ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis Data Science & Marketing Analytics

Micro and Macro Drivers of Deal Proneness: A Cross-National Study

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Date final version: 03-10-2023

Abstract

The purpose of this research is to investigate which factors influence deal proneness, and how these effects vary per country. Deal proneness refers to the tendency to make a purchase due to a promotion. The main question answered in this research is "How do individual and macro-societal factors influence consumer deal proneness?". To answer this question, survey data collected from 28 countries was analysed. The main method used to investigate this data is a multilevel model with various individual and country-level variables, supplemented by the use of a random forest. The variables that have been examined are age, gender, income and education on the individual level, and GDP, CPI, number of inhabitants and two of Hofstede's dimensions on the country level.

On the individual level, the results indicate that there is a negative relationship between age and deal proneness, such that younger customers are more deal prone. Additionally, it has been found that gender has a significant influence on deal proneness, indicating that men are more deal prone compared to women. Furthermore, the multilevel model revealed that significant differences in deal proneness exist among countries. Specifically, it has been found that the effects of gender and income on deal proneness vary across countries.

These findings can be helpful for managers in improving their promotional strategies, and to target deal prone consumers. Furthermore, this research contributes to the existing literature on deal proneness by also examining country-level factors, whereas previous research focused mostly on individual-level factors. However, it is important to note that there are also limitations to this research. These include the fact that deal proneness was measured by self-reported ratings of survey respondents, no distinction was made between various types of deals and the data used originated from 2004. Therefore it is recommended for further research to consider other data collection methods, take into account different types of deals and acquire more recent data.

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1 Introduction

"Buy one, get one free!". To many consumers, such a slogan may sound very appealing. The main reason for this is that deals provide benefits. Deals can increase a consumer's perception of their monetary resources. This mainly comes from two sources. First, promotions can provide actual savings. Second, they can provide consumers with a subjective experience of saving money, as they compare the promotional price to a reference price (Zhang et al., 2021). Furthermore, deals may enable customers to buy higher quality products, that could otherwise not be afforded at their full price, and thus provide more value for money (Martínez & Montaner, 2006). Benefits are provided for the customer, but simultaneously, these deals can take up a large part of the promotional budget of manufacturers. Therefore, it is important to maximize the effectiveness of these deals.

Deal proneness has frequently been a topic of research. According to Gázquez-Abad and Sánchez-Pérez (2009), almost 47% of consumers are considered to be deal prone. Especially now that countries have been experiencing high inflation, sometimes even as high as 10%, it might be that even more consumers will be sensitive to promotions (Forbes, 2022). Therefore, this is an important segment of customers to target. To be able to reach the right audience with promotions, it has to be identified which groups of customers are deal prone.

In previous studies, deal proneness has mostly been examined at the individual level. However, less research has looked into how deal proneness varies at a higher level, such as the difference per country. This leaves room for further research. Therefore, the question that will be answered in this research is: "How do individual and macro-societal factors influence consumer deal proneness?". To fully explore the factors that influence consumer deal proneness, this research will investigate several sub-questions. The first sub-question that will be answered is "How do individual differences in demographic characteristics influence deal proneness?". Furthermore, the question "How does deal proneness vary across different countries and cultures and what are the cultural and economic factors that influence this?" will be answered.

To answer these questions, the existing literature on the topic of consumer deal proneness will be reviewed and a data set containing information on consumers in more than 25 countries will be examined. To start, the managerial and the academic relevance of this research will be explained.

Next, the existing literature will be examined. This literature will result in a conceptual framework and hypotheses to be tested. The next part of this research will explain the data and the methodology. The data set mentioned above will be used, supplemented with information on the country level, such as the GDP and CPI. A multilevel model will be used to examine what individual-level and country-level characteristics are of influence on consumer deal proneness. This model allows for the analysis of data that is nested within multiple levels of hierarchy, such as individuals within countries (Greenland, 2000). Additionally, a random forest will be implemented to gain additional insights. Lastly, the results will be discussed, leading to a conclusion and managerial recommendations.

1.1 Academic relevance

The existing literature on deal proneness provides insights into the theory behind it, as well as how demographic and psychographic characteristics influence deal proneness. According to Lichtenstein et al. (1990), deal proneness can be defined as "a general proneness to respond to promotions predominantly because they are in deal form". Furthermore, Lichtenstein et al. (1995) examined in what manner the deal proneness construct is best conceptualized. Additionally, Lichtenstein et al. (1997) examined whether consumer segments are deal prone in general or only prone to certain types of deals. Schneider and Currim (1991) studied two types of deal proneness: active and passive, and how these types affect purchase behaviour. Blattberg et al. (1978) used a model of purchasing behaviour to identify which household characteristics affect deal proneness. Similarly, Martínez and Montaner (2006) analysed whether there are relationships between psychographic traits and deal proneness. DelVecchio (2005) researched the influence of the value of a promotion on the response of a deal prone consumer.

However, less research has been conducted regarding how the macro-societal context influences deal proneness. The relationship between culture and deal proneness has previously been examined by Sharma and Singh (2018), yet only for three countries and six cultural dimensions. This research will examine the effect of additional variables, such as the GDP and number of inhabitants measured per country, and the data covers more than 25 countries. Therefore, this research adds to the existing research on deal proneness.

1.2 Managerial relevance

First of all, this research can help managers to target deal prone customers and improve the effectiveness of their promotions. Using the information on which consumers are more deal prone, they are able to improve the targeting of these deals. The primary reason for the use of promotions is quite simple, promotions are known to increase sales. They tend to have an immediate effect on consumers. As a response, consumers buy a product earlier than usual, buy more than usual, or switch from the brand that they would usually purchase (Bell et al., 1999). So, with the insights resulting from this research, the consumers that will react to promotions can be targeted and even more sales can be realised.

Furthermore, the insights from this research can be used to see how deal proneness varies across countries and enable managers to adapt their promotional strategies accordingly. This can also be helpful when deciding on strategies in the case that a brand is expanding to new countries, as certain economic factors or cultural differences can have a big influence on consumer behaviour and therefore on deal proneness (Kwok & Uncles, 2005). For instance, income and education level can influence consumers' response to promotions. Companies will be able to target specific customer segments better when they possess more knowledge about what factors influence deal proneness.

2 Theoretical framework

In this section, prior literature regarding deal proneness will be explored. First, deal proneness will be discussed in general. Second, literature concerning the influence of certain demographic characteristics on deal proneness is reviewed. Additionally, the variation per country will be discussed. Furthermore, hypotheses will be formulated, which concern the expected results of this research. These hypotheses are visualized in a conceptual framework, that can be seen in Figure 1.

2.1 Deal proneness

Deal proneness can be defined as "a general proneness to respond to promotions predominantly because they are in deal form" (Lichtenstein et al., 1990). Thus, deal proneness refers to the tendency to make a purchase due to a promotion. Deal prone consumers are those who alter their purchase decision to take advantage of said promotion (Martínez & Montaner, 2006). Contrary to what might be expected, deal prone consumers primarily respond to promotions because they are in deal form, and not because they are cheaper (DelVecchio, 2005). Deal proneness is driven not only by the low price of the deal, but also by the transaction utility that a consumer derives from paying a price that is lower than their internal reference price. This reference price serves as a benchmark against which other prices are compared. For deal prone consumers, obtaining a deal can be more attractive than purchasing the product for the regular price, even if this price is the same. For instance, a 1 euro discount for a product priced 3 euros would be more attractive than purchasing the same product for 2 euros, even though both situations would result in the same net amount of money spend (Thaler, 1985; Burton et al., 1998).

As has been mentioned, Lichtenstein et al. (1995) examined in what manner the deal proneness construct is best conceptualized. They found that deal proneness can best be treated as a domain-specific construct, meaning that consumers might respond to some types of promotions but not to others. However, Lichtenstein et al. (1997) found evidence that there is a consumer segment that is deal prone across various types of promotions. According to Gázquez-Abad and Sánchez-Pérez (2009) this segment can be quite large, as they found that 47% of consumers in their study were deal prone, where both monetary and non-monetary promotions have an influence on their behaviour. These consumers were found to be price-sensitive and not possess a lot of brand loyalty. Furthermore, it was found that there are two types of deal proneness, active and passive.

Active deal proneness is present when actively searching for promotions, while passive deal proneness is defined as sensitivity to displays, meaning that the search happens only in-store (Schneider & Currim, 1991). Last, Schindler et al. (2021) investigated pairs of twins to explore the origins of deal proneness, and concluded that there is a significant genetic component contributing to this behaviour. Therefore, deal-prone consumers are likely to have deal-prone parents.

2.2 Influence of demographic variables on deal proneness

Previous research concluded that there is a relationship between various demographic characteristics and deal proneness. One of these characteristics is a consumer's education level. Consumers with a higher education level are expected to be more deal prone (Bell et al., 1999; Bawa & Shoemaker, 1987). They are expected to have better cognitive abilities to process information (Kwon & Kwon, 2007). Furthermore, more educated customers are found to be more variety-seeking and therefore more deal prone (Bawa & Shoemaker, 1987). This leads to the first hypothesis:

H1: There is a positive relationship between deal proneness and education level, i.e., consumers with a higher education level are more deal prone.

Regarding age, in multiple studies it has been found that deal proneness tends to increase as consumers get older (Webster, 1965; Bell et al., 1999; Pechtl, 2004). A possible explanation for this that over the years consumers gain knowledge about where to find a good deal (Webster, 1965). Furthermore, it could be that older consumers have more time available to do their shopping (Bell et al., 1999). On the other hand, Dastidar (2016) found the opposite, as results from a study in India showed that younger consumers have greater deal proneness. Similarly, Teel et al. (1980) found coupon-prone consumers to be younger. A possible explanation is that younger customers have a lower income and are therefore more inclined to purchase a promoted product. As these results are contradicting, age is an interesting factor to examine further. The following relationship is hypothesized:

H2: There is a positive relationship between deal proneness and age, i.e., older consumers are expected to be more deal prone.

Furthermore, in previous literature it has been found that there is a positive effect of income on deal proneness, as deal prone consumers tend to earn a higher income (Teel et al., 1980; Bawa & Shoemaker, 1987; Kwon & Kwon, 2007). A possible explanation is that households earning a higher income are frequently more educated (Bawa & Shoemaker, 1987). Another reason could be that households with higher incomes are more efficient shoppers. Furthermore, it might be that these households are more likely to buy brands that offer deals, as these brands tend to be the more expensive brands (Levedahl, 1988). Additionally, higher income consumers have more disposable income available to stock up when there is a good deal (Bell et al., 1999). Blattberg et al. (1978) also found that households with higher incomes were more deal prone. However, this effect became insignificant once the income was adjusted for household resources (such as home and car ownership). On the other hand, there is also an argument to be made for a negative relationship between income and deal proneness (Sharma & Singh, 2018). Lower income households are expected to have a lower opportunity cost of time and a greater incentive to save money, and therefore take more advantage of deals (Levedahl, 1988; Blattberg et al., 1978). However, as more arguments were found indicating a positive relationship, the following effect is expected:

H3: There is a positive relationship between deal proneness and income, i.e. those with a higher income are expected to be more deal prone.

Some studies found that gender does not have a significant impact on deal proneness (Webster, 1965; Sharma & Singh, 2018). However, Kwon and Kwon (2007) found that the effect varies depending on the type of deal. It was found that women use coupons more compared to men, whereas men use rebates more frequently. An explanation for the coupon use in women is that traditionally women do most household purchases and are more experienced shoppers. Additionally, some studies found that women are more prone to promotions than men, specifically free-product samples and coupons (Saleh et al., 2013; Harmon & Hill, 2003). This leads to the following hypothesis:

H4: There is a relationship between gender and deal proneness, such that women are more deal prone compared to men.

2.3 Variation in deal proneness per country

Not many researchers have studied how deal proneness varies across countries and cultures. As has been mentioned, Sharma and Singh (2018) did examine the link between culture and deal proneness. Specifically, the research was conducted in the USA, Thailand and Kenya and Hofstede's cultural dimensions were examined. These dimensions are explained in more detail below, as a couple of them will also be examined in this research. One of the findings of Sharma and Singh (2018) was that societies that are more feminine are more deal prone, compared to masculine societies. Furthermore, societies with a higher Power Distance Index (PDI) seem to be less prone to deals. Additionally, they found that societies with a higher individualism index are more deal prone, and consumers in countries that exhibit high uncertainty avoidance are less deal prone. The study proves that it is important to understand how deal proneness varies across cultures to be able to create effective promotions. However, it should be taken into account that the sample size was limited, as only three countries were examined, making it difficult to generalize the findings to other countries. Additionally, deal proneness might also be influenced by factors that were not present in the research.

Although not much is known about deal proneness across cultures, more research examined differences in consumer behaviour in different cultures. For example, Nayeem (2012) found that consumers from individualistic cultures reacted differently compared to consumers from collectivist cultures. One finding was that collectivist consumers are more likely to gather information from family and friends, while individualist consumers rely on the internet as their preferred source of information. Furthermore, it was concluded that countries with a high level of uncertainty avoidance are less likely to adopt new innovations. These and more findings indicate that consumers behave differently across cultures, and therefore it is likely that deal proneness also varies across cultures.

2.3.1 Hofstede's cultural dimensions

The first dimension is the *Power Distance Index* (PDI), which indicates the degree of equality or inequality among social classes in a society. This dimension indicates whether the less powerful accept that power is not distributed equally. A higher number indicates that hierarchy is clearly present in a society. A lower degree indicates that people might question authority. The second dimension, *individualism* (IDV) versus collectivism, refers to the degree in which individuals are integrated into groups. A higher score indicates individualists, while a lower score indicates collectivists. Next, *masculinity* (MAS) versus femininity is related to the distribution of roles between women and men. A higher score indicates more masculinity, while a lower score indicates more femininity. The next dimension, the *Uncertainty Avoidance Index* (UAI) indicates whether a society is able to deal with uncertainty. Higher numbers are given to uncertainty avoiding cultures that rely on an absolute truth and have more defined rules and laws. Lower numbers indicate more uncertainty accepting cultures where different opinions are more accepted. *Long Term Orientation* (LTO) versus short term orientation indicates whether people focus on the future or on the present and past. A lower number indicates a short-term orientation, while a higher number indicates a long-term orientation. Last, *Indulgence Versus Restraint* (IVR) is related to the pleasure versus control of human desires related to enjoying life. A higher number indicates more indulgence, while a lower score indicates more restraint (Hofstede, 2011).

2.3.2 Hypotheses

In this research, the relationship between some of Hofstede's cultural dimensions and deal proneness will be examined. First, the relationship between the individualism index and deal proneness will be examined. Sharma and Singh (2018) found that societies with a higher individualism index, i.e. countries that are more individualistic, are more deal prone. An explanation for this is that countries with high individualism scores emphasise the need for individual initiative and that everyone should form their own opinion (McGrath et al., 1992). Therefore, consumers in these countries might be more likely to try new things and hence utilize deals. This leads to the following hypothesis:

H5: There is a positive relationship between the individualism index and deal proneness, i.e. consumers in individualistic countries are more deal prone.

Additionally, the effect of the uncertainty avoidance index on deal proneness will be examined. In previous research, it was found that consumers in countries that exhibit high uncertainty avoidance are less deal prone, i.e. consumers in countries with low uncertainty avoidance are more deal prone (Sharma & Singh, 2018). A possible explanation for this is that consumers in high uncertainty avoidance countries prefer stability, so they prefer to have familiar products and are willing to pay extra for them. On the other hand, consumers in low uncertainty avoidance countries are more willing to take risks, and therefore they can be more receptive to deals (McGrath et al., 1992). Therefore, the following effect is expected to be found:

H6: There is a negative relationship between the uncertainty avoidance index and deal proneness, i.e. consumers in high uncertainty avoidance countries are less deal prone.

2.4 Conceptual framework

All previously mentioned hypotheses concerning both the individual and country level and their expected signs can be found in Figure 1. Furthermore, the country-level controls are included, which will be explained further in the next section.

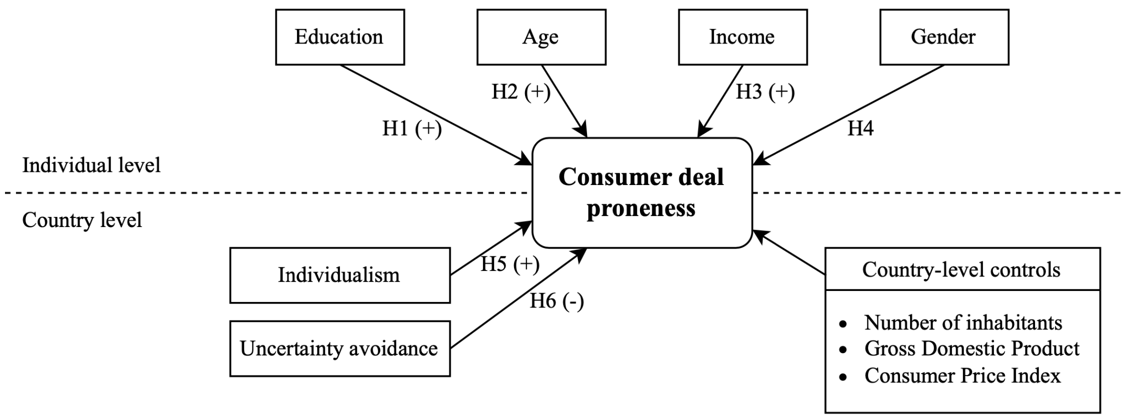


Figure 1: Conceptual framework

3 Data

The data that will be used in this research, was acquired via a survey. The data was collected in 2004. The respondents include 13,321 individuals originating from 28 countries which are located in 3 different continents. The corresponding country names can be found in Appendix A.

3.1 Deal proneness

As the dependent variable of this research, respondents' ratings of the statement "I love special promotional offers" will be used to measure their deal proneness. The respondents were asked to rate this statement on a 5-point Likert scale, as can be seen in the table below. The option "strongly disagree" indicates the lowest level of deal proneness, while "strongly agree" represents the highest level of deal proneness. Table 1 shows what proportion of people responded with each of the categories. As can be seen in the table, "agree" is the biggest category.

Table 1: Proportions of responses to "I love special promotional offers"

1. strongly disagree	2. disagree	3. neither agree nor disagree	4. agree	5. strongly agree
0.058	0.141	0.294	0.385	0.122

To improve the interpretability of the multilevel model, the choice has been made to convert the outcome variable, deal proneness, from a categorical variable to a continuous variable. The numbers 1 up to 5 have been assigned as values, according to the numbers that can be seen in Table 1. For example, a respondent that answered "strongly disagree" is assigned the value 1. By converting the Likert scale data to numerical data, it is assumed that the distance between the response options are the same.

In Figure 2, the distribution of the ratings of "I love special promotional offers" per country can be seen. The figure suggest that deal proneness varies across countries. The country names corresponding to the abbreviations in the figure can be found in Table 8 in Appendix A.

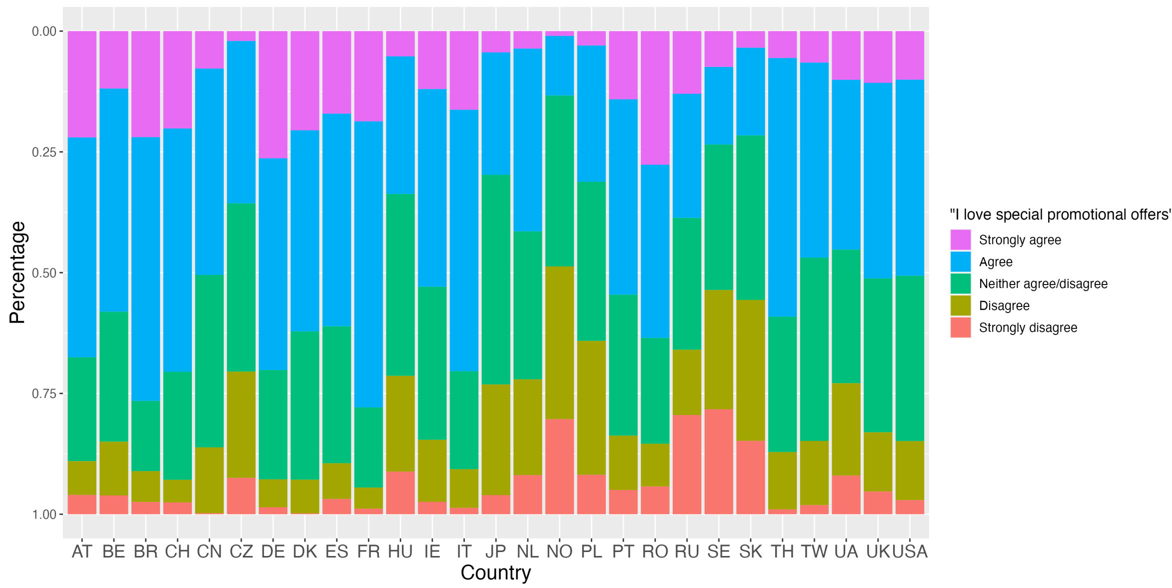


Figure 2: Distribution of deal proneness per country

3.2 Independent variables

3.2.1 Demographic characteristics

Regarding the demographic characteristics of the survey participants, age was measured as a numeric variable. The respondents are between 11 and 91 years old, where the average age is 39.29. Regarding the education level, the participants were asked to answer the following question: "Which of these best describes your highest level of education?". The options that could be chosen are: no formal education, education up to age 12/14/16/18, higher education or university. As this variable had many categories, the decision was made to include a dummy variable that indicates whether someone has a high or low education level. The low education level includes no formal education and education up to age 12/14/16/18, whereas high education level includes higher education and university. The low education category contains approximately 44% of the survey participants. Regarding income, the participants where asked to answer the question: "Please indicate the total yearly income of all wage earners in your household before taxes, from all sources including salaries, rents, dividends, self-employment income, etc.". To answer, options of different income ranges were presented, which can be seen in Table 2. Two new categories, low/unknown and high were created to represent these income ranges. These categories include approximately 55% and 45% of the participants respectively. Lastly, gender was measured by a binary variable indicating whether a participant is male or female. Around 54% of the participants were male.

Table 2: Categories of the income variable

Category	Description
Low/Unknown	Don't know/won't answer
	Up to £ 1,196.13 per year
	Between £ 1,196.13 and £ 2,990.46 per year
	Between £ 2,990.46 and £ 5,981.12 per year
	Between £ 5,981.12 and £ 11,962.23 per year
High	Between £ 11,962.23 and £ 23,925.12 per year
	Between £ 23,925.12 and £ 44,859.60 per year
	More than £ 44,859.60 per year

3.2.2 Data on country level

To be able to measure the variation in deal proneness on the country level, data was collected about the countries that have been mentioned before. Specifically, the number of inhabitants (The World Bank, 2022), the Gross Domestic Product (GDP) per capita (measured in US dollars) (UNdata, 2022) and the Consumer Price Index (CPI) (OECD Data, 2023). The number of inhabitants is included to account for potential variations in deal proneness related to the size of the market in each country. The GDP indicates a country's economic output per person (Investopedia, 2022). The inclusion of this variable accounts for possible economic influences on deal proneness. The CPI indicates the change in prices paid by consumers, and is used to measure inflation (Fernando, 2023). Including this variable helps to consider the impact of inflation on consumer behaviour. These three variables will be used as controls. Additionally, the scores of all countries on two cultural dimensions of Hofstede are included (Geert Hofstede, 2010). Namely, the individualism index (IDV) and the uncertainty avoidance index (UAI). By including these country-level variables, potential contextual influences that vary across countries are taken into consideration.

3.3 Scaling the numeric variables

The numeric variables, except the outcome variable, are standardized since these variables are measured on very different scales. This ensures that the effects are comparable, the coefficients are interpretable and that all variables contribute equally to the model. As a result of standardization, all variables have a mean of zero and a standard deviation of one (Schielzeth, 2010).

3.4 Exploratory analysis

In this section, the data and relationships between the variables will be explored. First of all, a two sample t-test was conducted to evaluate whether deal proneness differs per gender. The results show that the mean deal proneness for the male group (M = 3.277) was significantly lower than the mean deal proneness for the female group (M = 3.485). This difference is significant: t(13051) = -11.452, $p < 2.2e-16$. This is in line with the fourth hypothesis, where it was expected that women are more deal prone.

Next, the difference in deal proneness with regard to age is examined. As can be seen in Figure 3, deal proneness seems to be decreasing with age. This is not in line with the second hypothesis, where a positive relationship between deal proneness and age was expected. A Pearson's chi-squared test was performed to assess the association between deal proneness and the age groups. The test revealed a significant association between deal proneness and age ($\chi^2 = 292.05$, df = 24, $p < 2.2e-16$). As has been previously mentioned, a possible explanation for the negative relationship is that younger customers have a lower income and therefore take more advantage of deals.

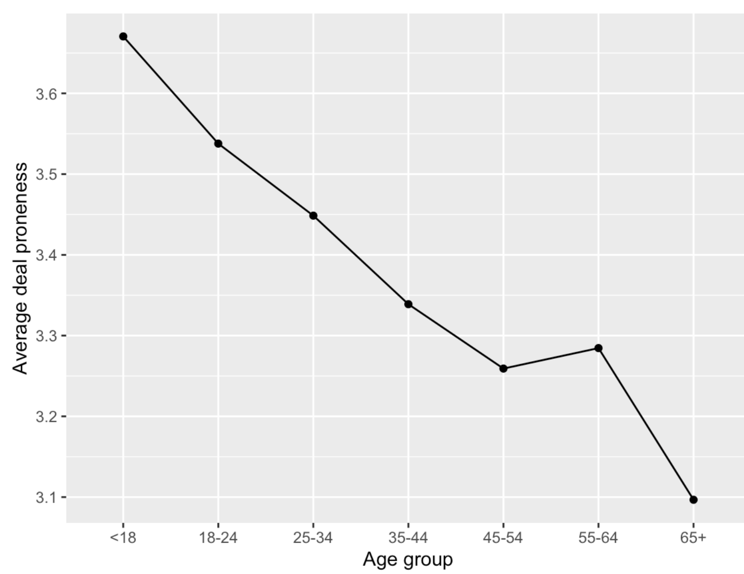
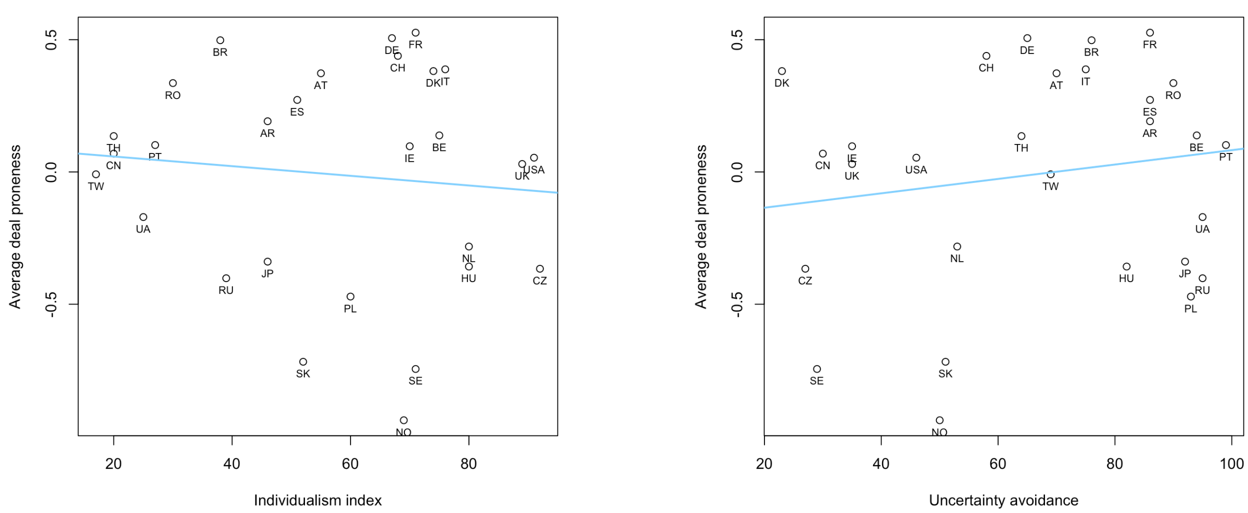


Figure 3: Average deal proneness across age groups

Furthermore, the relationship between deal proneness and education level was examined. A two-sample t-test was performed comparing deal proneness between individuals with a high education level (M = 3.367) and a low education level (M = 3.379). The results showed no significant difference in mean deal proneness between the two groups: t(12460) = -0.645, p = 0.519. Thus, there is no evidence to support the hypothesis of a positive relationship between deal proneness and education level.

Additionally, the influence of the income level on deal proneness is explored. A two-sample t-test was conducted to compare deal proneness between respondents with a low or unknown income (M = 3.376) and respondents with a high income level (M = 3.367). No significant difference in deal proneness was found between the two groups (t(13066) = -0.538, p = 0.590). Therefore, it can be concluded that there is no significant association between deal proneness and income level.



(a) Average deal proneness and individualism index per country

(b) Average deal proneness and uncertainty avoidance index per country

Figure 4

In Figure 4a, a scatter plot of the average deal proneness and the individualism index per country can be found. From previous literature it was hypothesized that consumers in individualistic countries are more deal prone. However, the countries present in the plot do not seem to exhibit a clear pattern. The regression line displayed in blue shows a slight downward trend, which is not what was expected. A correlation analysis was conducted to examine the relationship between the average deal proneness and the individualism index. The Pearson's correlation coefficient suggests a non-significant correlation ($r(26) = -0.103$, $p = 0.602$). This indicates that there is no strong evidence of a linear association between the two variables.

Additionally, Figure 4b shows a scatter plot of the average deal proneness and the uncertainty avoidance index per country. Again, the countries are widely dispersed. It was hypothesized that consumers in high uncertainty avoidance countries are less deal prone, but no evidence of this is found in the figure. On the other hand, the regression line shows a slight upward trend, which could indicate that consumers in high uncertainty avoidance countries are more deal prone. However, a correlation analysis was performed using Pearson's correlation coefficient, which revealed a non-significant correlation ($r(26) = 0.164$, $p = 0.406$). This suggests that the association between the variables is limited.

4 Methodology

4.1 Multilevel modelling

In this research, a multilevel modelling (MLM) approach, also known as hierarchical linear modelling, will be used to examine the relationship between deal proneness and several individual- and country-level factors. Multilevel modelling is useful when the data consists of individuals that are characterized by variables, while simultaneously being grouped into larger unit consisting of multiple individuals. Additionally, there are variables that describe these higher-level units. Consequently, this approach allows for the analysis of data that is nested within multiple levels of hierarchy, such as students within classes or individuals within countries (Bryk & Raudenbush, 1992). In this research, the individuals are the survey respondents and the higher level is the country level. There are demographic characteristics (education, age, income and gender) that describe the individuals, and there are variables that describe the countries (number of inhabitants, GDP, CPI, individualism index and uncertainty avoidance index). Multilevel models allow for the analysis of relations occurring at each level as well as across levels. Consequently, this method can be used to examine whether the individual-level factors vary across countries. Furthermore, it provides the ability to assess the amount of variation at each level (Bryk & Raudenbush, 1992). As in this research the data is nested and the intention is to account for varying effects of predictors across different levels, MLM is a very suitable method to use.

An additional advantage of MLM is that it relaxes some of the assumptions of regular ordinary least squares (OLS) regression. First of all, MLM does not assume the independence of observations, so observations are allowed to be correlated within groups or clusters, which in this case are countries. Second, OLS assumes that the effects of independent variables are the same in different contexts. However, this might not be the case, as it could be that e.g., education level is more influential in a certain country. In MLM, this assumption is relaxed such that regression effects are allowed to vary in different contexts (Robson & Pevalin, 2015).

Each of the levels in the hierarchical structure is represented by its own submodel. Each submodel captures relationships among variables specific to that level, and indicates how variables at one level can influence relationships at another level. Any number of levels can be used, however in this research a model with two levels will be used (Bryk & Raudenbush, 1992). The first model, the level-1 model, accounts for the relationship within lower level units, in this case the individuals. This model estimates the relationship between the dependent variable and the independent variables at the lower level, while accounting for the fact that the individuals are nested within countries. The second model, the level-2 model, models how the relationship within lower level units varies between units at the higher level, in this case between the countries. This model estimates the relationship between the dependent variable and the independent variables at the higher level, while accounting for the variation in the level-1 relationship (Woltman et al., 2012).

In a simple two-level model, the level-1 model includes one outcome variable, Y_i, and one predictor variable, X_i. The equation for this model can be seen in Equation 1. Y_{ij} represents the individual-level outcome variable. β_{0j} is the level-1 intercept and β_{1j} is the level-1 coefficient. X_{ij} is the individual-level predictor variable and r_{ij} represents the level-1 error term. The subscript i refers to the individuals, while j refers to the level-2 units or groups. A different level-1 model will be estimated for each of the j level-2 units. Next the equations for the level-2 model with one predictor, W_j, are presented in Equation 2. γ_{00} and γ_{10} are the level-2 intercepts, and γ_{01} and γ_{11} are the level-2 coefficients. u_{0j} and u_{1j} are the level-2 random errors (Bryk & Raudenbush, 1992).

$$\mathrm{Y}_{ij} = \beta_{0j} + \beta_{1j}\mathrm{X}_{ij} + r_{ij} \tag{1}$$

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + \gamma_{01}\mathrm{W}_j + u_{0j} \\ \beta_{1j} &= \gamma_{10} + \gamma_{11}\mathrm{W}_j + u_{1j} \end{aligned} \tag{2}$$

The individual level, level-1, equation for deal proneness can be seen in Equation 3 below.

$$\begin{aligned} &\text{Deal proneness}_{ij} = \beta_{0j} + \beta_{1j}\text{Male}_{ij} + \beta_{2j}\text{High education level}_{ij} + \beta_{3j}\text{High income}_{ij} \\ &+\beta_{4j}\text{Age}_{ij} + r_{ij} \end{aligned} \tag{3}$$

Deal proneness$_{ij}$, which is the individual-level outcome variable, represents the deal proneness of individual i in country j. This is a function of individual characteristics and an error term. The individual-level predictors gender, education and income for individual i in country j are represented by dummy variables as can be seen in Equation 3. The reference categories are female, low education level and low/unknown income for gender, education and income, respectively. The descriptions of the income categories can be found in Table 2. Age$_{ij}$ represent the individual-level predictor for age, for individual i in country j. The intercept β_{0j} represents the expected outcome when all predictor variables are zero, in country j. The regression coefficients, β_{1j}, β_{2j}, ..., β_{4j} provide insights into the distribution of the outcome within country j, taking into account the individual characteristics. r_{ij} represents the individual-level error term, which captures the parts of deal proneness that cannot be explained by the predictors. It accounts for unexplained variability at the individual level.

Second, the equation for the country level, level-2, can be seen in Equation 4 below. There are five level-2 equations, one for each of the regression coefficients in the level-1 equation.

$$\begin{aligned}\beta_{qj} = \gamma_{q0} + \gamma_{q1}\text{GDP}_j + \gamma_{q2}\text{CPI}_j + \gamma_{q3}\text{Inhabitants}_j + \gamma_{q4}\text{Individualism}_j \\ + \gamma_{q5}\text{Uncertainty avoidance}_j + u_{qj}\end{aligned} \tag{4}$$

In this equation, β_{qj} represents the deal proneness coefficient for country j regarding a particular predictor q. This depends on country-level variables and a unique effect associated with country j. GDP_j, CPI_j, and Inhabitants_j, Individualism_j and $\text{Uncertainty avoidance}_j$ represent the country-level predictors for GDP, CPI, number of inhabitants, individualism index and uncertainty avoidance index respectively. γ_{q0} represents the intercept at the country level specific to the predictor q. γ_{q1}, γ_{q2}, γ_{q3}, γ_{q4}, γ_{q5} represent the coefficients that quantify the relationships between the country-level predictors and the deal proneness coefficient β_{qj} for group j. For instance, γ_{q1} quantifies the relationship between the predictor GDP and the deal proneness coefficient β_{qj} for group j. A positive value of γ_{q1} indicates that an increase in GDP is associated with an increase in the deal proneness of country j, while a negative value indicates the opposite relationship. u_{qj} is a unique effect associated with country j (Bryk & Raudenbush, 1992).

4.2 Random forest

Predictions of deal proneness can be helpful in making informed decisions about targeting specific customers or segments with deals and optimizing marketing strategies. The prediction method that will be used is a random forest. Random forests are able to capture non-linear relationships in the data and, as an ensemble method, enhance prediction stability (Chapman & Feit, 2015). Because of the law of large numbers, random forests are less prone to overfitting. As there is a large number of trees in the random forest, the process ensures more stable and accurate predictions (Breiman, 2001). Additionally, the random forest results can identify the most important features contributing to deal proneness.

A random forest is an ensemble of decision trees that together classify the data. Each tree is optimized on a different subset of the observations (Chapman & Feit, 2015). This is called bagging. Each new set of observations to optimize on is drawn, with replacement, from the original training set of observations. This diversity among the trees helps to prevent overfitting. As each tree is exposed to a different subset of the data, they are less likely to fit noise or irrelevant patterns. When a new prediction is made, it is predicted by every tree and it is classified as the category that receives the most votes (Breiman, 2001).

Each time a split is made in a tree, only a random sample of predictors m is considered from the full set of predictors p (James et al., 2013). This is called random feature selection, which introduces diversity among the trees (Breiman, 2001). It prevents the random forest from always using the strongest predictors in the data set. The default value is $m = \sqrt{p}$, however this parameter can be tuned to obtain the optimal value. The optimal value of m is the value where the out-of-bag (OOB) error is lowest. The OOB error estimates the performance of the model on unseen data without the need for a separate validation set. Another parameter that can be tuned is the number of trees used in the random forest. The optimal number of trees should be chosen such that the error rate stabilizes (James et al., 2013).

Random forests can be used for both classification and regression, and since deal proneness has originally been measured in categories, classification is used. Regarding the data preparation, the data does not have to be scaled, as random forests make decisions at each split based on the individual features independently. The data has been divided into a training and a test set, where 80% of the respondents are part of the training set and the remaining 20% of the respondents make up the test set. The model will be trained on the training set, and afterwards its predictive performance is evaluated on the test set. The accuracy will be calculated, which measures how well the random forest is performing in terms of correctly classifying deal proneness. The accuracy is calculated by dividing the number of accurate predictions by the total number of predictions.

Finally, the variable importance can be computed. This can be computed using two metrics: Mean Decrease Accuracy and Mean Decrease Gini. Mean Decrease Accuracy evaluates a variable's importance by randomly permuting its values and then computing the model accuracy using these values. Next, this accuracy is compared to the accuracy with the actual data. If this accuracy is significantly lower, it is considered an important variable. On the other hand, if the accuracy remains relatively unchanged, a variable is deemed less important (Chapman & Feit, 2015). Additionally, the mean decrease in Gini impurity (Mean Decrease Gini) measures how much each predictor contributes to the model's predictive power by measuring the reduction in Gini impurity when each variable is used for splitting nodes in the decision trees (James et al., 2013).

5 Results

5.1 Results of the multilevel models

5.1.1 Null model

First the null model, or baseline model, was estimated. This model is used to test whether the values of the level-1 dependent variable, deal proneness, are clustered within groups defined by the level-2 grouping variable, the countries. This determines whether the assumption of independence of OLS regression is violated, which indicates the need for multilevel modelling. Furthermore, this model can serve as a benchmark to compare later models against. Models with additional predictor variables should have more accurate predictions and less error (Garson, 2019). The null model is a special case of the random intercept model, where there are no predictors included. In the random intercept model, only the intercept in the level-1 model, β_{0j} is allowed to vary at level 2 (Bryk & Raudenbush, 1992). The equations for this model are the following, where the first equation represents level 1 and the second equation level 2:

$$\begin{aligned} \text{Deal proneness}_{ij} &= \beta_{0j} + r_{ij} \\ \beta_{0j} &= \gamma_{00} + u_{0j} \end{aligned} \tag{5}$$

As there are no predictors included in this model, it is assumed that deal proneness is determined solely by the intercept. This intercept, β_{0j} represents the average outcome for the j^{th} country. The results of this model are displayed in Table 3. A fixed effect captures the average of an effect across all countries, while a random effect captures how much an effect varies across countries (Shaw & Flake, n.d.). So, the random effects estimate the variation in deal proneness that cannot be explained by the fixed effects alone. The random intercept represents the variability in deal proneness that is specific to each country, whereas the residual refers to unexplained variability in deal proneness after accounting for both the fixed effects and the random intercept. As can be seen in the table, the level-2 random intercept is significant ($p < 2.2e\text{-}16$), which indicates the need for multilevel modelling, as this means that the mean deal proneness varies across countries.

The AIC and BIC of this model are displayed in Table 4. Lower AIC and BIC values are an indication of better model fit. Furthermore, the intraclass correlation coefficient (ICC) can be calculated. This coefficient quantifies the proportion of variance in the dependent variable that is explained by the level-2 grouping variable. The ICC is calculated by dividing the variance

Table 3: Estimates of the models

		Null model	**Model 2**[1]	**Model 3**[2]
Random effects	Random intercept	0.159 (0.399)***	0.156 (0.395)***	0.144 (0.379)***
	Residual	0.956 (0.978)	0.932 (0.965)	0.932 (0.965)
Fixed effects	Intercept	3.363 (0.076)***	3.476 (0.077)***	3.477 (0.075)***
	Male		-0.210 (0.017) ***	-0.211 (0.017)***
	High education level		-0.025 (0.018)	-0.025 (0.018)
	High income		0.025 (0.022)	0.024 (0.022)
	Age		-0.112 (0.009)***	-0.112 (0.009)***
	Inhabitants			0.077 (0.084)
	GDP			0.048 (0.124)
	CPI			-0.041 (0.101)
	IDV			-0.006 (0.101)
	UAI			0.121 (0.092)

Note: For the random effects, the variance and the standard deviation are reported. Regarding the fixed effects, the estimates and standard errors are shown.

[1]Model 2 refers to the random intercept model with level-1 predictors.

[2]Model 3 refers to the random intercept model with all predictors.

component of the countries divided by the total of variance components, which is the country component plus the residual component (Garson, 2019). A value of 0 for the ICC indicates that there is no clustering of observations within groups. On the other hand, a value of 1 indicates complete clustering of observations within groups, meaning that everyone is the same within their groups. A rule of thumb is that if the ICC is larger than 0.1, one should consider using a multilevel model. The ICC of this model is 0.143, calculated by $\frac{0.159}{0.159+0.956}$, which means that 14.3% of the variation in deal proneness can be attributed to differences between countries (Robson & Pevalin, 2015). Therefore, a multilevel model is desirable.

5.1.2 Random intercept model with level-1 predictors

The equation for level-1 of the random intercept model is similar to in Equation 3 in the methodology section. However, in this equation, Equation 6, the j subscripts have been removed from the coefficients, as they are not allowed to vary between countries. The random and fixed effects of the model can be found in Table 3. The intercept term in the fixed effects section represents

Table 4: Model comparison

Model	AIC	BIC	ICC	Deviance
Null model	37324.7	37347.2	0.143	37318.7
Random intercept model with level-1 predictors	36998.9	37051.4	0.143	36984.9
Random intercept model with all predictors	37006.7	37096.6	0.133	36982.7
Random coefficient model	36905.5	37032.9	0.133	36871.5
Model with interaction between education and IDV	36900	37035	0.131	36864
Model with interaction between income and UAI	36901	37035.9	0.134	36865
Model with interaction between age and UAI	36897.2	37032.1	0.132	36861.2

the expected deal proneness when all predictor variables are zero. Regarding the fixed effects, for each variable, the estimate represents the expected change in the response variable for a one-unit increase in the corresponding predictor variable while holding other variables constant. For the dummy variables (for gender, education and income), this is in comparison to the reference categories which have previously been mentioned.

$$\begin{aligned} \text{Deal proneness}_{ij} = {} & \beta_{0j} + \beta_1 \text{Male}_{ij} + \beta_2 \text{High education level}_{ij} + \beta_3 \text{High income}_{ij} \\ & + \beta_4 \text{Age}_{ij} + r_{ij} \end{aligned} \tag{6}$$

The performance metrics of the model can be found in Table 4. As can be seen in the table, the AIC and BIC of this model are lower compared to the previous model, which indicates a better model fit. The ICC of this model is $\frac{0.156}{0.156+0.932}$, which is equal to 0.143. Looking at the deviance, which is a measure of error, this is lower for the second model which again indicates a better fit. Additionally, according to the likelihood ratio test, the random intercept model with level-1 predictors is significantly better in fit compared to the null model ($p < 2.2e\text{-}16$) (Garson, 2019).

5.1.3 Random intercept model with all predictors

The equations for level-1 and level-2 of the random intercept model are displayed in Equations 6 and 4. In the random intercept model, only the intercept is allowed to vary per country. Therefore, this two-level model can be written as a mixed-effects model by replacing β_{0j} in the level-1 equation by the level-2 equation:

$$\begin{aligned}\text{Deal proneness}_{ij} = \; & \gamma_{00} + \gamma_{01}\text{GDP}_j + \gamma_{02}\text{CPI}_j + \gamma_{03}\text{Inhabitants}_j + \gamma_{04}\text{Individualism}_j \\ & + \gamma_{05}\text{Uncertainty avoidance}_j + u_{0j} + \beta_1\text{Male}_{ij} + \beta_2\text{High education level}_{ij} \\ & + \beta_3\text{High income}_{ij} + \beta_4\text{Age}_{ij} + r_{ij}\end{aligned} \tag{7}$$

The estimates of the model can be seen in Table 3. As shown in the table, the added country-level predictors are not found to be statistically significant. This suggests that these predictors do not have a significant effect on deal proneness when considered individually. However, in one of the next models they will be included as interactions, which can potentially alter these results. Additionally, the performance metrics are presented in Table 4. Compared to the previous model, this model has slightly higher AIC and BIC values. These higher values indicates that adding these predictors does not improve the model fit. The ICC is calculated as $\frac{0.144}{0.144+0.932}$, resulting in a value of 0.133. It makes sense that the ICC is lower compared to the previous models, as the additional country-level predictors explain some of the variation that was previously attributed to the grouping variable. The deviance is quite similar to that of the previous model. Furthermore, a likelihood ratio test was performed to compare this model to the model with only level-1 predictors, which indicated that there is no significant difference between the models (p = 0.811).

5.1.4 Random coefficient model

In a random coefficient model, or random intercept and random slopes model, the level-1 slopes are allowed to vary randomly over the population of level-2 units. This indicates that different countries may have different relationships between the predictors and deal proneness. Each country can have its own regression equation (Bryk & Raudenbush, 1992). The equation looks the same as in the previous model, Equation 7. However, the difference is that in this model all coefficients of the individual-level predictors are allowed to vary between countries, which is indicated by the j subscripts of the coefficients.

$$\begin{aligned}\text{Deal proneness}_{ij} = \; & \gamma_{00} + \gamma_{01}\text{GDP}_j + \gamma_{02}\text{CPI}_j + \gamma_{03}\text{Inhabitants}_j + \gamma_{04}\text{Individualism}_j \\ & + \gamma_{05}\text{Uncertainty avoidance}_j + u_{0j} + \beta_{1j}\text{Male}_{ij} + \beta_{2j}\text{High education level}_{ij} \\ & + \beta_{3j}\text{High income}_{ij} + \beta_{4j}\text{Age}_{ij} + r_{ij}\end{aligned} \tag{8}$$

However, this model failed to converge to a solution. This means that no stable solution was found that accurately represents the relationships between the variables. One way to solve a non-convergence problem is to change your model (Shaw & Flake, n.d.). Therefore, some random slopes are removed from the model, essentially meaning that their variance terms are restricted to zero, in order to make the model more stable (Barr et al., 2013). The variance components for the education dummy (variance = 0.01) and the age variable (variance = 0.008) were small, so these are restricted to zero, which means that the effects of these variables are assumed to be the same in all countries. This results in Equation 9, where the education dummy and the age variable are only included as fixed effects. The estimates of this model can seen in Table 5.

$$\begin{aligned}\text{Deal proneness}_{ij} = \; & \gamma_{00} + \gamma_{01}\text{GDP}_j + \gamma_{02}\text{CPI}_j + \gamma_{03}\text{Inhabitants}_j + \gamma_{04}\text{Individualism}_j \\ & + \gamma_{05}\text{Uncertainty avoidance}_j + u_{0j} + \beta_{1j}\text{Male}_{ij} + \beta_2\text{High education level}_{ij} \\ & + \beta_{3j}\text{High income}_{ij} + \beta_4\text{Age}_{ij} + r_{ij}\end{aligned} \tag{9}$$

The performance metrics of the random coefficient model can be found in Table 4. As can be seen in the table, the AIC, BIC and deviance values of this model are lower compared to the previous ones, indicating a better fit. Furthermore, the ICC of this model is $\frac{0.150}{0.150+0.038+0.022+0.919}$ which is approximately 0.133. This is similar to the ICC of the random intercept model with all predictors. Additionally, a likelihood ratio test was performed to compare the random coefficient model to the random intercept model with all predictors, which indicated that the random coefficient model is significantly better in fit (p < 2.2e-16).

5.1.5 Random coefficient model with cross-level interactions

Next, cross-level interactions were explored to see whether level-2 characteristics influence level-1 relationships. A separate model was constructed for every possible interaction. As there were many possible interactions, only the models with a significant interaction effect are included in this research. Three interaction effects proved to be significant, the effect between high education level and the individualism index, the effect between high income and the uncertainty avoidance index and the effect between age and the uncertainty avoidance index. The equations of the corresponding models can be seen in Appendix B. The results of these models can be seen in Table 5.

The performance metrics of these models can be found in Table 4. The three models that include interaction effects are quite similar in terms of fit to the random coefficient model without cross-level interactions. The AIC and deviance values are slightly lower, which indicates that the model improved by adding the interaction terms. However, the BIC is a bit higher than that of the previous model without interactions for two of the new models. Furthermore, the ICC is lower for two of the new models, which makes sense as as there are country-level variables included in the interactions. Lastly, the likelihood ratio test confirms that the model including the interaction effect between high education and the individualism index ($p = 0.006$), the model that includes the interaction effect between high income and the uncertainty avoidance index ($p = 0.011$) and the model that includes the interaction effect between age and the uncertainty index ($p = 0.001$) all have a better fit compared to the previous random coefficient model without interaction effects.

5.2 Interpretation of the multilevel models

The estimates of the random coefficient model without cross-level interactions can be seen in the first column of Table 5. Regarding the fixed effects, the intercept is 3.481, which indicates the estimated mean deal proneness when all other predictors are zero. As the data is standardized and each variable now has a mean of zero, this means that the intercept is the estimated mean deal proneness when all predictors are at their average level. The negative coefficient for male indicates that the mean deal proneness for males is -0.207 lower compared to females, while holding all other predictors constant. Additionally, the negative coefficient for age indicates that deal proneness is negatively related to age. For one standard deviation increase in age, deal proneness is estimated to decrease by on average 0.111 standard deviation units, holding all other predictors constant. As the standard deviation for age was 15.880 before standardization, this means that if age increases by 15.880, deal proneness decreases by $15.880*0.111 = 1.769$. Furthermore, the coefficients for the remaining predictor variables are insignificant, meaning that there is no evidence that these variables have a significant effect on deal proneness.

Looking at the random effects, Table 5 shows that the random intercept is 0.150. This is the variability in the intercept across different countries, thus it shows how much deal proneness varies across countries after accounting for the fixed effects. Since the random intercept is significant, it can be concluded that highly significant differences exist among the mean deal proneness of the countries. The random effect for male, which is 0.038, shows how much the effect of male on deal proneness varies across countries. As this effect is significant, it can be inferred that the relationship between male and deal proneness varies significantly across countries. Additionally, the random effect of high income is significant, which indicates that the effect of high income on deal proneness differs across countries. Lastly, the residual indicates the unexplained variability in deal proneness that is specific to each country after accounting for both the fixed and random effects.

Table 5: Estimates of the models

		Model 4[3]	**Model 5**[4]	**Model 6**[5]	**Model 7**[6]
Random effects	Random intercept	0.150 (0.387)***	0.148 (0.385)***	0.149 (0.387)***	0.149 (0.386)***
	Male	0.038 (0.195)***	0.038 (0.195)***	0.038 (0.196)***	0.037 (0.193)***
	High income	0.022 (0.149)**	0.023 (0.153)**	0.01 (0.102)	0.026 (0.161)***
	Residual	0.919 (0.959)	0.919 (0.958)	0.919 (0.959)	0.918 (0.958)
Fixed effects	Intercept	3.481 (0.076)***	3.475 (0.076)***	3.484 (0.076)***	3.485 (0.076)***
	Male	-0.207 (0.041)***	-0.205 (0.041)***	-0.207 (0.041)***	-0.209 (0.041)***
	High education level	-0.023 (0.018)	-0.024 (0.018)	-0.023 (0.018)	-0.024 (0.018)
	High income	0.012 (0.038)	0.014 (0.039)	0.018 (0.031)	0.007 (0.040)
	Age	-0.111 (0.009)***	-0.112 (0.009)***	-0.111 (0.009)***	-0.108 (0.009)***
	Inhabitants	0.073 (0.082)	0.074 (0.081)	0.058 (0.082)	0.073 (0.082)
	GDP	0.057 (0.121)	0.058 (0.120)	0.063 (0.122)	0.053 (0.121)
	CPI	-0.043 (0.099)	-0.044 (0.098)	-0.028 (0.099)	-0.048 (0.099)
	IDV	-0.013 (0.099)	-0.037 (0.099)	-0.024 (0.099)	-0.010 (0.099)
	UAI	0.114 (0.090)	0.118 (0.090)	0.073 (0.091)	0.114 (0.090)
	High education level*IDV		0.050 (0.018)**		
	High income*UAI			0.088 (0.031)*	
	Age*UAI				-0.030 (0.009)**

Note: For the random effects, the variance and the standard deviation are reported. Regarding the fixed effects, the estimates and standard errors are shown.

[3]Model 4 refers to the random coefficient model without cross-level interactions.

[4]Model 5 refers to the random coefficient model with the interaction between high education and the individualism index included.

[5]Model 6 refers to the random coefficient model with the interaction between high income and the uncertainty avoidance index included.

[6]Model 7 refers to the random coefficient model with the interaction between age and the uncertainty avoidance index included.

Regarding the cross-level interactions, a positive coefficient of 0.050 has been found for the interaction of high education level with the individualism index. This indicates that for respondents with a high education level, the influence of the individualism index becomes more pronounced, resulting in higher estimated deal proneness when the individualism index is higher. So the effect of education is dependent on this level-2 variable. A possible explanation could be related to the fact that individualist countries encourage individual decision-making. Higher educated individuals might possess more skills needed to process information efficiently, assess the value of a deal and make informed decisions, as opposed to lower educated individuals in individualist countries.

Furthermore, the positive interaction effect of high income and the uncertainty avoidance index suggests that the effect of income is dependent on the uncertainty avoidance index. This means that in countries with a higher uncertainty avoidance index, the effect of having a high income on deal proneness is stronger compared to countries with a lower uncertainty avoidance index. An explanation for this might be that although in uncertainty avoidance countries individuals are less inclined to take risks, e.g. trying a new product, individuals with a higher income have a financial buffer against potential negative outcomes. Lastly, it was found that the relationship between age and deal proneness is influenced by the uncertainty avoidance index. As age increases, deal proneness tends to decrease more for individuals in a country with a higher uncertainty avoidance index, compared to individuals in countries with a lower uncertainty avoidance index. A possible reason for this negative interaction effect is that risk aversion might increase with age and therefore the negative effect of age is stronger in more uncertainty avoidant countries.

The estimated values of the random effect per country for the intercept, male dummy and high income dummy can be seen in Table 9 in Appendix C. These random effects have been extracted from the random coefficient model without cross-level interactions, and indicate the estimated deviations for each country from the fixed effects. Additionally, the coefficients of this model, which combine both the fixed and the random effects, are shown in Table 6. What is interesting when observing these coefficients, is that the coefficient of male is negative for most countries, but not all. For Czechia and Ireland there is a positive coefficient. This indicates that in these countries, contrary to what was found before, the average deal proneness is higher for men compared to women. Next, looking at the last column, it can be observed that the effect of having a high income is not consistent across countries. This variability in the coefficient of high income might also be the reason why the coefficient of the fixed effect of high income in Table 5 is not significant. Additionally, the variation in the intercept indicates that the average deal proneness is different for each country. To give an indication of which countries have a low or a high average deal proneness, these intercepts are displayed in Figure 5.

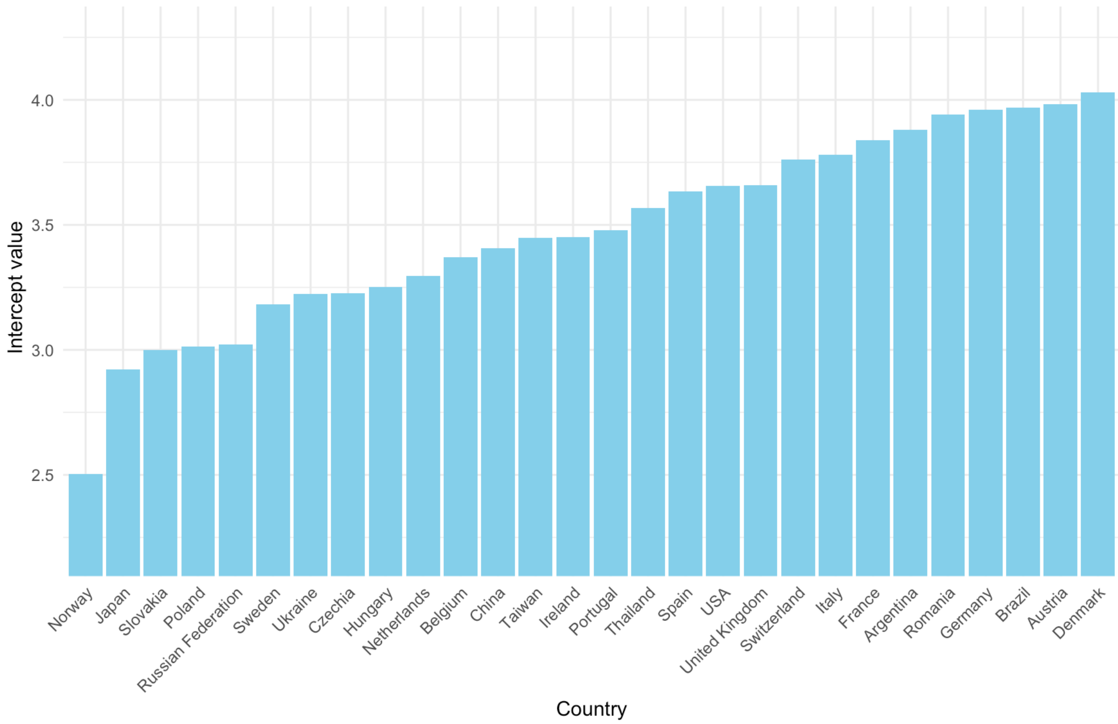


Figure 5: Estimated average deal proneness per country

Table 6: Coefficients

Country	Intercept	Male	High income
Argentina	3.880	-0.555	-0.092
Austria	3.983	-0.343	-0.102
Belgium	3.370	-0.072	0.096
Brazil	3.968	-0.200	-0.114
China	3.408	-0.209	0.012
Czechia	3.226	0.074	-0.135
Denmark	4.029	-0.320	0.000
France	3.838	-0.150	0.072
Germany	3.962	-0.261	0.037
Hungary	3.251	-0.344	0.102
Ireland	3.451	0.344	-0.076
Italy	3.782	-0.282	0.208
Japan	2.922	-0.090	-0.010
Netherlands	3.295	-0.399	0.092
Norway	2.504	-0.190	0.044
Poland	3.014	-0.276	0.179
Portugal	3.478	-0.279	-0.002
Romania	3.941	-0.337	-0.073
Russian Federation	3.023	-0.019	0.055
Slovakia	2.999	-0.210	-0.046
Spain	3.635	-0.343	0.151
Sweden	3.183	-0.447	-0.312
Switzerland	3.761	-0.098	0.022
Taiwan	3.448	-0.268	0.173
Thailand	3.566	-0.039	0.007
Ukraine	3.223	-0.054	0.064
United Kingdom	3.660	-0.082	-0.089
USA	3.656	-0.336	0.065

5.3 Hypothesis testing

Next, the hypotheses that have previously been formulated in section 2 will be evaluated based on the results of the random coefficient model. The first hypothesis stated that there is a positive relationship between deal proneness and education level, i.e. consumers with a higher education level are more deal prone. Since the effect of the high education level dummy on deal proneness is not significant, it is not possible to accept or reject this hypothesis. However, a significant interaction effect of high education level and the individualism index was found, as has been discussed in the previous section. For respondents with a high education level, the estimated deal proneness is higher in countries with a higher individualism index.

According to the second hypothesis, a positive relationship between age and deal proneness was expected, i.e. older consumers were expected to be more deal prone. However, in the random coefficient model a significant negative effect of age on deal proneness was found, so this hypothesis is rejected. The results indicate that older consumers are less deal prone compared to younger consumers. As has been mentioned in section 2.2, a possible reason for this is that younger customers have a lower income and are therefore more inclined to buy a promoted product. Additionally, a significant negative interaction effect of age and the uncertainty avoidance index was found.

The third hypothesis stated that there is a positive relationship between deal proneness and income, i.e. those with a higher income were expected to be more deal prone. However, no significant effect of income on deal proneness was found, as the estimated coefficient of high income was not significant as can be seen in Table 5. Therefore, this hypothesis cannot be accepted nor rejected. However, a significant positive interaction effect of high income and the uncertainty avoidance index was found.

Additionally, a relationship between gender and deal proneness was hypothesized. Women were expected to be more deal prone compared to men, according to the fourth hypothesis. As a significant negative coefficient was found for the male dummy in the random coefficient model, this hypothesis can be accepted. It can be concluded that women are more deal prone compared to men. Possible explanations for this are, as have been stated in section 2.2, that traditionally women do most of the household purchases and therefore are more experienced shoppers.

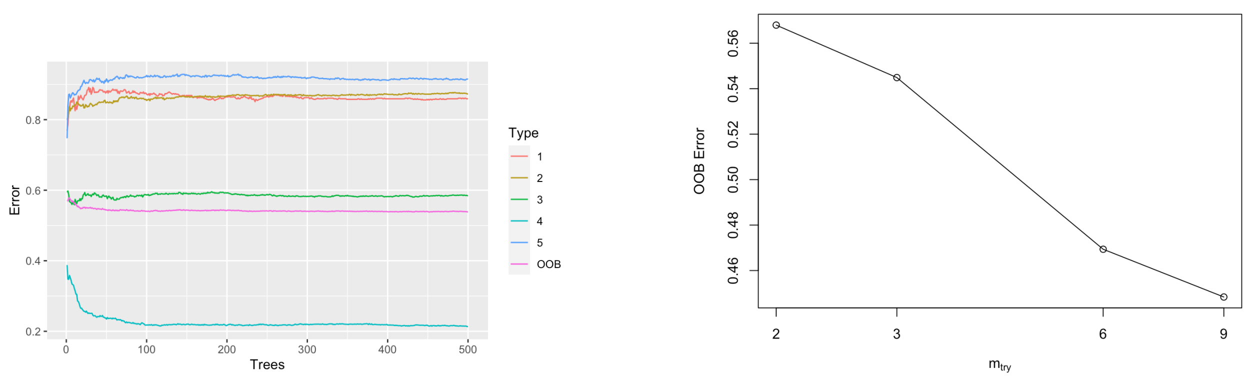
The fifth hypothesis stated that there is a positive relationship between the individualism index and deal proneness, i.e., consumers in individualistic countries are more deal prone. The effect of the individualism index on deal proneness is not significant, so this hypothesis cannot be accepted nor rejected. No evidence has been found of a direct relationship between the two variables. Similarly, the sixth hypothesis is not supported by the data. It hypothesized a relationship between the uncertainty avoidance index and deal proneness, i.e. consumers in high uncertainty avoidance countries are less deal prone. The coefficient of the effect of the uncertainty avoidance index on deal proneness was not found to be significant, so there is no evidence of a relationship. However, both these indexes were found to be part of significant interaction effects, as has been mentioned before. To conclude, an overview of all hypotheses and whether they have been accepted or rejected can be found in Table 7.

Table 7: Summary of hypothesis results

Hypothesis	**Result**
Hypothesis 1: Positive relationship between deal proneness and education level	Not significant
Hypothesis 2: Positive relationship between deal proneness and age	Rejected
Hypothesis 3: Positive relationship between deal proneness and income	Not significant
Hypothesis 4: Relationship deal proneness and gender, such that women are more deal prone compared to men	Accepted
Hypothesis 5: Positive relationship between deal proneness and individualism index	Not significant
Hypothesis 6: Negative relationship between deal proneness and uncertainty avoidance index	Not significant

5.4 Random forest results

First, a random forest was estimated using the default values for the parameters, the number of trees and the number of predictors that are randomly sampled at each split. The default value for the number of trees is 500, and the default number of predictors is the square root of the total number of predictors so $\sqrt{9} = 3$. The classification accuracy of this model is 45.2%. Next, the model's parameters were tuned. Figure 6a shows that the error rates have stabilised for 500 trees, so this number will stay the same. Regarding the number of predictors, the out-of-bag (OOB) error per number of predictors can be seen in Figure 6b. The OOB error is lowest when the number of predictors tried at each split m is equal to 9. This means that now the number of predictors sampled at each split m is equal to the total number of predictors p, which is actually equivalent to bagging. Next, the final model is estimated using the number of trees 500 and m equal to 9. The accuracy of this model is 54.8%, which represents an improvement over the previous model, although it is still not considered very high.

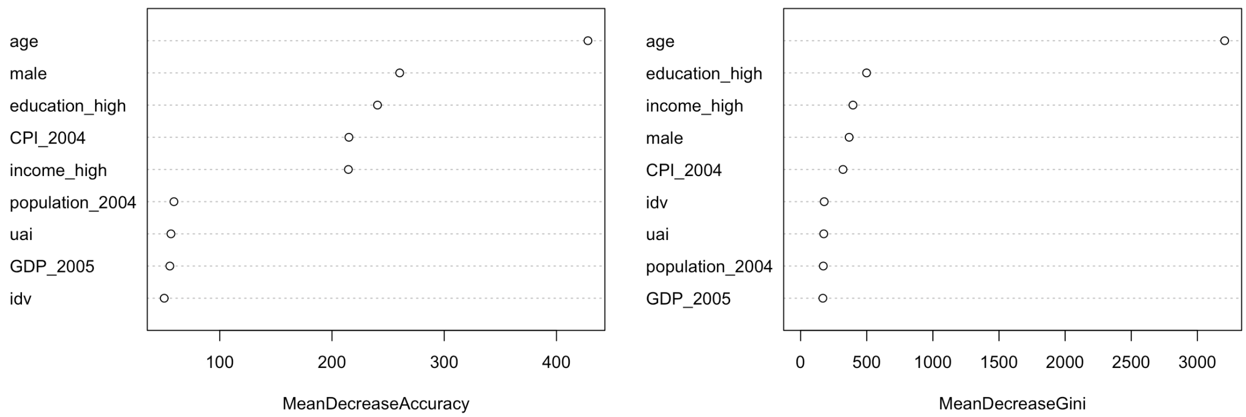


(a) Error rate per number of trees

(b) OOB error per number of predictors

Figure 6

Lastly, the variable importance of this model was evaluated, which is displayed in Figure 7. From these figures, it can be concluded that age is by far the most influential variable in making accurate predictions. This is in line with the results from the multilevel model, where the coefficient of age was significant and also one of the largest coefficients. Furthermore, it can be concluded that the individual-level variables are more important than the country-level variables in making accurate predictions, as these are located at the bottom of the figure. However, it is worth noting that according to Figure 7a, CPI appears to have a more significant impact compared to what is shown in Figure 7b. This indicates that this variable is more relevant in terms of maintaining accuracy than impurity reduction.



(a) Mean Decrease Accuracy

(b) Mean Decrease Gini

Figure 7: Variable importance plots

6 General Discussion

In conclusion, this research aimed to address the following main question: "How do individual and macro-societal factors influence consumer deal proneness?". To explore this question, two sub-questions have been investigated. The first sub-question was "How do individual differences in demographic characteristics influence deal proneness?". The results of the multilevel model revealed that age and gender are important factors in shaping consumer deal proneness, whereas income and education level did not show significant results.

A negative relationship was found between age and deal proneness, such that younger consumers are more deal prone compared to older consumers. The feature importance of the random forest confirmed that age is a very influential factor. Consequently, the second hypothesis is rejected, which stated that there is a positive relationship between deal proneness and age. Additionally, a relationship was found between gender and deal proneness, indicating that women are more deal prone compared to men. Therefore, the fourth hypothesis is accepted, where a relationship between deal proneness and gender was expected, such that women are more deal prone to men. Unfortunately, no evidence was found to either accept or reject the remaining hypotheses.

The second sub-question was: "How does deal proneness vary across different countries and cultures and what are the cultural and economic factors that influence this?". The presence of a significant random intercept in the multilevel model indicated that differences exist among the deal proneness of the countries. Specifically, variations exist in the effects of gender and income on deal proneness across countries. However, no significant relationships were found between the country-level variables and deal proneness.

Nevertheless, these country-level variables did reveal significant interaction effects. Positive interaction effects were observed between education level and the individualism index, as well as between high income and the uncertainty avoidance index. This indicates that the effect of education is is dependent on the individualism index, where its influence becomes more pronounced among individuals with higher education levels. Furthermore, the results suggest that in countries with higher uncertainty avoidance indexes, the effect of having a high income on deal proneness is also higher. Additionally, a negative interaction effect has been identified between age and the uncertainty avoidance index. As age increases, deal proneness decreases more for individuals in a country where the uncertainty avoidance index is higher.

Together, the answers to these two sub-questions answer the main research question. It has been found that various individual and macro-societal factors have a significant influence on deal proneness. Specifically, age and gender significantly impact deal proneness. Younger consumers and women are found to be more deal prone. Additionally, the results showed that differences exist among the mean deal proneness of the countries.

This research offers valuable managerial insights. By using these findings, managers can improve their strategies to more effectively target deal prone consumers, leading to potential increases in sales. Especially the findings indicating a negative relationship between deal proneness and age, as well as the higher deal proneness of women compared to men, present readily applicable insights for marketing strategies. This indicates that marketing efforts should be directed towards younger customers and women when promoting deals. Additionally, the results of this research suggests that deal proneness varies among different countries, which indicates that promotional strategies should be adapted accordingly. This is particularly valuable information for companies that are expanding to new markets.

In addition, this research contributes to the existing academic literature concerning deal proneness. The fact that this research includes data from 28 different countries is very innovative in this field. Previously, the most extensive research, in terms of the number countries, considered just three. Furthermore, the effect of a variety of country-level variables has been examined in this research, which is in contrast with earlier studies that predominantly focused on the influence of individual-level factors on deal proneness.

Furthermore, it is important to acknowledge the limitations of this research. First of all, one limitation relates to the measurement of the dependent variable, deal proneness, which relied on respondents' self-reported ratings of the statement "I love special promotional offers". However, this approach introduces a potential limitation as it is reported by the respondents themselves, which may introduce bias. This leads to a recommendation for further research to consider alternative data collection methods, such as experimental designs, to more objectively measure deal proneness.

Second, another limitation of this research is that deal proneness has been considered in general, as opposed to separately examining deal proneness based on the type of deal. For instance, it could be that the effect of age on deal proneness differs for various types of deals, such as coupons versus discounts. Therefore, it is advisable for further research to take these categories of deals into account to further explore how certain variables influence deal proneness. Last, it is important to note that the data used in this research was collected in 2004. As deal proneness might change over time, for example due to changing market conditions, an additional recommendation for further research is to acquire more recent data to conduct analyses on.

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Appendix

A Country names and their abbreviations

Table 8: Country names and their abbreviations

Country name	**Abbreviation**
Argentina	AR
Austria	AT
Belgium	BE
Brazil	BR
China	CN
Czech Republic	CZ
Denmark	DK
France	FR
Germany	DE
Hungary	HU
Ireland	IE
Italy	IT
Japan	JP
Netherlands	NL
Norway	NO
Poland	PL
Portugal	PT
Romania	RO
Russia	RU
Slovakia	SK
Spain	ES
Sweden	SE
Switzerland	CH
Taiwan	TW
Thailand	TH
Ukraine	UA
United Kingdom	UK
United States	USA

B Equations of the random coefficient models with interaction effects

The equation for the random coefficient model including the interaction effect between high education level and the individualism index looks as follows:

$$\begin{aligned}\text{Deal proneness}_{ij} = {} & \gamma_{00} + \gamma_{01}\text{GDP}_j + \gamma_{02}\text{CPI}_j + \gamma_{03}\text{Inhabitants}_j + \gamma_{04}\text{Individualism}_j \\ & + \gamma_{05}\text{Uncertainty avoidance}_j + u_{0j} + \beta_{1j}\text{Male}_{ij} + \beta_2\text{High education level}_{ij} \\ & + \beta_{3j}\text{High income}_{ij} + \beta_4\text{Age}_{ij} + \beta_5\text{High education level}_{ij} * \text{Individualism}_j \\ & + r_{ij}\end{aligned} \tag{10}$$

Next, the following equation represents the model that includes the interaction effect between high income and the uncertainty avoidance index.

$$\begin{aligned}\text{Deal proneness}_{ij} = {} & \gamma_{00} + \gamma_{01}\text{GDP}_j + \gamma_{02}\text{CPI}_j + \gamma_{03}\text{Inhabitants}_j + \gamma_{04}\text{Individualism}_j \\ & + \gamma_{05}\text{Uncertainty avoidance}_j + u_{0j} + \beta_{1j}\text{Male}_{ij} + \beta_2\text{High education level}_{ij} \\ & + \beta_{3j}\text{High income}_{ij} + \beta_4\text{Age}_{ij} + \beta_5\text{High income}_{ij} * \text{Uncertainty avoidance}_j \\ & + r_{ij}\end{aligned} \tag{11}$$

Last, the model that includes the interaction effect between age and the uncertainty avoidance index is shown in Equation 12.

$$\begin{aligned}\text{Deal proneness}_{ij} = {} & \gamma_{00} + \gamma_{01}\text{GDP}_j + \gamma_{02}\text{CPI}_j + \gamma_{03}\text{Inhabitants}_j + \gamma_{04}\text{Individualism}_j \\ & + \gamma_{05}\text{Uncertainty avoidance}_j + u_{0j} + \beta_{1j}\text{Male}_{ij} + \beta_2\text{High education level}_{ij} \\ & + \beta_{3j}\text{High income}_{ij} + \beta_4\text{Age}_{ij} + \beta_5\text{Age}_{ij} * \text{Uncertainty avoidance}_j + r_{ij}\end{aligned} \tag{12}$$

C Estimates of random effects

Table 9: Estimates of random intercept and coefficients for male and high income

Country	**Intercept**	**Male**	**High income**
Argentina	0.399	-0.349	-0.104
Austria	0.502	-0.137	-0.114
Belgium	-0.110	0.134	0.084
Brazil	0.487	0.006	-0.125
China	-0.073	-0.002	0.001
Czechia	-0.255	0.280	-0.147
Denmark	0.548	-0.114	-0.012
France	0.358	0.057	0.060
Germany	0.482	-0.054	0.026
Hungary	-0.229	-0.138	0.090
Ireland	-0.029	0.551	-0.088
Italy	0.302	-0.076	0.197
Japan	-0.559	0.117	-0.022
Netherlands	-0.185	-0.192	0.080
Norway	-0.977	0.017	0.033
Poland	-0.466	-0.069	0.167
Portugal	-0.002	-0.073	-0.014
Romania	0.461	-0.130	-0.084
Russian Federation	-0.457	0.188	0.043
Slovakia	-0.482	-0.003	-0.058
Spain	0.155	-0.136	0.140
Sweden	-0.298	-0.240	-0.323
Switzerland	0.280	0.109	0.010
Taiwan	-0.033	-0.061	0.161
Thailand	0.086	0.168	-0.004
Ukraine	-0.257	0.153	0.052
United Kingdom	0.179	0.125	-0.101
USA	0.175	-0.129	0.053