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Willingness to pay for ski passes in Slovakia

BACHELOR THESIS

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Declaration of Authorship

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Prague, August 1, 2023

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Abstract

The aim of this thesis is to analyze the willingness to pay for ski passes of consumers in Slovakia. Ordinal logistic regression is utilized on data collected by a self-developed online questionnaire. The dependent variable, Resort, represents four resort types categorized from the least to the most expensive. The length of a usual ski resort visit in days, the length of the slopes in km, the difficulty of the slopes, the resort's locality, and the option to buy ski passes online were shown to have a positive effect and be statistically significant in the final model. The presence of a ski lift for kids in the resort and the ability to arrive at a resort by car in less than an hour were shown to be statistically significant with a negative effect. The only statistically significant demographic variable was shown to be the consumers' income in thousands of euros with a positive effect.

JEL Classification	C25, D12, L83, Z32
Keywords	Willingness to pay, ski pass, ordinal logistic regression, Slovakia

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Abstrakt

Cílem této práce je analyzovat ochotu platit za skipasy na Slovensku. Ordinální logistická regrese se používá na datech shromážděných ze samostatně vyvinutého online dotazníku. Závislá proměnná Resort představuje čtyři typy resortů kategorizované vzestupně podle ceny. Délka obvyklé návštěvy lyžařského střediska ve dnech, délka sjezdovek v km, obtížnost sjezdovek, lokalita střediska a možnost nákupu skipasů online mají pozitivní a statisticky významný efekt v konečném modelu. Přítomnost lyžařského vleku pro děti ve středisku a možnost přijet do střediska autem za méně než hodinu se ukázaly jako statisticky významné faktory s negativním účinkem. Jediná statisticky významná demografická proměnná byl příjem spotřebitelů v tisících eur, která měla pozitivní efekt.

Klasifikace JEL	C25, D12, L83, Z32
Klíčová slova	Ochota platit, skipas, pořádkový logit, Slovensko

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Acronyms

AIC Akaike Information Criteria

AME Average Marginal Effect

APE Average Partial Effect

CBC Choice-based Conjoint Analysis

CDF Cumulative Distribution Function

MLE Maximum Likelihood Estimation

OR Odds ratio

OLS Ordinary Least Squares

PEA Partial Effect at the Average

TMR Tatry Mountain Resorts

WTP Willingness to pay

Chapter 1

Introduction

Winter sports like skiing or snowboarding have become increasingly popular in the last few decades, attracting a great number of tourists to the mountains for recreation, even in freezing temperatures. A crucial aspect influencing the choice of which resort to visit is the price of ski lift tickets. The cost of the trip, including the ski pass price, is among the most significant factors considered during the decision-making process for both selecting a resort and determining whether to visit at all. The price of a ski lift ticket usually represents a significant share of the total expenses. Identifying the determining factors of consumers' willingness to pay for ski passes is crucial not only for ski resort operators but also for researchers or policymakers. Deepening the understanding of these determinants could help optimize pricing strategies, meet the increasingly high expectations and standards of visitors, or help with optimizing resource allocation. Moreover, the significance of analyzing the willingness to pay will grow in the future as climate change starts to threaten winter sports' existence and sustainability.

The objective of this thesis is to analyze consumers' willingness to pay for ski lift tickets in Slovakia and provide insight into the factors influencing it. Similar research has already been conducted in various countries, but to the author's best knowledge, none involved Slovakia. Empirical data was collected via an online questionnaire.

The thesis is structured as follows: Chapter 2 explains the concepts of willingness to pay and conjoint analysis, in addition to introducing their types and methods customarily used. Furthermore, it provides some insight into ski resorts in Slovakia and their characteristics. In Chapter 3, the current state of the topic-related research performed is reviewed. Chapter 4 outlines the methodology by explaining the binary choice models, latent variables, the odds ratio, and, finally, the ordinal logistic regression utilized for data analysis. Chapter 5 describes the process of data collection and defines the dependent and independent variables analyzed in this thesis. Further description of the data collected is also provided in addition to the introduction of the empirical model. The analysis results can be found in Chapter 6. Supplemental information about the limitations is contained in this section as well. Chapter 7 summarizes the findings of this thesis.

Chapter 2

Theoretical Background

2.1 Willingness to pay

Willingness to pay (WTP) is a basic microeconomic concept that helps understand the price sensitivity of consumers. It is characterized as the maximum price a consumer is willing to pay for a service or product. If the price is higher, then the consumer will not make a purchase. A reservation price is an individual's maximum willingness to pay for something. It is the price for which they are indifferent about the purchase of the good; therefore, it is the highest price for which the good would still be purchased by the person (Varian, 2010). Willingness to pay depends on the individual characteristics of the consumers and differs significantly among individuals. In addition, Homburg *et al.* (2005) find evidence of a positive relationship between WTP and consumer satisfaction with the most significant impact at the extremities of the satisfaction distribution.

Breidert *et al.* (2006) distinguish between two main types of data collection methods. The first category includes surveying techniques. This way the stated preferences are extracted. Surveys can be divided into direct and indirect. Customer surveys and expert judgments are direct surveys. Discrete choice analysis or conjoint analysis are indirect survey methods. The second category consists of preference-revealing data obtained from actual or simulated price responses. These can be further divided into experiments and market data. Field experiments, laboratory experiments, and auctions are the types of experiments that were identified. The market data approach utilizes actual purchases of products and not only intentions to purchase that were stated by consumers. However, for new products with different parameters, the WTP cannot be estimated using this method. Using direct surveys is beneficial when market data are not available, for example, for products that are differentiated, as they offer a more affordable and less time-consuming alternative. Indirect surveys, on the other hand, were pointed out to be cognitively less demanding and, therefore, easier and more enjoyable for respondents to complete.

2.2 Conjoint analysis

Conjoint analysis is a method used to evaluate the importance of features for customers usually used later for product design (Gustafsson *et al.*, 1999). Surveys are distributed among customers where available options are organized into a collection of products, each accompanied by a distinct set of attributes and corresponding levels. The part-worths of the variables are their relative importance evaluated based on consumers' stated preferences. These part-worths are, afterward, used to define the individual feature's importance (Breidert *et al.*, 2006).

2.2.1 Types of conjoint analysis

The types of conjoint analysis characterized by qualtrics include menu-based, full-profile, choice-based, self-explicated, max-diff conjoint analysis, two-attribute trade-off analysis, and Hierarchical Bayes analysis.

One of the earliest methods of conjoint analysis includes the two-attribute trade-off analysis. Choices were presented with two attributes at a time where different combinations were presented, and consumers indicated their preferred ranking. However, this method is very time-consuming. While choosing between two attributes is not that mentally demanding, people are prone to creating a pattern in order to complete the task.

Similarly, the full-profile analysis, likewise, suffers from these drawbacks. After multiple concepts are presented, consumers rate each option based on how likely they are to make a purchase.

The most common type is the choice-based conjoint analysis (CBC), which is also called the discrete-choice conjoint analysis. Sets of 3 to 5 concepts are presented to consumers to choose from in this type of analysis. They repeatedly choose the most desirable full-profile option for them.

The menu-based analysis helps identify luxury and must-have features. Consumers choose features for their ideal product from a list of features with their prices included, so they trade options for one another, simulating buying situations in the real world. Consequently, this method is gaining popularity as it is more engaging for the participants.

An uncomplicated but robust approach is provided by the self-explicated conjoint analysis. Full-profile concept development is not necessary with this hybrid approach. The choice is not focused on a bundle of features but rather on individual features themselves. Firstly, consumers eliminate feature levels not acceptable under any conditions, and afterward, the most and least appealing options are selected. Secondly, according to the most and least liked levels, each feature's remaining levels are ranked.

The Max-diff conjoint is also referred to as the Best/Worst conjoint. Consumers are asked to pick the most and least favorable concepts in a set as it is easier for them than trying to understand how they feel about the rest of the concepts and rate them accordingly.

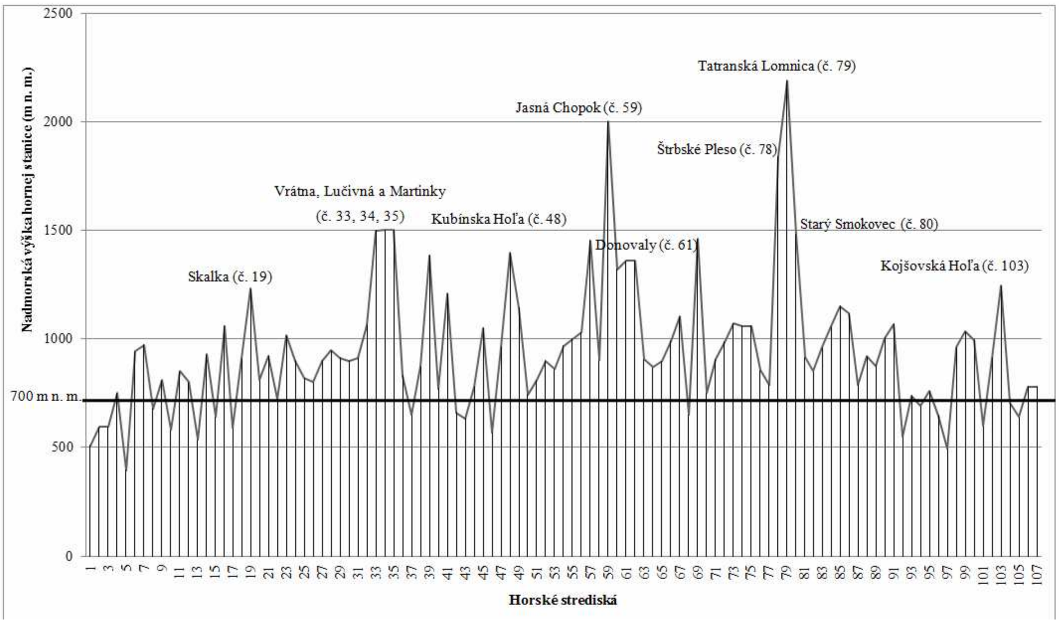
Hierarchical Bayes analysis, on the other hand, uses averages of the attribute levels when an attribute level has low variability, and then focuses individually on attributes with high level variability. This way, less data needs to be collected from each respondent in order to estimate a greater number of attributes and their levels.

2.3 Ski resorts in Slovakia

As of 2014, there were over 100 ski resorts in Slovakia with around 5 million skiers annually. In addition, around 18% of the population skis. The average length of a ski slope was 4.87 km, with around 56 km of ski slopes in the country. Around 45% of the slopes were marked as blue, with the lowest difficulty, and 47% were red with moderate difficulty. Only 8% of the slopes were identified as very difficult and, therefore, marked as black.

The majority of resorts is in the northern part of the country, primarily because of the Tatra mountains which are situated in that region. The largest operator of ski resorts in Slovakia is Tatry Mountain Resorts (TMR).

Figure 2.1: Altitude comparison of ski resorts' highest base stations



Source: Ministry of Transport and Construction of the Slovak Republic (2015)

Resorts were sorted into 3 categories. A total of 8 resorts were classified as big resorts with at least 2 chairlifts, 7km of ski slopes, and 100 000 annual visitors in the winter season. These resorts were Bachledova Dolina, Donovaly, Jasná Chopok, Ski Park Kubínska Hoľa, Veľká Rača, Štrbské Pleso, Tatranská Lomnica, and Vrátna Free Time Zone. 12 resorts were categorized as medium-sized with meeting the conditions of at least 1 chairlift, a minimum of 4 km of ski slopes, and at least 50 000 visitors annually, for example, Winter park Martinky or Starý Smokovec. Resorts that did not meet conditions to be sorted into either of these groups were labeled as small resorts.

Jasná Chopok, Štrbské Pleso, Tatranská Lomnica, Starý Smokovec, Donovaly, Vrátne Free Time Zone, Veľká Rača and Ružomberok- Malinô Brdo were identified as the most competitive among all Slovak ski resorts.

The aspects influencing the number of resort visitors were divided into two categories. External factors included the weather, natural ski resort conditions, global warming, the financial situation of visitors, the number of vacation days tourists have including holidays, rival resorts in the country and abroad, accommodation possibilities and attractions nearby, local laws, and the state of transport infrastructure. On the other hand, the internal factors included the resort's management, employees and their motivation, wages, and education, the financial situation of the resort and its ability to afford necessary repairs, marketing, or motivation for innovation.

Transport services such as ski lifts were identified as the most profitable with a profitability of just over 50%, followed by the hospitality services with 41.5%. The profitability of ski lifts is, however, mostly dependent on the snow conditions. The high return on hospitality services is compensating for the fact that they operate only for a few months each year. Additional services, including ski gear rental shops, had a profitability of 32.5%.

Several factors that prevent the development of ski resorts were also identified. These factors were divided into external and internal as well. External factors included, for example, insufficient state support, the legislative environment being burdensome, unsettled ownership situations, disproportionate requirements for nature protection, difficult accessibility of some resorts due to their geographical location, seasonal character of their operation, and therefore significant employee fluctuations, global warming, rising fuel prices, or low returns on investment. The internal factors involved difficulties securing investments, the substantial tax burden on tourism, or the lack of viability, professionalism, and management skills of entrepreneurs and managers (Ministerstvo dopravy, výstavby a regionálneho rozvoja SR, 2015).

Chapter 3

Literature review

Ski lift ticket prices have been studied from different perspectives, including either internal, external characteristics of ski resorts or their combination. One of the factors affecting consumers' willingness to pay for ski passes, which appears to be more pronounced in the literature, is crowdedness or congestion. A decline in skiers' satisfaction, in addition to a lower willingness to pay for ski passes, was shown to occur with congestion in ski-lift queues and slope congestions (Walsh & Davitt, 1983). These findings were confirmed in a hedonic price analysis of ski resorts in Austria (Falk, 2008). High distaste for congestion and higher willingness to pay for enthusiastic skiers, where the expected number of rides was the bases for the expected utility of skiers, can be found in one of the earlier examples of such research (Barro & Romer, 1987). A substantial reduction in the quantity of ski-lift tickets demanded and in customers' willingness to pay for them was revealed when fewer slopes were in operation by examining the relationship with different proportions of slopes closed (Malasevska *et al.*, 2017). However, some level of crowdedness was pointed out to be preferred by consumers, and a nonlinear relationship between the level of crowdedness and the ticket prices was revealed. This is caused by the fact that consumers prefer skiing in a social manner (Fonner & Berrens, 2014). Results from US resorts support these findings by revealing that while high levels of crowding on slopes are associated with a negative marginal impact on ticket prices, low levels of crowding exert a positive marginal impact, as it does not interfere with skiers' enjoyment but rather strengthens their social experience (Fonner & Berrens, 2014). Haugom *et al.* (2021) second the previous findings by their results utilizing alternative methodological approaches and suggest reducing peak demand by applying dynamic pricing, which is a practice used for decades in hospitality, electricity or airline industries. The potential increase in revenues by adopting a more dynamic pricing approach was explored and confirmed with a survey of 3 resorts in an inland region of Norway (Malasevska & Haugom,2018). Adaptation of dynamic pricing could result in a revenue increase from 0.5% to 7.5%. Nevertheless, the risks of implementation include a pronounced decrease in revenues in case of a switch to cheaper alternatives of many consumers with a high willingness to pay (Malasevska *et al.*, 2020). Another possible solution would be to expand the lift and slope capacities to deal with congestion (Haugom *et al.*, 2021). Similarly, the effects of employing faster lifts were explored by Mulligan & Llinares (2003). Such mentioned demand peaks with crowded slopes and long waiting times for ski lifts are caused by the substantial dependence of demand fluctuations on weather conditions as it has been demonstrated in the literature (Holmgren & McCracken, 2014; Malasevska *et al.*, 2017; Malasevska & Haugom, 2018).

The literature considerably focuses on analyzing the relative importance of different attributes which determine the prices of ski-lift tickets. The reputation of a resort was found to be important regarding consumers' perception of resort quality. Additionally, resorts should invest in lifts and equipment for snow-making. On the other hand, the establishment of night skiing or expanding the skiable surface was not shown to be very profitable regarding the customers' value-for-money perception (Rosson & Zirulia, 2018). A positive and statistically significant effect of the total length of ski slopes has been confirmed in multiple studies (Falk, 2008; Alessandrini, 2012; Lien *et al.*, 2022). The base altitude of the resort and the vertical drop also had a positive effect on the price (Fonner & Berrens, 2014; Lien *et al.*, 2022). The capacity of the lifts was another recurring positive determinant researched (Falk, 2008; Alessandrini, 2012; Fonner & Berrens, 2014). Additional attributes which were found to have a significant association with lift ticket prices include the snow-making capabilities, lifts' speed, on-site lodgings, the presence of gondola lifts (Fonner & Berrens, 2014), the share of intermediate ski slopes (Lien *et al.*, 2022) or the length of the season (Alessandrini, 2012).

Unpleasant weather conditions lower visitors' willingness to pay, with the most significant decrease present in case of rain or a blizzard. Implementation of discounts based on weather conditions was shown to noticeably increase revenues; however, optimal discounts for various weather conditions differ significantly (Malasevska *et al.*, 2017). Attributes related to weather were shown to be the second most important for skiers when considering a resort visit, only surpassed by the prices (Demiroglu *et al.*, 2015). Additionally, the willingness to pay for ski passes is shown to be higher during the weekends than during the weekdays (Haugom *et al.*, 2021).

Willingness to pay of ski resort visitors in New England was shown to be higher in the case of larger resorts with better slope coverage, more off-mountain services, and which are closer to visitors' residences. Competition and ski pass prices were shown to be negatively correlated (Klein, 2019).

The most frequent methodical approaches in the relevant literature include conjoint framework and hedonic price models. The conjoint framework is used by Haugom *et al.* (2021); choice-based conjoint questionnaire estimating dynamic prices for revenue maximization by Malasevska *et al.* (2020); or supplemented by Ordinary Least Squares (OLS) regression with dummy variables by Demiroglu *et al.* (2015). Hedonic price models were used by Lien *et al.* (2022); Rosson & Zirulia (2018); Fonner & Berrens (2014); linear and logarithmic hedonic regression models by Alessandrini (2012), or by Falk (2008), complementary to OLS and robust regression techniques similarly as Klein (2019).

In connection with ski resorts in Slovakia, a study comparing resorts in Slovakia, Poland, and the Czech Republic was conducted by Nowacki (2017). 245 resorts were compared using the Free Disposable Hull analysis with a Principal Components analysis based quality index. Moreover, differences in offered quality in relation to prices were analyzed to identify the best resorts. Some of the features included in this study were the price of a one-day ski pass, the length of the longest slope in the resort, the length of the ski season, the number of ski lifts, and the length of trails for beginners. The findings point out that Poland has the most expensive tickets, while tickets in Slovakia are the cheapest on average. However, the resort with the highest quality of parameters in Slovakia, which is the Jasná Resort in Chopok, had a ski lift ticket more expensive than the most expensive ticket in either Poland or the Czech Republic. Resorts in Poland were found to be of significantly higher quality than those in Slovakia or the Czech Republic. Nevertheless, the centers in Poland have the highest average inefficiency. Examples of the least efficient resorts in Slovakia were Štrbské Pleso and Starý Smokovec, with high prices due to their exceptional location. Slovakia was, additionally, reported to have the longest trail length among the three countries observed (Nowacki, 2017). A case study of a Slovak ski resort concerning climate change and snow reliability and their effect on winter and ski tourism in Slovakia shows that climate change will negatively affect ski resorts and ski pass sales by increasing the costs of snow production. Nonetheless, other factors influencing ski pass prices, like presenting new products and events which are not as dependent on the climate or focusing on tourist behavior and appropriate pricing strategy, should be taken into consideration in order to balance the negative effects of climate change (Demiroglu *et al.*, 2015).

Chapter 4

Methodology

The theoretical framework in this chapter was written based on Wooldridge (2013).

Firstly, a limited dependent variable model was needed because our dependent variable was of a particular type. Limited dependent variable models are used when the range of the dependent variable is significantly restricted. Examples of such variables are a categorical variable with ordered outcomes or with more than two unordered outcomes if it represents counts, duration or a corner solution, and lastly, if the variable is binary. Then the models use ordinal logistic regression, multinomial logistic regression, Poisson model, Cox model, Tobit model, or lastly, probit or logit model. A binary variable explains a qualitative event. Consequently, it can attain only the values of either 0 or 1, with one usually meaning a given condition is met and 0 meaning it is not. The probability function of a binary choice model is

$$f(y) = p^y(1-p)^{1-y}$$

The linear probability model is a linear regression model where the dependent variable Y_i is binary:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_k X_{ki} + u_i$$

where

$$E(Y|X_1, X_2, ..., X_k) = P(Y = 1|X_1, X_2, ..., X_k)$$

and

$$P(Y = 1|X_1, X_2, ..., X_k) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_k X_{ki}$$

Based on the ceteris paribus, which means keeping other factors constant, the interpretation of the coefficient β_j is not that it represents the change in y if x_j increases by one unit but is rather that it represents the change in the probability that Y_i is equal to 1, or in other words, the probability of success.

However, the linear probability models have multiple disadvantages. Firstly, the predicted probabilities can be unbounded. As linear probability models utilize linear equations, which have no bounds, the values predicted by such models might be outside of the interval [0,1], and therefore, these unrestricted estimated probabilities would cause problems. Secondly, the partial effect of any control variable is assumed to be constant because of the linearity in the parameters property of linear probability models. The third disadvantage is the heteroskedasticity of disturbances.

To solve these limitations, the binary response model, logit, is used. It models the probability with a nonlinear function with values in the (0,1) range assumed and, as a result, prevails over the limitations of the linear probability models. However, this model also has a disadvantage, and that is its difficult interpretation.
A binary response model:

$$P(y_i = 1|\boldsymbol{x}) = G(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k) = G(\beta_0 + \boldsymbol{x\beta})$$

Where G is any nonlinear function taking values strictly between 0 and 1: $0 < G(z) < 1$, and $\boldsymbol{x}$ is a full set of control variables.

In the logit model, the G function is the logistic function (the CDF for the standard logistic random variable):

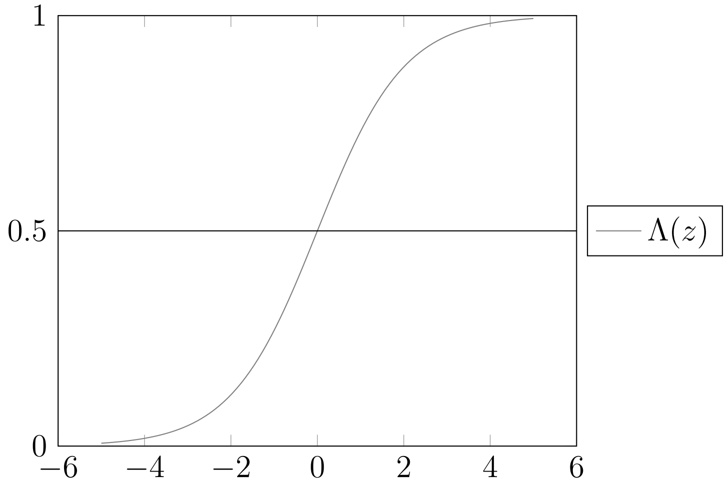
$$G(z) = \frac{1}{1 + exp(z)} = \Lambda(z)$$

And the logit model itself:

$$P(y = 1|\boldsymbol{x}) = \Lambda(\beta_0 + \boldsymbol{x\beta})$$

where $G(z) = \Lambda(z)$.

Figure 4.1: CDF for the standard logistic random variable



Source: author's computations.

The binary choice models are derived from the latent (unobserved) variable y^*, linearly influenced by the control variables x:

$$y^* = \beta_0 + \boldsymbol{x\beta} + e$$

We do not observe the latent variable itself, but instead we observe a binary variable:

$$y = \begin{cases} 1, & \text{if } y^* > 0 \\ 0, & \text{if } y^* \leq 0 \end{cases}$$

Assuming that e has standard logistic distribution while being independent of x and due to the symmetry of the error assumption, the response probability for y is:

$$P(y = 1|\boldsymbol{x}) = P(y^* > 0|\boldsymbol{x}) = P[e > -(\beta_0 + \boldsymbol{x\beta})|\boldsymbol{x}] =$$

$$1 - G[-(\beta_0 + \boldsymbol{x\beta})] = G(\beta_0 + \boldsymbol{x\beta})$$

In order to ensure that the estimated response probabilities are in the [0,1] interval, the logit model is often used.

The Maximum Likelihood Estimation (MLE) is required because of the non-linear nature of the logit model. The MLE is asymptotically normal, asymptotically efficient, and consistent under very general conditions. Consequently, single hypotheses can be tested using asymptotic standard errors for estimates which can be easily derived.

The density function of y_i given x_i necessary for the derivation of the MLE:

$$f(y|\boldsymbol{x_i};\boldsymbol{\beta}) = [G(\boldsymbol{x_i}\boldsymbol{\beta}]^y[1 - G(\boldsymbol{x_i}\boldsymbol{\beta})]^{(1-y)}$$

$$y = \{0, 1\}$$

By maximizing the log-likelihood function:

$$\mathcal{L}(\boldsymbol{\beta}) = \sum_{i=1}^{n} y_i log[G(\boldsymbol{x_i}\boldsymbol{\beta})] + (1 - y_i)log[1 - G(\boldsymbol{x_i}\boldsymbol{\beta})]$$

we derive the Maximum Likelihood Estimator of $\boldsymbol{\beta}$, assuming a sample of size n. $\hat{\boldsymbol{\beta}}$ is the logit estimator if G is the standard logistic CDF.

The interpretation of results is difficult as a consequence of the nonlinearity in this model. We are mostly interested in the effect of x on $P(y = 1|x)$, the probability of success. To obtain this effect, the following derivative is applied:

$$\frac{\partial P(y = 1|x)}{\partial x_j} = g(\beta_0 + \boldsymbol{x_i}\boldsymbol{\beta})\beta_j$$

The function g is λ.

That being the case, the magnitudes of the β_j coefficients are not directly interpretable as they are when using OLS. However, the signs of the partial effect of each regressor on the response probability are given by the coefficients and reveal the direction of the effect. Keeping other factors constant, if $\hat{\beta}_j > 0$, then if x increases, the probability of y=1 increases as well, with no notion of the magnitude of this effect.

4.1 Goodness-of-Fit

For linear probability models the percent correctly predicted, a goodness-of-fit measure, can be calculated. If the predicted probability is lower than 0.5 then the predictor of the binary variable y_i is equal to zero, otherwise it is one.

$$\hat{y}_i = \begin{cases} 1, & \text{if } G(\hat{\beta}_0 + \boldsymbol{x_i}\hat{\boldsymbol{\beta}}) \geq 0,5 \\ 0, & \text{if } G(\hat{\beta}_0 + \boldsymbol{x_i}\hat{\boldsymbol{\beta}}) < 0,5 \end{cases}$$

This measure shows the proportion of observations for which the model correctly predicts the outcome. It is shown how well y_i is predicted by $\hat{y}_i$ across all observations. However, despite the fact that it is a helpful goodness-of-fit measure, it can also be misleading when a relatively high value of percentages correctly predicted is obtained even if the least likely outcome is not predicted satisfactorily.

Another possibility of a goodness-of-fit measure is the pseudo R^2, as R^2 cannot be used in most cases with linear probability models because it does not have relevant interpretation since the dependent variable is binary while the regressors are continuous; therefore, the regression line will never fit the data in a perfect way. McFadden's pseudo R^2 is based on the log-likelihood: $1 - \frac{\mathcal{L}_u}{\mathcal{L}_r}$, where $\mathcal{L}_u$ is the log-likelihood of the full model and $\mathcal{L}_r$ is the log-likelihood of a model with only the intercept.

4.2 Ordinal logistic regression

The response variable y is an ordered response. The values assigned to every outcome are no longer arbitrary. The outcomes are ordered on a scale, for example from 0 to 6, where $y = 0$ is the lowest and $y = 6$ is the highest rating. The rating itself only has ordinal meaning, despite the fact that 4 is a better rating than 3. It cannot be said that the difference between 0 and 1 is 2x less important than the difference between 2 and 4.

The latent variable can again be used to derive the ordinal logistic model:

$$y^* = \beta_0 + \boldsymbol{x}\beta + e$$

$e|\boldsymbol{x}$ ~N(0,1), where $\alpha_1 < \alpha_2 < ... < \alpha_j$ are unknown cut points (threshold parameters) and

$$y = \begin{cases} 0 & \text{if } y^* \leq \alpha_1 \\ 1 & \text{if } \alpha_1 < y^* \leq \alpha_2 \\ ... & \\ J & \text{if } y^* > \alpha_J \end{cases}$$

If y takes on values 0, 1, 2, and 3 then the cut points are α_1, α_2 and α_3. The probability that a person i will choose option j given x_i is:

$$P(y_i = j|x_i) = \begin{cases} P(y^* < \alpha_1|x_i) = G(\alpha_1 - z_1) & \text{for } j = 0 \\ P(\alpha_j < y^* \leq \alpha_{j+1}|x_i) = G(\alpha_{j+1} - z_i) - G(\alpha_j - z_i) & \text{for } 0 < j < J \\ P(y^* > \alpha_J|x_i) = 1 - G(\alpha_J - z_i) & \text{for } j = J \end{cases}$$

(Cottrell & Lucchetti, 2012)

4.3 Odds ratio

As the coefficients of the logit model are difficult to interpret, the odds ratio (OR) can be used to make the interpretation easier. The odds ratio is the exponential of the model coefficients $\exp(\beta_j)$. For the coefficients of dummy variables, the unit difference in x_i is the difference between the respondent being a member of a category or belonging to the omitted category (DeMaris, 1995). [1]

[1]Different measures used to simplify the interpretation include the Average Marginal Effect and the Marginal Effect at the Average (see: Appendix B).

Chapter 5

Data and empirical model

5.1 Data collection

The data for this thesis was gathered through the utilization of an online questionnaire. This method of data collection was chosen because it is free, time-saving, and allows for a relatively sizeable number of responses to be collected. As the focus of this thesis is on the willingness to pay for ski passes in Slovakia, the questionnaire was only in the Slovak language to ensure only respondents from Slovakia would answer the questions. It was developed using Google Forms and shared through email and Facebook groups dedicated to alpine skiing, snowboarding, or ski resorts in April 2023. It took approximately 5 minutes to complete the questionnaire, which contained 26 questions. All questions but one were mandatory and multiple-choice, where only one option for each question could be chosen. Some questions allowed respondents to write their own answers if they did not fit into any of the provided categories.

5.2 Variables

5.2.1 The dependent variable

The dependent variable Resort:

Willingness to pay in this thesis was measured by utilizing the conjoint analysis approach and offering 4 options with different parameters for respondents to choose from. The parameters of these resorts were being upgraded, and the price was increasing with each option. To reflect real-life choices better, the ski resorts and their parameters offered were inspired by real existing resorts in Slovakia.

Resort number 1 included 1 downhill track with a total length of 1.2km, 3 ski lifts, 1 restaurant, and the highest point of the resort at 810 mamsl (metres above mean sea level). The price of a ski pass for 1 day in this resort was set at 15€. This resort was inspired by the Ski Brodok resort near Poráč.

Resort number 2 included 3 downhill tracks with a total length of 1.5km, 7 ski lifts, 2 restaurants, and the highest point of the resort at 705 mamsl. The price of a ski pass for 1 day in this resort was set at 30€. This resort was inspired by the Jahodná resort near Košice.

Resort number 3 included 8 downhill tracks with a total length of 8km, 6 ski lifts, 2 ski cableways, 6 restaurants, and the highest point of the resort at 1160 mamsl. The price of a ski pass for 1 day in this resort was set at 39€. This resort was inspired by the Bachledka Ski & Sun resort in Bachledova Dolina.

Resort number 4 included 13 downhill tracks with a total length of 12km, 3 ski lifts, 7 ski cableways, 7 restaurants, and the highest point of the resort at 2634 mamsl. The price of a ski pass for 1 day in this resort was set at 49€. This resort was inspired by the resort Tatranská Lomnica in Tatranská Lomnica in the High Tatras.

5.2.2 The independent variables

After answering the question about the choice of a ski resort, the questionnaire was divided into 3 parts. Firstly, respondents were asked for more detailed information about their usual trips to ski resorts. In the following section, respondents were asked to indicate how important given parameters, features, or characteristics associated with a ski resort are for them. This indication could be done utilizing the Likert scale by choosing an integer between 0-3, where 0 meant that the feature was totally unimportant for them when deciding which resort to visit, 1 implying that it is a little important, 2 that it is important, and 3 indicating that this feature is extremely important when making a decision. In the final part of the questionnaire, 6 questions were incorporated to gain further information about the respondents themselves.

Table 5.1: Independent variables

Independent variable	**Variable description**	**Values**
	Section 1	
Sport	The usual purpose of the ski resort visit	1: skiing or snowboarding 0: other
TripLength	The length of a usual resort visit	1: 1-day trips 2: 2-3 days 3: >3 days
Company	Who the respondent visits the resort with	1: alone 2: family 3: friends 4: someone else
Plan	How long in advance the average trip is usually planned	1: that day 2: 1 day 3: 2-5 days 4: a week 5: 2-3 weeks 6: a month 7: >a month
	Section 2	
TrackLength	Length of the downhill tracks in km	0: not important 1: a little important 2: important 3: very important
Difficulty	Difficulty of the downhill tracks	0: not important 1: a little important 2: important 3: very important
Crowdedness	Number of skiers on the tracks	0: not important 1: a little important 2: important 3: very important

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Table 5.1 – Continued from previous page

Independent variable	**Variable description**	**Values**
WaitTimes	Waiting times for ski lifts < 5 min	0: not important 1: a little important 2: important 3: very important
Cableway	Whether the resort has an above-ground cablecar or cableway	0: not important 1: a little important 2: important 3: very important
Transport	Quality of access to the resort (parking, trains, buses, highways, road conditions)	0: not important 1: a little important 2: important 3: very important
HourCar	Possibility to arrive at the resort by car in < 1 hour	0: not important 1: a little important 2: important 3: very important
Locality	The locality of the resort (altitude, surroundings, region beauty, situated in a national park)	0: not important 1: a little important 2: important 3: very important
Accommodation	Availability of accommodation in the resort or its proximity	0: not important 1: a little important 2: important 3: very important
Online	Possibility to buy ski passes online	0: not important 1: a little important 2: important 3: very important
School	Availability of ski school and gear rental shop in the resort	0: not important 1: a little important 2: important 3: very important

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Table 5.1 – Continued from previous page

Independent variable	**Variable description**	**Values**
KidsActivity	Availability of activities for children in the resort	0: not important 1: a little important 2: important 3: very important
KidsLift	Availability of childrens' ski lift in the resort	0: not important 1: a little important 2: important 3: very important
Attractions	Availability of other attractions in or near the resort (ice rink, wellness)	0: not important 1: a little important 2: important 3: very important
Food	The food quality in the resort's restaurants	0: not important 1: a little important 2: important 3: very important
	Section 3	
Gender	Gender of the participant	0: male 1: female 2: other
Age	The respondent's age in years	0- approx. 100
Education	Highest level of education achieved	0: without elementary 1: elementary 2: high-school 3: university degree
Occupation	Status of the respondent	0: unemployed 1: student 2: employee 3: entrepreneur 4: pensioner
Income	Net monthly income in euros	≥ 0

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Table 5.1 – Continued from previous page

Independent variable	**Variable description**	**Values**
Region	Which region does the respondent live in	1: Bratislava 2: Trnava 3: Trenčín 4: Nitra 5: Žilina 6: Banská Bystrica 7: Prešov 8: Košice

Two new variables were added in order to improve the interpretability of the variables Occupation and Income:

Employed is equal to 0 for unemployed participants, students, and pensioners. Otherwise, it is equal to 1. It replaces the Occupation variable in the regression.

IncomeK is the income in thousands of euros. It replaces the variable Income in the regression.

5.3 Empirical model

As the dependent variable has four categories that can be ordered, with Resort 1 being the cheapest and Resort 4 being the most expensive with the best services and resort characteristics out of the 4 options, ordinal logistic regression is used for the analysis. Moreover, only the observations where the variable Sport equals 1 were analyzed, as this thesis focuses mainly on visitors who ski or snowboard. Additionally, only observations where the variable Employed equals 1 were considered. The following ordered logit model was used in this thesis:

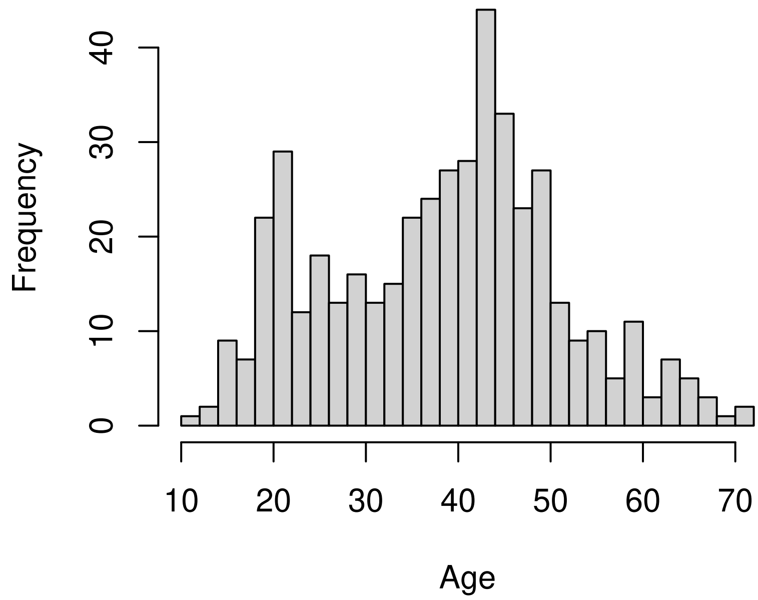
$$\begin{aligned}
P(Willingness = j|x) = G(&\beta_0 + \beta_1 TripLength + \beta_2 Company \\
&+ \beta_3 Plan + \beta_4 TrackLength + \beta_5 Difficulty \\
&+ \beta_6 Crowdedness + \beta_7 WaitTimes + \beta_8 Cableway \\
&+ \beta_9 Transport + \beta_{10} HourCar + \beta_{11} Locality \\
&+ \beta_{12} Accommodation + \beta_{13} Online + \beta_{14} School \\
&+ \beta_{15} KidsActivity + \beta_{16} KidsLift + \beta_{17} Attractions \\
&+ \beta_{18} Food + \beta_{19} Gender + \beta_{20} Age + \beta_{21} Education \\
&+ \beta_{22} Employed + \beta_{23} IncomeK)
\end{aligned}$$

5.4 Data description

472 respondents have filled out the questionnaire. The data set was then preprocessed. 18 answers in total have been removed due to missing values (in the question about income), suspicious answer choices, incoherency, or the lack of logical consistency. Consequently, 454 answers were left to analyze. The data set was then further processed to ensure its suitability for the model and subsequent analysis. For example, if there was a range given in the question about income, for example, 500-600€, the value was averaged. Moreover, answers were assigned to their corresponding values based on the given variable specifications.

42.7% of the respondents were women while 57.3% were men. The age of the respondents ranged from 10 years old to the oldest respondent being 71 years old. The age of 43 years had the highest frequency, with 26 respondents falling into this category. The following most frequent ages were 21 and 50, each reported by 16 participants. The average age of the questionees was 38.8 years, with the median age being equal to 40.

Figure 5.1: Age distribution of the respondents



Source: author's computations.

Only 0.5% of the respondents had no education or incomplete elementary education and 3.5% had completed elementary education, followed by 40% with high-school education and 56% with a university degree. About 2% of the participants stated that they were unemployed, followed by 3.5% pensioners, 15% entrepreneurs, and 16.5% students. The largest group was the employees, around 63%. The fact that most of the respondents were employed and that the median age was 40 years is plausible because of the characteristics of skiing and snowboarding. The lack of pensioners in the data set can be explained by the fact that skiing can be slightly physically demanding and unsafe; therefore, there might not be many older people on the slopes. In addition, there are not many children present in the data set because the purpose of this paper is to study willingness to pay, and therefore, such feedback was not relevant to the analysis.

In order to make sure data was not collected only from certain regions of the country, a question about residence was included. Around 40% of the responses indicated residence in the Košice region, followed by 18% in the Prešov region, around 14% in the Bratislava region, 8% in the Banská Bystrica region, 7% in the Žilina region, 5% in the Trenčín region and 4% in both the Nitra and the Trnava regions. It is, therefore, clear that answers were collected from every region. The differences in percentages across regions might be explained by several characteristics of said regions. Firstly, the Košice and Prešov regions have the most residents while the Trnava and Trenčín have the least. Moreover, the higher percentage from the Košice region compared to the Prešov region could be explained by its proximity to the High Tatras. Furthermore, Bratislava is the region with the highest value of the average monthly salary; therefore, it gained the third highest percentage despite its size, as skiing is one of the more expensive sports.

The median income of the questionees was 1000€, and the mean value was 1505.02€. However, after removing outliers from this observed variable, the median remained constant, while the mean value of the income decreased to 1222.82€.

Regarding the average trip to a resort, most of the answers indicated a visit that lasted 1 day (67%) followed by a trip for 2-3 days with 18% and, lastly, trips that lasted longer than 3 days, 15%. The trip itself was planned on the day of the trip by only 3% of the respondents. 29% had planned the trip the day before. The majority, 48%, have planned the trip between 2 days to a week in advance. The trip planning took place 2 or more weeks in advance in around 20% of the cases. While 60% of the respondents usually take the trip accompanied by family members and 28% go with friends, around 8.5% of the participants usually go alone. This question included an open-ended option for respondents to provide their own answers, and 3.5% of participants utilized this option. Some of the responses indicated that they typically visit a resort with their students or participate in ski club training. 96% of the respondents chose skiing or snowboarding as the most common purpose of their visit. Most of the remnant answers stated ski mountaineering or just supervising children.

Regarding the question about the dependent variable, the most favored option was Resort number 3, which gained a total of 139 votes, or 30.6%. Resort number 1 and number 4 followed with 124 and 123 votes accordingly, each amounting to about 27%. Lastly, Resort number 2 was chosen by only 15% of the respondents.

Table 5.2: Frequency of demographic variables

Variable	Frequency	Percentage
Gender		
Men	260	57.27%
Women	194	42.73%
Age		
0-15	4	0.88%
16-30	125	27.53%
31-45	191	42.07%
46-60	113	24.89%
60+	21	4.63%
Income		
0-750	125	27.53%
751-2000	279	61.46%
2001-5000	46	10.13%
5000+	4	0.88%
Occupation		
Unemployed	8	1.76%
Student	75	16.52%
Employee	286	63%
Entrepreneur	69	15.2%
Pensioner	16	3.52%
Education		
Without elementary	2	0.44%
Elementary	15	3.3%
High-school	182	40.09%
University degree	255	56.17%
Regions		
Bratislava	61	13.44%
Trnava	20	4.40%
Trenčín	24	5.29%
Nitra	19	4.18%
Žilina	33	7.27%
Banská Bystrica	37	8.15%
Prešov	80	17.62%
Košice	180	39.65%

Table 5.3: Likert scale variables

	TrackLength	Difficulty	Crowdedness	WaitTimes
0	17	13	3	10
1	78	63	44	51
2	235	226	151	156
3	124	152	256	237
	Cableway	Transport	HourCar	Locality
0	83	40	127	79
1	139	105	144	147
2	116	151	91	158
3	116	158	92	70
	Accommodation	Online	School	KidsActivity
0	150	144	279	258
1	118	132	103	116
2	95	104	36	59
3	91	74	36	21
	KidsLift	Attractions	Food	
0	258	175	47	
1	85	145	135	
2	59	95	177	
3	52	39	95	

This table, focusing on the Likert scale variables from the second part of the questionnaire, shows that most of the respondents do not like to wait longer than 5 minutes for the ski lifts, with very few respondents rating this factor as not important for them. The same can be said about crowdedness on the slopes. On the other hand, the presence of a ski school and activities for kids are not important for most respondents. The questions about the Cableway, Accommodation, HourCar, and Online variables had the most evenly distributed answers.

5.5 Predictions

Some expectations and relationships between variables might be predicted by further analyzing the data collected. The respondents have been divided into four groups based on their resort choice in order to possibly identify some patterns and dependencies. Tables with the distribution of the answers are included in Appendix B.

The only noticeable pattern among the variables from the first section of the questionnaire was present in the TripLength variable. A bigger share of respondents indicated longer trips if they chose the more expensive resorts. Consequently, we can predict this variable to have a positive effect, and it may also be statistically significant.

Secondly, some patterns were identified among the Likert scale variables. Zero was the highest frequency value regardless of the resort choice for the variables School and KidsActivity. As consumers did not perceive them as important when making a decision and the data did not have significant variability across resorts, it can be predicted that these variables would probably not be statistically significant. Each group of consumers had a different value with the highest frequency in the case of the HourCar variable. In the case of Resort 4, the majority of respondents expressed that this particular attribute was not crucial for their selection. However, among those who opted for the least expensive resort, this attribute was deemed very important by a significant portion of the respondents, representing the largest subgroup within that resort category. We can predict that this variable will be significant and its effect will be negative. The Food variable seems to have a similar distribution in the answers, with the value 2 chosen by most consumers. We can therefore conclude that this variable has a substantial chance of being insignificant. Additionally, the variables Crowdedness and WaitTimes also have similarly distributed values where Crowdedness was marked as important in most of the cases. These variables may also be shown as insignificant. Very few respondents marked the variables TrackLength and Difficulty as unimportant, with both variables becoming increasingly important with more expensive resort choices. A positive effect can be predicted for both of these variables as a result. In the case of the remaining variables, the author found no apparent patterns.

Regarding the demographic variables, respondents from the Košice region chose the cheaper resorts more often, while respondents from the Bratislava region usually chose the more expensive ones. Respondents with an average monthly salary below 750€ chose mostly Resort 1, while those with income above 5000€ chose only Resort 4. As a result, this variable might have a positive and statistically significant effect.

Chapter 6

Results

Before conducting the regression, outliers were identified and omitted from the data set. Only the variable Income had outliers. Afterward, the assumptions of ordinal logistic regression were verified. The assumptions of the explained variable being ordered and that at least one of the explanatory variables was categorical, ordinal, or continuous were met by the definition of these variables. The Brant test, the Likelihood Ratio Test, and the Variance Inflation Factor were used to test the necessary assumptions. The proportional odds assumption was violated in the full model. In addition, multicollinearity was also present in the model. These issues were targeted by comparing different models and assessing which variables caused these issues. The models used and the test results are inclded in Appendix B.

The presence of multicollinearity was not unexpected as some of the independent variables represented factors that were, to some extent, similar or were in some way related. For example, the variables Crowdedness and WaitTimes were found to be problematic. This might be explained by the fact that if a person does not like crowded slopes, they would probably negatively perceive longer lines for ski lifts, too. Another example was the pair of variables Plan and TripLength, as longer trips probably require more planning while shorter trips do not. Furthermore, the Age and Employed variables could be problematic due to the fact that students and pensioners are usually not employed. After eliminating variables that caused assumption violations, the model still contained statistically non-significant variables. To obtain the final model, a step-wise algorithm and model Akaike Information Criteria (AIC) values were utilized. As lower AIC is preferred, and this function penalizes for additional model features included, the variables which should be removed from the model without resulting in a significant loss of information were identified. This way, the significant features were selected, and the simplified model was chosen by a step-wise AIC algorithm.

Table 6.1: Full model estimation

	Dependent variable:
	Resort
TripLength	0.492***
	(0.173)
TrackLength	0.775***
	(0.157)
Difficulty	0.310**
	(0.148)
Transport	0.005
	(0.119)
HourCar	−0.442***
	(0.103)
Locality	0.335***
	(0.127)
Accommodation	−0.079
	(0.129)
Online	0.232**
	(0.102)
School	−0.064
	(0.136)
KidsActivity	−0.064
	(0.161)
KidsLift	−0.224*
	(0.128)
Attractions	0.014
	(0.126)
Food	0.120
	(0.128)
Gender	−0.136
	(0.217)
IncomeK	0.557***
	(0.143)
Observations	392
Note:	*p<0.1; **p<0.05; ***p<0.01

The final model:

$$\begin{aligned}P(Willingness = j|x) = G(&\beta_0 + \beta_1 TripLength + \beta_2 TrackLength\\&+ \beta_3 Difficulty + \beta_4 HourCar + \beta_5 Locality\\&+ \beta_6 Online + \beta_7 KidsLift + \beta_8 IncomeK)\end{aligned}$$

Table 6.2: Final model estimation

	Dependent variable:
	Resort
TripLength	0.441***
	(0.146)
TrackLength	0.765***
	(0.154)
Difficulty	0.292**
	(0.146)
HourCar	−0.438***
	(0.100)
Locality	0.341***
	(0.118)
Online	0.221**
	(0.096)
KidsLift	−0.276***
	(0.100)
IncomeK	0.586***
	(0.136)
Observations	392
Note:	*p<0.1; **p<0.05; ***p<0.01

The final model included 392 observations with the McFadden pseudo R^2 of 0.17 and statistical significance with $\chi^2 = 177.97$ and p-value 0.

A total of 8 variables were shown to be statistically significant. From the first part of the questionnaire, where further information about the average trip to a ski resort was requested, only one variable was shown to be statistically significant. This variable was TripLength, and it had a predicted effect with a positive sign. A total of 6 variables were shown to be significant in the second part of the questionnaire. These variables focused on how much consumers agreed with statements about the importance of individual resort attributes and services offered. These variables had both positive and negative effects. Variables TrackLength, Difficulty, Locality, and Online had positive effects. The positive and statistically significant effect of the length of the tracks is consistent with the findings in the literature (Falk, 2008; Alessandrini, 2012; Lien *et al.*, 2022). On the other hand, HourCar and KidsLift had a negative effect. Concerning the demographic variables incorporated in the final part of the questionnaire, only the variable IncomeK was shown to be statistically significant in addition to having a positive effect predicted.

The final model selected based on the AIC includes all variables where coefficients were shown to be statistically significant at the 0.1 significance level. Variables that were not shown to be statistically significant in the full model with a positive effect were Transport, Attractions, and Food. Non-significant variables with negative effects were Accommodation, School, KidsActivity, and Gender.

Changes in the log-odds of advancing to a higher category as opposed to remaining in the current one for a one-unit change in the independent variable, assuming the ceteris paribus, are given by the model coefficients. For a one-unit rise in the variable TripLength, the log odds of moving to a higher category (choosing a more expensive resort in this case) increase by 0.44. The log odds also increase in case of a one-unit rise in the TrackLength variable by 0.765; in the Difficulty variable by 0.292; in the Locality variable by 0.341; in the Online variable by 0.221; and in the case of the IncomeK variable by 0.586. Meanwhile, the log odds decrease with a one-unit increase in the variable HourCar by 0.438 and in the variable KidsLift by 0.276. Nevertheless, the interpretation of these values is somewhat difficult to understand and not very intuitive.

6.1 Odds ratio

The odds ratio (OR) for every significant variable is shown in the following table:

Table 6.3: Odds ratio values for the final model's coefficients

Variable	TripLength	TrackLength	Difficulty	HourCar
OR	1.554	2.149	1.339	0.645
Variable	Locality	Online	KidsLift	IncomeK
OR	1.406	1.247	0.759	1.797

Employing the ceteris paribus, meaning keeping other variables except for the one we are focusing on constant, the odds ratio values have the following interpretation: if the odds ratio is higher than one, then with a one-unit increase in the independent variable, the odds of progressing to a higher category increase. If the value is smaller than one, then the odds decrease. Finally, if the odds ratio is exactly one, then the independent variable may not have an effect on the odds of moving to a higher category. None of the odds ratios for the regressors are equal to one; therefore, they all have an effect on the odds of moving up to a higher category of the regressand. With a one-unit increase in the length of the average trip to a ski resort for a customer, their odds of moving up to a higher category versus the combined lower categories are 1.554 times greater. Skiers who usually visit the resort for extended periods are likelier to belong to a higher resort category.

With a one-unit increase in the TrackLength, the odds of moving up to a higher category increase 2.15 times. This suggests that if the length of the downhill tracks is more important for a consumer, then they are 2.15 times more likely to belong to a higher resort category. 1.34 times increased odds of advancing to a higher category were present in the case of the Difficulty variable. Visitors who are more choosy about the type of slopes usually belong to the higher-ranked categories. A one-unit increase in the Locality variable leads to 1.4 times higher odds of moving up a category. Consumers who were more selective regarding the resort's locality had greater odds of moving up a category. On the other hand, with a one-unit increase in the HourCar or KidsLift variables, the odds of moving up to a higher category decreased 0.65 times in the case of the HourCar variable and 0.76 times in the case of the KidsLift variable. Consumers who valued a lift for kids in the resort or the closeness of the resort more were less likely to belong to a higher category. For skiers who appreciate the opportunity to buy tickets online more, the odds of moving up a category rise by a factor of 1.25 with a unit increase in the Online variable.

Regarding the demographic variables, a one-unit increase in the IncomeK variable, equivalent to an increase in the average monthly salary by 1000€, the odds of moving up to a higher category increase by a factor of 1.8. This result is quite intuitive as resorts in the higher category tend to be more expensive, and visitors with higher incomes are more likely to be able to afford them.

6.2 Limitations

One of the most significant limitations of this thesis is the data collected. The process of collecting the data utilizing an online questionnaire has many drawbacks. Firstly, the questionnaire was distributed online, which means people without an internet connection could not participate. In addition, the questionnaire was mainly distributed through Facebook groups. Notwithstanding the fact that chosen groups were focused on winter sports enthusiasts to ensure that the respondents were mainly people visiting these resorts, mainly members of these groups were given the opportunity to answer this questionnaire. Therefore, we do not have a random selection, and the results might suffer from sampling bias. Consequently, the findings may not be generalizable to the whole population of Slovakia. Secondly, the questionnaire was distributed online so respondents could answer the questions untruthfully and there would be no way to identify these answers were they not too noticeable. Additionally, non-response and self-selection bias might also be present as only people who wanted to responded to the questionnaire. These people might have had certain characteristics that those who did not participate did not have and, for that reason, would have created bias. Thirdly, respondents could have overemphasized or underemphasized their willingness to pay or preferences in question for various reasons, as it is difficult to assess one's own preferences. Idiosyncratic preferences, also known as individual preferences, which are specific to an individual and might not conform to the preferences of the general public, could also lead to biased results. Furthermore, a part of the participants might have misunderstood some questions and biased the results. Another problem might be caused by the season variability of the demand for ski passes, so the timing of when the questionnaire was sent out could have had an impact on the results as respondents might answer them differently in the winter season when they actively visit the resorts and outside of the season. Finally, as the predicted variable was of ordinal nature, the depth of insight of such analysis was limited, and the results were less intuitive than if a different approach was utilized.

Chapter 7

Conclusion

This thesis examined consumers' willingness to pay for ski passes in Slovakia. The main objective was to identify the pivotal factors influencing their WTP. Ordinal logistic regression was utilized for the analysis.

Data for this thesis was collected by distributing a self-developed anonymous online questionnaire. Respondents chose one of the four resorts presented with different attribute levels and prices at the beginning of the questionnaire based on their usual ski resort visit. Afterward, the questionnaire was divided into three parts. In the first part, they answered four questions concerning their usual resort visit. Secondly, the participants assigned the magnitude of importance to variables on a Likert scale, with 0 meaning not important and 3 meaning very important. The final section was dedicated to gathering demographic information from the participants.

The only statistically significant variable from the first section of the questionnaire was TripLength, illustrating the usual length of the trip. It was shown to have a positive effect. Regarding the second section containing variables on the Likert scale, variables shown to be statistically significant with a positive effect described the length of all tracks in a resort in km (TrackLength), the difficulty of the slopes (Difficulty), the option to buy a ski pass online (Online), and the characteristics of the resort's locality (Locality). The convenience of an online purchase of ski passes seems to be valued by consumers as the Online variable has a positive effect. Resort managers could utilize this finding and invest in improving their digital services and online ticket-selling systems in order to improve visitors' satisfaction and stimulate their willingness to pay. Statistically significant but with a negative effect were the variables HourCar, describing whether it is possible for the respondent to arrive at the resort by car in less than an hour, and KidsLift, marking the presence of a lift for children in the resort. On the other hand, the variables describing the quality of access to the resort (Transport), the quality of food (Food), and the presence of other attractions like wellness (Attractions) had a positive effect but were not shown to be statistically significant. The non-significant variables with a negative effect included the presence of accommodating facilities in the resort or nearby (Accommodation), the presence of a ski school or rental shop in the resort (School), and the presence of activities for children (KidsActivity). The fact that the variable KidsActivity was shown to have a non-significant effect implies that child-friendly services may not be one of the primary factors considered when choosing a resort. However, offering such facilities could still prove to be valuable in attracting a certain group of skiers. From the demographic variables, only the respondents' income in thousands of euros (IncomeK) was revealed to be statistically significant with a positive effect. This highlights the importance of targeting richer consumers with special offers and experiences and utilizing segmenting pricing strategies. On the other hand, the variable Gender with a negative effect was not statistically significant. While some of the variables did not show statistical significance (Food, Attractions, Transport), they still had a positive effect on the WTP and, therefore targeting these factors could contribute to customers' loyalty and satisfaction despite their non-significant degree of impact on visitors' decisions.

The most prominent limitation of this thesis was the data collection process itself. As it is difficult to achieve a random selection perfectly representative of the population, the results might be, to some extent, biased. Therefore, the interpretation of the findings should be considered with keeping this limitation in mind.

Ski resort managers and policymakers could draw inspiration from these results and, consequently, make an informed decision about which factors of the resort to target and improve in order to upgrade visitors' experience and their WTP. Policymakers could leverage this information to support sustainable development in the industry and support the expansion and prosperity of ski tourism in Slovakia.

A possible extension of the approach used could be, for example, cross-validating and comparing the model to different regression models in order to assess its robustness. Moreover, additional predictors could be incorporated into the analysis, for example, weather conditions or skiing proficiency. Furthermore, the impact of economic conditions influencing the WTP or conducting the analysis regionally could yield valuable insights into the dynamics of ski tourism in Slovakia.

The contribution of this thesis is its focus on consumers from Slovakia, as no other study measuring consumers' willingness to pay for ski passes involved Slovakia, to the author's best knowledge. Consequently, there are numerous opportunities for additional research to expand the topic and provide a more comprehensive analysis of the results obtained in this thesis.

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Appendix A

Online questionnaire

Dotazník o voľbe lyžiarskeho strediska pre voľnočasové aktivity na Slovensku (Questionnaire on choosing a ski resort for leisure activities in Slovakia)

Vážení respondenti,
som študentkou Inštitútu ekonomických štúdií na Karlovej Univerzite v Prahe.
Tento anonymný dotazník o

voľbe lyžiarskeho strediska pre voľnočasové aktivity na Slovensku slúži na zber dát k mojej bakalárskej práci.
Vopred ďakujem za Váš čas!
(Dear respondents,
I am a student at the Institute of Economic Studies at Charles University in Prague.
This anonymous questionnaire about the choice of a ski resort for leisure activities in Slovakia serves to collect data for my bachelor's thesis.
Thank you in advance for your time!)

* Označuje povinnú otázku

Výber strediska (The resort choice)

V tejto časti dotazníka Vám budú predstavené parametre 4 lyžiarskych stredísk a cena celodenného skipasu. Vyberte, prosím, pre Vás najviac lákavú ponuku. (

In this part of the questionnaire, you will be presented with the parameters of 4 ski resorts and the price of a one day ski pass. Please choose the most attractive offer for you.)

1. Pri danej cene skipasu by som najviac pravdepodobne navštívil/a stredisko: *
(Given the price of the ski pass, I would most likely visit the resort:)

Označte iba jednu elipsu.

1 zjazdovka (1,2km)
3 vleky
vrchol 810 m n. m.
1 reštaurácia
celodenný skipas:
15 €

- Stredisko 1

3 zjazdovky (1,5km)
7 vlekov
vrchol 705 m n. m.
2 reštaurácie
celodenný skipas:
30 €

- Stredisko 2

8 zjazdoviek (8km)
2 lanovky, 6 vlekov
vrchol 1160 m n. m.
6 reštaurácií
celodenný skipas:
39 €

- Stredisko 3

13 zjazdoviek (12km)
7 lanoviek, 3 vleky
vrchol 2634 m n. m.
7 reštaurácií
celodenný skipas:
49 €

- Stredisko 4

Doplňujúce otázky (Additional questions)

Odpovedzte prosím na nasledujúce otázky: (Please answer the following questions:)

2. Najčastejšie chodievam do lyžiarskeho strediska: *
(I usually go to the ski resort to):

Označte iba jednu elipsu.

- Lyžovať (ski)
- Snowboardovať (snowboard)
- Iné: ______________________

3. Najčastejšie chodievam do lyžiarskeho strediska: (I usually visit the ski resort): *

Označte iba jednu elipsu.

- Na 1 deň (for 1 day)
- Na 2-3 dni (for 2-3 days)
- Na viac ako 3 dni (for more than 3 consecutive days)

4. Najčastejšie chodievam do lyžiarskeho strediska: (I usually visit the ski resort): *

Označte iba jednu elipsu.

- Sám (by myself)
- S rodinou (with my family)
- S priateľmi (with friends)
- Iné: ______________________________

5. Návštevu lyžiarskeho strediska väčšinou plánujem: (I usually plan the ski resort visit): *

Označte iba jednu elipsu.

- V ten deň (that day)
- Deň vopred (the day before)
- 2-5 dní vopred (2-5 days in advance)
- Týždeň vopred (a week in advance)
- 2-3 týždne vopred (2-3 weeks in advance)
- Mesiac vopred (a month in advance)
- Viac ako mesiac vopred (more than a month in advance)

Výber odpovede zo škály

Označte prosím, do akej miery sú pre Vás dôležité nasledujúce parametre pri výbere lyžiarskeho strediska:
(

Please indicate to what extent are the following parameters important to you when choosing a ski resort):

Význam škály:
0= nedôležité
1= menej dôležité
2= dôležité
3= veľmi dôležité
(The meaning of the scale: 0= not important at all, 1=a little bit important, 2= important, 3=very important)

6. Dĺžka zjazdoviek je pre mňa veľmi dôležitá: (the length of the downhill tracks is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité) (no, not important)

0 ⬭

1 ⬭

2 ⬭

3 ⬭

áno (veľmi dôležité) (yes, very important)

7. Náročnosť zjazdoviek je pre mňa veľmi dôležitá: (the difficulty of the downhill tracks is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)

0 ⬭

1 ⬭

2 ⬭

3 ⬭

áno (veľmi dôležité)

8. Množstvo lyžiarov na zjazdovkách je pre mňa dôležité: (the crowdedness of the tracks is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)

0 ⬭

1 ⬭

2 ⬭

3 ⬭

áno (veľmi dôležité)

9. Čakacie doby kratšie ako 5 minút na vleky a lanovky sú pre mňa veľmi dôležité: (waiting times for ski lifts shorter than 5 minutes are very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)

0 ⬭

1 ⬭

2 ⬭

3 ⬭

áno (veľmi dôležité)

10. Výskyt sedačkovej alebo kabínkovej lanovky v stredisku je pre mňa veľmi dôležitý: (whether the resort has a above-ground cablecar or ski cableway is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)

0 ⬭

1 ⬭

2 ⬭

3 ⬭

áno (veľmi dôležité)

11. Dobrá dopravná dostupnosť (blízkosť diaľnice, kvalitné cesty, autobusy, vlaky, parkovanie) je pre mňa veľmi dôležitá: (the quality of access to the resort including parking, trains, buses, highways or the condition of roads is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)

0 ◯

1 ◯

2 ◯

3 ◯

áno (veľmi dôležité)

12. Je pre mňa dôležité, aby bolo stredisko do 1 hodiny dojazdu autom od miesta môjho bydliska: (It is important fot me that it is possible to arrive to the resort by car in less than an hour): *

Označte iba jednu elipsu.

nie (nedôležité)

0 ◯

1 ◯

2 ◯

3 ◯

áno (veľmi dôležité)

13. Lokalita, v ktorej sa stredisko nachádza je pre mňa dôležitá (nadmorská výška, národný park, okolie, prírodné krásy) : (the locality in which the resort is situated including the surroundings, altitude, whether it is situated in a national park or the beauty of nature in the region is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)
0 ◯
1 ◯
2 ◯
3 ◯
áno (veľmi dôležité)

14. Možnosť ubytovania sa v okolí lyžiarskeho strediska je pre mňa veľmi dôležitá: (whether accommodation is available in the resort or its proximity is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)
0 ◯
1 ◯
2 ◯
3 ◯
áno (veľmi dôležité)

15. Možnosť zakúpenia skipasu online je pre mňa veľmi dôležitá: (whether skipases can be bought online is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)

0 ◯

1 ◯

2 ◯

3 ◯

áno (veľmi dôležité)

16. Prítomnosť lyžiarskej školy a požičovne v stredisku je pre mňa veľmi dôležitá: (whether there is a ski school and ski gear rental shop in the resort is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)

0 ◯

1 ◯

2 ◯

3 ◯

áno (veľmi dôležité)

17. Prítomnosť atrakcií pre deti v stredisku je pre mňa veľmi dôležitá: (whether there are activities for children present in the resort is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)
0 ⬭
1 ⬭
2 ⬭
3 ⬭
áno (veľmi dôležité)

18. Prítomnosť detského vleku v stredisku je pre mňa veľmi dôležitá: (whether there is a children's ski lift or a magic carpet in the resort is very important for me): *

Označte iba jednu elipsu.

nie (nedôležité)
0 ⬭
1 ⬭
2 ⬭
3 ⬭
áno (veľmi dôležité)

19. Dostupnosť doplnkových atrakcií (napr. wellness, ľadová plocha...) v stredisku (alebo v jeho blízkosti) v prípade nepriaznivého počasia je pre mňa veľmi dôležitá: (whether there are other attractions like wellness, an ice rink or others in case of bad weather in the resort or in it's proximity is very important for me): *

Označte iba jednu elipsu.

	nie (nedôležité)
0	⬭
1	⬭
2	⬭
3	⬭
	áno (veľmi dôležité)

20. Kvalita jedla v stredisku je pre mňa veľmi dôležitá: (the quality of food in the resort's restaurants is very important for me): *

Označte iba jednu elipsu.

	nie (nedôležité)
0	⬭
1	⬭
2	⬭
3	⬭
	áno (veľmi dôležité)

Demografické otázky (Demogrphics)

21. Pohlavie: (gender) *

Označte iba jednu elipsu.

- Žena (female)
- Muž (male)
- Iné: ____________________

22. Vek: (age) *

____

23. Najvyššie ukončené vzdelanie: (Highest completed education) *

Označte iba jednu elipsu.

- Bez vzdelania alebo neúplné základné vzdelanie (without education or not complete elementary education)
- Základné (elementary)
- Stredoškolské (high-school)
- Vysokoškolské (university)

24. Pracovný stav: (occupation) *

Označte iba jednu elipsu.

- Študent (student)
- Zamestnanec (employee)
- Podnikateľ (entrepreneur)
- Nezamestnaný (unemployed)
- Dôchodca (pensioner)

25. V akom rozmedzí sa nachádza Váš čistý mesačný príjem? (± 100 €) *
(My net monthly income is (± 100 €))

26. Bývam v: (I live in the region): *

Označte iba jednu elipsu.

- Bratislavskom kraji (Bratislava region)
- Trnavskom kraji (Trnava region)
- Trenčianskom kraji (Trenčín region)
- Nitrianskom kraji (Nitra region)
- Žilinskom kraji (Žilina region)
- Banskobystrickom kraji (Banská Bystrica region)
- Prešovskom kraji (Prešov region)
- Košickom kraji (Košice region)

Ďakujem za vyplnenie! (Thank you for completing the questionnaire!)

Appendix B

Results

B.1 Models

- model1 = Resort~TripLength+ Company+ Plan+ TrackLength+ Difficulty+ Crowdedness+ WaitTimes+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Genger+ Age+ Education+ Employed+ Income
- n02 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income
- n03 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes
- n04 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes+ Crowdedness
- n05 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes+ Age
- n06 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes+ Age+ Education

- n07 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes+ Age+ Education+ Employed
- n08 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes+ Age+ Education+ Difficulty
- n09 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes+ Age+ Education+ Difficulty+ TrackLength
- n10 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes+ Age+ Education+ Difficulty+ TrackLength+ TripLength
- n11 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes+ Age+ Education+ Difficulty+ TrackLength+ TripLength+ Plan
- n12 = Resort~Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ WaitTimes+ Age+ Education+ Difficulty+ TrackLength+ TripLength+ Company
- a1 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income
- a2 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ Age
- a3 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ Age+ Education

- a4 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ Age+ WaitTimes
- a5 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ Age+ WaitTimes+ TrackLength
- a6 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ Age+ WaitTimes+ TrackLength+ Difficulty
- d1 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income
- d2 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ TrackLength
- d3 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ TrackLength+ Difficulty
- d4 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ TrackLength+ Difficulty+ WaitTimes
- d5 = Resort~TripLength+ Cableway+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ TrackLength+ Difficulty+ Age
- f1 = Resort~TripLength+ Transport+ HourCar+ Locality+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ TrackLength+ Difficulty
- f2 = Resort~TripLength+ Transport+ HourCar+ Accommodation+ Online+ School+ KidsActivity+ KidsLift+ Attractions+ Food+ Gender+ Income+ TrackLength+ Difficulty

- finalmodel = Resort ~ TripLength + HourCar + Locality + Online + KidsLift + IncomeK + TrackLength + Difficulty

B.2 Marginal Effects

To interpret the parameters, the partial or marginal effects are used. A unit change in x does not lead to a $\hat{\beta}$ change in y with the nonlinear models. The partial effect at the average PEA and the average marginal/partial effect (AME/APE) are used to get a measure of the partial effects. To determine the partial effect at the average, these marginal effects are calculated on the sample averages for all x:

$$PEA = g(\hat{\beta}_0 + \hat{\beta}_1 \overline{x_{1i}} + ... + \hat{\beta}_k \overline{x_{ki}})\hat{\beta}_j$$

The main difficulties with the partial effect at the average include the uncertainty in the correct choice of approach when a continuous explanatory variable is in the form of a nonlinear function (can be either a quadratic or a natural logarithm). It is not clear whether to plug the average into the nonlinear function or just take the average of the whole function, specifically with a log variable, whether to take the log of the average or the average of the log. In addition, regarding binary explanatory variables, for example, gender, the interpretation becomes difficult as the averages of discrete variables may not represent anyone in the sample or the population. Concerning the interpretation of the PEA, an increase or decrease in the probability that the outcome corresponding to $y = 1$ will occur by the estimated value will be caused by a unit increase of the average of x_j while keeping other predictors constant at their average values.

Alternatively, the average marginal effect is computed by taking the partial effect at the average for each observation and then taking the average across the sample:

$$APE = \frac{1}{n}\sum_{i=1}^{n} g(\hat{\beta}_0 + \hat{\beta}_1 \overline{x_{1i}} + ... + \hat{\beta}_k \overline{x_{ki}})\hat{\beta}_j$$

The average marginal effect is interpreted as the average estimated increase or decrease in the probability that $y = 1$ when y_i increases by one unit, while all other predictor variables are held constant at their average values. The average partial effect offers a different measure of the relationship between the explanatory variables and the logistic regression model's outcomes, conveying distinct information from the odds ratio values.

Table B.1: APE values for the final model's coefficients

Variable	TripLength	TrackLength	Difficulty	HourCar
APE	0.04	0.07	0.03	-0.04
Variable	Locality	Online	KidsLift	IncomeK
APE	0.03	0.02	-0.03	0.05

The APE values represent the average change in probability of the outcome variable for fluctuations in the independent variables, keeping other factors constant. A one-unit increase in the HourCar and KidsLift variables lead to a decrease in the probability of belonging to a higher resort category by 0.07 and 0.04, respectively. On average, a one-unit increase in the independent variables Difficulty and Locality increases the average probability of belonging to a higher resort category by 0.03. For an additional unit increase, the average likelihood of advancing to a higher category increases by 0.04 for the TripLegth variable, by 0.07 for the TrackLength variable, by 0.02 for the Online variable, and, finally, increase by 0.05 for a 1000€ increase in the IncomeK variable.

B.3 Tests and variables

Table B.2: LR Test Results

Likelihood Ratio Test	Chisq	Pr(>Chisq)
lrtest(n02, n03)	3.7448	0.05297.
lrtest(n04, n03)	1.7439	0.1866
lrtest(n03, n05)	3.4902	0.06173.
lrtest(n05, n06)	3.5432	0.05979.
lrtest(n06, n07)	0.0023	0.962
lrtest(n06, n08)	8.3765	0.003801**
lrtest(n08, n09)	15.794	7.062e-05***
lrtest(n09, n10)	8.7249	0.003139**
lrtest(n10, n11)	2.0123	0.1561
lrtest(n10, n12)	0.9633	0.3264
lrtest(a1, a2)	2.9317	0.08685.
lrtest(a2, a3)	2.6558	0.1032
lrtest(a2, a4)	3.5119	0.06093.
lrtest(a4, a5)	21.94	2.813e-06***
lrtest(a5, a6)	3.5006	0.06135.
lrtest(d1, d2)	25.233	5.079e-07***
lrtest(d2, d3)	4.1035	0.04279*
lrtest(d3, d4)	1.101	0.294
lrtest(d3, d5)	1.1783	0.2777
lrtest(f2, f1)	7.0824	0.007784**

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table B.3: VIF Estimation for Predictor Variables

Predictor Variable	VIFmodel1	VIFn10	VIFa6	VIFd3	VIFf1	VIFfinal
TripLength	5.87	4.68	4.67	1.52	1.53	1.09
Cableway	2.65	2.65	2.63	1.22	-	-
Transport	4.43	4.41	4.42	1.30	1.29	-
HourCar	3.07	2.91	2.86	1.25	1.24	1.15
Locality	3.36	3.38	3.35	1.39	1.38	1.21
Accommodation	3.29	3.24	3.22	2.09	2.08	-
Online	2.21	2.23	2.23	1.30	1.26	1.11
School	2.14	2.10	2.07	1.61	1.61	-
KidsActivity	2.87	2.84	2.84	1.97	1.97	-
KidsLift	2.79	2.80	2.78	1.87	1.86	1.12
Attractions	2.44	2.44	2.42	1.53	1.51	-
Food	4.19	4.02	4.00	1.31	1.30	-
Gender	2.31	2.33	2.36	1.20	1.20	-
Income	4.08	3.51	3.14	1.16	1.15	1.03
WaitTimes	8.49	6.94	6.91	-	-	-
TrackLength	6.69	6.66	6.59	1.23	1.21	1.15
Difficulty	6.80	6.49	6.37	1.12	1.13	1.10
Company	6.28	-	-	-	-	-
Plan	6.51	-	-	-	-	-
Crowdedness	10.60	-	-	-	-	-
Age	9.33	8.96	8.03	-	-	-
Education	15.46	13.75	-	-	-	-
Employed	5.85	-	-	-	-	-

Table B.4: Brant test for model d3

	X2	df	probability
Omnibus	53.17	32.00	0.01
TripLength	1.42	2.00	0.49
Cableway	12.10	2.00	0.00
Transport	3.51	2.00	0.17
HourCar	2.57	2.00	0.28
Locality	7.69	2.00	0.02
Accommodation	3.76	2.00	0.15
Online	3.12	2.00	0.21
School	2.25	2.00	0.32
KidsActivity	0.30	2.00	0.86
KidsLift	0.65	2.00	0.72
Attractions	0.93	2.00	0.63
Food	0.49	2.00	0.78
Gender	0.05	2.00	0.97
Income	0.17	2.00	0.92
TrackLength	4.16	2.00	0.13
Difficulty	1.30	2.00	0.52

Table B.5: Brant test for model f1

	X2	df	probability
Omnibus	42.33	30.00	0.07
TripLength	0.80	2.00	0.67
Transport	4.41	2.00	0.11
HourCar	3.13	2.00	0.21
Locality	5.83	2.00	0.05
Accommodation	3.42	2.00	0.18
Online	3.24	2.00	0.20
School	2.36	2.00	0.31
KidsActivity	0.28	2.00	0.87
KidsLift	0.69	2.00	0.71
Attractions	1.28	2.00	0.53
Food	0.49	2.00	0.78
Gender	0.05	2.00	0.98
Income	0.52	2.00	0.77
TrackLength	4.83	2.00	0.09
Difficulty	1.51	2.00	0.47

Table B.6: Frequency of variables with trip details based on resort choice

Plan	**Resort 1**	**Resort 2**	**Resort 3**	**Resort 4**
On that day	8	0	3	2
1 day before	58	17	31	25
2-5 days in advance	39	32	43	38
1 week in advance	12	10	23	20
2-3 weeks before	1	4	16	11
1 month in advance	4	2	14	10
> 1 month in advance	2	3	9	17
Company	**Resort 1**	**Resort 2**	**Resort 3**	**Resort 4**
Visit alone	4	2	4	5
With family	14	1	14	10
With friends	76	52	79	66
Else	30	13	42	42
Trip Length	**Resort 1**	**Resort 2**	**Resort 3**	**Resort 4**
1 day trip	107	52	88	57
2-3 days trip	11	10	30	31
> 3 days	6	6	21	35

Table B.7: Likert scale variables- Resort1

	TrackLength	Difficulty	Crowdedness	WaitTimes
0	10	9	3	5
1	48	25	14	23
2	55	61	44	40
3	11	29	63	56
	Cableway	Transport	HourCar	Locality
0	46	21	14	35
1	44	31	38	47
2	23	39	30	35
3	11	33	42	7
	Accommodation	Online	School	KidsActivity
0	68	59	78	68
1	31	38	28	33
2	14	17	12	17
3	11	10	6	6
	KidsLift	Attractions	Food	
0	59	65	20	
1	24	32	45	
2	22	18	42	
3	19	9	17	

Table B.8: Likert scale variables- Resort2

	TrackLength	Difficulty	Crowdedness	WaitTimes
0	2	3	0	2
1	13	12	4	8
2	43	34	23	29
3	10	19	41	29
	Cableway	Transport	HourCar	Locality
0	18	2	16	9
1	20	13	15	17
2	21	29	23	37
3	9	24	14	5
	Accommodation	Online	School	KidsActivity
0	18	17	35	29
1	20	17	21	20
2	17	25	5	14
3	13	9	7	5
	KidsLift	Attractions	Food	
0	31	20	3	
1	15	23	20	
2	11	19	30	
3	11	6	15	

Table B.9: Likert scale variables- Resort3

	TrackLength	Difficulty	Crowdedness	WaitTimes
0	2	1	0	1
1	10	12	11	12
2	83	79	47	53
3	44	47	81	73

	Cableway	Transport	HourCar	Locality
0	13	8	47	24
1	39	27	51	51
2	42	49	22	44
3	45	55	19	20

	Accommodation	Online	School	KidsActivity
0	38	38	84	83
1	42	38	35	38
2	29	41	10	15
3	30	22	10	3

	KidsLift	Attractions	Food	
0	85	50	13	
1	28	52	42	
2	12	28	55	
3	14	9	29	

Table B.10: Likert scale variables- Resort4

	TrackLength	Difficulty	Crowdedness	WaitTimes
0	3	0	0	2
1	7	14	15	8
2	54	52	37	34
3	59	57	71	79

	Cableway	Transport	HourCar	Locality
0	6	9	50	11
1	36	34	40	32
2	30	34	16	42
3	51	46	17	38

	Accommodation	Online	School	KidsActivity
0	26	30	82	78
1	25	39	19	25
2	35	21	9	13
3	37	33	13	7

	KidsLift	Attractions	Food	
0	83	40	11	
1	18	38	28	
2	14	30	50	
3	8	15	34	

Table B.11: Frequency of demographic variables based on resort choice

Education	Resort 1	Resort 2	Resort 3	Resort 4
Without elementary	0	1	1	0
Elementary	2	7	2	4
High school	62	19	55	46
University degree	60	41	81	73
Occupation	**Resort 1**	**Resort 2**	**Resort 3**	**Resort 4**
Unemployed	3	0	4	1
Student	15	14	25	21
Employee	78	41	88	79
Entrepreneur	19	10	20	20
Pensioner	9	3	2	2
Region	**Resort 1**	**Resort 2**	**Resort 3**	**Resort 4**
Bratislava	4	6	26	25
Trnava	4	3	7	6
Trenčín	4	4	7	9
Nitra	3	2	10	4
Žilina	5	5	8	15
Banská Bystrica	6	6	15	10
Prešov	24	15	25	16
Košice	74	27	41	38
Gender	**Resort 1**	**Resort 2**	**Resort 3**	**Resort 4**
Female	45	28	56	65
Male	79	40	83	58
Age	**Resort 1**	**Resort 2**	**Resort 3**	**Resort 4**
0-15	1	2	1	0
16-30	30	16	41	38
31-45	51	34	63	43
46-60	32	13	30	38
60+	10	3	4	4
Income	**Resort 1**	**Resort 2**	**Resort 3**	**Resort 4**
0-750	44	22	35	24
751-2000	72	38	91	78
2001-5000	8	8	13	17
5000+	0	0	0	4