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Factors Influencing the Frequency and Continued Use of Ride-Hailing Apps in Portugal

Beyond UTAUT2: Exploring the Drivers of Ride-Hailing Usage in Portugal

Afonso Turégano Caetano Morão Lourenço

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

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by

Afonso Turégano Caetano Morão Lourenço

Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Marketing Intelligence

Supervised by

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisboa, 15/07/2024

DEDICATION

This thesis is dedicated to my family, specially my mom and dad for all the love, support and patience they have provide for me for many years, a special thanks for never giving up on me and believing in me. Also to my brother for always giving me the best advices and for being a great example of an older brother.

Also I would like to dedicate this thesis to my girlfriend, for all the love that you provide me and for making every day happier for me. Life is much more colorful with you by my side.

Thank you for everything I am very lucky to have all of you by my side.

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ABSTRACT

This thesis examines the factors influencing the continued use and frequency of use of ride-hailing apps in Portugal. The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) was the model used, alongside with additional constructs such as Perceived Safety, Environmental Awareness, and Accuracy. Despite the popularity of ride-hailing services globally, there is a notable gap in the research focusing on the specific drivers of user behavior inside the Portuguese market. This study aims to fill this gap by exploring how various psychological and situational factors impact users' intentions to continue using ride-hailing apps and their actual usage frequency. Data was collected through a structured questionnaire using Qualtrics, the survey had 219 valid responses of Portuguese ride-hailing users, the results were analyzed using Smart PLS. This thesis contributes for a better understanding of the factors influencing ride-hailing continued use and frequency of use in the Portuguese Market. The findings from this study suggest that performance Expectancy and habit were the main predictors of both the intention to continue using and the frequency of use of ride-hailing. Also significant with the users intention to continue using ride-hailing was indirectly accuracy, and directly effort expectancy and value for price. The constructs environmental awareness, social influence and perceived safety risk were not significant with the users intention to continue using the application and the frequency of use.

KEYWORDS

Ride-Hailing Apps; UTAUT2; User Behavior; Technology Use; Portugal

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

Acronym A Explanation of acronym A Explanation of acronym A Explanation of acronym A Explanation of acronym A Explanation of acronym A Explanation of acronym A

Acronym B Explanation of acronym B Explanation of acronym B Explanation of acronym B Explanation of acronym B Explanation of acronym B Explanation of acronym B

1. INTRODUCTION

Ride-hailing services allow to “dynamically match drivers supply and customers demand and allow customers to hire drivers to send them to destinations through online ride-hailing platforms” (Chen et al., 2023). This type of services have become a crucial element of the urban transportation framework, significantly facilitating residents' travel needs while also influencing new commuting behaviors and broadening the range of mobility options in cities (Liu et al., 2022).

Ride-hailing services are also known as on-demand ride services or transportation network companies (TNC’s) is one of the most rapidly growing forms of shared-mobility services, Ride-hailing platforms have revolutionized transportation by allowing passengers to book rides, monitor drivers’ real-time location, handle payments, and evaluate their trip all through a mobile app, none of these features had been available before in taxi services before the spread of ride-hailing services (Alemi et al., 2019).

Uber's (Uber Technologies, Inc. - Financials, 2022.) financial report from 2021 to 2022, Uber grew its revenue by 83%, their trips by 20% and its Monthly Active Platform Consumers (“MAPCs”) grew by 11%. According to (Ride-Hailing - Worldwide / Statista Market Forecast, 2024.) , the number of ride-hailing users is expected to reach 1.97bn by 2028 and their revenue is expected to reach US$167.60bn by the end of this year and US$212.80bn by 2029.

Ride-Hailing Portugal in Portugal (Ride-Hailing - Portugal / Statista Market Forecast, 2024) its anticipated that in this year 2024, this market reaches US$109.80m in Revenue. In addition, an expected yearly increase (CAGR 2024-2028) of 3.02% is anticipated for the revenue, translating into a projected market volume of US$123.70m by 2028. With a predicted user penetration of 20.4% in 2024 and 22.4% by 2028, the market is predicted to have 2.27 million users by that time.

Similar studies have been conducted on understanding the use and the frequency of use of ride-hailing apps in many different countries like the United States (Alemi, Circella, Handy, et al., 2018; Lavieri & Bhat, 2019), Spain (Gomez et al., 2021), Chile (Tirachini & del Río, 2019) Mexico (Sabogal-Cardona et al., 2021) and Ghana (Acheampong et al., 2020). There is a significant gap in the literature and fair as my knowledge goes there is no existent studies that analyze the drivers of use and use frequency of ride-hailing applications in the Portuguese context. According to (Gomez et al., 2021) there is a need for more studies to extend the research of the factors determining ride hailing usage in other European countries and we want to fill this gap of the literature in this study.

The focus of many researches is the adoption of ride-hailing (Acheampong et al., 2020; Alemi, Circella, Handy, et al., 2018; Gomez et al., 2021) however this type of services and platforms are available in Portugal since 2014 and are widely used in the country with approximately 2 million users (Ride-Hailing - Portugal / Statista Market Forecast, 2024), the adoption phase is probably outdated, in this study we want to also address this gap, regarding what drives the users to continue using this type of services in the Portuguese market.

This research investigates the factors influencing the continued use and frequency of use of ride-hailing apps in Portugal. Utilizing the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model (Venkatesh et al., 2012), the study integrates additional constructs such as Perceived Safety, Environmental Awareness, and Accuracy to examine their impact on user behavior. Data were gathered through a structured questionnaire distributed via Qualtrics, with a total of 219 valid responses from Portuguese users of ride-hailing apps analyzed using Smart PLS software. This approach not only provides a comprehensive understanding of the existing theoretical framework but also explores the specific context of Portugal.

The results from this study revealed that Performance Expectancy and Habit are the predictors of both the intention to continue using and the frequency of use of ride-hailing apps. Found to be also significant was Effort Expectancy and Value for Price. Interestingly Accuracy was found to indirectly influence continued usage intentions through Performance Expectancy, however it did not directly impact users' continued use intentions.

This study contributes significantly to the existing literature by applying the UTAUT2 model integrated with specific additional constructs on the Portuguese ride-hailing market. This study a provides empirical evidence on how various factors influence user intentions and behavior, offering insights that are crucial for service providers to enhance user experience and increase customer retention.

2. LITERATURE REVIEW

2.1. RIDE-HAILING APPS INDUSTRY

The first company to launch this type of business was Uber in the United States, the idea of developing this type of platform was idealized by Travis Kalanick and Garret Camp in Paris when they couldn't get a ride. In 2009, Uber launches in San Francisco and in 2010, in the same city the first ever Uber trip was requested. In Europe, the app arrived in the same city the idea was born, Paris in the year of 2011 (*Uber Newsroom*, n.d.). In the context that this study focuses on the market (Ride-Hailing - Portugal / Statista Market Forecast, n.d.) is dominated by Uber and Bolt. Bolt is an Estonian company founded in 2013 by Markus Villig, Martin Villig and Oliver Leisalu the name Bolt is rebrand made by the company, the former name was Taxify (The Story of Bolt / *Bolt* Blog, 2023).

Ride-hailing belongs to the sharing economy, ride-hailing are app-based platforms that exchange capital, assets, and services between individuals. Ride-hailing platforms enable the connection between a driver with a traveler who requested a specific trip, if the driver is willing to fulfill that need they are matched in the mobile application. This type of service is referred in the literature by several names such as ride-hailing services, ride sourcing, app-based ride services, ride-booking, on demand ride services. Providers can be mentioned has Transportation Network Companies (TCNs) (Tirachini, 2020).

The rise and magnitude of ride-hailing applications has been facing an huge growth since Uber the first company to launch this type of services emerged in San Francisco, other companies emerged in the market in various locations around the world, such as Lyft, Cabify, Ola and Didi Chuxing. For instance Didi Chuxing, since its launch in 2012 didi has grown to 450 million users, 21 million drivers, and more than 30 million daily trips in more than 400 Chinese cities, making it it the largest company in terms of daily rides. Ola that was founded in 2010 in more than 110 cities in India. Uber like it was mentioned before launched in 2009, in 2016 was in 400 cities and in 2018 was present in almost 800 cities worldwide (Tirachini, 2020).

Today ride-hailing apps accounts with 1.75 billion users worldwide with a prevision of hitting 1.97 billion users by 2028. According to projection the ride-hailing market is expected to reach approximately 166 billion dollars by the end of 2024 (*Ride-Hailing - Worldwide | Statista Market Forecast*, 2024).

2.2. INTENTION AND FREQUENCY OF USE OF RIDE-HAILING APPLICATIONS

Mostly, ride-hailing applications are used by young individuals, particularly millennials, they are more likely to use ride hailing services and to use them more frequently (Alemi, Circella, Mokhtarian, et al., 2018; Lavieri & Bhat, 2019; Rayle et al., 2016). These findings are consistent with various geographical regions including North America, Europe and parts of Africa (Acheampong et al., 2020; Clewlow & Mishra, 2017; Gomez et al., 2021)

Some studies found that its more likely for well-educated individuals, especially those with a bachelor's degree or higher, to use ride-hailing app and also individuals that possess higher levels of income (Alemi, Circella, Mokhtarian, et al., 2018; Gomez et al., 2021; Lavieri & Bhat, 2019).

Gender differences in the use of ride-hailing apps differ from study to study, some studies found that there is an higher use of this type of applications among women (Alemi, Circella, Mokhtarian, et al., 2018; Gomez et al., 2021; Sabogal-Cardona et al., 2021). Race is also aborded in the literature, it was found that African American's individuals are less likely to use this services. (Dias et al., 2019) found that the vast majority of ride-hailing users are white and the race with less frequent users is African American's .

The presence of a car in the ride-hailing users households is often mentioned in the literature, according to (Young & Farber, 2019) most of ride-hailing users come from zero-vehicle households, they don't have any own vehicles and this increases the use and the need of ride-hailing services, similar findings in (Circella et al., 2018), the author found that coming from a zero-vehicle household is related with an higher frequency of use of this services.

(Alemi, Circella, Handy, et al., 2018; Gomez et al., 2021; Lavieri & Bhat, 2019) state that individuals who have an higher degree of experience with new technologies, have an higher use rate of ride-hailing apps. Also the environmental consciousness of the individuals is examined in the literature, (Gomez et al., 2021) found that the individuals that possessed an higher environmental consciousness tended to reduce the use and the frequency of use of this type of services, on the contrary (Alemi et al., 2019) states that individuals who support pro-environmental policies are more frequent users.

2.3. EXTEND UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT 2)

The unified theory of acceptance and use of technology (UTAUT) is a crucial method for understanding user engagement and technology use across multiple sectors. Created by (Venkatesh et al., 2003) this method represents a comprehensive examination of eight well-known models. According to this concept, four constructs performance expectancy, effort expectancy, social influence, and facilitating conditions—determine behavioral intentions and use behavior. Since its development in 2003, the Unified Theory of Acceptance and Use of

Technology (UTAUT) has been predominantly used to understand technology adoption within organizational settings (Venkatesh et al., 2012). The model was subsequently adapted to better-fit consumer contexts, a revision that involved the addition of three new constructs—hedonic motivation, price value, and habit. This adaptation also modified some of the original relationships posited by UTAUT and introduced several new ones. Furthermore, the revised model proposes that individual differences such as age, gender, and experience may moderate the influence of these constructs on both the behavioral intention to use technology and its actual usage (Venkatesh et al., 2012).

UTAUT 2 includes constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. These constructs cover a wide range of factors influencing user adoption and continued use of technology. Also the unified theory of acceptance and use of technology (UTAUT) is a very adaptable theory that can fit in different cultural and contextual settings, making it suitable for examining ride-hailing app usage across various demographics and regions (Blut et al., 2022).

This theory is widely used in the literature to study users intention to use different technologies, like mobile payment (Oliveira et al., 2016), internet banking (Rahi et al., 2019), determinants of purchasing flights from low-cost carrier (LCC) websites (Escobar-Rodríguez & Carvajal-Trujillo, 2014). Also, in transportation-related technologies (Korkmaz et al., 2022; Madigan et al., 2016, 2017). Most studies that used UTAUT show that this theory has been empirically validated in numerous studies across different technologies and user groups, demonstrating its strong predictive power in explaining behavioral intentions in the use of technology.

3. RESEARCH MODEL DEVELOPMENT

For this research, I adapted the UTAUT 2 original hypothesis to fit in the context of this research – Intention for continued use and use frequency of ride-hailing applications. I used 5 constructs of the UTAUT 2 model, more precisely Performance Expectancy, Effort Expectancy, Social Influence, Habit and Price Value. Additionally, I used 3 different constructs: Accuracy, Environmental Counsciousness and perceived safety risk and adapted the hypothesis to better fit in the context of this study.

3.1. PERFORMANCE EXPECTANCY

According to (Venkatesh et al., 2012) Performance Expectancy is defined as the degree of believe which an individual has towards using a technology, will provide benefits to the individual in performing certain tasks. When a user perceives some specific technology has benefic to the performance of their work affectively, this means that the user has a strong performance expectancy towards the technology and the greater this expectancy of performance is, the more likely they are to use the technology.

In a study related with the ride-hailing industry, Performance Expectancy is positively associated with costumer acceptance of uber (Almunawar et al., 2020), however in another study (Ooi et al., 2020) found that performance expectancy didn't have a significant relation with behavioral intention to use m-taxi. Other researches in other realms found that Performance Expectancy positively effects behavioral intention to use different technologies (Oliveira et al., 2016; Rahi et al., 2019; Slade et al., 2015). In this study its hypothesized that:

H1: Performance Expectancy will positively affect behavioral intention to continue using ride-hailing applications.

3.2. EFFORT EXPECTANCY

Effort Expectancy is defined by (Venkatesh et al., 2012) has the degree simplicity or complexity that user perceives the use of a certain technology.

In the study's related with the transportation sector some find that Effort Expectancy wasn't significant with the behavioral intention to use a transportation related technology (Madigan et al., 2017; Ooi et al., 2020), on the other hand the same author in another study that analyzed the intention to use the same technology, found that effort expectancy was significant with behavioral intention to use, it's noticeable to account that this significance was very low in value. In other studies that found to have a positive influence towards the behavioral intention to use a certain technology (Martins et al., 2014; Rahi et al., 2019). Furthermore, its hypothesized that:

H2: Effort Expectancy will positively affect behavioral intention to continue using ride-hailing applications.

3.3. SOCIAL INFLUENCE

Social influence is defined by (Venkatesh et al., 2012) has the degree to which customers feel that others, such as family and friends, think they should use a specific technology.

In two similar studies, Social influence was significant with the intention to use a transportation related technology (Madigan et al., 2016; Madigan et al., 2017). Also in other studies, Social Influence had a significant effect with behavioral intention (Escobar-Rodríguez & Carvajal-Trujillo, 2014; Martins et al., 2014) on the other hand (Escobar-Rodríguez & Carvajal-Trujillo, 2013) found that the relationship between behavioral intention and social influence was not significant. However, in this study it's hypothesized that:

H3: Social Influence will positively affect behavioral intention to continue using ride-hailing applications.

3.4. HABIT

Added by (Venkatesh et al., 2012) to the most recent version of the UTAUT was the Habit construct, Habit is defined by (Gardner & Lally, 2023) as the process where repeatedly performing a behavior in a specific context forms an association between the context and the response. This association creates an impulse to perform the response again when exposed to similar context cues. (Venkatesh et al., 2012) defines Habit as the extent to which behaviors are performed automatically due to learning. In researches is highlighted the importance of habit to adopt a new platform and on intention to use a platform (Escobar-Rodríguez & Carvajal-Trujillo, 2014; Slade et al., 2015)

The post-adoption IT model suggests that as people use IT more frequently, their actions become more habitual and less conscious. This means, the more someone automatically performs a behavior based on learned responses, the more often they will engage in that behavior. Essentially, because habitual behaviors are easier and quicker to execute than those that require deliberate thought, the frequency of IT use is likely to increase (Lankton et al., 2010), if the literature indicates that habit will positively influence the intention to continue using the platform, it will might also positively influence the frequency of use of ride-hailing. According to this, in this study it's hypothesized that:

H4: Habit will positively affect behavioral intention to continue using ride-hailing applications.

H5: Habit will positively affect the frequency of use of ride-hailing apps

3.5. PRICE VALUE

Price Value is one of the latest constructs added to the most recent version of the UTAUT, price value is defined as the consumers weigh of the utility, they perceive from the benefits of the application against the required financial investment to use them. (Venkatesh et al., 2012). In the context of this study is refers to the users' perception of the cost-benefit ratio of using the services inside the application, because there is no cost associated with using the application because the technology is available for free. This construct is going to measure how users perceive the economic value provided by the service relative to the price they pay. In a study that analyze the factors influencing millennial travelers intentions it was found that Price Value significantly influenced intentions to use ride hailing services (Korkmaz et al., 2022; S. Lee et al., 2021) find that price value didn't had a significant effect on the behavioral intention to use a transportation related service. In this study it's hypothesized that:

H6: Price value of the service will positively affect behavioral intention to continue using ride-hailing applications.

3.6. PERCEIVED SAFETY RISK

Perceived Safety Risk is the perception of the riders that his welfare it's secure with the use of this services, nowadays its easier for anyone to be a part of these services as drivers, even individuals who are not professional taxi drivers. Due to this fact riders can easily be judged by their driving skills, or the potential of being harmed by the stranger that is providing this service, one fact that is increasing in importance due to the increase of reported crimes in platforms like Uber (C. K. H. Lee & Wong, 2021). In a study conducted by (Panagiotopoulos & Dimitrakopoulos, 2018) it was found that if there is an existent concern regarding safety in autonomous. In the study developed by (C. K. H. Lee & Wong, 2021) it was hypothesized that perceived safety risk would have an negative effect on word-of-mouth and consequently on purchase intention but in the results I was found otherwise found that perceived safety risk had a negative effect on word-of-mouth this meant that they were not worried about criminal activities that could might occur when using ride-hailing services. However in this study from the rider's perspective is going to be hypothesized that an increase in perceived safety risk is going to lead to a decrease in intention to continue using ride-hailing and also a decrease in the frequency that people use them

H7: Perceived safety risk will negatively affect behavioral intention to continue using ride-hailing applications.

H8: Perceived safety risk will negatively affect the frequency of use

3.7. ENVIRONMENTAL COUNSCIOUSNESS

The construct Environmental consciousness is widely mentioned in ride-hailing literature (Gomez et al., 2021; Lavieri & Bhat, 2019).

In this study I am to explore the influence of environmental-friendly preferences on consumer behavior within the ride-hailing industry. Specifically, the construct investigates the extent to which a higher preference for environmental-friendly vehicles supposedly like the electric car, influence the use of ride-hailing services.

(Gomez et al., 2021) found that individuals with a lower environmental consciousness are more car-oriented that is liked to a more intense use of ride-hailing, oppositely it was also found that individuals that had an higher environmental consciousness, this type of people tended to reduce their use of ride-hailing and use more environmental-friendly options like public transportation. Here in this study it's hypothesized that:

H9: Environmental consciousness will negatively affect behavioral intention to continue using ride-hailing applications.

H10: Environmental consciousness will negatively affect frequency of use.

3.8. ACCURACY

Accuracy is defined by (Wixom & Todd, 2005) has the representation of the user perception that the information is correct, these dimension impact's the user's perception of the quality of the information inside the system, the higher the satisfaction with the information produced by the system, the more likely it will positively influence the user perceptions that the application will enhance his work performance. In (Wixom & Todd, 2005) it was found that accuracy was the most significant construct affecting information quality and consequently affecting Intention. In (Yao & Murphy, 2007) study it was found that accuracy was one the most important constructs to impact the individuals intention to perform a certain behavior.

H11: Information Accuracy will positively affect behavioral intention to continue using ride-hailing applications.

H12: Information Accuracy will positively affect performance expectancy

3.9. BEHAVIORAL INTENTION FOR CONTINUED USE

Behavioral intention for continued use resides on the desire of the user to continue to use the technology in the future (Hsieh et al., 2008). In this study we hypothesize that:

H13: Behavioral intention for continued use will positively influence frequency of use

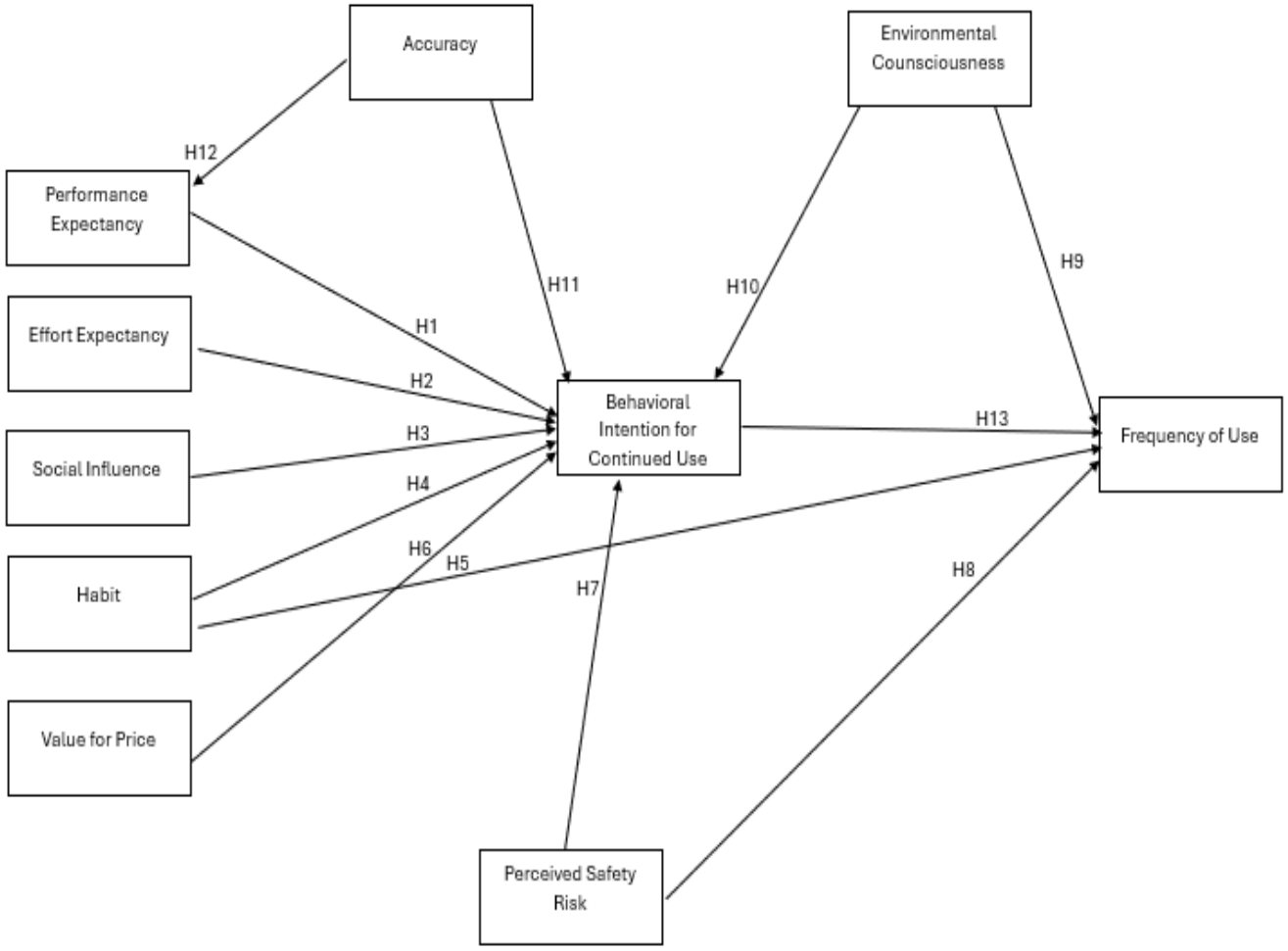

Figure 1 - Proposed Model

4. METHODOLOGY

In this study the data was collected via a structured questionnaire survey, focusing on the specific issues that are relevant to the research objectives and the nature if the variables. The questionnaire was developed and employed using the Qualtrics platform, most items were adapted from other studies and the scales used for them, most of the items were measured trough a seven-point Likert type scale where 1 means “Totally disagree” and a 7 means “Totally agree”. The sampling of the data as a total of 267 respondents but only 219 responses were considered valid. The target population of this survey was potential Portuguese ride-hailing users with 18 years old or more.

The data of the survey was collected between April 2024 and March 2024, the survey respondents were recruited from online platforms like Facebook, Instagram and WhatsApp, the link of the survey was distributed by direct messaging and posts on this type of platforms, also requests to answer the survey were sent by e-mail to all University students. The main goal of this type of approach was to capture individuals who were more active digitally and in consequence who use ride-hailing apps more often and possessed a higher awareness of the subject that is being study. The method that the data was collected was designed to verify the importance of different constructs to the use of the main ride-hailing applications and the frequency of use of this type of services.

Due to the way that this study recruited their respondents, there is an high representation of younger participants like it was expected and a limited representation of older groups particularly individuals with 55 years old or above they compose 8.7% of the population and the majority of the respondents to this survey have ages between 18 and 34 years old, corresponding to 72.6% of the total sample, individuals with ages between 18-24 account for 41.55% and people with 25 and 34 years old correspond to nearly 31%. In this survey most of the respondents where males, 113 males that represent 51.60% of the sample, the number of female respondents where 105 that represented 47.94% of the whole sample. Only 1 individual preferred not to mention his gender, only accounting for 0.46% of the population. Regarding the level of education 104 respondents had a bachelor’s degree, accounting for 47.49% this degree level has the highest representation, individuals with a Master’s degree was the second most representative level of education, 61 individuals had this level of education representing 27.85% of the whole sample, the vast majority of the population most precisely 89.5% of the sample has a bachelor degree or superior level that indicates a high level of education of the sample, included in this percentage and important to highlight are 9 individuals with a Doctorate degree accounting for 4.11% . Regarding the level of income, this type of demographic variable was the one that was more well distributed by the different types of income, the difference between the levels of income mentioned in this study differs by small percentages, the most representative group are individuals who earn 1000€ to 1500€, representing 23.29% of the sample this higher representation of this level of income makes sense, according to (*Salário médio por trabalhador atingiu 1.505 euros*

em 2023, n.d.) the median salary in Portugal in 2023 were 1505€ gross, following this level of income, the second with an higher representation is individuals earning 2000€ or more monthly, with a representation of 20,09%, it seems unfair to take any conclusions on the level of income of the survey population because down by just 2 individuals when compared to the previous group comes a much lower level of income, individuals earning between 800€ and 1000€.

Table 1 – Respondants' Demographic

Characteristics (n=219)	Obs	%
Gender		
Male	113	51.60%
Female	105	47.94%
Prefer not to say	1	0.46%
Age		
18-24	91	41.55%
25-34	68	31.05%
35-44	21	9.59%
45-54	20	9.13%
55-64	16	7.31%
65 or more	3	1.37%
Education Level		
Primary School	1	0.46%
High School	22	10.05%
Bachelor's degree	104	47.49%
Postgraduate degree	22	10.05%
Master's degree	61	27.85%
Doctorate degree	9	4.11%
Income (Gross)		
Less than 800€	7	3.20%
800€ to 1000€	42	19.18%
1000€ to 1500€	51	23.29%
1500€ to 2000€	38	17.35%
More than 2000€	44	20.09%
Don't have Income	37	16.89%

When it comes to which ride-hailing application the user prefers to use, in this sample Uber has more people using only their application then Bolt, 65 individuals use only Uber representing 29.68% and 30 individuals use only Bolt accounting for 13.70% of the sample, but the vast majority of the survey respondents use both applications, 112 individuals stated that they use both applications, representing 51.14% of the sample.

Table 2 - Respondants' Application Use

Characteristics (n=219)	Obs	%
Application Use		
Uber	65	29.68%
Bolt	30	13.70%
Uber and Bolt	112	51.14%
None	12	5.48%

5. MODEL ESTIMATION

5.1. MEASUREMENT MODEL

In the present study, the model was estimated using the SmartPLS4 program.

The partial least squares structural equation modelling more known by the abbreviation PLS-SEM it's an method that is widely used in Information Systems field as well as in other fields like marketing (J. Hair et al., 2017). PLS-SEM is becoming more and more popular due to its higher prediction capability (Sabol et al., 2023) this model is a modern method of multivariate analysis that has the capacity to estimate theoretically established cause-effect relationship models (Zeng et al., 2021). In this study this method was chosen for several reasons being the main ones the small sample size and the complexity of the model. The small sample size of the study's is most common reason used by researchers to use this method, due to the high level of statistical power of this method with small sample sizes and complex models (Hair et al., 2017). The sample of this study has only 219 valid responses.

This study is going to follow the guidelines of (Sarstedt et al., 2022), the following statistical methods are going to be used: Cronbach's Alpha and Composite Reliability (CR) to assess the constructs internal reliability and Average Variance Extracted (AVE) for the convergent validity and finally Heterotrait-Monotrait Ratio (HTMT) Fornell-Larcker measure for the discriminant validity.

First step involves the assessment of the constructs internal consistency reliability, in order to do that I am going to use Cronbach's Alpha and Composite Reliability (CR) like it is advised by (Sarstedt et al., 2022). First for the assessment of internal consistency is going to be used Composite reliability from (Jöreskog, 1971), for this criterion the higher the values the higher level of reliability. According to (Sarstedt et al., 2022) for the Composite reliability criterion values between 0.60 and 0.70 are considered "acceptable in exploratory research", in the case of this study there is no value between this two. Results between 0.70 and 0.95 represent "satisfactory to good" reliability levels, levels higher than 0.95 can indicate problems with answers provided in the questionnaire it can indicate an undesirable pattern of responses, in the case of this study the Composite reliability values are between 0.855 being the lowest one and 0.94 being the highest with this results it can be stated that the constructs have high levels of reliability.

Cronbach alpha is another statistical method used to assess the reliability of the constructs, there is no other statistic to have been reported more than Cronbach's Alpha has a quality indicator (Sijtsma, 2009), usually Cronbach presents lower values being consider the lower bound while Compose Reliability is considered the upper bound that's why researchers should consider both measures. In the case of this study all Cronbach's values are above the minimum 0.70 (J. F. Hair et al., 2019) .

The next step is the Convergent Validity, that is the degree to which a concept explains the variance of the items by converging in its indicators, in order to do this the convergent validity is going to be assessed by the Average variance extracted (AVE), The Average Variance Extracted (AVE) is calculated by taking the average of the squared factor loadings for each indicator tied to a specific construct. The acceptable AVE value should be higher than 0.50 this demonstrates that the construct explains more than 50% of the variation of its elements (Sarstedt et al., 2022), in this case all AVE values are above the 0.5 mentioned.

Table 3 - Indicators Measurements

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Behavioral Intention for Continued use	0.905	0.940	0.840
Accuracy	0.817	0.881	0.715
Environmental Consciousness	0.817	0.868	0.694
Effort Expectancy	0.864	0.917	0.785
Habit	0.870	0.919	0.791
Performance Expectancy	0.753	0.855	0.664
Perceived Safety Risk	0.755	0.890	0.803
Social Influence	0.837	0.902	0.755
Value for price	0.900	0.931	0.770

After the reliability and the convergent validity are successfully validated the next and final step is to assess their discriminant validity (Sarstedt et al., 2022), Three criteria will be used to test the discriminant validity: Cross-loadings, Heterotrait-Monotrait Ratio (HTMT) and Fornell-Larcker measure.

The Cross-loading criterion states that the loading of each indicator is expected to exceed all of its cross-loadings also This criterion says that loading for the items in each

construct must be greater than 0.7 (Henseler et al., 2009), all values in table are supporting this criteria except for 1, that as a value of 0.696 very close the minimum 0.7.

Table 4 - Cross Loadings

	ACC_0	BIFC_0	EC_0	EE_0	FREQ_0	HA_0	PE_0	PSR_0	SI_0	VFP_0
ACC_01	0.696									
ACC_02	0.918									
ACC_03	0.905									
BIFC_01		0.909								
BIFC_02		0.929								
BIFC_03		0.911								
EC_01			0.957							
EC_02			0.895							
EC_03			0.603							
EE_01				0.871						
EE_02				0.879				-		
EE_03				0.908						
FREQ_01					1.000					
HA_01						0.933				
HA_02						0.926				

HA_03	0.804			
PE_01		0.840		
PE_02		0.876		
PE_03		0.719		
PSR_01			0.880	
PSR_02			0.912	
SI_01				0.889
SI_02				0.911
SI_03				0.803
VFP_01				0.826
VFP_02				0.893
VFP_03				0.921
VFP_04				0.868

A less liberal criteria is the Fornell-Larcker measure, created by (Fornell & Larcker, 1981) the criterion states that discriminant validity is established when the square root of the Average Variance Extracted (AVE) for each construct is greater than the constructs highest correlation with any other construct in the model (Fornell & Larcker, 1981), that's it's what exactly happened with all the constructs in this study, so we can conclude that with the Fornell Larcker discriminant validity is established – Table X

Table 5 - Fornell Larcker measure

	ACC	BIFCU	EC	EE	FOU	HA	PE	PSF	SI	VFP
Accuracy	0.846									
Behavioral Intention for Continued Use	0.159	0.916								
Environmental Counsciousness	-0.070	-0.134	0.833							
Effort Expectancy	0.353	0.333	-0.272	0.886						
Frequency of use	-0.049	0.294	-0.128	0.127	1.000					
Habit	0.115	0.593	0.027	0.266	0.416	0.890				
Performance Expectancy	0.173	0.593	-0.105	0.242	0.275	0.519	0.815			
Perceived Safety Risk	-0.173	0.017	0.056	-0.105	0.091	0.092	-0.009	0.896		
Social Influence	0.098	0.327	0.148	0.132	0.172	0.540	0.404	0.051	0.869	
Value For Price	0.325	0.334	0.001	0.238	0.110	0.267	0.181	-0.078	0.187	0.878

The last criteria to test the discriminant validity is Heterotrait-Monotrait ratio. According to (Sarstedt et al., 2022) if the HTMT as an high value this indicates discriminant validity problems, according to (Henseler et al., 2015) the HTMT values should be below 0.9, values that are above this value suggest a lack of discriminant validity. In this study all HTMT values are below 0.9, for that reason its concluded that the constructs demonstrated to possess discriminant validity.

Table 6 - Heterotrait-Monotrait ratio of the correlations

	ACC	BIFC	EA	EE	FOU	HA	PE	PSR	SI	VFP
Accuracy										
Behavioral Intention for Continued Use	0.170									
Environmental Consciousness	0.105	0.143								
Effort Expectancy	0.433	0.377	0.366							
Frequency of Use	0.044	0.308	0.128	0.136						
Habit	0.129	0.641	0.111	0.281	0.438					
Performance Expectancy	0.176	0.688	0.157	0.275	0.298	0.623				
Perceived Safety Risk	0.243	0.042	0.136	0.131	0.105	0.125	0.073			
Social Influence	0.128	0.373	0.178	0.160	0.188	0.631	0.506	0.101		
Value for Price	0.386	0.370	0.046	0.270	0.116	0.301	0.211	0.095	0.216	

5.2. STRUCTURAL MODEL

In this chapter is going be dedicated for the structural model, the model is going to be evaluated using the guidelines of (Hair Jr. et al., 2021).

(1): In this step the in order to assess the model's explanatory power we need to have the coefficient of determination R2 of the endogenous variables, R2 is a measure of explanatory power. The values of R2 range from 0 to 1, if the values are higher indicating a great explanatory power. R2 guidelines state that values of 0.75 are considered substantial, values of 0.50 moderate and 0.25. In the case of this study, Behavioral Intention for continued use (0.512) has a substantial value and Frequency of use (0.197) weak values

(2): According to (Sarstedt et al., 2022) f2, or the effect size, is a measure used to assess the strength of the relationship between an independent latent variable and a dependent latent variable in the model. Only on the relations that were significant, According to (Sarstedt et al., 2022) Accuracy of information on BIFC (0.031) Performance expectancy on BIFC (0.189), Habit on BIFC (0.148) and Habit on Frequency of use (0.118), Value for Price on BIFC and Environmental awareness on BIFC (0.022) yield small effects.

(3): To evaluate the models predictive relevance we need the Q2 cross-validation redundancy in order to have this values i used the PLSpredict with 7 folds and 10 the number

of repetitions, the Q2 values of the key targets of this study are above 0 for behavioral intention for continued use and for Frequency of use, according to (Ali et al., 2018) this is an incidence of predictive relevance and all the Q2 values of the main key targets of this study have a moderate predictive relevance.

6. RESULTS

To evaluate if the hypothesis is supported or not supported, we need to see the significance of the path coefficients in order to this the bootstrapping technique with 5000 samples was used to assess the path coefficients. Following a significance level of 10%, 6 of the 13 hypotheses were supported and the model explains 51.2% of the variation in BIFC and 19.7% of the variation in the frequency of use.

Analyzing the results obtained with bootstrapping was found that Performance Expectancy (H1) ($\beta = 0.369$; $p < 0.1$) and Habit ($\beta = 0.359$; $p < 0.1$) (H4) are the most significant relations in explaining BIFC. Also highly significant, being the most significant relation of this model is (H5) ($\beta = 0.387$; $p < 0.1$) explaining frequency of use. These constructs have the highest impact one the model and are robust positive correlations with highly significance, hypothesis H1, H4 and H5 are supported.

Another positively correlated relations with BIFC are, Effort Expectancy (H2) ($\beta = 0.110$; $p < 0.1$) and Value for Price (H6) ($\beta = 0.167$; $p < 0.1$) (H6) is supported. Also, the hypothesis (H12) is the relationship between Accuracy and Performance Expectancy ($\beta = 0.173$; $p < 0.1$). H2, H6 and H12 hypothesis is also supported.

Other significant relationship is the relation between Accuracy, Performance Expectancy and BIFC with a p value lower than 0.1

All the other correlations were not statistically significant, more precisely Accuracy of information (H11) ($\beta = -0.038$; $p > 0.1$) has a weak and not significant influence on BIFC this hypothesis is rejected. Also not statistically significant is social influence (H3) ($\beta = -0.048$; $p > 0.1$) with BIFC. The construct Perceived Safety Risk (H7) ($\beta = 0.012$; $p > 0.1$) doesn't have statistical influence with BIFC and also with frequency of use (H8) ($\beta = 0.063$; $p > 0.1$), both the hypothesis is rejected (H7) and (H8). Also not statistically significant is BIFC (H13) ($\beta = 0.045$; $p > 0.1$). Finally, like it was expected in the hypothesis development the construct environmental awareness is not significant with BIFC (H9) ($\beta = -0.070$; $p > 0.1$) and with Frequency of use (H10) ($\beta = -0.136$; $p > 0.1$) however in this case the negative correlation is higher with a p-value of 0.159.

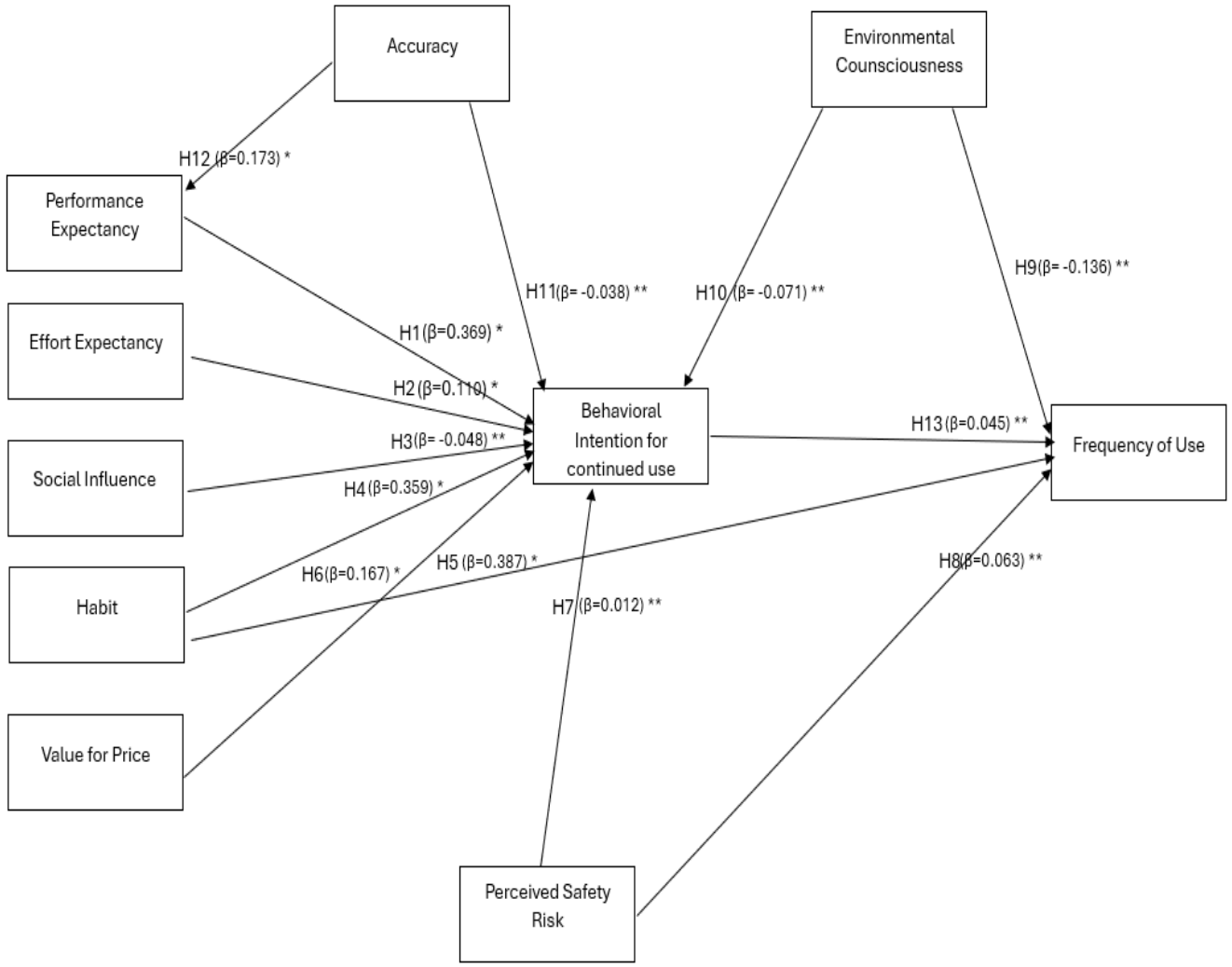

Figure 2 - Final Model

*Statistically significant at p < 0.1, ** not statistically significant p > 0.1

Table 7 - β and p-value

	β	p-value	t-value	Results
H11: Accuracy → BIFC	-0.038	0.501	0.673	Rejected
H12: Accuracy → Performance Expectancy	0.173	0.014	2.447	Supported
H13: BIFC → Frequency of use	0.045	0.509	0.661	Rejected
H10: Environmental Awareness → BIFC	-0.071	0.190	1.313	Rejected
H11: Environmental Awareness → Frequency of use	-0.136	0.159	1.410	Rejected
H2: Effort Expectancy → BIFC	0.110	0.085	1.722	Supported
H4: Habit → BIFC	0.359	0.000	5.372	Supported
H5: Habit → Frequency of use	0.387	0.000	6.089	Supported
H1: Performance Expectancy → BIFC	0.369	0.000	5.159	Supported
H7: Perceived Safety Risk → BIFC	0.012	0.868	0.166	Rejected
H8: Perceived Safety Risk → Frequency of use	0.063	0.302	1.032	Rejected
H3: Social Influence → BIFC	-0.048	0.466	0.729	Rejected
H6: Value for Price → BIFC		0,004	2.864	Supported

7. DISCUSSION

The purpose of this study is to explore and understand the factors that influence users' intentions to continue using ride-hailing apps and use the services more frequently.

7.1. ACCURACY

Accuracy is the perception of the user that the information is correct, in the context of this study is the refers to the precision and reliability of the information provided by the service, such as the correctness of the estimated time of arrival of the driver, if the location of the user is correct when he requests a ride-hailing trip.

In this model the construct is examined for its effect on Performance expectancy and behavioral intention for continued use, according to the relation of accuracy with performance expectancy it was found to be a positive and statistically significant relationship, this positive relation mean that the accuracy of the information increases so does the user's expectation of the app's performance, this suggests that the users who experience a more accurate information provided by the ride-hailing application provider will develop higher expectation for the app and consequently users will associate it with a more reliable and trustworthy service, it will shape for the better the users perceptions of the app

On the contrary of the findings in (Yao & Murphy, 2007) in this study it was found that the relationship between accuracy and BIFC was not a significant relationship, this suggests that even though accuracy enhances the users performance expectancy it does not directly translates into a stronger intention to continue using ride-hailing apps. Another interesting discovery of this research was, the relationship between accuracy, performance expectancy and BIFC was found to be significant this suggests that even though accuracy doesn't directly influences the user's intentions to continue using the service but does so by improving users' perceptions of the application's performance.

7.2. PERFORMANCE EXPECTANCY

Contrary to the study conducted by (Razi et al., 2019), One of the most significant relation of this model is the relationship between performance expectancy and behavioral intention for continued use, these findings are similar with another studies (Oliveira et al., 2016; Rahi et al., 2019; Slade et al., 2015).

The significance positive of the relation suggests that Performance Expectancy is a strong predictor of Behavioral Intention for Continued Use, is one of the strongest in this model. This positive relation suggests that as users' expectations regarding the performance of the ride-hailing app increase, more specifically the users' expectations on how the performance of the application will effectively meet their needs to provide for the transportation services, the intention to continue using the application also increases. Also

means that the user's place an high value on the functionality of the app itself, whether it be the timely pickups, the accuracy of route calculations, the actual usage of the app.

7.3. Effort Expectancy

On the contrary to what was found in (Madigan et al., 2017; Ooi et al., 2020) but similarly to (Martins et al., 2014; Rahi et al., 2019) in this research, findings suggest that the relationship between effort expectancy and BIFC is significant, this results mean the effort required to use the ride-hailing application decreases (i.e, as the app becomes easier to use) user's intentions to continue using the app increase. The low significance of this relationship might be related to most of the survey respondents, more precisely 72,60% have ages between 18 and 34 years old can suggest that because this generation is associated with an higher use of this type of applications and they might be already familiar with this type of applications and find it easy to use them so the degree of influence of effort expectancy on behavioral intention decreases and is not has high has for example performance expectancy.

7.4. Social Influence

In this study it was found that the relation between social influence and BIFC was not significant like it was found in other studies (Escobar-Rodríguez & Carvajal-Trujillo, 2013; Naranjo-Zolotov et al., 2018) .

These findings suggest that the lack of significance between social influence and BIFC could mean that the user's decisions to continue using the ride-hailing applications are more determined by the users themselves then affected by other's opinions or social pressures. Even though this relation is not significant the negative coefficient could mean that there is a small negative sentiment towards this type of applications, on the survey respondents social circle and this can lead to a reduction of use of ride-hailing apps to align with group norms or to avoid a social disapproval. Also the lack of significance can be explained by the fact that the usage of this type of applications is completely voluntary, this findings goes according to previous literature that states, when the use is perceived as voluntary, social influence is less important (Naranjo-Zolotov et al., 2019).

7.5. Habit

One of the most significant relationships in this models is between habit and BIFC, similar to the results found in another studies, this relationship is significant (Escobar-Rodríguez & Carvajal-Trujillo, 2014; Slade et al., 2015) this significance implies that once the habit is formed, once the users incorporate the app into their daily routines they are more likely to intend to continue to use the application, this intention can be boosted by the familiarity and comfort with the ride-hailing app provider, that comes with the habitual use, this implies that the companies should aim towards strategies that encourage regular use of the application until it becomes a habit, like major discounts for example.

The most significant relationship in this model is between habit and frequency of use, this even greater relationship reinforces the power of habitual behavior in driving consistent need for the applications services, as users become accustomed to the app's interface and the services that offer, in this case rid-hailing trips, the use becomes more frequent and automatic.

7.6. PRICE VALUE

Like in the study of (Lee et al., 2021) that in this research it was found that the the relation between price value and BIFC was also significant, this observation aligns with previous findings, that indicate that saving money are among the most common advantages perceived by millennials when using products and services within the sharing economy (Amaro et al., 2019).

This significance mean that as the users perceive a greater value between the price they pay and the service that is provided, the intention to continue using the application increases, this highlights the importance of the importance of perceived economic value in the retention of users inside ride-hailing applications, users are more likely to continue using them if they feel that they are receiving fair or advantageous value relative to the costs involved, this costs could include not only monetary ones but also time savings, convenience and service quality.

7.7. PERCEIVED SAFETY RISK

On the contrary to what was expected and what was found in the (Lee & Wong, 2021) study, in this research the relationship between perceived safety risk and behavioral intention for continued use was not statistically significant, this result suggests that the user's concern about their own safety do not significantly affect their intentions, neither positively or negatively, to continue using the application. This could mean that the users don't perceive the drivers of the application providers has dangerous and there are not concerned of their safety, users may value efficiency and the utility of the application more heavily. Also users might trust the safety mechanisms that ride-hailing companies claim to have like the drivers background checks and in app-safety features and this could mitigate the perceived safety risk.

Slightly higher that the first relation but steel not significant is the relationship between perceived safety risk and frequency of use this indicates that safety concerns that some users might have could impact more on the frequency that people use the application that they impact the intention to continue using them, although this relationship is ot strong enough and not even significant so it also indicates that the users might don't have safety concerns when using this ride-hailing services.

7.8. ENVIRONMENTAL COUNSCIOUSNESS

Based on the results obtained, the relationship between the construct environmental consciousness and behavioral intention for continued use is not significant, however there is a negative beta coefficient, like it was expected, suggest that individuals with an higher preference for environmental friendly transportation inside the application is associated with a slight decrease in the behavioral intention to continue using, although this conclusion can be made this lack of significance implies that this construct is not a strong predictor of users intention to continue using the service in the context of this study.

Also not significant but a stronger relationship that before is the link between environmental awareness and frequency of use, similarly to what was found in (Gomez et al., 2021) here also the negative beta suggests that individuals that have higher levels of preference for environmental friendly vehicles, reduce their frequency of use of ride-hailing services, this direction could be interpreted that this individuals with higher preferences for electric cars inside the application may prefer to take other types of transportations, similar to what was found in (Gomez et al., 2021) an individual with an higher environmental consciousness might tend to reduce the use of this type of services they are more likely to use more environmental friendly transportations like public transport.

8. MANAGERIAL IMPLICATIONS

Given the results and insights derived from this study, there are several managerial implications for the ride-hailing industry.

The findings of this study underlined the significant impact of performance expectancy on continued use intentions of the individuals, ride-hailing providers should focus on continuing enhancing the application functionality, ensuring that the service meets or exceeds the users expectations, in areas such as reliability, responsiveness and accuracy of the information provided. Regular updates and technological advancements to improve the application performance can retain the existing customers and attract new ones, these could include a more accurate GPS tracking system, faster matching algorithms or a more responsive costumer service.

The role of effort expectancy was also significant influencer of the user's intention to continue using the application, ride-haling companies should continue to invest in intuitive and simpler user interfaces by simplifying the booking process and ensuring the app is easy to navigate, also it's important for this companies to provide clear instructions, tutorials and support to assist new and less tech-savvy users, ensuring that all demographic groups find the app accessible and straightforward to use

Due to the significant impact of habit on continued use and also in frequency of use Ride-hailing industry should also encourage the regular use of this type of services, companies should design marketing strategies that encourage this regular use, promotional campaigns such as discounts and loyalty programs, also promoting a smooth ride-hailing experience can help in habit formations, this includes cutting down wait times, reducing interruptions and providing a consistent service quality.

Also there clear and competitive pricing remains crucial, companies should provide users with a transparent pricing information may help build trust and improve the perception of the users that they are getting a good value for the money they are spending. Also companies should use marketing methods to clearly explain how dynamic pricing and inform the users how can costumers can save money by using this services during less busy times and areas.

9. LIMITATIONS AND FUTURE RESEARCH

The first limitation of this study is regarding the location where the participants of the questionnaire are from, the data from this survey was collected in a specific demographic region more precisely inside Portugal, caution is needed because the findings of this study might not be generalizable to other ride-hailing users from other demographic regions. Also most of the respondents of this study have ages between 18 and 34 years old, caution is needed when generalizing the findings of this study for other age groups more specifically older groups of users. This limitations suggests that future researches should consider expanding other geographic regions both within and outside Portugal, also future studies that analyze the factors impacting users' intentions to continue using ride-hailing apps and frequency of use inside Portugal should include a wider range of age groups, particularly older adults beyond the age of 34 years old.

Other limitation from this study is that the majority of the survey respondents have a bachelor's degree or a superior level of education, more precisely approximately 89% this level of education may not be reflective of the whole population, future studies should aim to include participants with a broader range of educational background, especially targeting individuals with lower levels of education, this would help understand if the factors influencing ride-hailing usage differ significantly based on the educational background.

Furthermore the lack of survey respondents of this study represents another limitation of this study, a relatively small sample of 219 respondents may not capture the full variability and nuances of the ride-hailing app usage behaviors. Future research in the realm could benefit from a larger and more diverse sample to enhance the reliability and applicability of the findings across broader populations

Other limitation from this study is that is found that constructs like Perceived Safety Risk, Environmental Awareness and Social Influence didn’t had any effect on continued use and use frequency, further researches can investigate this constructs in different geographical location and scenarios in which these constructs can have more significance in continued use intention and use frequency.

Also a limitation of this study is the lack of predictive power of the model on explaining the frequency of use of ride-hailing applications, in future research the model should be refined and tested in different contests, and identifying new constructs that help increase the predictive power of the model.

10. CONCLUSION

This study has examined the factors that influence continued use and use frequency of ride-hailing apps in Portugal, utilizing the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) alongside with additional constructs such as Perceived Safety, Environmental Awareness, and Accuracy. The findings provide an understanding of how various psychological and situational factors shape users' intentions to continue using these services and their actual use frequency.

In this study it was revealed that the constructs Performance Expectancy and Habit are critical drivers of the users intention to continue to use the application underlining the importance of app functionality and user habituation in user retention. Also other constructs like Accuracy, Effort Expectancy and Value for price were important predictors of ride-hailing continued use this underlines the importance that ride-hailing companies provide accurate and reliable service information, the necessity to be user-friendly and offer good value for money, these factors can be crucial in maintaining user satisfaction and loyalty, thereby encouraging regular use of the service.

Despite the development of safety features for riders in the context of this study it was found that riders don't perceive drivers has dangerous users are not concerned about their safety when using this type of services. Also the findings regarding social influence suggest that that users' decisions to keep using these services are more influenced by other factors than social pressures or recommendations. Furthermore, even though the relationships are not significant it was found those that the users that preferred environmentally friendly options inside the application are less inclined to continue using the applications and use these services less frequently

The results of this study offer valuable insights for ride-hailing service providers on prioritizing features and improvements that enhance user experience and retention. It also lays the groundwork for future research in other geographical or demographic settings to see if these findings hold in different contexts.

Future studies should consider expanding the demographic and geographic diversity of respondents to enhance the generalizability of the findings. Additionally, as the ride-hailing market evolves, continuous research will be required to understand the dynamics of these factors and their impact on user behavior in the face of new challenges and technological advancements.

This thesis not only fills a significant gap in existing literature by providing targeted insights into the Portuguese ride-hailing app market but also suggests practical strategies for service providers aiming to optimize their operations and customer satisfaction levels in similar markets globally.

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12. ANNEXES

12.1. SURVEY QUESTIONS AND ADAPTATIONS

Construct	Reference	Original Question	Adapted Question
Accuracy	(Wixom & Todd, 2005)	_____ Produces correct information	The information in these applications is accurate (E.g. Location, GPS, Prices)
Accuracy	(Wixom & Todd, 2005)	_____ Produces correct information	There are few errors in the information I obtain in these applications (E.g. Location, GPS, Prices)
Accuracy	(Wixom & Todd, 2005)	The information provided by _____ is accurate.	There are few errors in the information I obtain in these applications (E.g. Location, GPS, Prices)
Performance Expectancy	(Venkatesh, Thong, & Xu, 2012)	I find mobile Internet useful in my daily life	These applications are useful in my daily life
Performance Expectancy	(Venkatesh, Thong, & Xu, 2012)	Using mobile Internet helps me accomplish	Using these apps helps me get things done faster.

		things more quickly.	
Performance Expectancy	(Venkatesh, Thong, & Xu, 2012)	Using mobile Internet increases my productivity.	Using these applications increases my productivity.
Effort Expectancy	(Venkatesh, Thong, & Xu, 2012)	I find mobile Internet easy to use	These applications are easy to use.
Effort Expectancy	(Venkatesh, Thong, & Xu, 2012)	Learning how to use mobile Internet is easy for me	Learning to use these applications is easy for me
Effort Expectancy	(Venkatesh, Thong, & Xu, 2012)	My interaction with mobile Internet is clear and understandable.	My interaction with these applications is clear and easy to understand
Social Influence	(Venkatesh, Thong, & Xu, 2012)	People who are important to me think that I should use mobile Internet.	My colleagues think I should use these types of applications.
Social Influence	(Venkatesh, Thong, & Xu, 2012)	People who influence my behavior think that I should	My friends prefer that I use these types of applications.
		use mobile Internet.	
Social Influence	(Venkatesh, Thong, & Xu, 2012)	People whose opinions that I value prefer that I use mobile Internet.	My family thinks I should use these types of applications.
Habit	(Venkatesh, Thong, & Xu, 2012)	The use of mobile Internet has become a habit for me.	Using these applications has become a habit for me.
Habit	(Venkatesh, Thong, & Xu, 2012)	I must use mobile Internet.	I must use this type of services.
Habit	(Venkatesh, Thong, & Xu, 2012)	Using mobile Internet has become natural to me.	Using these applications has become natural for me.
Price Value	(Venkatesh, Thong, & Xu, 2012)	Mobile Internet is reasonably priced.	At the prices these applications currently have, they provide good value.
Price Value	(Venkatesh, Thong, & Xu, 2012)	Mobile Internet is a good value for the money.	A trip on these apps is reasonably priced.
Price Value	(Venkatesh, Thong, & Xu, 2012)	At the current price, mobile Internet	A trip of this type has a good

		provides a good value.	price-quality ratio.
Perceived Safety Risk	(Lee & Wong, 2021)	The Drivers are not safe.	I think that the drivers of these applications are not safe
Perceived Safety Risk	(Lee & Wong, 2021)	I am concerned about criminal activities that may occur while using ride-hailing.	I am concerned about criminal activities that may occur while traveling
Perceived Safety Risk	(Lee & Wong, 2021)	I am afraid that the drivers will not provide safe services.	I am worried that drivers will not provide me with a safe service
Environmental Consciousness			When I use the application, I select an electric car
Environmental Consciousness			I don't mind paying more for the vehicle to be electric
Environmental Consciousness			If the vehicle is not electric, I prefer not to travel

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