The respondents which scored higher on buying clothing through social media (SMPurchase) have a lower chance of voting for VL chance of switching to another brand, compared to H chance of switching to another brand, because the estimate value is negative (VL,SMPurchase = -0.496). The exponential estimate is 0.609, which means that respondents which scored higher on buying clothing through social media have 0.609 times lower chance, for every one unit increase in clothing purchased through social media, of falling in the VL category compared to the H category of switching to another brand (Exp(B) = 0.609; P = .025<0.05).

Similar results are observer for interest in clothing containing AI produced art (AICLInterest). For every one unit increase in AI clothing interest the respondents have 0.312 times lower chance of falling in the VL category compared to the H category of switching to another brand (Exp(B) = 0.312; P = .000<.05).

Compared to females, males have a 0.863 times lower chance of falling in the VL category compared to the H category of switching to another brand (Exp(B) = 0.863; P = .022<.05)

The other variables for VL chance, compared to H chance, of switching to another brand do not have significant values, which means this model cannot significantly state that the other variables have influence on the difference between VL chance and H chance of switching to another brand.

The low chance (L) of switching to another brand compared to high (H) chance of switching to another brand was analysed next.

A similar effect is visible for SMPurchase as for the VL chance of switching to another brand. Thus, for every one unit increase in 'SMPurchase', the respondents have 0.623 lower chance of falling in the L chance of switching to another brand, compared to H chance of switching to another brand (Exp(B) = 0.623; P = .027<.05).

For every one unit increase in 'AICLInterest' the respondents have a 0.560 lower chance of falling in the L chance of switching to another brand, compared to H chance of switching to another brand (Exp(B) = 0.560; P= .007 < .05)

Compared to people living in the South, people living in the North have a 0.129 times lower chance of falling in the L chance of switching to another brand, compared to the H chance of switching to another brand (Exp(B) = 0.129; P = .008 < .05)

The other variables for L chance, compared to H chance, of switching to another brand do not have significant values, which means that in this model there is no significant effect of the other variables on the difference between L chance and H chance of switching to another brand.

After that, the neutral (N) chance of switching to another brand compared to high (H) chance of switching to another brand was analysed.

Compared to people which achieved WO as their highest education, people which achieved MBO as their highest education have a 4.307 times higher chance of falling into the N chance, compared to the H chance, of switching to another brand (Exp(B) = 0.623; P = .019 < .05).

Compared to people living in the South, people living in the North, East and West have, respectively, a 0.083, 0.238, 0.213 times lower chance of falling in to the N chance, compared to the H chance, of switching to another brand (Respectively, Exp(B) = 0.083, 0.238, 0.213; P = .000, .019, .005 < .05).

The other variables do not show a significant difference between N chance, compared to H chance, of switching to another brand.

Lastly, very high (VH) chance of switching to another brand was compared with high (H) chance of switching to another brand.

A one unit increase in family influence on clothing purchases (Finfluence) decreases the chance of falling in the VH chance, compared to the H chance, of switching to another brand by 0.238 (Exp(B) = 0.238; P = .001 < .05).

Respondents which scored one unit higher in interest in AI compared to respondents which scored 1 unit lower, have a 2.797 higher chance to fall into the VH chance, compared to the H chance, of switching to another brand (Exp(B) = 2.797; P = .036 < .05).

The other variables did not show a significant difference between VH chance, compared to H chance, of switching to another brand.

Table 4. Parameter estimates of the multinomial logistic regression (Other brand)

Obrand		B	SE	Exp(B)	95% CI LL	95% CI UL	Sig.
VL	Intercept	7.034	1.696				0.000
	Info search						
	Spurchase	-0.141	0.198	0.869	0.590	1.280	0.477
	SDesign	-0.418	0.241	0.659	0.411	1.056	0.083
	WPurchase	0.082	0.189	1.086	0.750	1.572	0.663
	WDesign	0.244	0.242	1.276	0.795	2.048	0.313
	SMPurchase	-0.496	0.221	0.609	0.395	0.939	0.025
	SMAds	0.408	0.214	1.504	0.989	2.288	0.057
	Finfluence	-0.287	0.193	0.751	0.515	1.095	0.137
	EAsk	-0.135	0.238	0.874	0.548	1.393	0.570
	EInfluence	-0.054	0.257	0.948	0.572	1.569	0.835
	AI						
	AIKnowledge	0.086	0.214	1.090	0.716	1.659	0.688
	AIInterest	-0.132	0.250	0.876	0.537	1.430	0.597
	AICLInterest	-1.166	0.232	0.312	0.198	0.491	0.000
	Age						
	<18	-0.629	2.968	0.533	0.002	179.232	0.832
	18-24	-0.477	2.735	0.621	0.003	132.172	0.862
	25-34	-0.082	2.742	0.922	0.004	199.049	0.976
	35-44	-0.080	2.771	0.923	0.004	210.894	0.977
	45-54	0.860	2.740	2.363	0.011	508.394	0.754
	55-64	-0.140	2.669	0.870	0.005	162.591	0.958
	Gender						
	Male	-1.025	0.448	0.359	0.149	0.863	0.022
	Work status						
	Full-time	-0.419	2.663	0.658	0.004	121.533	0.875
	Part-time	-0.755	2.696	0.470	0.002	92.752	0.779
	Unemployed	-15.305	1875.810	2.256E-07	0.000	.[c]	0.993
	Not Working	-0.401	8109.048	0.670	0.000	.[c]	1.000
	Student	-0.221	2.756	0.802	0.004	177.712	0.936
	Education						
	<Hschool	-0.388	1.950	0.678	0.015	30.987	0.842
	Hschool	0.211	0.655	1.234	0.342	4.453	0.748
	MBO	0.887	0.691	2.427	0.626	9.408	0.200
	HBO	-0.366	0.535	0.694	0.243	1.980	0.494
	Region						
	North	-1.549	0.803	0.212	0.044	1.026	0.054
	East	-0.615	0.693	0.540	0.139	2.101	0.374
	West	-0.608	0.625	0.545	0.160	1.854	0.331
L	Intercept	4.901	1.617				0.002
	Info search						
	Spurchase	-0.271	0.188	0.762	0.527	1.102	0.149

	SDesign	-0.064	0.240	0.938	0.586	1.501	0.789
	WPurchase	0.013	0.180	1.013	0.712	1.442	0.942
	WDesign	0.222	0.235	1.248	0.788	1.978	0.345
	SMPurchase	-0.473	0.214	0.623	0.410	0.947	0.027
	SMAds	0.327	0.203	1.386	0.932	2.063	0.107
	Finfluence	-0.126	0.185	0.881	0.613	1.267	0.495
	EAsk	-0.147	0.221	0.864	0.560	1.331	0.506
	EInfluence	0.280	0.241	1.323	0.825	2.123	0.245
	AI						
	AIKnowledge	-0.243	0.204	0.784	0.525	1.170	0.234
	AIInterest	0.093	0.246	1.098	0.678	1.777	0.704
	AICLInterest	-0.579	0.215	0.560	0.368	0.854	0.007
	Age						
	<18	-0.838	2.739	0.433	0.002	92.758	0.760
	18-24	-0.383	2.419	0.682	0.006	78.167	0.874
	25-34	-0.115	2.431	0.892	0.008	104.583	0.962
	35-44	0.485	2.450	1.624	0.013	197.553	0.843
	45-54	0.796	2.424	2.217	0.019	256.443	0.743
	55-64	0.087	2.329	1.091	0.011	104.852	0.970
	Gender						
	Male	-0.450	0.423	0.638	0.278	1.461	0.288
	Work status						
	Full-time	-1.218	2.310	0.296	0.003	27.372	0.598
	Part-time	-1.693	2.349	0.184	0.002	18.374	0.471
	Unemployed	-0.022	2.676	0.978	0.005	185.572	0.993
	Not Working	16.835	576.111	20486618	0.000	.[c]	0.977
	Student	-0.962	2.400	0.382	0.003	42.172	0.688
	Education						
	<Hschool	-16.880	4009.127	4.667E-08	0.000	.[c]	0.997
	Hschool	0.053	0.630	1.055	0.307	3.624	0.932
	MBO	0.544	0.687	1.722	0.448	6.621	0.429
	HBO	0.022	0.492	1.023	0.390	2.682	0.964
	Region						
	North	-2.052	0.779	0.129	0.028	0.592	0.008
	East	-0.764	0.675	0.466	0.124	1.750	0.258
	West	-0.870	0.599	0.419	0.129	1.355	0.146
N	Intercept	3.437	1.536				0.025
	Info search						
	Spurchase	-0.006	0.165	0.994	0.719	1.373	0.970
	SDesign	-0.072	0.216	0.930	0.609	1.421	0.739
	WPurchase	0.113	0.161	1.120	0.816	1.537	0.482
	WDesign	0.124	0.217	1.132	0.740	1.733	0.567
	SMPurchase	-0.220	0.188	0.803	0.556	1.160	0.242
	SMAds	0.223	0.186	1.250	0.868	1.798	0.230
	Finfluence	-0.231	0.167	0.794	0.572	1.102	0.168
	EAsk	0.078	0.201	1.081	0.729	1.602	0.700

	EInfluence	0.004	0.223	1.004	0.648	1.555	0.986
	AI						
	AIKnowledge	-0.066	0.186	0.936	0.650	1.347	0.721
	AIInterest	0.151	0.221	1.163	0.754	1.793	0.495
	AICLInterest	-0.325	0.194	0.723	0.494	1.058	0.095
	Age						
	<18	-0.509	2.526	0.601	0.004	84.875	0.840
	18-24	-0.149	2.370	0.861	0.008	89.693	0.950
	25-34	0.574	2.390	1.775	0.016	191.971	0.810
	35-44	0.360	2.411	1.433	0.013	161.467	0.881
	45-54	0.761	2.386	2.140	0.020	229.927	0.750
	55-64	0.191	2.333	1.211	0.013	117.144	0.935
	Gender						
	Male	-0.848	0.380	0.428	0.204	0.902	0.026
	Work status						
	Full-time	-0.772	2.322	0.462	0.005	43.744	0.739
	Part-time	-1.309	2.357	0.270	0.003	27.380	0.579
	Unemployed	0.518	2.612	1.678	0.010	280.867	0.843
	Not Working	17.979	576.109	64264837	0.000	.[c]	0.975
	Student	-0.871	2.399	0.419	0.004	46.121	0.717
	Education						
	<Hschool	0.028	1.659	1.028	0.040	26.553	0.987
	Hschool	0.647	0.575	1.911	0.619	5.894	0.260
	MBO	1.460	0.623	4.307	1.271	14.597	0.019
	HBO	-0.217	0.460	0.805	0.327	1.985	0.638
	Region						
	North	-2.492	0.690	0.083	0.021	0.320	0.000
	East	-1.440	0.613	0.237	0.071	0.788	0.019
	West	-1.546	0.548	0.213	0.073	0.623	0.005
VH	Intercept	-1.471	2.991				0.623
	Info search						
	Spurchase	0.175	0.341	1.191	0.611	2.324	0.608
	SDesign	-0.504	0.439	0.604	0.256	1.427	0.250
	WPurchase	-0.157	0.347	0.855	0.433	1.688	0.651
	WDesign	0.397	0.474	1.488	0.588	3.767	0.402
	SMPurchase	0.209	0.382	1.233	0.583	2.607	0.584
	SMAds	-0.141	0.403	0.868	0.394	1.912	0.725
	Finfluence	-1.437	0.432	0.238	0.102	0.554	0.001
	EAsk	0.206	0.464	1.228	0.495	3.049	0.658
	EInfluence	-0.279	0.555	0.756	0.255	2.246	0.615
	AI						
	AIKnowledge	0.401	0.370	1.494	0.724	3.083	0.278
	AIInterest	1.029	0.491	2.797	1.069	7.320	0.036
	AICLInterest	-0.442	0.387	0.643	0.301	1.372	0.253
	Age						
	<18	12.526	576.110	275411.12	0.000	.[c]	0.983

18-24	11.176	576.109	71426.366	0.000	.[c]	0.985
25-34	11.253	576.109	77121.987	0.000	.[c]	0.984
35-44	10.553	576.110	38309.373	0.000	.[c]	0.985
45-54	9.473	576.110	13007.035	0.000	.[c]	0.987
55-64	-9.635	576.865	6.543E-05	0.000	.[c]	0.987
Gender						
Male	-0.972	0.782	0.378	0.082	1.752	0.214
Work status						
Full-time	-11.910	576.109	6.723E-06	0.000	.[c]	0.984
Part-time	-11.113	576.110	1.492E-05	0.000	.[c]	0.985
Unemployed	-10.990	576.113	1.688E-05	0.000	.[c]	0.985
Not Working	8.804	0.000	6658.259	6658.259	6658.26	
Student	-12.694	576.111	3.068E-06	0.000	.[c]	0.982
Education						
<Hschool	-0.467	2.229	0.627	0.008	49.459	0.834
Hschool	0.842	1.185	2.322	0.228	23.680	0.477
MBO	0.925	1.204	2.522	0.238	26.698	0.442
HBO	-0.458	0.946	0.632	0.099	4.036	0.628
Region						
North	0.149	1.805	1.161	0.034	39.882	0.934
East	0.511	1.488	1.666	0.090	30.781	0.732
West	1.003	1.338	2.726	0.198	37.508	0.453

Table 4 shows the results of the Parameter estimates of the multinomial logistic regression analysis with 'OBrand' as the dependent variable. 'Obrand' is the dependent variable which corresponds to the stated chance of a respondent switching to another brand if their favourite brand would sell clothing containing AI produced art. 'VL', 'L', 'N', 'H', 'VH' correspond to, respectively a very low chance, low chance, neutral chance, high chance and very high chance of switching to another brand. The 'H' chance of switching to another brand was used as the reference category. 'Info search' corresponds to the information search process variables. The variables have the following meanings: 'SPurchase', 'WPurchase', 'SMPurchase' are the variables which correspond to the stated amount of, respectively store purchases, web purchases and social media purchases. 'SDesign' and 'WDesign' are the variables which correspond to the influence of, respectively the store design and web design, on the purchase intentions of the respondents. 'SMAds' corresponds to the variable which indicates the stated influence of social media advertisements on the purchase intentions of the participants. 'FInfluence' and 'EInfluence' correspond to the influence of, respectively family and employees, on the purchase intentions of the participants. 'EAdvice' corresponds to the effect of advice from the employees on the purchase intentions of the participants. ‘AIKnowledge’ and ‘AIInterest’ correspond, respectively to the perceived knowledge in AI and the interest in AI of the participants. All of the independent ordinal variables were measured on a 5-point Likert scale ranging from very low to very high. The demographic variables used for the table are ‘Age’, ‘Gender’, ‘Work status’, ‘Education’ and ‘Region’. For the ‘Age’ variables, ‘65>’ was used as the reference category. For the ‘Gender’ variables, ‘female’ was used as the reference category. For the ‘Work status’ variables, ‘retired’ was used as the reference category. For the ‘Education’ variables, ‘WO’ was used as the reference category. The ‘<Hschool’ corresponds to a highest education of lower than high school. ‘Hschool’ corresponds to a highest education of high school. ‘MBO’ corresponds to a highest education of ‘secondary vocational education’. ‘HBO’ corresponds to a highest education of ‘higher professional education’. ‘WO’ corresponds to a highest education of ‘University education’. For the ‘Region’ variables, ‘South’ was used as the reference category. The regions were distributed based on the provinces of the Netherlands. North corresponds to Groningen, Friesland and Drenthe. East corresponds to Overijssel and Gelderland. ‘West’ corresponds to Utrecht, Noord-Holland, Zuid-Holland and Flevoland. South corresponds to Noord-Brabant, Limburg and Zeeland.

6.3. Willingness to pay

These results will answer sub-question 4:

1. What is the effect of AI-produced art in clothing on the willingness to pay?

Table 5. The different combinations of attributes shown for the conjoint analysis

Card no.	Brand	Price	Quality	Art produced by
1	No brand	Average	Low	AI
2	No brand	Low	High	Human
3	Social-cause	High	Low	Human
4	Social-cause	Low	Average	AI
5	Social-cause	Average	High	Undisclosed
6	Well-known	Low	Low	Undisclosed
7	No brand	High	High	AI
8	Well-known	High	Average	Undisclosed
9	Well-known	Average	Average	Human

Table 5 shows the different combinations of attributes which are shown to the participants. The cards are shown in a random order for every participant and the participants give each card a rating from 1-10.

No assumption was made for the relationship between brand and rating. And no assumption was made for the relationship between ‘art produced by’ and rating. The assumptions were made that an increase in price results in a decrease in rating and an increase in quality results in an increase in rating (Table 23 in the Appendix).

The preferences for the 4 attributes were observed. For the attribute brand, 52.2% of the respondents preferred No Brand, 26.3% preferred the Social Cause brand and 21.5% preferred the Well-Known brand.

The findings from this research have the same order of ranking compared to the research of Gouvea et al (2018), but the proportions of the preferences are different. According to their analysis 38% preferred no brand, 33% social cause and 29% Well-Known.

For the attribute Art, 39.4% preferred art produced by a human, 38.7% preferred art produced by AI and 21.9% preferred that who produced the art should be undisclosed.

Price and quality levels had the expected effects, where an increase in price meant a decrease in willingness to pay and an increase in quality meant an increase in willingness to pay. For price from low, average, high, respectively, 61.1%, 27%, 11.9%. And for quality from low, average, high, respectively, 4.8%, 19.1%, 76.1%.

Furthermore, the average importance levels of each attribute were analysed. The results showed that for the sample the average importance of quality was the highest with a score of 34%, which is followed by Brand with an average importance of 23.2%, third is the average importance of Art, with a score of 21.8% and last Price with a score of 21%. The results of Gouvea et al. (2018) showed that quality was the most important factor with an average importance of 43.3%, followed by brand with 32.7% and price with 24%. Both results follow a similar ranking of attributes.

Lastly, the impact of the coefficients quality and price were analysed. Price had an estimated coefficient of -0.817 and quality had an estimated coefficient of 1.381. Which means that the estimated coefficient of quality has 69% more impact compared to price. While in the analysis of Gouvea et al. (2018) the estimated coefficient of quality had 77% more impact compared to the estimated coefficient of price.

When the analysis is split among gender and region the following results are observed. For the brand males preferred No Brand with 53.6%, Social Cause with 24.1% and Well-Known with 22.3%. And females preferred No Brand with 51.5%, Social Cause with 28% and Well-Known with 20.5%.

For the Art males preferred AI with 41.5%, Human with 37.4% and Undisclosed with 21.2%. And females preferred Human with 41.4%, AI with 36.2%, Undisclosed with 22.4%

In the data collected, the males had a preference of 24.1% towards the social cause brand and females had a preference of 28%, which is in line with the analysis of Gouvea et al. (2018). According to their conjoint analysis females had a higher acceptance towards social cause brands, compared to males.

For Brand the following results were observed per region. The respondents living in the North mostly preferred brand was No Brand (44.6%), followed by Social cause (31.9%) and Well-known (23.5%). The East mostly preferred No Brand (53.4%), followed by Social Cause (27.6%) and Well-known (19%). The West mostly preferred No Brand (53.3%), followed by Social Cause (24.7%) and Well-known (22%). Lastly the South mostly preferred No Brand (52.1%), followed by Social Cause (26.5%) and Well-known (21.5%). All the regions followed the same ranking, with the biggest difference being that the North had a high preference for the Social Cause brand compared to the other regions.

For the attribute art the differences are more distinct. The North mostly preferred Human (42.3%), followed by AI (35.4%) and Undisclosed (22.3%). The East mostly preferred Human (43.5%), followed by AI (37.4%) and Undisclosed (19.1%). The West mostly preferred AI (42.6%), followed by Human (36.7%) and Undisclosed 20.7%. The South mostly preferred Human (40%), followed by AI (33.4%) and Undisclosed (26.6%).

These results show that males have a higher willingness to pay compared to females towards AI clothing. Furthermore, the willingness to pay decreases when the respondents do not know if the clothing contains AI or Human produced art. 3 out of 4 regions prefer art produced by humans more than art produced by AI. The only exception is that the respondents from the West prefer AI produced art on clothing, compared to art which is produced by a human.

Some exploratory analysis was done on the gender and age variables, because there is a difference between the AI clothing interest of males and females. The Art attribute was analysed based on Males per age group and females per age group. All of the different age groups had a sample size which is lower than 111, which could mean that the interpretations are not significant. But when the preferences based on the exponential estimates are analysed the following results are observed.

Males who are under 18 (N = 2) have a preference for AI (45.3%), followed by Undisclosed (40.4%) and Human (14.3%). Males between the ages of 18-24 (N = 19) have a preference for AI (41.3%), followed by Human (38.7%) and Undisclosed (20%). Males between the ages of 25-34 (N = 27) have a preference for AI (40.3%), followed by Human (38.1%) and Undisclosed (21.6%). Males between the ages of 35-44 (N = 12) have a preference for AI (40.3%), followed by Human (38.4%) and Undisclosed (21.2%). Males between the ages of 45-54 (N = 13) have a preference for AI (48.7%), followed by Human (35.5%) and Undisclosed (16.9%). Males between the ages of 55-64 (N = 4) have a preference for Human (48.8%), followed by AI (27.7%) and Undisclosed (23.4%). Lastly Males aged above 65 (N = 3) have a preference for AI (39.8%), followed by Human (30.1%) and Undisclosed (30.1%).

If the sample size was significantly high enough, this would mean that Males aged between 45-54 have the highest preference for clothing with AI produced art, compared to clothing with Human produced art. The only age group which prefers clothing with human produced art, compared to clothing with AI produced art is males aged between 55-64.

For females, the following observations are made. Females who are under 18 (N = 4) have a preference for Human (50.9%), followed by Undisclosed (28.2%) and AI (20.9%). Females between the ages of 18-24 (N = 50) have a preference for Human (42.8%), followed by AI (35.8%) and Undisclosed (21.3%). Females between the ages of 25-34 (N = 21) have a preference for AI (40.9%), followed by Human (39.2%) and Undisclosed (19.9%). Females between the ages of 35-44 (N = 13) have a preference for Human (35%), followed by AI (29.9%) and Undisclosed (35.1%). Females between the ages of 45-54 (N = 6) have a preference for Human (48.7%), followed by AI (34.2%) and Undisclosed (17.1%). Females between the ages of 55-64 (N = 6) have a preference for AI (45.3%), followed by Human (34.2%) and Undisclosed (20.5%). Lastly Females aged above 65 (N = 3) have a preference for AI (46.1%), followed by Human (36.5%) and Undisclosed (17.4%).

If the sample size was significantly high enough, this would mean that females aged between <18 - 24 and 35 – 54 have a preference for clothing containing human art, compared to clothing containing AI art. Females aged between 25 – 34 and aged above 55 have a preference for clothing containing AI art, compared to clothing containing Human art.

7. Conclusion

The increase in interest and the increase in development of Artificial Intelligence (AI) was the reason that consumer behaviour on AI produced art on clothing was analysed in this paper. The analyses consist of ordinal logistic regression, multinomial logistic regression and conjoint analysis. The first two regression analyses were not the initial proposed analysis methods, but because of the nature of the collected data these two models were used to interpret the collected data.

The sample size after data cleaning was 396 for the ordinal and multinomial logistic regression and for the conjoint analysis the sample size was 185. The difference in sample sizes can be explained by the fact that some participants did not understand the questioning for the conjoint analysis part.

For the representativeness of the sample, stratified sampling was conducted with the regional proportions of the Dutch population as the baseline.

The ordinal logistic regression tested whether the information search processes of consumers have influence on the interest in clothing containing AI produced art. The tested information search processes of consumers which had a significant effect on the interest on AI clothing are the amount of purchases made in stores and the purchases made through social media. Both of these information search processes positively increase the chance of a consumer falling into a higher category of interest in clothing containing AI produced art.

When looking at the influence of AI interest, results imply that when a consumer has a higher interest in AI, the chance of that consumer having interest in clothing containing AI produced art on clothing also increases.

Furthermore, the chance of a consumer being interested in clothing containing AI produced art increases when the consumer’s highest finished education is HBO, compared to consumers which have a highest education level of WO.

Compared to people living in the eastern and southern part of the Netherlands, people living in the western part of the Netherlands have a higher chance of falling into a higher category of interest in clothing containing AI produced art.

The multinomial logistic regression tested whether the observed chance of switching to another brand was influenced by clothing containing AI produced art. The respondents were asked what the chance is that they would switch to another brand if their favourite brand would offer clothing containing AI produced art.

Compared to females, males have a lower chance of falling in to the very low chance category of switching to another brand, compared to the high chance category of switching to another brand.

The respondents which purchased clothing more often through social media have a lower chance of falling into a very low or low chance category of switching to another brand, compared to a high chance category of switching to another brand.

Respondents which had higher influence from their family with regard to clothing purchases have a higher chance of falling into a very high chance category of switching to another brand, compared to a high chance category of switching to another brand.

Compared to respondents which achieved WO as their highest education, the respondents which achieved MBO have a higher chance of falling into a neutral chance category of switching to another brand compared to a high chance category of switching to another brand.

If the interest on clothing containing AI produced art is higher for a specific respondent, that respondent will have a lower chance of falling in to the very low or low chance category of switching to another brand, compared to a high chance category of switching to another brand.

If the interest in AI is higher for a specific respondent, that respondent will have a higher chance of falling into the very high chance category of switching to another brand, compared to the high chance category of switching to another brand.

Compared to people living in the southern part of the Netherlands, people living in the northern part of the Netherlands have a lower chance of falling in to the low or neutral chance category of switching to another brand, compared to the high chance category of switching to another brand. While the people living in the eastern and western parts, compared to the southern part, of the Netherlands have a lower chance of falling in to the neutral chance category of switching to another brand, compared to the high chance category of switching to another brand.

The results of the conjoint analysis imply that males have a higher willingness to pay for clothing containing AI produced art compared to females. Males even had a higher willingness to pay for clothing containing art produced by AI compared to clothing containing art produced by humans. When the different regions were compared the respondents which lived in the western parts of the Netherlands had a higher willingness to pay for clothing containing AI produced art, compared to clothing containing art produced by humans. The other regions had a higher willingness to pay for clothing containing art produced by humans, compared to clothing containing AI produced art.

Some exploratory analysis was done which resulted in different willingness to pay between gender and age groups, in which different age groups for males and for females showed different preferences towards AI or human produced art on clothing, the frequencies per age group were relatively low. These results can be seen in the results section and could indicate that further analysis per age group and gender could be relevant.

The results in this research should be interpreted with caution, because this paper was written on a time and budget constraint. Firstly the data was collected with manual labour for survey distribution, during the distribution a preference was made for people sitting on terraces. Some mistakes were made with the formulation of some of the questions. The question which asked the participants their monthly family income, included a portion where it stated ‘if you prefer not to answer, you can skip this question’, this resulted in a missing value proportion of almost 10%, which resulted in the decision to drop this variable for the ordinal and multinomial regressions. Because of this, the final models have one less variable which influences the independent variable. For the conjoint analysis, a high proportion of missing values was obtained and many reversals were observed during the analysis, which led to a very high reduction in sample size, from 396 to 186.

7.1. Future research

The R-squared for both the ordinal logistic regression and multinomial logisitic regression are both below 0.7, this indicates that more variables would increase the explanation on the changes in the independent variable. Thus in future research more variables should be included in the tests.

The results of this paper show that there is difference between the regions and their interest in AI produced art in clothing, but the significance is based on small sample sizes. In future research extensive analysis could be done per region with bigger sample sizes to observe the significant differences per region.

The willingness to pay between gender and age groups on clothing containing AI produced art could be tested on a bigger scale to further analyse if the differences are significant.

The conjoint analysis could be conducted in a separate survey to minimize the respondents fatigue and addition of holdout questions would increase the validity of the utilities. The extreme respondent bias could be reduced by thoroughly testing the conjoint analysis questions on preview participants, in which the participants could be asked if they properly understand the questioning for the conjoint analysis. The proportion of males and females in the final conjoint analysis was, respectively 42.9% and 56.1%. In future research the proportions of males and females should be weighted as well to increase the representativeness of the results.

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9. Appendix

Table 6. Kolmogorov-Smirnov test of normality

	Statistic	df	Sig.
Store purchase	.233	396	<.001
Store design	.301	396	<.001
Web purchase	.184	396	<.001
Web design	.269	396	<.001
SM purchase	.249	396	<.001
SM ads	.176	396	<.001
Family influence	.171	396	<.001
Employee advice	.274	396	<.001
Employee influence	.215	396	<.001
AI knowledge	.254	396	<.001
AI interest	.240	396	<.001

The table shows the results of the Kolmogorov-Smirnov test of normality of the multiple regression analysis with ‘AI Clothing Interest’ as the dependent variable.

Table 7. Kolmogorov-Smirnov test of normality (log)

	Statistic	df	Sig.
Log store purchase	.191	396	<.001
Log store design	.322	396	<.001
Log web purchase	.197	396	<.001
Log web design	.311	396	<.001
Log SM purchase	.280	396	<.001
Log SM ads	.227	396	<.001
Log family influence	.224	396	<.001
Log employee advice	.298	396	<.001
Log employee influence	.241	396	<.001
Log AI knowledge	.260	396	<.001
Log AI interest	.252	396	<.001

The table shows the results of the Kolmogorov-Smirnov test of normality of the multiple regression analysis with ‘AI Clothing Interest’ as the dependent variable and with the log of the independent variables.

Table 8. Case processing summary

		N	Marginal %
AI clothing interest	VL Interest	61.10	15.4%
	L Interest	98.81	25.0%
	Neutral	147.39	37.2%
	H Interest	72.16	18.2%
	VH Interest	16.39	4.1%
Gender	Male	187.86	47.5%
	Female	207.99	52.5%
Highest education	< High school	5.15	1.3%
	High school	89.42	22.6%
	MBO	83.88	21.2%
	HBO	125.59	31.7%
	WO	91.82	23.2%
Employment status	Full-time	187.63	47.4%
	Part-time	79.39	20.1%
	Unemployed	9.84	2.5%
	Not Working	8.55	2.2%
	Student	85.13	21.5%
	Retired	25.31	6.4%
Region	North	39.48	10.0%
	East	75.36	19.0%
	West	189.91	48.0%
	South	91.10	23.0%

The table shows the results of the case processing summary of the ordinal logistic regression analysis with ‘AI Clothing Interest’ as the dependent variable.

Table 9. Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1143.871			
Final	999.804	144.066	24	<.001

The table shows the results of the model fitting information of the ordinal logistic regression analysis with ‘AI Clothing Interest’ as the dependent variable.

Table 10. Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	1425.336	1556	.992
Deviance	999.804	1556	1.000

The table shows the results of the goodness-of-fit tests of the ordinal logistic regression analysis with ‘AI Clothing Interest’ as the dependent variable.

Table 11. Pseudo R-Square

Cox and Snell	.305
Nagelkerke	.323
McFadden	.126

The table shows the results of the pseudo R-squared tests of the ordinal logistic regression analysis with 'AI Clothing Interest' as the dependent variable.

Table 12. Test of Parallel Lines

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	999.804			
General	916.883[b]	82.922[c]	72	.178

The table shows the results of the test of parallel lines of the ordinal logistic regression analysis with 'AI Clothing Interest' as the dependent variable.

Table 13. Parameter estimates of the ordinal logistic regression

	B	Exp(B)	SE	95% CI		Sig.
				LL	UL	
Dependent						
AICLINT = VL	1.909		0.932	0.083	3.735	0.041
AICLINT = L	3.595		0.944	1.745	5.444	0.000
AICLINT = N	5.621		0.966	3.728	7.514	0.000
AICLINT = H	7.773		1.005	5.803	9.742	0.000
Info search						
SPurchase	0.186	1.204	0.093	0.003	0.370	0.046
SDesign	-0.028	0.972	0.116	-0.255	0.198	0.806
WPurchase	0.126	1.134	0.091	-0.052	0.304	0.166
WDesign	0.150	1.162	0.109	-0.064	0.363	0.169
SMPurchase	0.016	1.016	0.104	-0.188	0.219	0.879
SMAds	0.290	1.336	0.102	0.090	0.490	0.004
FInfluence	-0.067	0.935	0.090	-0.243	0.109	0.455
EAdvice	0.132	1.141	0.113	-0.089	0.353	0.243
EInfluence	0.078	1.081	0.124	-0.165	0.320	0.531
AI						
AIKnowledge	0.035	1.036	0.100	-0.162	0.232	0.727
AIInterest	0.897	2.452	0.120	0.663	1.132	0.000
Gender						
Male	-0.224	0.799	0.216	-0.648	0.200	0.300
Work status						
Full-time	-0.849	0.428	0.676	-2.175	0.476	0.209
Part-time	-0.967	0.380	0.694	-2.327	0.393	0.164
Unemployed	-0.677	0.508	0.881	-2.402	1.049	0.442
Retired	-0.856	0.425	0.762	-2.349	0.638	0.262
Student	-0.792	0.453	0.704	-2.171	0.587	0.260

Education						
<HSchool	-0.911	0.402	0.884	-2.643	0.820	0.302
HSchool	-0.419	0.658	0.293	-0.992	0.155	0.153
MBO	-0.412	0.662	0.273	-0.948	0.124	0.132
WO	-0.817	0.442	0.265	-1.336	-0.298	0.002
Region						
North	-0.138		0.339	-0.802	0.525	0.683
East	-0.514	0.598	0.260	-1.023	-0.004	0.048
South	-0.538	0.584	0.250	-1.027	-0.049	0.031

The table shows the results of the Parameter estimates of the ordinal logistic regression analysis with ‘AI Clothing Interest’ as the dependent variable. ‘AICLINT’ is the dependent variable which corresponds to the stated AI clothing interest of the participants. ‘VL’, ‘L’, ‘N’, ‘H’, ‘VH’ correspond to the stated AI clothing interest of the participants, respectively very low, low, neutral, high and very high. The ‘VH’ interest was used as the reference category. ‘Info search’ corresponds to the information search process variables. The variables have the following meanings: ‘SPurchase’, ‘WPurchase’, ‘SMPurchase’ are the variables which correspond to the stated amount of, respectively store purchases, web purchases and social media purchases. ‘SDesign’ and ‘WDesign’ are the variables which correspond to the influence of, respectively the store design and web design, on the purchase intentions of the respondents. ‘SMAds’ corresponds to the variable which indicates the stated influence of social media advertisements on the purchase intentions of the participants. ‘FInfluence’ and ‘EInfluence’ correspond to the influence of, respectively family and employees, on the purchase intentions of the participants. ‘EAdvice’ corresponds to the effect of advice from the employees on the purchase intentions of the participants. ‘AIKnowledge’ and ‘AIInterest’ correspond, respectively to the perceived knowledge in AI and the interest in AI of the participants. All of the independent ordinal variables were measured on a 5-point Likert scale ranging from ‘VL’ to ‘VH’. The demographic variables used for the table are ‘Gender’, ‘Work status’, ‘Education’ and ‘Region’. For the ‘Gender’ variables, ‘female’ was used as the reference category. For the ‘Work status’ variables, ‘not working’ was used as the reference category. For the ‘Education’ variables, ‘HBO’ was used as the reference category. The ‘<Hschool’ corresponds to a highest education of lower than high school. ‘Hschool’ corresponds to a highest education of high school. ‘MBO’ corresponds to a highest education of ‘secondary vocational education’. ‘HBO’ corresponds to a highest education of ‘higher professional education’. ‘WO’ corresponds to a highest education of ‘University education’. For the ‘Region’ variables, ‘West’ was used as the reference category. The regions were distributed based on the provinces of the Netherlands. North corresponds to Groningen, Friesland and Drenthe. East corresponds to Overijssel and Gelderland. ‘West’ corresponds to Utrecht, Noord-Holland, Zuid-Holland and Flevoland. South corresponds to Noord-Brabant, Limburg and Zeeland.

Table 14. Goodness-of-Fit of the ordinal logistic regression (Other brand)

	Chi-Square	df	Sig.
Pearson	2019.780	1549	<.001
Deviance	1037.907	1549	1.000

The table shows the results of the Goodness-of-Fit tests for the ordinal logistic regression analysis with ‘Other Brand’ as the dependent variable.

Table 15. Case Processing Summary of the multinomial logistic regression (Other brand)

		N	Marginal %
Other Brand	VL Chance	83.61	21.1%
	L Chance	81.60	20.6%
	Neutral	151.07	38.2%
	H Chance	62.85	15.9%
	VH Chance	16.73	4.2%
Age	<18	12.31	3.1%
	18-24	137.80	34.8%
	25-34	100.51	25.4%
	35-44	42.60	10.8%
	45-54	48.67	12.3%
	55-64	29.93	7.6%
	65>	24.04	6.1%
Gender	Male	187.86	47.5%
	Female	207.99	52.5%
Highest Education	< High school	5.15	1.3%
	High school	89.42	22.6%
	MBO	83.88	21.2%
	HBO	125.59	31.7%
	WO	91.82	23.2%
Employment Status	Full-time	187.63	47.4%
	Part-time	79.39	20.1%
	Unemployed	9.84	2.5%
	Not Working	8.55	2.2%
	Student	85.13	21.5%
	Retired	25.31	6.4%
Region	North	39.48	10.0%
	East	75.36	19.0%
	West	189.91	48.0%
	South	91.10	23.0%

The table shows the results of the Case Processing Summary of the multinomial logistic regression analysis with ‘Other Brand’ as the dependent variable.

Table 16. Model Fitting Information of the multinomial logistic regression (Other brand)

	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1145.974			
Final	929.000	216.973	124	<.001

The table shows the results of the Model Fitting Information of the multinomial logistic regression analysis with 'Other Brand' as the dependent variable.

Table 17. Goodness-of-Fit of the multinomial logistic regression (Other brand)

	Chi-Square	df	Sig.
Pearson	1550.469	1456	.042
Deviance	929.000	1456	1.000

The table shows the results of the Goodness-of-Fit tests for the multinomial logistic regression analysis with 'Other Brand' as the dependent variable.

Table 18. Pseudo R-Square of the multinomial logistic regression (Other brand)

Cox and Snell	.422
Nagelkerke	.447
McFadden	.189

The table shows the results of the Pseudo R-Square tests for the multinomial logistic regression analysis with 'Other Brand' as the dependent variable.

Table 19. Likelihood Ratio Tests of the multinomial logistic regression (Other brand)

		Chi-Square	df	Sig.
Intercept	929.000[a]	.000	0	.
Store purchase	933.084	4.083	4	.395
Store design	934.432	5.431	4	.246
Web purchase	930.226	1.226	4	.874
Web design	930.614	1.613	4	.806
SM purchase	937.928	8.928	4	.063
SM ads	934.122	5.121	4	.275
Family influence	944.950	15.950	4	.003
Employee advice	931.293	2.292	4	.682
Employee influence	932.477[b]	3.477	4	.481
AI knowledge	934.331	5.330	4	.255
AI interest	936.361	7.360	4	.118
AI clothing interest	962.435	33.434	4	<.001
Age	944.491	15.490	24	.906
Gender	936.449	7.449	4	.114
Highest education	946.122	17.122	16	.378
Employment status	947.795	18.795	20	.535
Region	952.772	23.772	12	.022

The table shows the results of the Likelihood Ratio tests for the multinomial logistic regression analysis with 'Other Brand' as the dependent variable.

Table 20. Model prediction accuracy test of the multinomial logistic regression (Other brand)

	VL Chance	L Chance	Neutral	H Chance	VH Chance	% Correct
VL Chance	46.11	10.86	21.02	5.62	0	55.1%
L Chance	13.05	21.43	38.10	8.25	.77	26.3%
Neutral	16.29	14.13	107.76	10.84	2.04	71.3%
H Chance	5.92	7.96	25.05	22.90	1.02	36.4%
VH Chance	3.83	0	6.01	2.04	4.85	29.0%
Overall %	21.5%	13.7%	50.0%	12.5%	2.2%	51.3%

The values shown in this table indicate what the percentage of correctly guessed results are for the predicted model based on the observed model. This means that Neutral chance of switching to another brand respondents were correctly predicted by the model 71.3% of the time. People that responded with a very low chance of switching to another brand were correctly predicted by the model 55.1% of the time. The high chance, very high chance and low chance responses were predicted poorly with a respective chance of 36.4%, 29% and 26.3%.

Table 21. Parameter estimates of the multinomial logistic regression (Other brand)

Obrand		B	SE	Exp(B)	95% CI LL	95% CI UL	Sig.
VL	Intercept	7.034	1.696				0.000
	Info search						
	Spurchase	-0.141	0.198	0.869	0.590	1.280	0.477
	SDesign	-0.418	0.241	0.659	0.411	1.056	0.083
	WPurchase	0.082	0.189	1.086	0.750	1.572	0.663
	WDesign	0.244	0.242	1.276	0.795	2.048	0.313
	SMPurchase	-0.496	0.221	0.609	0.395	0.939	0.025
	SMAds	0.408	0.214	1.504	0.989	2.288	0.057
	Finfluence	-0.287	0.193	0.751	0.515	1.095	0.137
	EAsk	-0.135	0.238	0.874	0.548	1.393	0.570
	EInfluence	-0.054	0.257	0.948	0.572	1.569	0.835
	AI						
	AIKnowledge	0.086	0.214	1.090	0.716	1.659	0.688
	AIInterest	-0.132	0.250	0.876	0.537	1.430	0.597
	AICLInterest	-1.166	0.232	0.312	0.198	0.491	0.000
	Age						
	<18	-0.629	2.968	0.533	0.002	179.232	0.832
	18-24	-0.477	2.735	0.621	0.003	132.172	0.862
	25-34	-0.082	2.742	0.922	0.004	199.049	0.976
	35-44	-0.080	2.771	0.923	0.004	210.894	0.977
	45-54	0.860	2.740	2.363	0.011	508.394	0.754
	55-64	-0.140	2.669	0.870	0.005	162.591	0.958
	Gender						
	Male	-1.025	0.448	0.359	0.149	0.863	0.022
	Work status						
	Full-time	-0.419	2.663	0.658	0.004	121.533	0.875
	Part-time	-0.755	2.696	0.470	0.002	92.752	0.779
	Unemployed	-15.305	1875.810	2.256E-07	0.000	.[c]	0.993
	Not Working	-0.401	8109.048	0.670	0.000	.[c]	1.000
	Student	-0.221	2.756	0.802	0.004	177.712	0.936
	Education						
	<Hschool	-0.388	1.950	0.678	0.015	30.987	0.842
	Hschool	0.211	0.655	1.234	0.342	4.453	0.748
	MBO	0.887	0.691	2.427	0.626	9.408	0.200
	HBO	-0.366	0.535	0.694	0.243	1.980	0.494
	Region						
	North	-1.549	0.803	0.212	0.044	1.026	0.054
	East	-0.615	0.693	0.540	0.139	2.101	0.374
	West	-0.608	0.625	0.545	0.160	1.854	0.331
L	Intercept	4.901	1.617				0.002
	Info search						
	Spurchase	-0.271	0.188	0.762	0.527	1.102	0.149

	SDesign	-0.064	0.240	0.938	0.586	1.501	0.789
	WPurchase	0.013	0.180	1.013	0.712	1.442	0.942
	WDesign	0.222	0.235	1.248	0.788	1.978	0.345
	SMPurchase	-0.473	0.214	0.623	0.410	0.947	0.027
	SMAds	0.327	0.203	1.386	0.932	2.063	0.107
	Finfluence	-0.126	0.185	0.881	0.613	1.267	0.495
	EAsk	-0.147	0.221	0.864	0.560	1.331	0.506
	EInfluence	0.280	0.241	1.323	0.825	2.123	0.245
	AI						
	AIKnowledge	-0.243	0.204	0.784	0.525	1.170	0.234
	AIInterest	0.093	0.246	1.098	0.678	1.777	0.704
	AICLInterest	-0.579	0.215	0.560	0.368	0.854	0.007
	Age						
	<18	-0.838	2.739	0.433	0.002	92.758	0.760
	18-24	-0.383	2.419	0.682	0.006	78.167	0.874
	25-34	-0.115	2.431	0.892	0.008	104.583	0.962
	35-44	0.485	2.450	1.624	0.013	197.553	0.843
	45-54	0.796	2.424	2.217	0.019	256.443	0.743
	55-64	0.087	2.329	1.091	0.011	104.852	0.970
	Gender						
	Male	-0.450	0.423	0.638	0.278	1.461	0.288
	Work status						
	Full-time	-1.218	2.310	0.296	0.003	27.372	0.598
	Part-time	-1.693	2.349	0.184	0.002	18.374	0.471
	Unemployed	-0.022	2.676	0.978	0.005	185.572	0.993
	Not Working	16.835	576.111	20486618	0.000	.[c]	0.977
	Student	-0.962	2.400	0.382	0.003	42.172	0.688
	Education						
	<Hschool	-16.880	4009.127	4.667E-08	0.000	.[c]	0.997
	Hschool	0.053	0.630	1.055	0.307	3.624	0.932
	MBO	0.544	0.687	1.722	0.448	6.621	0.429
	HBO	0.022	0.492	1.023	0.390	2.682	0.964
	Region						
	North	-2.052	0.779	0.129	0.028	0.592	0.008
	East	-0.764	0.675	0.466	0.124	1.750	0.258
	West	-0.870	0.599	0.419	0.129	1.355	0.146
N	Intercept	3.437	1.536				0.025
	Info search						
	Spurchase	-0.006	0.165	0.994	0.719	1.373	0.970
	SDesign	-0.072	0.216	0.930	0.609	1.421	0.739
	WPurchase	0.113	0.161	1.120	0.816	1.537	0.482
	WDesign	0.124	0.217	1.132	0.740	1.733	0.567
	SMPurchase	-0.220	0.188	0.803	0.556	1.160	0.242
	SMAds	0.223	0.186	1.250	0.868	1.798	0.230
	Finfluence	-0.231	0.167	0.794	0.572	1.102	0.168
	EAsk	0.078	0.201	1.081	0.729	1.602	0.700

	EInfluence	0.004	0.223	1.004	0.648	1.555	0.986
	AI						
	AIKnowledge	-0.066	0.186	0.936	0.650	1.347	0.721
	AIInterest	0.151	0.221	1.163	0.754	1.793	0.495
	AICLInterest	-0.325	0.194	0.723	0.494	1.058	0.095
	Age						
	<18	-0.509	2.526	0.601	0.004	84.875	0.840
	18-24	-0.149	2.370	0.861	0.008	89.693	0.950
	25-34	0.574	2.390	1.775	0.016	191.971	0.810
	35-44	0.360	2.411	1.433	0.013	161.467	0.881
	45-54	0.761	2.386	2.140	0.020	229.927	0.750
	55-64	0.191	2.333	1.211	0.013	117.144	0.935
	Gender						
	Male	-0.848	0.380	0.428	0.204	0.902	0.026
	Work status						
	Full-time	-0.772	2.322	0.462	0.005	43.744	0.739
	Part-time	-1.309	2.357	0.270	0.003	27.380	0.579
	Unemployed	0.518	2.612	1.678	0.010	280.867	0.843
	Not Working	17.979	576.109	64264837	0.000	.[c]	0.975
	Student	-0.871	2.399	0.419	0.004	46.121	0.717
	Education						
	<Hschool	0.028	1.659	1.028	0.040	26.553	0.987
	Hschool	0.647	0.575	1.911	0.619	5.894	0.260
	MBO	1.460	0.623	4.307	1.271	14.597	0.019
	HBO	-0.217	0.460	0.805	0.327	1.985	0.638
	Region						
	North	-2.492	0.690	0.083	0.021	0.320	0.000
	East	-1.440	0.613	0.237	0.071	0.788	0.019
	West	-1.546	0.548	0.213	0.073	0.623	0.005
VH	Intercept	-1.471	2.991				0.623
	Info search						
	Spurchase	0.175	0.341	1.191	0.611	2.324	0.608
	SDesign	-0.504	0.439	0.604	0.256	1.427	0.250
	WPurchase	-0.157	0.347	0.855	0.433	1.688	0.651
	WDesign	0.397	0.474	1.488	0.588	3.767	0.402
	SMPurchase	0.209	0.382	1.233	0.583	2.607	0.584
	SMAds	-0.141	0.403	0.868	0.394	1.912	0.725
	Finfluence	-1.437	0.432	0.238	0.102	0.554	0.001
	EAsk	0.206	0.464	1.228	0.495	3.049	0.658
	EInfluence	-0.279	0.555	0.756	0.255	2.246	0.615
	AI						
	AIKnowledge	0.401	0.370	1.494	0.724	3.083	0.278
	AIInterest	1.029	0.491	2.797	1.069	7.320	0.036
	AICLInterest	-0.442	0.387	0.643	0.301	1.372	0.253
	Age						
	<18	12.526	576.110	275411.12	0.000	.[c]	0.983

18-24	11.176	576.109	71426.366	0.000	.[c]	0.985
25-34	11.253	576.109	77121.987	0.000	.[c]	0.984
35-44	10.553	576.110	38309.373	0.000	.[c]	0.985
45-54	9.473	576.110	13007.035	0.000	.[c]	0.987
55-64	-9.635	576.865	6.543E-05	0.000	.[c]	0.987
Gender						
Male	-0.972	0.782	0.378	0.082	1.752	0.214
Work status						
Full-time	-11.910	576.109	6.723E-06	0.000	.[c]	0.984
Part-time	-11.113	576.110	1.492E-05	0.000	.[c]	0.985
Unemployed	-10.990	576.113	1.688E-05	0.000	.[c]	0.985
Not Working	8.804	0.000	6658.259	6658.259	6658.26	
Student	-12.694	576.111	3.068E-06	0.000	.[c]	0.982
Education						
<Hschool	-0.467	2.229	0.627	0.008	49.459	0.834
Hschool	0.842	1.185	2.322	0.228	23.680	0.477
MBO	0.925	1.204	2.522	0.238	26.698	0.442
HBO	-0.458	0.946	0.632	0.099	4.036	0.628
Region						
North	0.149	1.805	1.161	0.034	39.882	0.934
East	0.511	1.488	1.666	0.090	30.781	0.732
West	1.003	1.338	2.726	0.198	37.508	0.453

The table shows the results of the Parameter estimates of the multinomial logistic regression analysis with ‘Other Brand’ as the dependent variable. ‘Obrand’ is the dependent variable which corresponds to the stated chance of a respondent switching to another brand if their favourite brand would sell clothing containing AI produced art. ‘VL’, ‘L’, ‘N’, ‘H’, ‘VH’ correspond, respectively a very low chance, low chance, neutral chance, high chance and very high chance of switching to another brand. The ‘H’ chance of switching to another brand was used as the reference category. ‘Info search’ corresponds to the information search process variables. The variables have the following meanings: ‘SPurchase’, ‘WPurchase’, ‘SMPurchase’ are the variables which correspond to the stated amount of, respectively store purchases, web purchases and social media purchases. ‘SDesign’ and ‘WDesign’ are the variables which correspond to the influence of, respectively the store design and web design, on the purchase intentions of the respondents. ‘SMAds’ corresponds to the variable which indicates the stated influence of social media advertisements on the purchase intentions of the participants. ‘FInfluence’ and ‘EInfluence’ correspond to the influence of, respectively family and employees, on the purchase intentions of the participants. ‘EAdvice’ corresponds to the effect of advice from the employees on the purchase intentions of the participants. ‘AIKnowledge’ and ‘AIInterest’ correspond, respectively to the perceived knowledge in AI and the interest in AI of the participants. All of the independent ordinal variables were measured on a 5-point Likert scale ranging from very low to very high. The demographic variables used for the table are ‘Age’, ‘Gender’, ‘Work status’, ‘Education’ and ‘Region’. For the ‘Age’ variables, ‘65>’ was used as the reference category. For the ‘Gender’ variables, ‘female’ was used as the reference category. For the ‘Work status’ variables, ‘retired’ was used as the reference category. For the ‘Education’ variables, ‘WO’ was used as the reference category. The ‘<Hschool’ corresponds to a highest education of lower than high school. ‘Hschool’ corresponds to a highest education of high school. ‘MBO’ corresponds to a highest education of ‘secondary vocational education’. ‘HBO’ corresponds to a highest education of ‘higher professional education’. ‘WO’ corresponds to a highest education of ‘University education’. For the ‘Region’ variables, ‘South’ was used as the reference category. The regions were distributed based on the provinces of the Netherlands. North corresponds to Groningen, Friesland and Drenthe. East corresponds to Overijssel and Gelderland. ‘West’ corresponds to Utrecht, Noord-Holland, Zuid-Holland and Flevoland. South corresponds to Noord-Brabant, Limburg and Zeeland.

Table 22. The different combinations of attributes shown for the conjoint analysis

Card no.	Brand	Price	Quality	Art produced by
1	No brand	Average	Low	AI
2	No brand	Low	High	Human
3	Social-cause	High	Low	Human
4	Social-cause	Low	Average	AI
5	Social-cause	Average	High	Undisclosed
6	Well-known	Low	Low	Undisclosed
7	No brand	High	High	AI
8	Well-known	High	Average	Undisclosed
9	Well-known	Average	Average	Human

Table 23. Model Description

	N of Levels	Relation to Scores
Brand	3	Discrete
Price	3	Linear (less)
Quality	3	Linear (more)
Art	3	Discrete

All factors are orthogonal.

Table 24. Utilities (N = 185)

		Utility Est.	SE
Brand	Well-Known	-.365	.487
	Social Cause	-.159	.487
	No brand	.524	.487
Art	AI	.185	.487
	Human	.202	.487
	Undisclosed	-.387	.487
Price	Low	-.817	.422
	Average	-1.635	.843
	High	-2.452	1.265
Quality	Low	1.381	.422
	Average	2.762	.843
	High	4.144	1.265
(Constant)		4.345	1.241

Observed results for the entire dataset.

Table 25. Average importance score per category (N = 185)

Brand	23.241
Art	21.785
Price	20.960
Quality	34.014

Observed results for the entire dataset.

Table 26. Estimated coefficients of price and quality (N = 185)

	B
Price	-.817
Quality	1.381

Observed results for the entire dataset.

Table 27. Correlation tests between observed and estimated preferences (N = 185)

	Value	Sig.
Pearson's R	.944	<.001
Kendall's tau	.833	<.001

Observed results for the entire dataset.

Table 28. Utilities (N = 80)

		Utility Est.	SE
Brand	Well-Known	-.317	.479
	Social Cause	-.241	.479
	No brand	.558	.479
Art	AI	.259	.479
	Human	.155	.479
	Undisclosed	-.413	.479
Price	Low	-.781	.415
	Average	-1.562	.830
	High	-2.344	1.245
Quality	Low	1.450	.415
	Average	2.900	.830
	High	4.350	1.245
(Constant)		4.150	1.222

Observed results for male participants.

Table 29. Average importance score per category (N = 80)

Brand	22.699
Art	20.812
Price	20.683
Quality	35.806

Observed results for male participants.

Table 30. Estimated coefficients of price and quality (N = 80)

	B
Price	-.781
Quality	1.450

Observed results for male participants.

Table 31. Correlation tests between observed and estimated preferences (N = 80)

	Value	Sig.
Pearson's R	.948	<.001
Kendall's tau	.833	<.001

Observed results for male participants.

Table 32. Utilities (N = 104)

		Utility Est.	SE
Brand	Well-Known	-.411	.490
	Social Cause	-.099	.490
	No brand	.510	.490
Art	AI	.116	.490
	Human	.249	.490
	Undisclosed	-.365	.490
Price	Low	-.838	.424
	Average	-1.676	.848
	High	-2.514	1.273
Quality	Low	1.308	.424
	Average	2.616	.848
	High	3.925	1.273
(Constant)		4.525	1.249

Observed results for female participants.

Table 33. Average importance score per category (N = 104)

Brand	23.746
Art	22.662
Price	21.152
Quality	32.440

Observed results for female participants.

Table 34. Estimated coefficients of price and quality (N = 104)

	B
Price	-.838
Quality	1.308

Observed results for female participants.

Table 35. Correlation tests between observed and estimated preferences (N = 104)

	Value	Sig.
Pearson's R	.940	<.001
Kendall's tau	.778	.002

Observed results for female participants.

Table 36. Utilities (N = 19)

		Utility Est.	SE
Brand	Well-Known	-.316	.447
	Social Cause	-.009	.447
	No brand	.325	.447
Art	AI	.094	.447
	Human	.274	.447
	Undisclosed	-.368	.447
Price	Low	-.667	.387
	Average	-1.333	.775
	High	-2.000	1.162
Quality	Low	1.051	.387
	Average	2.103	.775
	High	3.154	1.162
(Constant)		4.778	1.141

Observed results for participants living in the North.

Table 37. Average importance score per category (N = 19)

Brand	22.921
Art	17.684
Price	22.896
Quality	36.500

Observed results for participants living in the North.

Table 38. Estimated coefficients of price and quality (N = 19)

	B
Price	-.667
Quality	1.051

Observed results for participants living in the North.

Table 39. Correlation tests between observed and estimated preferences (N = 19)

	Value	Sig.
Pearson's R	.924	<.001
Kendall's tau	.778	.002

Observed results for participants living in the North.

Table 40. Utilities (N = 35)

		Utility Est.	SE
Brand	Well-Known	-.470	.441
	Social Cause	-.095	.441
	No brand	.565	.441
Art	AI	.175	.441
	Human	.324	.441
	Undisclosed	-.499	.441
Price	Low	-.791	.382
	Average	-1.582	.764
	High	-2.372	1.146
Quality	Low	1.496	.382
	Average	2.993	.764
	High	4.489	1.146
(Constant)		3.974	1.125

Observed results for participants living in the East.

Table 41. Average importance score per category (N = 35)

Brand	24.935
Art	22.180
Price	18.369
Quality	34.517

Observed results for participants living in the East.

Table 42. Estimated coefficients of price and quality (N = 35)

	B
Price	-.791
Quality	1.496

Observed results for participants living in the East.

Table 43. Correlation tests between observed and estimated preferences (N = 35)

	Value	Sig.
Pearson's R	.959	<.001
Kendall's tau	.889	<.001

Observed results for participants living in the East.

Table 44. Utilities (N = 89)

		Utility Est.	SE
Brand	Well-Known	-.333	.503
	Social Cause	-.219	.503
	No brand	.552	.503
Art	AI	.289	.503
	Human	.141	.503
	Undisclosed	-.430	.503
Price	Low	-.843	.436
	Average	-1.685	.872
	High	-2.528	1.308
Quality	Low	1.439	.436
	Average	2.878	.872
	High	4.317	1.308
(Constant)		4.337	1.283

Observed results for participants living in the West.

Table 45. Average importance score per category (N = 89)

Brand	24.105
Art	22.417
Price	20.149
Quality	33.329

Observed results for participants living in the West.

Table 46. Estimated coefficients of price and quality (N = 89)

	B
Price	-.843
Quality	1.439

Observed results for participants living in the West.

Table 47. Correlation tests between observed and estimated preferences (N = 89)

	Value	Sig.
Pearson's R	.945	<.001
Kendall's tau	.889	<.001

Observed results for participants living in the West.

Table 48. Utilities (N = 43)

		Utility Est.	SE
Brand	Well-Known	-.365	.526
	Social Cause	-.156	.526
	No brand	.521	.526
Art	AI	.016	.526
	Human	.197	.526
	Undisclosed	-.213	.526
Price	Low	-.852	.456
	Average	-1.705	.911
	High	-2.557	1.367
Quality	Low	1.310	.456
	Average	2.619	.911
	High	3.929	1.367
(Constant)		4.479	1.341

Observed results for participants living in the South.

Table 49. Average importance score per category (N = 43)

Brand	20.179
Art	21.929
Price	23.947
Quality	33.945

Observed results for participants living in the South.

Table 50. Estimated coefficients of price and quality (N = 43)

	B
Price	-.852
Quality	1.310

Observed results for participants living in the South.

Table 51. Correlation tests between observed and estimated preferences (N = 43)

	Value	Sig.
Pearson's R	.931	<.001
Kendall's tau	.778	.002

Observed results for participants living in the South.