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THE DRIVERS OF DIGITAL INVESTMENT BROKER ADOPTION

Lucia Castro Saldanha

Dissertation presented as partial requirement for obtaining the Master's degree in Information Management

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by

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Dissertation presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Business Intelligence

Advisor: Prof. Rui Alexandre Henriques Gonçalves, Ph.D

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DEDICATION

I dedicate this thesis to my parents, Osmar and Cristina, who regardless of distance, have always supported me and made themselves present in the most important moments of my life.

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ABSTRACT

Consumers around the world are more active in financial markets and have taken greater responsibility for their financial well-being, increasingly adopting digital investment brokers to perform their financial investments. Also, there has been increased competition in financial markets over the years, with more players in the investment landscape. In order to understand the factors that lead to the adoption of a digital investment broker, which is the main goal of the research, a model adapted from Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) was developed.

An initial sample of 279 Brazilians was obtained, of which 126 are adopters of digital investment brokers. From this sample, the model was tested and among the conclusions of the research it is highlighted that perceived usefulness, data visualization and subject norm have a significant positive impact on behavioral intention of digital investment broker adoption. Also, the perceived ease of use positively but indirectly influences, through the data visualization, the intention of digital investment broker adoption. Finally, as there is still a lack of research on the adoption of digital investment brokers, it was recommended that new studies be carried out in different countries, and that new studies include different variables in the research model, in order to obtain a better understanding of the individual investor behavior in the adoption of digital investment brokers.

Keywords: Financial Technology; Digital Investment Broker; Technology Acceptance Model; Unified Theory of Acceptance and Use of Technology.

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LIST OF ABBREVIATIONS AND ACRONYMS

ANOVA	Analysis of Variance
AVE	Average Variance Extracted
BDA	Big Data Analytics
DIBA	Digital Investment Broker Adoption
DV	Data Visualization
ETF	Exchange Traded Fund
FinTech	Financial Technology
HTMT	Heterotrait-Monotrait
ICT	Information and Communication Technologies
IO	Information Offered
ISSM	Information System Success Model
KPI	Key Performance Indicator
MFI	Microfinance Institution
PEOU	Perceived Ease of Use
PLS	Partial Least Squares
PLS-SEM	Partial Least Squares Structural Equation Modelling
PU	Perceived Usefulness
SEM	Structural Equation Modelling
SN	Subject Norm
TAM	Technology Acceptance Model
UTAU	Unified Theory of Acceptance and Use of Technology
VIF	Validating Formative Indicators

1. INTRODUCTION

Retail investment has been growing. Consumers around the world are increasingly active in the financial markets (Vohra & Kaur, 2017, p. 16) and have taken on greater responsibility for their financial well-being (Stolper & Walter, 2017, p. 582). According to CFPB (2017, p. 6) financial well-being can be defined as a state where people can fully meet current and ongoing financial obligations, can feel that their financial future are secure, and is able to make choices that allow them to enjoy life. In order to meet this state of life, today, retail investors have access to real-time information and increasingly sophisticated investment tools, making them more skilled than ever (Deloitte, 2021, p. 1). The main changes fueling this boom are the result of the major digital transformation that has taken place in recent years in the financial sector.

The digital transformation has enabled the emergence of new digital services and products, such as new digital trading platforms (Deloitte, 2021, p. 4). Also, some trends in retail investment are emerging and are playing their roles in popularizing digital investment services: retail investment has been fueled by the prevalence of easy-to-use applications, often integrated with payment applications, which facilitate money transfers; the gamification of investment in brokerage platforms; the growing adoption of new promotional tactics that encourage frequent trading (Deloitte, 2021, p. 1). Furthermore, not requiring a minimum amount to be invested makes investment accessible to individuals previously excluded from financial markets (Deloitte, 2021, p. 4) and the rise of the commission-free brokerage changed the investment landscape to retail investors (van der Beck & Jaunin, 2021, p. 2).

According to Sahi (2017, p. 511), there has been an increase in competition in the financial markets over the years, with more players in that investment landscape. Financial institutions have adapted to the new demands of their customers, competitors, and market, and for this they have adopted a set of technological strategies, changing traditional channels to digital channels (online channel and mobile channel). This provides the financial consumer a huge amount of investment opportunities to direct their savings to (Annamalah et al., 2019, p. 1–2). So, they need to make a greater number of decisions (Yeo & Fisher, 2017, p. 81). However, Sahi (2017, p. 511) also considers that the investor is not well prepared to evaluate all these available opportunities in order to maximize his financial good. For that purpose, individual investors around the world rely on financial advisors, often obtained through investment broker, to guide their investment decisions (Linnainmaa et al., 2021, p. 488), which also justifies the growth of digital broker service in the financial market.

Digital investment broker can be considered as the financial service where financial transactions are conducted through application using complex software (Khvostenko et al., 2019, p. 411). As an individual investor, you cannot trade stocks or bonds unless you have a broker or are a broker. This does not mean, however, that there must necessarily be a human being for negotiation. Online brokers also allow you to trade electronically, without the need to speak to a person (Epstein & Roze, 2017, p. 31). The main advantages of a digital investment broker are direct access to stock information, online instruments for technical analysis and forecasting prices on assets, online monitoring of current market positions, low brokers' commission due to lack of paperwork and other transaction costs, low entrance threshold, providing a wide range of financial instruments, providing a loan leverage, operational technical support and much more (Khvostenko et al., 2019, p. 411).

Given these different characteristics, and that established brokers and their operations are likely to be impacted by the growing influence of retail investors (Deloitte, 2021, p. 6), it is essential to gather deeper insights about the financial behavior of the investor, in order to better understand the financial consumer, his attitudes, choices and financial decision-making (Sahi, 2017, p. 511), also regarding the adoption of digital investment broker. While there are many studies on the adoption of digital technology services, such as mobile banking and online payments, research on the adoption of digital investment brokers is lacking. These are the main motivations for the development of this thesis, focused on analyzing which are the drivers for the adoption of digital investment brokers.

This dissertation seeks to assist in the development and evolution of digital investment brokers, adapting them even more to the financial behavior of individual investors, also known as retail investors. As a theoretical application, it will help advance studies and research related to this topic and, as a practical application, it will help digital investment brokers to generate greater value to clients and maximize the profits of both. Thus, it allows to answer the research question of this study, which consists of the question: "What are the drivers for the adoption of a digital investment broker?".

Complementarily, and in order to help answer the research question, 3 specific objectives were defined for the dissertation:

- Identify the profile of clients who adopt the services of digital investment brokers.
- Identify whether the data visualization capabilities are important in digital investment broker adoption.
- Identify whether the information offered is important in digital investment broker adoption.

Thus, it is possible to understand the drivers of individual investors in the digital investment broker adoption process. In order to achieve the proposed objectives and answer the research question presented, a methodological approach from the natural sciences is used. Natural science aims to understand the reality and includes traditional research in the physical, biological, social and behavioral domains (March & Smith, 1995, p. 253), thus making sense of its application in this research. To collect the data to understand the research intended reality, a survey is carried out, which is a research method used to investigate social phenomena and understand society (Brenner, 2020, p. 2). With the survey results, ANOVA analysis and Partial Least Squares Structural Equation Modeling (PLS-SEM) are applied. ANOVA analysis, often called as one-way analysis of variance or simple one-way ANOVA, has the purpose to determine if there are significant differences between the population of the groups, assumed to be independent samples from populations that are normally distributed (Gillard, 2020, p. 91). PLS-SEM is a statistical analysis technique that allows the capture of a "complex multivariate world" in a system of equations that enables the study of the interaction relationships between one or more dependent variables and multiple independent variables (Hair Jr et al., 2019, p. 457).

The research is divided into 5 different chapters. In the first chapter, which corresponds to the introduction of the research, the context, the study relevance and the study importance are identified, the research questions and objectives are defined, and the motivations to the elaboration of this project are described. The second chapter is the literature review which covers the concepts relevant to the research and it serves as support for all its development and evolution, resulting in the theoretical foundations for the research itself and the research hypotheses. The literature review is mainly on financial technology and digital investment broker adoption and the concepts that contribute to a better understanding of it. The third chapter is the research methodology, which describes the research design, the survey structure, the research variables and the methods and techniques used to address the research objective, the research questions, and the research hypotheses. As already mentioned, ANOVA and PLS-SEM are applied, and it will be better described next in this third chapter. The fourth chapter corresponds to the findings and discussion of the results obtained. It presents and discusses the main results obtained in the surveys answered, with a focus on understanding the drivers of digital investment broker adoption. The results are analyzed in detail, in order to understand and justify the models presented. First, the sociodemographic description of the sample is carried out, followed by the statistical description of the results of the survey responses. After that, an ANOVA analysis is performed, and finally the model is tested using the PLS-SEM technique. Finally, the fifth chapter explains the research's final conclusions and considerations, its academic and business contributions, the study limitations, and it provides suggestions for future research.

2. THEORETICAL BACKGROUND

This chapter discusses the results of a literature review on financial technology and digital investment broker adoption and the concepts that contribute to a better understanding of it. Based on this, the research hypotheses are developed and linked to the theoretical framework.

2.1. FINANCIAL TECHNOLOGY

The world is changing, the internet has changed everything (Epstein & Roze, 2017, p. 47), both in business and in people's personal lives, due to the use of financial technologies (Wang, 2021, p. 1). The development of information technology and the internet has brought, in recent years, changes in the performance of traditional services (Carranza et al., 2021, p. 3). Advances and innovations in technology and digitization of business processes and business models in the area of financial services are rapidly converting physical and virtual environments (Jünger & Mietzner, 2020, p. 1; World Bank Group, 2020, p. 2–3). In recent years, the industry has had to rethink its services to respond to these changes (Khanboubi et al., 2019, p. 78–79), and it has resulted in new digital financial services (World Bank Group, 2020, p. 2–3), services that rely on digital technologies to be delivered and used by consumers (World Bank Group, 2020, p. 1). These new services can reduce costs, increase transparency, security and convenience, and enable the delivery of personalized financial services (World Bank Group, 2020, p. 2–3), and these characteristics are sufficiently attractive to consumers (EY, 2019, p. 11). Also, the global financial crisis enabled innovations through digital technologies, advances in e-finance and mobile technology for financial companies (Suryono et al., 2020, p. 1), made many people believe that traditional banks were on the verge of extinction and about to be replaced or fundamentally interrupted by financial technology companies (Stulz, 2019, p. 86), also known as FinTech (Hasan et al., 2020, p. 1).

FinTech is often seen as a unique combination of financial services and information and communication technologies (ICT) (Wang, 2021, p. 4), which is an interdisciplinary area of research with great influence on society and people's lives that is driven and shaped by the rapid development of computing, communication and Internet technologies (Alwahaishi & Snásel, 2013). Billion (2016, p. 7) defines FinTech as financial technology, which focuses on the innovative power that these technologies bring to financial services. Some of the purposes of FinTech are to improve user experience and banking efficiency (Hu et al., 2019, p. 2) and it seeks to improve and automate the delivery and use of financial services (Kagan & Estevez, 2020, p. 1). Fintech is being used to help companies, entrepreneurs and consumers to better manage their financial operations, processes and life, using specialized software and algorithms that are used on computers and smartphones (Kagan & Estevez, 2020, p. 1). With these in mind, the term FinTech refers to banks, "non-bank" financial institutions, microfinance institutions (MFIs), retail banking, fundraisings and companies that develop the technology (Billion, 2016, p. 7; Kagan & Estevez, 2020, p. 2). However, for Stulz (2019, p. 86), FinTech can be defined as a financial innovation that is based on the use of digital technologies and big data. In this thesis, financial technology will be explored as digital mechanism for financial services for retail investors, such as digital investment brokers. Investments in that case means assets purchased with the aim of providing additional income from the asset itself (Garman & Forgue, 2010, p. 5). Financial technologies allow new ways to invest in different instruments like bonds, mutual funds, or money market funds. Furthermore, by offering automated services, enabled by machine learning, they add value by offering the possibility of investment advice and financial planning services to retail investors through the collection of consumer financial data (World Bank Group, 2020, p. 7).

Through the use of digital technologies, it is possible to have access to many existing financial services in a more efficient and improved way (Stulz, 2019, p. 86). Therefore, it has the potential to impact the entire value chain of the financial sector and brings financial inclusion to the next level (Billion, 2016, p. 2–3). In addition, FinTech can be a game changer for millions of people, as it does not depend on physical bank branches (Billion, 2016, p. 6). Farida et al. (2021, p. 87) says that the use of financial technology allows consumers to use financial services that are easily accessible on their mobile devices. This results in less interaction with financial advisors and commercial agents, since consumers no longer need to go to banks physically (Farida et al., 2021, p. 87) and generally do not need assistance of a person (Kagan & Estevez, 2020, p. 4). In addition, Yeo and Ficher (2017, p. 80) point out that there has been a significant advance in wireless technology and innovative applications in cell phones that offer many opportunities for consumers around the world. Among the opportunities that are being explored and adopted by consumers are mobile financial services, such as banking services, cash management, stock trading, financial investments, payments, money transfers, managing investments, mobile transactions and exchange of financial information, for the purpose of financial management and personal finance (Kagan & Estevez, 2020, p. 4; Yeo & Fisher, 2017, p. 80). Stulz (2019, p. 89–91) lists data, computing and the interface as the main ingredients of FinTech. For him, the best way to highlight these main ingredients is through the products available, which can be used on cell phones, are considered friendly to the consumer, and create a more satisfying user experience. Stulz (2019, p. 90) brings as an example of the value of a FinTech, a broker that offers through technology in a mobile application, commission-free trading of stocks, cryptocurrencies, ETFs and options.

EY (2019, p. 5–7) in a 2019 trends report, shows that, worldwide, 96% of consumers know at least one alternative FinTech service available to help them transfer money and make payments, and that, across 27 surveyed markets, 64% of the digitally active population, on average, adopt at least some type of financial technology, including insurances, money transfer and payments, savings and investment brokers, budgeting and financial planning. Brazil, the focus market of this research, is in the top 20 markets that most adopt financial technologies, also with 64% of the population digitally active adopting some financial technology. EY (2019, p. 9) also reveals that 78% of consumers are aware of Fintech services of savings and investments. Also related to savings and investments, EY (2019, p. 10) identifies this category as one of the top 3 show strong growth potential, along with budgeting and financial planning.

2.2. Digital Investment Broker Adoption

In the past, there was a great dependence on social security and pension plans, which today are often replaced, or supplemented, by long-term investments to finance retirement (Stolper & Walter, 2017, p. 582). Nowadays, consumers are more responsible for self-management within their investment portfolios, and for the success in ensuring financial stability (Yeo & Fisher, 2017, p. 81). So, financial products have received more attention and have attracted more people to make investments in order to obtain extra gains (Annamalah et al., 2019, p. 1–2). Thus, financial services product portfolios are becoming more diversified as well as more complex (Okay & Köse, 2015, p. 69), and investors want to carefully balance an investment portfolio between long, short and intermediate term bonds, and growth stocks, value stocks, domestic stocks and foreign stocks (Epstein & Roze, 2017, p. 8).

Through the use of digital technologies, it is possible to have access to many existing financial services in a more efficient and improved way (Stulz, 2019, p. 86). The most common expression used in the market, and also in past studies, is internet banking. However, today, internet banking features does not include only basic banking activities such as payments and banking transactions, but also comprises personal finance management, funds transfer, loan applications and investment activities (Akhlaq & Ahmed, 2013, p. 115). Taking this definition into account, in this research it is considered that digital investment broker also comprises an internet banking activity. digital investment brokers have recently undergone a radical transformation with the advent of globalization and the rise of information technologies, and are one of the most important components of the financial infrastructure (Okay & Köse, 2015, p. 69), which allows the retail investors to perform their financial investments.

French et al. (2020, p. 314), in their study, showed that apps generate changes in attitudes and motivations, generating a greater sense of effectiveness and confidence in the ability to improve decision-making. People who use smartphone apps feel more aware of their future financial needs and think more about how financial advice and guidance can help them (French et al., 2020, p. 315). Most broker firms have websites that you can go to for information, and many allow you to trade on your own (Epstein & Roze, 2017, p. 33). Brokers provide a wide range of online research and trading tools for their clients, which include market research, charting capabilities, streaming pricing and news services (Epstein & Roze, 2017, p. 48–55). Epstein and Roze (2017, p. 49), cite some of the things that can be done when managing an investment account using a computer and an internet connection: executing trades and monitoring open orders, controlling and tracking order routing, monitoring and analyzing your portfolio and all open positions, tracking profits and losses, analyzing your trading history, and receiving almost instantaneous fill reports.

For Epstein and Roze (2017, p. 36–41), it is not advisable to choose a broker based on price only, the choice of brokers should be based on much more than who can offer the cheapest price. Although price is an important factor in broker selection, it is just one among many factors that need to be considered (Epstein & Roze, 2017, p. 41). For Epstein and Roze (2017, p. 41), the most important factors are the services offered by the broker and the broker's effectiveness and efficiency in performing those services. So, it is necessary to know the types of services offered to allow you to make the appropriate deals for each profile (Epstein & Roze, 2017, p. 33). It should be analyzed, for example, what order types are supported, whether data tools are offered, and what types of charts are provided (Epstein & Roze, 2017, p. 33).

In recent years, several explanatory models have been developed to determine the factors influencing the adoption of emerging technologies and digital financial services. The purpose of the model in this research is to explain the behavior and expectations of consumers related to digital investment broker adoption. In order to develop the research model, we started exploring the Technology Acceptance Model (TAM), proposed by Davis (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003).

The Technology Acceptance Model (TAM) is indicated to study the intention to adopt specific technologies (Carranza et al., 2021, p. 3) as it offers a powerful explanation for usage behavior and user acceptance of information technology (Sharma, 2019, p. 816). TAM is one of the most influential models immensely used to study the determinants technology acceptance, including internet banking (Jayasiri et al., 2018, p. 181; Sharma, 2019, p. 816). It has been widely discussed in the literature in relation to internet banking services, which created a competitive environment for banks in the market and allowed reaching and serving a wider range of customers at a lower cost (Alhassany & Faisal, 2018, p. 2). The TAM theory emphasizes that a technology that is easy to use and perceived as useful will have a positive influence on users' attitudes, increasing intention to use the technology that generates the adoption behavior, so, according to this original model, the user's intention to adopt a new technology is determined by the perception of usefulness and ease of use (Jayasiri et al., 2018, p. 181).

Perceived ease of use can be defined as the degree to which a person believes it is easy to use a particular system, both physically and mentally (Davis, 1989). With proper guidance and instruction, users can easily make and manage their financial investments on mobile devices and FinTech investment broker systems. In his study, Alhassany & Faisal show that users prefer to use clear and easy-to-use websites (2018, p. 18), which can be extended to applications. Besides that, EY (EY, 2019, p. 11) show that over 45% of the financial technology adopters feel comfortable to use a digital, branchless financial services provider. Based on this, the following research hypothesis was elaborated:

> ***H1:*** *the perceived ease of use of digital investment brokers is positively and significantly associated with the intention of digital investment broker adoption.*

Perceived usefulness is described as the degree to which consumers believe that using a system will increase performance (Davis, 1989) and productivity (Alhassany & Faisal, 2018, p. 5–6) and it plays an important role in influencing the adoption decision (Alhassany & Faisal, 2018, p. 18). In the investment broker context, it is possible to make an analogy with mobile banking, and say that perceived usefulness can positively affect the adoption investment broker, since users can realize that they will obtain advantages when using the app to perform their financial investments (Malaquias & Silva, 2020, p. 2). Internet banking has solved the problem of time spent in traditional banking accessing your account, access information or financial needs (Fawzy & Esawai, 2017, p. 111). Fawzy & Esawai consider Internet banking useful and convenient (Fawzy & Esawai, 2017, p. 111). Therefore, the following research hypothesis was developed:

> ***H2:*** *the perceived usefulness of digital investment brokers is positively and significantly associated with the intention of digital investment broker adoption.*

Even though, many researches use the Technology Acceptance Model (TAM) to determine and justify the adoption of financial technologies such as e-banking (Carranza et al., 2021), other researchers argue that the perceived usefulness and the perceived ease of use of the systems alone cannot explain the adoption of technology as a whole. There is an argument that personality, cognitive and behavioral dimensions have an impact on this choice. In studies on FinTech, the modified TAM was applied to investigate different topics such as biometric identification in Fintech applications (Wang, 2021), the internet banking adoption (Alhassany & Faisal, 2018), e-service (Ahmad et al., 2020).

Furthermore, there is another theory, called Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies four driver factors in predicting behavioral intention to adopt a technology: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2016, p. 329). Social influence, also known in other theories as subject norm, is defined as the degree to which an individual perceives that most people who are important to him believe that he should use a new technology (Venkatesh et al., 2003, p. 451). The role of subject norm in the decision-making process is complex and subject, but it represents the explicit or implicit idea that the human behavior is influenced by how the individual believes that others will see them because they have adopted certain technology (Venkatesh et al., 2003, p. 451–452). When individuals are in groups, certain rules, norms, or beliefs determine appropriate behavior (Irimia-Diéguez et al., 2023, p. 7). According to Irimia-Dièguez et al. (Irimia-Diéguez et al., 2023, p. 7), in a Fintech context, a way to capture the inferred behavior of other people can be through comments made by users, experts and media about Fintech practice and experiences. This leads to the development of the following research hypothesis:

> ***H3:*** *the subject norm is positively and significantly associated with the intention of digital investment broker adoption.*

For Ahmad et al. (2020, p. 505), in the banking sector, customers are more sophisticated and this has forced banks to re-evaluate the quality of their services. As there are still consumers reluctant to make online transactions because they think they can get low quality service, this factor has an impact on the adoption of certain digital services (Ahmad et al., 2020, p. 514). EY (EY, 2019, p. 11) show that 60% of the financial technology adopters would prefer to view their financial products in one place through an online or app-based tool. Owusu Kwateng et al. (2018, p. 139) believes that to attract new customers, the financial institutions should offer user-friendly platforms. The characteristics of the website are considered one of the main factors that affect customers' perception of the ease of use of internet banking technology (Fawzy & Esawai, 2017, p. 111). One of these characteristics, in an investment brokerage, is, for example, the visualization of investment data over time, which is possible due to emerging digital technologies, such as big data analytics (BDA) resources for comprehensively analyze customer financial data and other financial data in order to enhance financial operations (Edu, 2022, p. 3). Big data analytics capabilities provide financial institutions with data sources, data analysis, insights, also throughout data visualizations, and storing such data and information on collaborative platforms for fast and real-time decision-making (Edu, 2022, p. 3).

According to Mohammed et al. (2022, p. 2), data visualization is the representation of data in a user-friendly graphical format for examining and analyzing data in real time. This can provide resources for data analytics, prediction, and decision making (Hirve & Reddy Ch, 2019, p. 1). The decision-making processes have become more efficient in the financial sector, due to the extensive application of data analysis (Hirve & Reddy Ch, 2019, p. 6). Real-time quotes, sophisticated graphics and extensive order entry capabilities make customers better informed and better equipped than ever before (Epstein & Roze, 2017, p. 48). Some of the best and most common techniques used in data visualization, which give simplified results that are easy to understand by the decision maker, cited by Mohammed et al.

(2022, p. 3–6) are: number chart, which is a graph that continually updates a given key performance indicator (KPI); line chart, which are used to show trends, accelerations, decelerations and volatility. Data changes over time are represented by these charts, which illustrate the correlations; pie chart, which are used to represent the proportional composition of a given variable over a period of time; tables, that although it is recognized that tables are not always considered a type of data visualization, there are times when a table is all that is needed to display the data in its most basic form; and bar charts that include horizontal and vertical columns and are used respectively in a comparison arrangement, such as when sorting the top five of a given category, and for displaying chronological data such as growth over time and comparing data across categories in the business sector. Thus, based on these concepts and on concepts already mentioned above, three more research hypotheses were developed:

H4: *the data visualization of the digital investment broker is positively and significantly associated with the intention of digital investment broker adoption.*

H5: *the perceived ease of use of digital investment brokers is positively and significantly associated with the data visualization of the digital investment broker.*

H6: *the perceived ease of use positively, significantly, and indirectly influences, through the data visualization, the intention of digital investment broker adoption.*

Also, in addition to how the information is presented, the type of data and the information offered by an investment broker is crucial (Epstein & Roze, 2017, p. 37). Thus, to analyze the success of an information system, there is the Information System Success Model (ISSM), updated in 2003 by DeLone and McLean. It is one of the promise models which analyzes the relationship between the variables system quality, information quality, use, user satisfaction, individual impact, and organizational impact. The wealth of information online that can help improve investments results is simply remarkable (Epstein & Roze, 2017, p. 48). Most brokers provide basic stock quotes, usually in real time, and some may even provide market data with a much deeper view of the market including current sales information and past sales information (Epstein & Roze, 2017, p. 37). To get a higher level of data, it is necessary to open a broker account with a company that provides the desired level of data (Epstein & Roze, 2017, p. 37). Prices for different data tools may vary between brokers (Epstein & Roze, 2017, p. 37). For Epstein and Roze (2017, p. 37), some examples of what information can be offered by a digital investment broker are: price charts, rating service information, analyst reports, company reports, economic reports, business news, market indexes and trading statistics. When the site meets an individual's needs, he will be satisfied (Fawzy & Esawai, 2017, p. 111). Due to the accurate information provided, and with the latency in the information minimized (Fawzy & Esawai, 2017, p.

111), the investors will be encouraged to invest (Annamalah et al., 2019, p. 19). This helps generate a positive image among investors of the brokers efforts to prevent and control risks, while contributing to stable development (Jiang et al., 2018, p. 110). User satisfaction with websites directly impacted their choice of sites visited, demonstrating that users were most concerned with information content (Jalil et al., 2014). To capture users' attention, financial applications must include high-quality information to meet their customers' needs, which implies that rich information or quality content will increase adoption (Okonkwo et al., 2022, p. 14). Based on this, the last 3 research hypotheses were developed:

H7: *the information offered by the digital investment broker is positively and significantly associated with the intention of digital investment broker adoption.*

H8: *the perceived usefulness of digital investment brokers is positively and significantly associated with the information offered by the digital investment broker.*

H9: *the perceived usefulness positively, significantly, and indirectly influences, through the information offered, the intention of digital investment broker adoption.*

Besides that, Abreu and Mendes (2020, p. 1266), evidenced in their research that individual investors with different demographic profiles have a different behavior when making investment decisions. Demographic variables are the most used factors to differentiate customers (Jayasiri et al., 2018, p. 182), and socioeconomic factors have a significant relationship with investment behavior (Annamalah et al., 2019, p. 19).

2.3. Theoretical Framework and Hypothesis Development

The following table summarizes some of the studies analyzed during the literature review, some of which have already been mentioned. The table focuses on identifying the factors proposed in each study, the subjects of the study, in addition to the analytical methods that were used to obtain the findings of each of the studies.

Authors name	The proposed factors	The study subjects	The analytical approach
(Bakri et al., 2023)	• Performance expectancy • Effort expectancy • Social influence • Hedonic motivation • Price value • Habit • Trust	Blockchain	Partial Least Square for Structure Equation Modeling (PLS-SEM)

continue…

Authors name	The proposed factors	The study subjects	The analytical approach
(Irimia-Diéguez et al., 2023)	• Subject norm • Self-Efficacy • Attitude • Perceived behavior control	Fintech Innovation	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Jangir et al., 2023)	• Perceived usefulness • Continuation • Satisfaction	Fintech Services	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Alduais & Al-Smadi, 2022)	• Performance expectation • Effort expectation • Social influence • Facilitating condition	e-payments	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Almajali et al., 2022)	• Perceived usefulness • Perceived privacy • Perceived certainty • Perceived ease of use	Mobile payment apps	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Baber & Baki Billah, 2022)	• Perceived usefulness • Perceived ease of use • Compliance • Attitude • Subject norm • Perceived behavior control	Fintech	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Edu, 2022)	• IT capability • BDA usage • Financial service agility	Financial service	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Hayat et al., 2022)	• Perceived ease of use • Perceived usefulness • Perceived trust • Lifestyle compatibility • Social influence • Facilitating conditions	Smart wearable payment device	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Matar & Alkhawaldeh, 2022)	• Perceived usefulness • Perceived ease of use • Perceived awareness • Perceived credibility • Reference group influence • Security concerns	Electronic cards	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Okonkwo et al., 2022)	• Compatibility • Image • Relative advantage • Perceived ease of use • Perceived usefulness • Information quality • System quality • Service quality	Mobile wallets	Partial Least Square for Structure Equation Modeling (PLS-SEM)

continue…

Authors name	The proposed factors	The study subjects	The analytical approach
(Purohit et al., 2022)	• Performance expectation • Effort expectancy • Social influence • Facilitating conditions • Price value	Mobile payment	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Carranza et al., 2021)	• Perceived usefulness • Perceived ease of use	e-banking	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Hu et al., 2019)	• Perceived ease of use • Perceived usefulness • Attitudes • Trust • Brand image • Perceived risk • Government support • User innovativeness	FinTech	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Sharma, 2019)	• Perceived usefulness • Perceived ease of use • Autonomous motivation • Controlled motivation • Trust	Mobile banking	Structural Equation Modeling (SEM) and Neural Netword
(Alhassany & Faisal, 2018)	• Perceived usefulness • Perceived ease of use • Personal innovativeness • Subject norm • Expected risk factor	Internet Banking	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Ryu, 2018)	• Perceived benefits • Perceived risks	FinTech	Partial Least Square for Structure Equation Modeling (PLS-SEM)
(Zhang et al., 2018)	• Perceived usefulness • Perceived ease of use • Perceived enjoyment • Consumer innovativeness • Trust in the bank • Perceived privacy • Perceived reliability • Attitudes	Mobile Banking	Partial Least Square for Structure Equation Modeling (PLS-SEM)

Table 1 – Summary of the Theoretical Foundation

The model used in this research is classified as an extension of a part of the UTAUT and TAM since it only includes some part of the original structure, and it is combined with additional constructs. To investigate and determine the drivers of digital investment broker adoption, the following hypotheses and the following constructs Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Subject Norm (SN), Information Offered (IO), Data Visualization (DV) and digital investment Broker Adoption (DIBA) were developed.

H1: the perceived ease of use of digital investment brokers is positively and significantly associated with the intention of digital investment broker adoption.

H2: the perceived usefulness of digital investment brokers is positively and significantly associated with the intention of digital investment broker adoption.

H3: the subject norm is positively and significantly associated with the intention of digital investment broker adoption.

H4: the data visualization of the digital investment broker is positively and significantly associated with the intention of digital investment broker adoption.

H5: the perceived ease of use of digital investment brokers is positively and significantly associated with the data visualization of the digital investment broker.

H6: the perceived ease of use positively, significantly, and indirectly influences, through the data visualization, the intention of digital investment broker adoption.

H7: the information offered by the digital investment broker is positively and significantly associated with the intention of digital investment broker adoption.

H8: the perceived usefulness of digital investment brokers is positively and significantly associated with the information offered by the digital investment broker.

H9: the perceived usefulness positively, significantly, and indirectly influences, through the information offered, the intention of digital investment broker adoption.

	Hypothesis	**Expected Relationship**
H1	Perceived Ease of Use -> Digital Investment Broker Adoption	+
H2	Perceived Usefulness -> Digital Investment Broker Adoption	+
H3	Subject Norm -> Digital Investment Broker Adoption	+
H4	Data visualization -> Digital Investment Broker Adoption	+
H5	Perceived Ease of Use -> Data visualization	+
H6	Perceived Ease of Use -> Data visualization -> Digital Investment Broker Adoption	+
H7	Information Offered -> Digital Investment Broker Adoption	+
H8	Perceived Usefulness -> Information Offered	+
H9	Perceived Usefulness -> Information Offered -> Digital Investment Broker Adoption	+

Table 2 – Research Hypotheses

To test the hypotheses, five indicators were developed to assemble each research constructs above-mentioned (Perceived Usefulness, Perceived Ease of Use, Subject Norm, Information Offered, Data Visualization and Digital Investment Broker Adoption), and also the research survey.

	PU | Perceived Usefulness
PU1	Using online investment brokers gives me more control over my financial investments.
PU2	Using online investment brokers provides me with convenient access to my investment accounts.
PU3	Using online investment brokers saves my time and allows me to do my investing activities quickly, saving my time and increasing my productivity.
PU4	Using online investment brokers is compatible with my lifestyle.
PU5	Overall, I find online investment brokerages useful for me.
	PEOU | Perceived Ease of Use
PEOU1	Using online investment brokers is easy for me.
PEOU2	I feel comfortable using online investment brokers.
PEOU3	I find all the content of online investment brokers understandable.
PEOU4	I can use online investment brokers without asking for help, without any problem.
PEOU5	Overall, I find it easy to use online investment brokers.
	SN | Subject Norm
SN1	My family and friends think I should use online investment brokers.
SN2	I learn about online investment brokerages from my friends and family.
SN3	I discuss online investment brokerages with my friends and family.
SN4	My friends and family recommended online investment brokers to me.
SN5	My friends, family and I share experiences and information about online investment brokers.
	IO | Information Offered
IO1	Investment and financial market information is important to me.
IO2	For me it is important to have accurate and up-to-date information about investments and the financial market.
IO3	Investment and financial market information helps me in my financial investment decisions.
IO4	Before adopting an online investment broker, I like to know about the information it offers on investments and the financial market.
IO5	Investment and financial market information improves my ability to plan my financial investments.
	DV | Data Visualization
DV1	Data visualization about financial investments is important to me.
DV2	Data visualization about investment helps me understand my financial investments.
DV3	A good data visualization about investment improves my experience using online investment brokers.
DV4	Before adopting an online investment broker, I like to know about the data visualization they offer.
DV5	Data visualization helps me to have a clear and understandable interaction when using online investment brokers.
	DIBA | Digital Investment Broker Adoption
DIBA1	It is valuable for me to use online investment brokers.
DIBA2	It is important for me to use online investment brokers.
DIBA3	I use online investment brokers frequently.
DIBA4	Online investment brokers are not a waste of money and resources.
DIBA5	I do not think online investment brokers are meaningless.

Table 3 – Indicators of the Constructs

During the bibliographic research, it was identified that possibly the most appropriate method would be the Partial Least Square Structural Equation Modelling (PLS-SEM). This method is normally applied to estimate casual-effect relations between independent and dependent variables, and this method is consisted by the combination of the measurement model with the structural model (Ramos, 2017, p. 10). Each latent variable has a scale, which means a set of indicators with their own specific loading. The path model shows the connections of the variables based on theory and logic to visually display the hypotheses that will be tested (Ramos, 2017, p. 10). The research model configuration can be seen in the Figure 1 below.

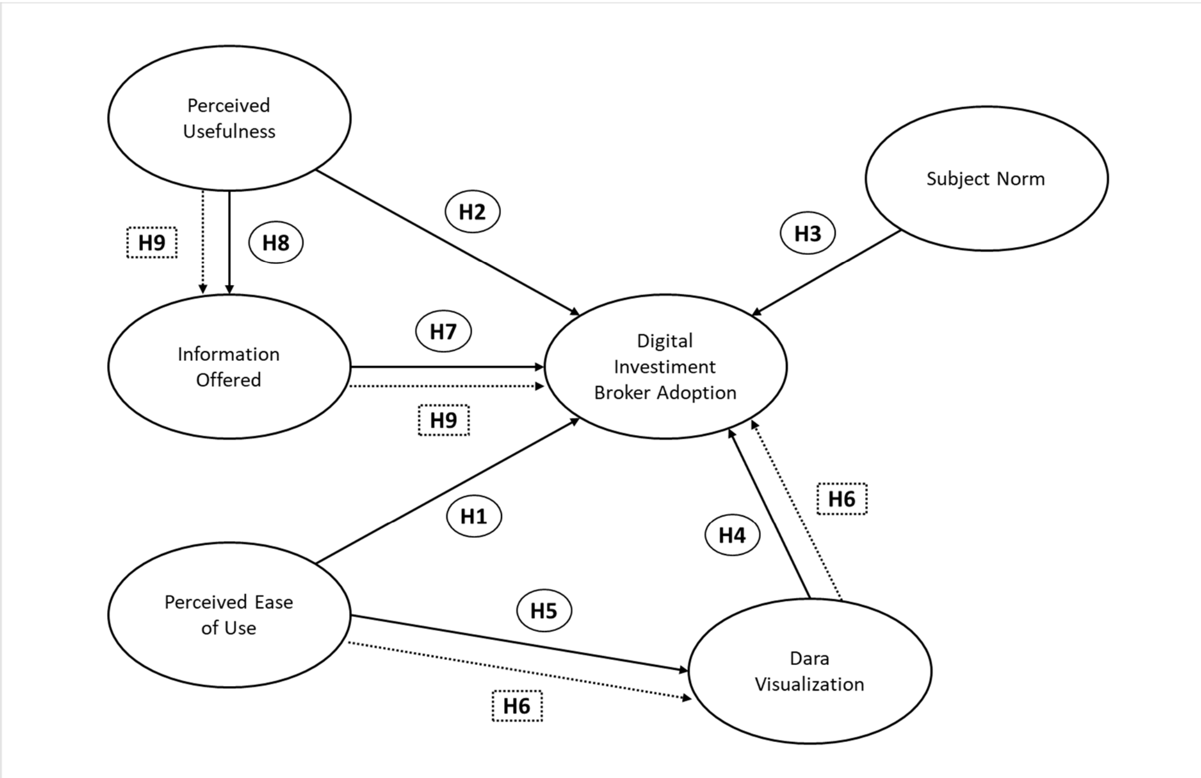

Figure 1 – Conceptual Framework | Model Configuration

3. RESEARCH METHODOLOGY

This section presents all the research methodologies. Starting in the research design, going through the survey structure, the research variables, the data collection, and ending in the analysis techniques and methods.

3.1. Research Design

In order to provide an answer and a tailor-made solution to the objectives and problems of the study already described, this thesis will be structured in 4 phases, which are represented in Table 4 and described below.

Research Design
Phase 1 – Literature Review
Financial Technology
Investment Broker Adoption
Explanatory Models
Phase 2 – Model and Survey Development
Hypotheses and Model Development
Survey Development
Phase 3 – Data Collection and Data Exploration
Survey Application and Data Collection
Data Exploration
Application of PLS-SEM Methodology
Phase 4 – Research Results Analysis
Analysis of Research Results
Discussions and Conclusions

Table 4 – Research Design

The first phase of the research is the literature review, mainly focused on scientific articles from the last 5 years, related to topics relevant to the research and its development, such as financial technologies, digital investment broker adoption and theories and models of acceptance and adoption of technology. The second phase is the development of the model, the elaboration of research hypotheses, and the development of the research survey for data collection. The research survey, which will be better described below, has 2 sections: the first designed to identify the sociodemographic profile of the respondents and the second to identify the factors for digital investment broker adoption. The third phase of the research corresponds to the survey application, the data collection and the data exploration. ANOVA and PLS-SEM are applied in data exploration. ANOVA was used to determine if there are significant differences between the population of the groups and PLS-SEM, that is recommended for testing and validating exploratory models, was used to analyze the relationship between variables. This methodology has been widely used in studies to analyze the adoption of digital technologies and services. In the last phase of the research, the results are analyzed in order to address the research questions and the research objective. Furthermore, it explains the research's final conclusions and considerations, its academic and business contributions, the study limitations, and it provides suggestions for future research.

3.1. Survey Structure and Research Variables

Survey is a systematic method of collecting information from a sample of entities for the purpose of building quantitative descriptors of the attributes of the larger population of which the entities are members (Groves et al., 2011, p. 2) used to investigate a social phenomenon and understand society (Brenner, 2020, p. 2). To collect data for this research, a web-based survey was designed and constructed using the Google Forms tool, which represents a good distribution and analyses tool for questionnaires providing a set of data for forward statistical analysis. The survey was developed based on the literature review, and considering that the analysis of the data would be performed using PLS-SEM. All the participants were informed about the purpose of the research and ensured that their data would be anonymous and used only for research purposes.

The survey was composed of two main sections: the first section aims to identify the sociodemographic profile of the respondent and it is composed of single-answer questions related to and five controls: age, gender, education level, income and location; the second section is about the indicators for the constructs of the proposed model, where the goal is evaluating the respondents' agreement on topics based on previous studies, to determine the behavioral intention of digital investment broker adoption. To rate the degree to which respondents agree or disagree with a statement, this second section uses the Likert scale for the answers to the questions. The Likert scale is a psychometric response scale used to obtain participants' opinion, preferences or degree of agreement with a statement or set of statements (Bertram, 2007, p. 1). The scale that will be used is a scale defined between 1 and 7, where 1 represents the most negative answer, "Strongly Disagree", and 7 the most positive answer, "Strongly Agree".

The main dependent variable of the research is Digital Investment Broker Adoption (DIBA). Other variables included as potential determinants are Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Subject Norm (SN), Information Offered (IO) and Data Visualization (DV). Each one of the variables was extracted by summing up the answers to five questions presented in the second section of the research survey, as detailed in Table 3, previously presented.

3.2. DATA COLLECTION

The survey focused and was only distributed in Brazil, the researcher's country of birth and where the researcher has lived most of her adult life. The platform chosen to support the survey was Google Forms, which is a user-friendly tool and allows easy creation, management, and data collection. Google Forms is available free of charge to all registered Google users.

The survey was shared on several channels, such as the social networks Facebook, LinkedIn, and WhatsApp. These channels were chosen due to the large number of users and the cost of sharing information. The analyzed data corresponded to the period between October 1st, 2022, and October 29th, 2022, when the survey was no longer available.

Data processing was performed by summarizing the demographic data of each person who answered the survey, analyzing the results, grouping the collected data according to the research objectives, in order to structure their analysis and interpretation of the data collected in the survey. Before testing the information, it was checked and ensured that the data were clean, without noisy, inconsistent or missing information, ensuring the quality of the conclusions (Ramos, 2017, p. 12).

3.3. ONE-WAY ANALYSIS OF VARIANCE | ANOVA

ANOVA, often called as one-way analysis of variance or simple one-way ANOVA, is a method to analyze an experiment that has over two groups of observations (Gillard, 2020, p. 91). The purpose of ANOVA is to determine if there are significant differences between the population of the groups, assumed to be independent samples from populations that are normally distributed. The ANOVA analysis is based on the variation between and within groups (Gillard, 2020, p. 91).

As one-way ANOVA can only be used to identify that there are statistically significant differences in the population of groups of data and does not show what are the particular groups that differ from the others, there is a need to other tests, normally called multiple comparison tests (Gillard, 2020, p. 96). So, if an ANOVA shows a significant difference among the population means of the groups, multiple comparison tests can be used to see which population means differ from which (Gillard, 2020, p. 96).

3.4. PARTIAL LEAST SQUARE STRUCTURAL EQUATION MODELLING | PLS-SEM

The growth in the number of Partial Least Squares Structural Equation Modeling (PLS-SEM) articles conducted by scholars and researchers in recent years is noticeable. It has become a key methodology for studying the relationship between variables and provides a platform for researchers to easily formulate a model according to a theory (Yuan & Deng, 2021, p. 557). It is a statistical analysis technique that allows the capture of a "complex multivariate world" in a system of equations that provides the study of interactions relationships between one or more dependent variables and multiple independent variables (Hair Jr et al., 2019, p. 457).

The PLS-PM algorithm creates linear combinations of indicators for all types of constructions, which means for latent variables and artifacts (Müller et al., 2018, p. 3). A structural equation model with latent constructs has two components: the first component is the structural model, which shows the relationships, also known as paths, between the latent constructs, and the second component of the structural equation model comprises the measurement models, which include the unidirectional predictive relationships between each latent construct and its associated observed indicators (Hair, J. F. et al., 2011, p. 141).

In confirmatory research, the main focus is on the research question, and the structural model is based on testing the theory (Müller et al., 2018, p. 4). It is defined which constructs are included in the model and how they are interrelated. These interrelationships are normally assumed to be linear and recursive, that is, the model does not contain any feedback loops. The constructs are the focus entities of SEM and represent conceptual variables (Müller et al., 2018, p. 4).

Hair Jr et al. (2019, p. 458) mentions some advantages of PLS-SEM, such as, the data does not need to be normally distributed, the sample does not necessarily need to be very large, but it can also be very small, complex models do not lead to identification problems, as with other SEM approaches, the research interest can be test of theory and prediction and, solutions are possible if the missing values are minimal and coded correctly.

4. FINDINGS AND DISCUSSION

This section presents and discusses the main results obtained in the surveys answered, with a focus on understanding the drivers of digital investment broker adoption. First, the sociodemographic description of the sample is carried out, followed by the statistical description of the results of the survey responses. After that, an ANOVA analysis is performed, and finally the model is tested using the PLS-SEM technique.

4.1. SAMPLE DESCRIPTION

To test the formulated hypotheses, the data collection took place in November 2022. The target respondents of this study were Brazilian citizens, and it got 279 responses, with the majority (over 80%) being adults aged between 25 and 55 years old, that is, people economically active and more likely to manage their own finances.

The survey contained the scale items for the constructs of Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Subject Norm (SN), Information Offered (IO), Data Visualization (DV), and Digital Investment Broker Adoption (DIBA), and all of the constructs were measured as self-reported, and each of the proposed construct's item was answered on a seven-point Likert-type scale. The survey also contained items related to the sociodemographic profile, such as age, gender, education level, income, and location. In the end of the survey an extra question asking if the investors prefer investing through digital investment brokers to traditional banks was placed. The main objective of this question is to understand the preference of individual investors.

Having the sample closed and all the necessary results from the research survey, an analysis of all the variables that could statistically and objectively characterize the sample was first carried out, mainly in terms of sociodemographic characteristics, with the aim of understanding its nature. This analysis is described below, and all the variables are detailed in the Table 5.

The research survey was answered by 279 Brazilians, of which 152 (54.48%) are women and 127 (45.52%) are men. Most of them, 204 people (73.12%), are between 25 and 45 years old, 46 people (16.49%) are over 55 years old, 20 people (7.17%) are between 46 and 55 years old, and only 9 people (3.23%) are young people under 25 years old.

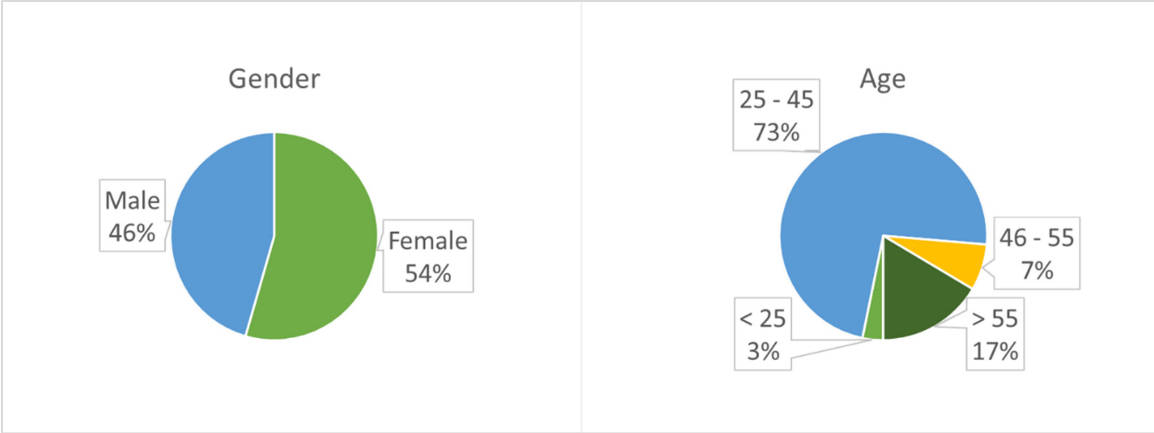

Figure 2 – Sample Description | Gender and Age

Regarding the educational level of people in the sample, 169 (60.57%) have a university degree, 81 (29.03%) have a master's degree, 21 (7.53%) have high school, and only 8 (2.87%) have a degree higher than those already mentioned. Furthermore, in terms of income, 129 (46.24%) has it between 4 and 10 minimum wages, 75 (26.88%) has it between 10 and 20 minimum wages, 50 (17.92%) has it under 4 minimum wages, and only 25 (8.96%) has it over 20 minimum wages.

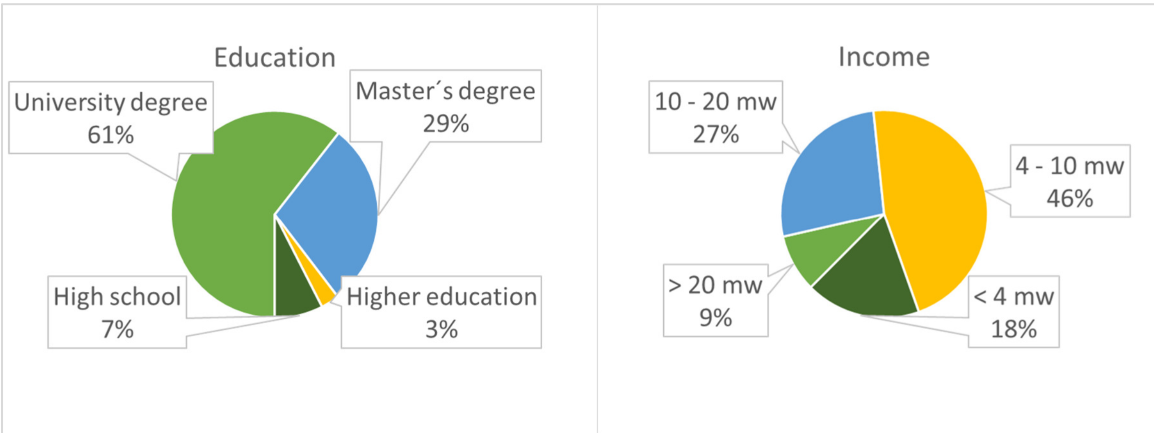

Figure 3 – Sample Description | Education and Income

As already said, all the respondents are from Brazil, and this country can be divided into 5 regions: *Centro-Oeste, Nordeste, Norte, Sul and Sudeste*. However, the responses obtained in the survey were of people from only 4 regions: *Centro-Oeste* (only 9 people – 3.23%), *Nordeste* (only 8 people – 2.87%), *Sul* (211 people – 75.63%), and *Sudeste* (51 people – 18.28%). Most of the answers obtained were from the region *Sul*, a phenomenon that can be explained by the fact that the researcher comes from this region of Brazil, making it easier to obtain answers to the questionnaire from people also from there.

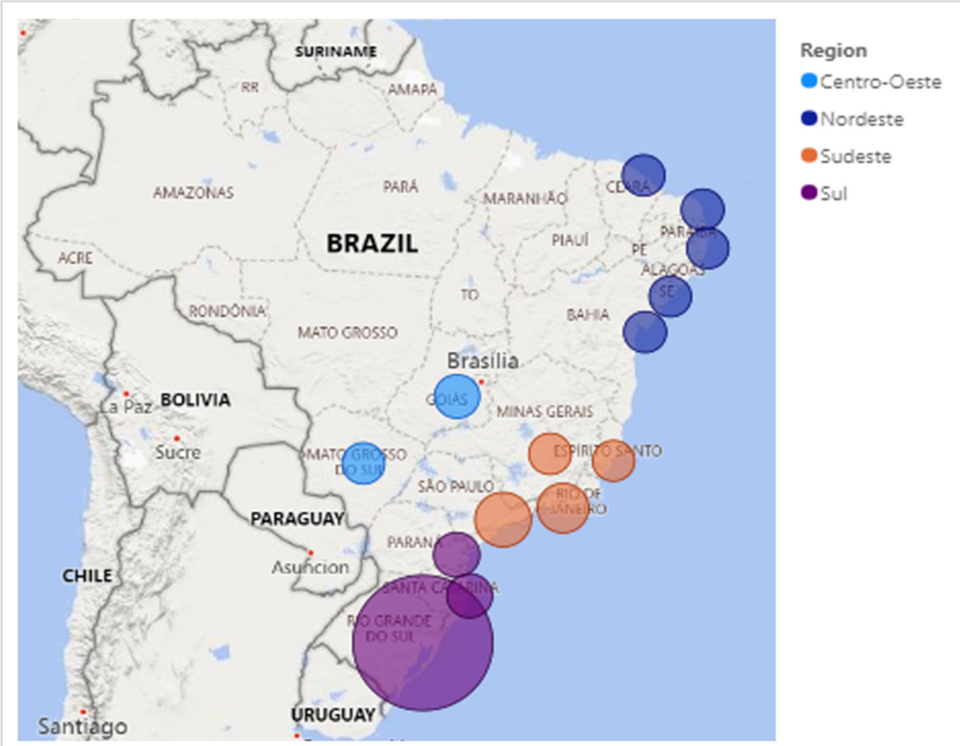

Figure 4 – Sample Description | Location

The table below summarizes all the sociodemographic variables and their categories, and identifies the code used in the SmartPLS software and the frequency of the answers in absolute number and in percentage.

Variable	Code	Frequency (number)	Frequency (%)
Gender			
Female	1	152	54.48%
Male	2	127	45.52%
Age (years)			
< 25	1	9	3.23%
25 – 45	2	204	73.12%
46 – 55	3	20	7.17%
> 55	4	46	16.49%
Education Level			
High school	10	21	7.53%
University degree	20	169	60.57%
Master´s degree	30	81	29.03%
Higher education	40	8	2.87%
Income (minimum wages)			
< 4	4	50	17.92%
4 – 10	3	129	46.24%
10 – 20	2	75	26.88%
> 20	1	25	8.96%

continue…

Variable	Code	Frequency (number)	Frequency (%)
Location			
Centro-Oeste		**9**	**3.23%**
Distrito Federal	10.1	7	2.51%
Mato Grosso do Sul	10.2	2	0.72%
Nordeste		**8**	**2.87%**
Bahia	20.1	2	0.72%
Ceará	20.2	2	0.72%
Pernanbuco	20.3	1	0.36%
Rio Grande do Norte	20.4	2	0.72%
Sergipe	20.5	1	0.36%
Sul		**211**	**75.63%**
Paraná	30.1	9	3.23%
Rio Grande do Sul	30.2	194	69.53%
Santa Catarina	30.3	8	2.87%
Sudeste		**51**	**18.28%**
Espírito Santo	40.1	1	0.36%
Minas Gerais	40.2	2	0.72%
Rio de Janeiro	40.3	19	6.81%
São Paulo	40.4	29	10.39%

Table 5 – Sample Description | Sociodemographic Characteristics

In order to be able to answer the research questions, a specific question was asked in the survey to serve as a filter and to make it possible to separate people who invest from people who do not invest. The question asked was "Do you invest through digital investment brokers?" and it was identified that from the initial sample, 126 people (45.16%) invest through digital investment brokers, and 153 people (54.84%) do not. So, a subsample with these 126 respondents was defined, and the same analysis of all the variables that could statistically and objectively characterize the subsample was carried out. The analysis is described below, and all the variables are detailed in the Table 7.

	Frequency (number)	Frequency (%)
Yes	126	45.16%
No	153	54.84%
Total	**279**	**100.00%**

Table 6 – Digital Investment Broker Adoption Rate

The subsample has 126 people, of which 53 (42.06%) are women and 73 (57.94%) are men. Most of them, 107 people (84.92%), are between 25 and 45 years old, 12 people (9.52%) are over 55 years old, 5 people (3.97%) are between 46 and 55 years old, and only 2 people (1.59%) are young people under 25 years old. That is, the demographic profile shows that the majority of investors (almost 90%) are adults between the ages of 25 and 55, who are normally economically active and more likely to manage their own finances.

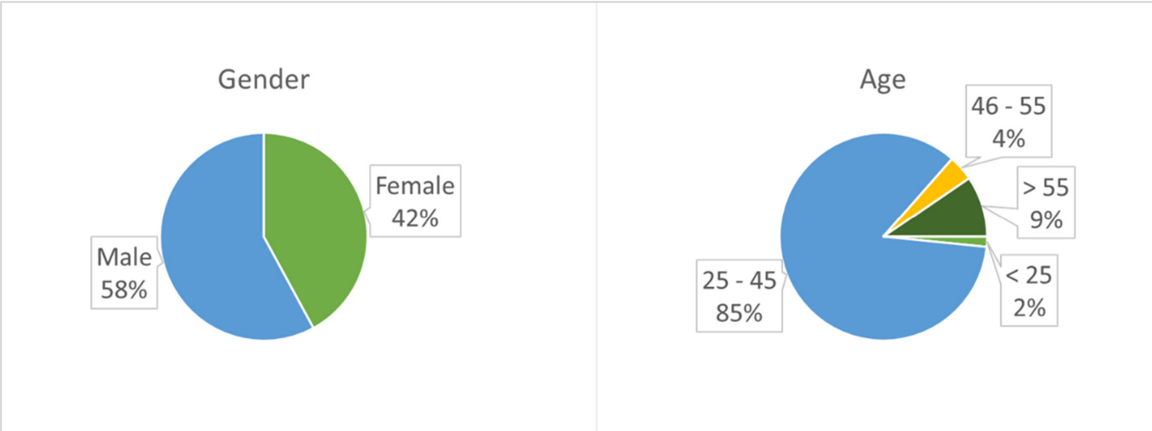

Figure 5 – Subsample Description | Gender and Age

Regarding the educational level of the people in the sample, 79 (62.70%) have a university degree, 43 (34.13%) have a master's degree, and only 4 (3.17%) have high school. All the people who answer the survey and have higher education do not invest, that is why this educational level does not appear in the subsample. In terms of income, 49 people (38.89%) have it between 10 and 20 minimum wages, 48 people (38.10%) has it between 4 and 10 minimum wages, 15 people (11.90%) has it over 20 minimum wages, and 14 people (11.11%) has it under 4 minimum wages.

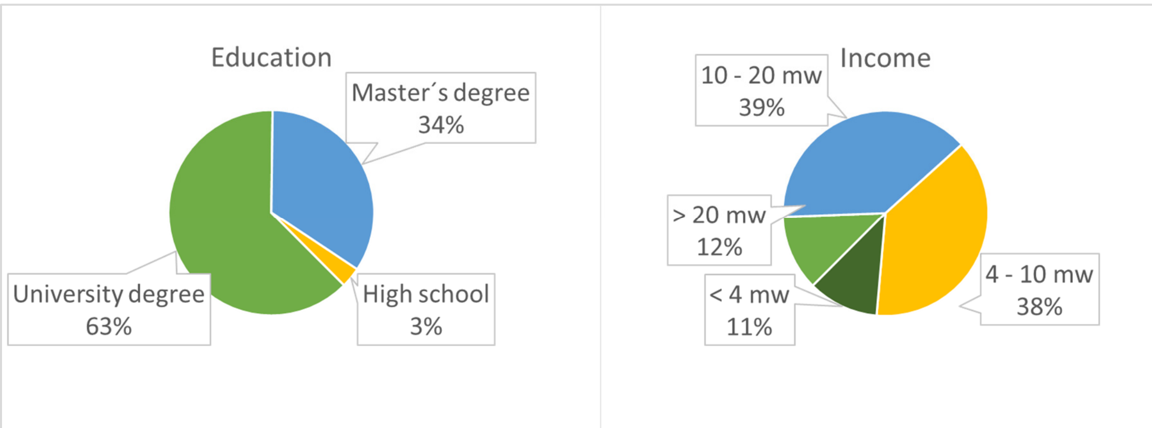

Figure 6 – Subsample Description | Education and Income

The responses in the subsample were of people also from only 4 regions, but instead of 14 states as the original sample, people from only 10 states are investors: *Centro-Oeste* (only 4 people – 3.17%), *Nordeste* (only 2 people – 1.59%), *Sul* (89 people – 70.63%), and *Sudeste (*31 people – 24.60%).

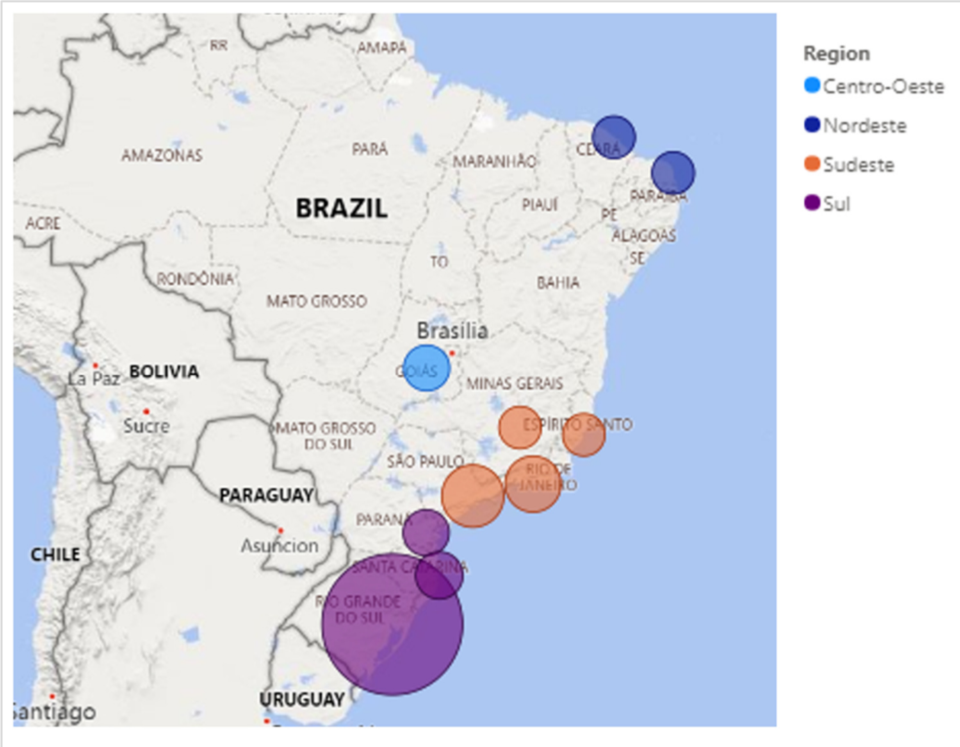

Figure 7 – Subsample Description | Location

The table below summarizes all the sociodemographic variables and their categories, and identifies the code used in the SmartPLS software and the frequency of the answers in absolute number and in percentage.

Variable	Code	Frequency (number)	Frequency (%)
Gender			
Female	1	53	42.06%
Male	2	73	57.94%
Age (years)			
< 25	1	2	1.59%
25 – 45	2	107	84.92%
46 – 55	3	5	3.97%
> 55	4	12	9.52%
Education Level			
High school	10	4	3.17%
University degree	20	79	62.70%
Master´s degree	30	43	34.13%
Income (minimum wages)			
< 4	4	14	11.11%
4 – 10	3	48	38.10%
10 – 20	2	49	38.89%
> 20	1	15	11.90%

continue…

Variable	Code	Frequency (number)	Frequency (%)
Location			
Centro-Oeste		**4**	**3.17%**
Distrito Federal	10.1	4	3.17%
Nordeste		**2**	**1.59%**
Ceará	20.2	1	0.79%
Rio Grande do Norte	20.4	1	0.79%
Sul		**89**	**70.63%**
Paraná	30.1	4	3.17%
Rio Grande do Sul	30.2	80	63.49%
Santa Catarina	30.3	5	3.97%
Sudeste		**31**	**24.60%**
Espírito Santo	40.1	1	0.79%
Minas Gerais	40.2	1	0.79%
Rio de Janeiro	40.3	12	9.52%
São Paulo	40.4	17	13.49%

Table 7 – Subsample description about sociodemographic characteristics

At the end of the survey, there was an extra question in order to verify, among investors, whether they prefer to invest through digital investment brokers or traditional banks. It was verified that almost 85% of the investors gave some kind of positive answer to this question. Among people who invest, 62.70% strongly agree with the statement "I prefer investing through digital investment brokers to traditional banks.", 13.49% agree, 8.73% somewhat agree, 7.14% are neutral, 3.97% somewhat disagree, 3.97% strongly disagree and no one checked the option "Disagree".

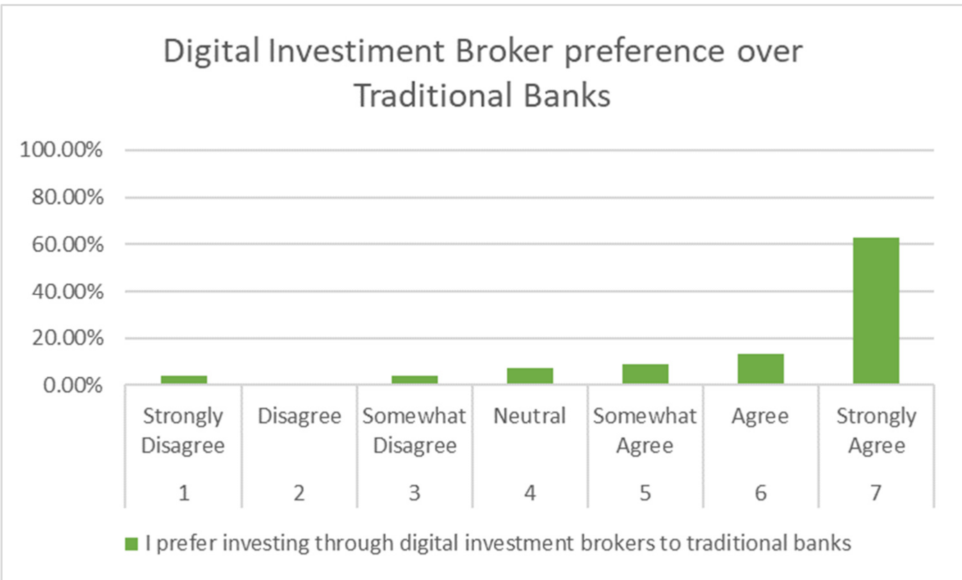

Figure 8 – Digital Investment Broker preference over Traditional Banks

4.1. Descriptive Statistics

After analyzing the sample, an analysis of the descriptive statistics of each one of the factors identified in the research model was carried out. As previously mentioned, the Likert scale was adopted for the answers to the questions in the questionnaire, which is defined between 1 and 7, where 1 represents the most negative answer (strongly disagree) and 7 the most positive answer (strongly agree). Answers from 1 to 3 are considered negative answers, answers equal to 4 are considered neutral and answers from 5 to 7 are considered positive answers. A brief summary of the descriptive statistics of the research survey responses is described below, however they can be seen in detail in the Appendix 8 – Descriptive Statistics | Smart PLS.

Regarding questions about Perceived Usefulness (PU), over 95% of the answers are positive to some degree (responses from 5 to 7), with approximately 66% completely agreeing with the statements. The observed minimum value is 1 and the observed maximum value is 7. The mean is equivalent to 6.47 and the median is 7. The mean standard deviation is 0.917.

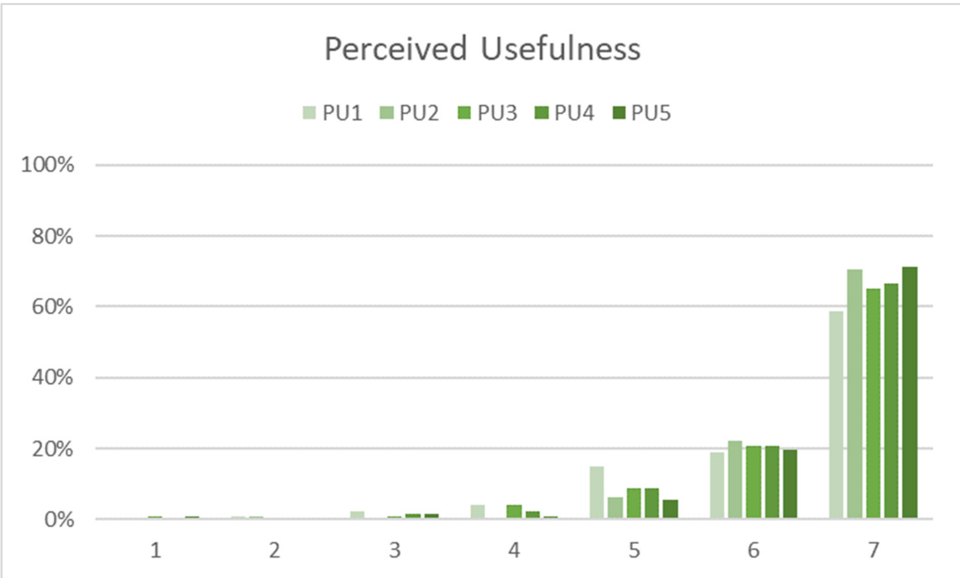

Figure 9 – Perceived Usefulness Answers Distribution

Regarding questions about Perceived Ease of Use (PEOU), over 87% of the answers are positive to some degree (responses from 5 to 7), with approximately 36% completely agreeing with the statements. The observed minimum value is 1 and the observed maximum value is 7. The mean is equivalent to 5.84 and the median is 7. The mean standard deviation is 1.073.

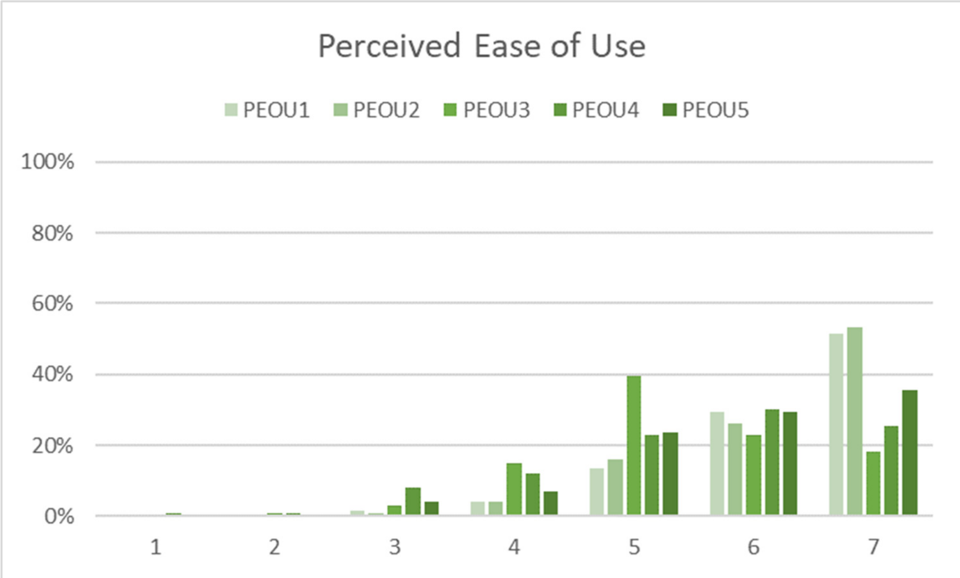

Figure 10 – Perceived Ease of Use Answers Distribution

Regarding questions about Subject Norm (SN), over 27% of the answers are negative to some degree (responses from 1 to 3), approximately 22% are neutral (responses equal to 4), and over 50% are positive to some degree (responses from 5 to 7. The observed minimum value is 1 and the observed maximum value is 7. The mean is equivalent to 5.84 and the median is 7. The mean standard deviation is 1.739.

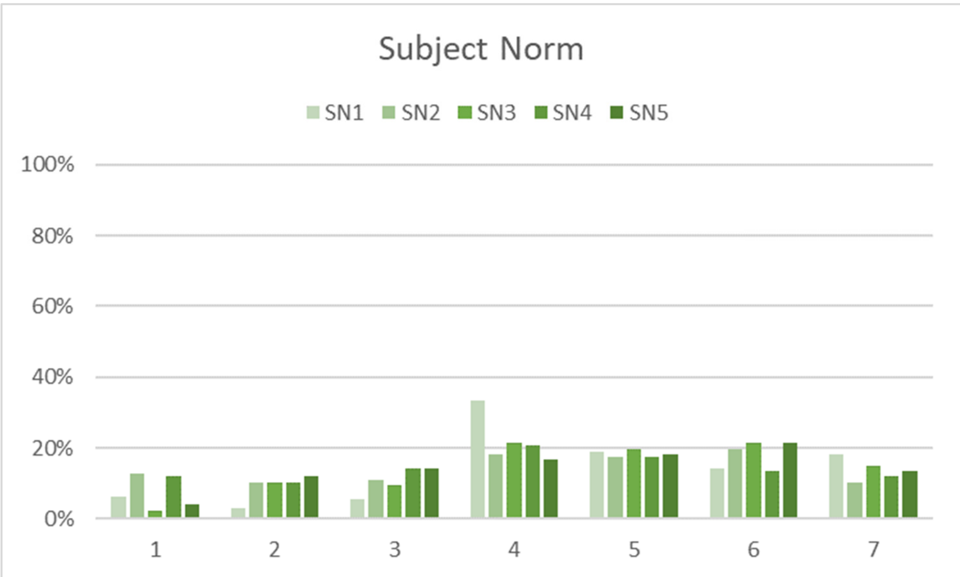

Figure 11 – Subject Norm Answers Distribution

Regarding questions about Information Offered (IO), over 88% of the answers are positive to some degree (responses from 5 to 7), with over 55% completely agreeing with the statements. The observed minimum value is 1 and the observed maximum value is 7. The mean is equivalent to 6.13 and the median is 7. The mean standard deviation is 1.282.

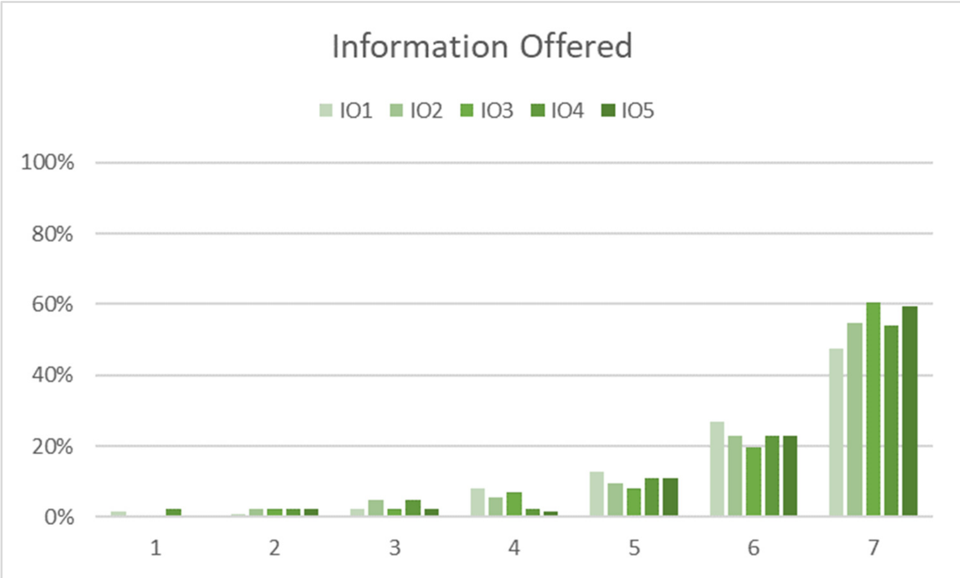

Figure 12 – Information Offered Answers Distribution

Regarding questions about Data Visualization (DV), over 91% of the answers are positive to some degree (responses from 5 to 7), with approximately 61% completely agreeing with the statements. The observed minimum value is 1 and the observed maximum value is 7. The mean is equivalent to 6.26 and the median is 7. The mean standard deviation is 1.082.

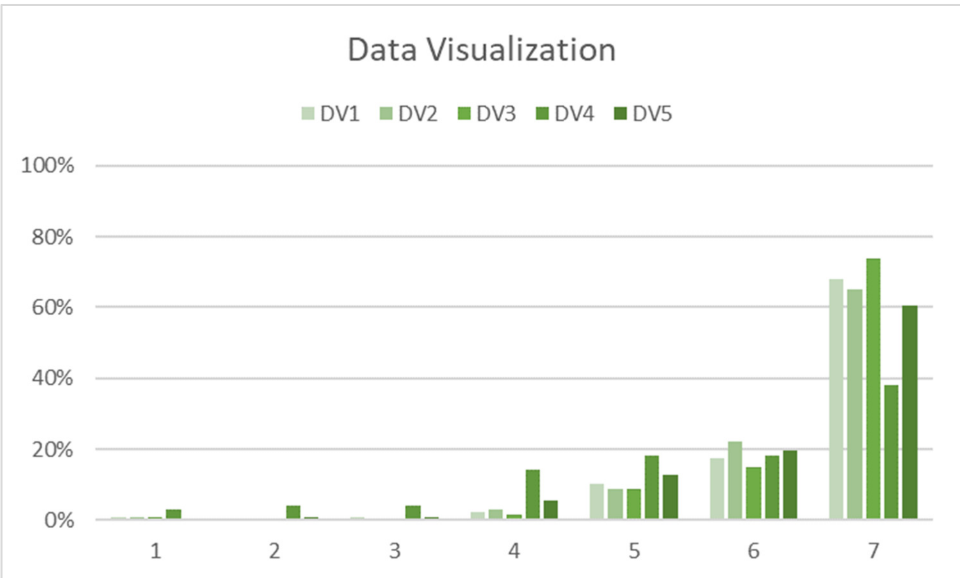

Figure 13 – Data Visualization Answers Distribution

Regarding questions about Digital Investment Broker Adoption (DIBA), over 87% of the answers are positive to some degree (responses from 5 to 7), with approximately 50% completely agreeing with the statements. The observed minimum value is 1 and the observed maximum value is 7. The mean is equivalent to 5.98 and the median is 7. The mean standard deviation is 1.364.

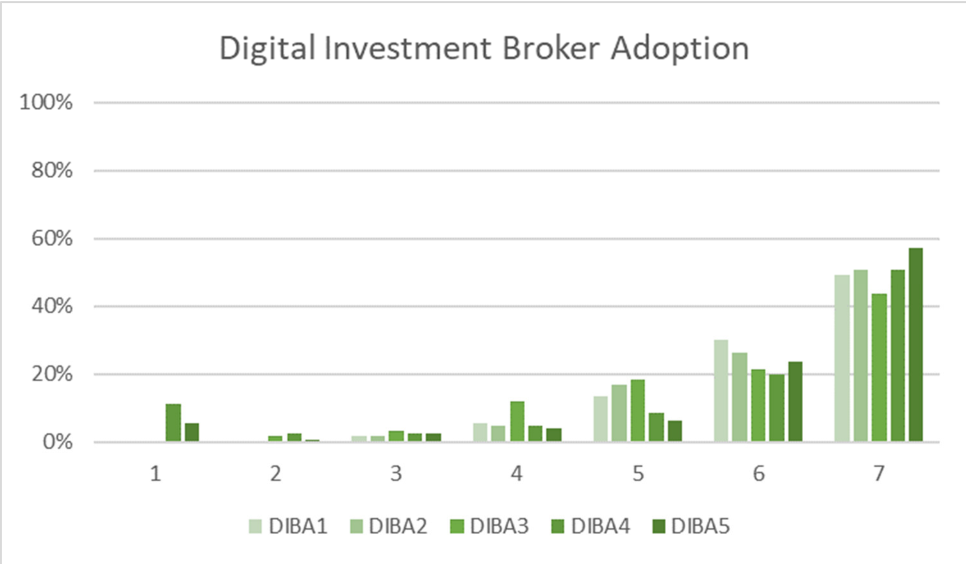

Figure 14 – Digital Investment Broker Adoption Answers Distribution

Below is placed a summary table where it is possible to observe that all constructs have a minimum observed value of 1 and a maximum observed value of 7. Four out of the six constructs have a median of 7 – PU, IO, DV and DIBA – one construct, PEOU, has a median of 6 and one construct, SN, has a median of 4. The constructs PU, DV and IO have the highest means, 6.47, 6.26 and 6.13, respectively, all of them above 7. The construct SN has the lowest mean of 4.44. And the constructs PEOU and DIBA have intermediate means, 5.84 and 5.98, respectively, both closer to 6.

	Mean	Median	Observed min	Observed max	Standard deviation
PU	6.47	7.00	1.00	7.00	0.917
PEOU	5.84	6.00	1.00	7.00	1.073
SN	4.44	4.00	1.00	7.00	1.739
IO	6.13	7.00	1.00	7.00	1.282
DV	6.26	7.00	1.00	7.00	1.082
DIBA	5.98	7.00	1.00	7.00	1.364

Table 8 – Summarized Descriptive Statistics

4.1. ANOVA One-Way Analysis

The analysis of the answers to the research survey questions was performed ANOVA one-way analysis of variance in order to determine differences between groups. ANOVA one-way it is possible to obtain the calculations to test the significance of the differences between the arithmetic means of data samples. The results of each ANOVA one-way analysis, are summarized and described below, focusing on the approach for each Sig. value < 0.05.

Regarding the education factor, differences are identified in 5 questions, 1 related to PU (Perceived Usefulness), 1 related to SN (Subject Norm) and 3 questions related to DV (Data Visualization) with Sig. < 0.05. This means that, in the sample collected, the education level can influence the digital investment broker adoption regarding the perceived usefulness, subject norm and data visualization. Once these differences have been identified, a multiple comparison test was carried out to verify between which educational levels these differences are, the ones with Sig. < 0.05. With the multiple comparison test it is possible to conclude that for the question related to PU (Perceived Usefulness) the differences are between high school and master's degree, for the questions related to SN (Subject Norm) the differences are between high school and university degree, and for all the 3 questions related to DV (Data Visualization) the differences are between high school and both university degree and master's degree. No difference was identified between university degree and master's degree.

Multiple Comparisons | Education

Scheffe

Dependent Variable	(I) COD_Education	(J) COD_Education	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PU2	High School	University degree	-0.845	0.365	0.073	-1.75	0.06
		Master`s degree	-.971*	0.372	0.037	-1.89	-0.05
	University degree	High School	0.845	0.365	0.073	-0.06	1.75
		Master`s degree	-0.126	0.135	0.648	-0.46	0.21
	Master`s degree	High School	.971*	0.372	0.037	0.05	1.89
		University degree	0.126	0.135	0.648	-0.21	0.46
SN3	High School	University degree	-2.060*	0.821	0.047	-4.1	-0.02
		Master`s degree	-1.948	0.838	0.071	-4.02	0.13
	University degree	High School	2.060*	0.821	0.047	0.02	4.1
		Master`s degree	0.112	0.304	0.934	-0.64	0.87
	Master`s degree	High School	1.948	0.838	0.071	-0.13	4.02
		University degree	-0.112	0.304	0.934	-0.87	0.64
DV1	High School	University degree	-1.756*	0.474	0.001	-2.93	-0.58
		Master`s degree	-1.808*	0.483	0.001	-3.01	-0.61
	University degree	High School	1.756*	0.474	0.001	0.58	2.93
		Master`s degree	-0.052	0.175	0.957	-0.49	0.38
	Master`s degree	High School	1.808*	0.483	0.001	0.61	3.01
		University degree	0.052	0.175	0.957	-0.38	0.49
DV2	High School	University degree	-1.731*	0.45	<.001	-2.85	-0.62
		Master`s degree	-1.831*	0.459	<.001	-2.97	-0.69
	University degree	High School	1.731*	0.45	<.001	0.62	2.85
		Master`s degree	-0.1	0.166	0.834	-0.51	0.31
	Master`s degree	High School	1.831*	0.459	<.001	0.69	2.97
		University degree	0.1	0.166	0.834	-0.31	0.51
DV3	High School	University degree	-1.896*	0.416	<.001	-2.93	-0.87
		Master`s degree	-1.878*	0.424	<.001	-2.93	-0.83
	University degree	High School	1.896*	0.416	<.001	0.87	2.93
		Master`s degree	0.018	0.154	0.993	-0.36	0.4
	Master`s degree	High School	1.878*	0.424	<.001	0.83	2.93
		University degree	-0.018	0.154	0.993	-0.4	0.36

*. The mean difference is significant at the 0.05 level.

Table 9 – Multiple Comparison | Education – Indicators with Sig < 0.05

Regarding the gender factor, differences are identified in 2 questions related to PEOU (Perceived Ease of Use) and 2 questions related to IO (Information Offered) with Sig. < 0.05. This means that, in the sample collected, gender can influence the digital investment broker adoption regarding the perceived ease of use and the information offered.

Regarding the age factor, there is no significant differences between the age groups (< 25 year, 25 – 45 years, 46 – 55 years and > 55 years). All the hypotheses have Sig. > 0.05, which means that, in the sample collected, age does not influence the digital investment broker adoption, all the age groups have the same behavior.

Regarding the income factor, there are significant differences for the question *"I prefer investing through digital investment brokers to traditional banks."*. This difference is between the social classes C and D, which are represented by the income ranges 4 - 10 minimum wages and < 4 minimum wages, respectively. That means that these social classes have different behaviors in the preferences between digital investment brokers and traditional banks. Also, differences are identified in 5 other questions, 2 related to IO (Information Offered), 1 related to DV (Data Visualization) and 2 questions related to DIBA (Digital Investment Broker Adoption) with Sig. < 0.05. This means that, in the sample collected, the income can influence the digital investment broker adoption, regarding the information offered, data visualization and digital investment broker.

Once these differences have been identified, a multiple comparison test was also carried out to verify between which income ranges these differences are, the ones with Sig. < 0.05. With the multiple comparison test it is possible to conclude that for the question IO1 related to IO (Information Offered) the differences are between the social class D (< 4 minimum wages) and the other ones – A (> 20 minimum wages), B (10 - 20 minimum wages) and C (4 - 10 minimum wages), for the question IO3 also related to IO (Information Offered) the differences are between classes A (> 20 minimum wages) and D (< 4 minimum wages), for the question DV1 related to DV (Data Visualization) the differences are between the social class D (< 4 minimum wages) and both social classes B (10 - 20 minimum wages) and C (4 - 10 minimum wages), for the question DIBA2 related to DIBA (Digital Investment Broker Adoption) the differences are between the social classes A (> 20 minimum wages) and D (< 4 minimum wages), and for the question DIBA3 also related to DIBA (Digital Investment Broker Adoption) the differences are between the social classes D (< 4 minimum wages) and C (4 - 10 minimum wages). The multiple comparison analysis allows concluding that the differences are always between social class D (< 4 minimum wages) and one of the other classes. Social classes A (> 20 minimum wages), B (10 - 20 minimum wages) and C (4 - 10 minimum wages) do not differ from each other, they have the same behavior.

Multiple Comparisons | Income							
Scheffe							
Dependent Variable	(I) COD_Income	(J) COD_Income	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
IO1	> 20 minimum wages	10 - 20 minimum wages	0.303	0.364	0.875	-0.73	1.34
		4 - 10 minimum wages	0.425	0.365	0.717	-0.61	1.46
		< 4 minimum wages	1.610*	0.459	0.008	0.31	2.91
	10 - 20 minimum wages	> 20 minimum wages	-0.303	0.364	0.875	-1.34	0.73
		4 - 10 minimum wages	0.122	0.251	0.972	-0.59	0.83
		< 4 minimum wages	1.306*	0.374	0.009	0.25	2.37
	4 - 10 minimum wages	> 20 minimum wages	-0.425	0.365	0.717	-1.46	0.61
		10 - 20 minimum wages	-0.122	0.251	0.972	-0.83	0.59
		< 4 minimum wages	1.185*	0.375	0.022	0.12	2.25
	< 4 minimum wages	> 20 minimum wages	-1.610*	0.459	0.008	-2.91	-0.31
		10 - 20 minimum wages	-1.306*	0.374	0.009	-2.37	-0.25
		4 - 10 minimum wages	-1.185*	0.375	0.022	-2.25	-0.12
IO3	> 20 minimum wages	10 - 20 minimum wages	0.433	0.354	0.685	-0.57	1.44
		4 - 10 minimum wages	0.696	0.355	0.284	-0.31	1.7
		< 4 minimum wages	1.371*	0.446	0.027	0.11	2.64
	10 - 20 minimum wages	> 20 minimum wages	-0.433	0.354	0.685	-1.44	0.57
		4 - 10 minimum wages	0.263	0.244	0.761	-0.43	0.95
		< 4 minimum wages	0.939	0.364	0.089	-0.09	1.97
	4 - 10 minimum wages	> 20 minimum wages	-0.696	0.355	0.284	-1.7	0.31
		10 - 20 minimum wages	-0.263	0.244	0.761	-0.95	0.43
		< 4 minimum wages	0.676	0.365	0.334	-0.36	1.71
	< 4 minimum wages	> 20 minimum wages	-1.371*	0.446	0.027	-2.64	-0.11
		10 - 20 minimum wages	-0.939	0.364	0.089	-1.97	0.09
		4 - 10 minimum wages	-0.676	0.365	0.334	-1.71	0.36
DV1	> 20 minimum wages	10 - 20 minimum wages	0.11	0.275	0.984	-0.67	0.89
		4 - 10 minimum wages	-0.046	0.276	0.999	-0.83	0.74
		< 4 minimum wages	0.957	0.346	0.059	-0.03	1.94
	10 - 20 minimum wages	> 20 minimum wages	-0.11	0.275	0.984	-0.89	0.67
		4 - 10 minimum wages	-0.156	0.189	0.878	-0.69	0.38
		< 4 minimum wages	.847*	0.283	0.033	0.05	1.65
	4 - 10 minimum wages	> 20 minimum wages	0.046	0.276	0.999	-0.74	0.83
		10 - 20 minimum wages	0.156	0.189	0.878	-0.38	0.69
		< 4 minimum wages	1.003*	0.283	0.007	0.2	1.81
	< 4 minimum wages	> 20 minimum wages	-0.957	0.346	0.059	-1.94	0.03
		10 - 20 minimum wages	-.847*	0.283	0.033	-1.65	-0.05
		4 - 10 minimum wages	-1.003*	0.283	0.007	-1.81	-0.2
DIBA2	> 20 minimum wages	10 - 20 minimum wages	0.565	0.283	0.268	-0.24	1.37
		4 - 10 minimum wages	0.333	0.283	0.71	-0.47	1.14
		< 4 minimum wages	1.095*	0.356	0.027	0.09	2.1
	10 - 20 minimum wages	> 20 minimum wages	-0.565	0.283	0.268	-1.37	0.24
		4 - 10 minimum wages	-0.231	0.195	0.703	-0.78	0.32
		< 4 minimum wages	0.531	0.29	0.346	-0.29	1.35
	4 - 10 minimum wages	> 20 minimum wages	-0.333	0.283	0.71	-1.14	0.47
		10 - 20 minimum wages	0.231	0.195	0.703	-0.32	0.78
		< 4 minimum wages	0.762	0.291	0.082	-0.06	1.59
	< 4 minimum wages	> 20 minimum wages	-1.095*	0.356	0.027	-2.1	-0.09
		10 - 20 minimum wages	-0.531	0.29	0.346	-1.35	0.29
		4 - 10 minimum wages	-0.762	0.291	0.082	-1.59	0.06
DIBA3	> 20 minimum wages	10 - 20 minimum wages	0.143	0.367	0.985	-0.9	1.18
		4 - 10 minimum wages	-0.083	0.368	0.997	-1.13	0.96
		< 4 minimum wages	1.071	0.462	0.152	-0.24	2.38
	10 - 20 minimum wages	> 20 minimum wages	-0.143	0.367	0.985	-1.18	0.9
		4 - 10 minimum wages	-0.226	0.252	0.849	-0.94	0.49
		< 4 minimum wages	0.929	0.377	0.114	-0.14	2
	4 - 10 minimum wages	> 20 minimum wages	0.083	0.368	0.997	-0.96	1.13
		10 - 20 minimum wages	0.226	0.252	0.849	-0.49	0.94
		< 4 minimum wages	1.155*	0.378	0.029	0.08	2.23
	< 4 minimum wages	> 20 minimum wages	-1.071	0.462	0.152	-2.38	0.24
		10 - 20 minimum wages	-0.929	0.377	0.114	-2	0.14
		4 - 10 minimum wages	-1.155*	0.378	0.029	-2.23	-0.08
I prefer investing through digital investment brokers to traditional banks.	> 20 minimum wages	10 - 20 minimum wages	0.574	0.44	0.637	-0.67	1.82
		4 - 10 minimum wages	0.158	0.441	0.988	-1.09	1.41
		< 4 minimum wages	1.533	0.554	0.058	-0.04	3.1
	10 - 20 minimum wages	> 20 minimum wages	-0.574	0.44	0.637	-1.82	0.67
		4 - 10 minimum wages	-0.416	0.303	0.597	-1.27	0.44
		< 4 minimum wages	0.959	0.452	0.217	-0.32	2.24
	4 - 10 minimum wages	> 20 minimum wages	-0.158	0.441	0.988	-1.41	1.09
		10 - 20 minimum wages	0.416	0.303	0.597	-0.44	1.27
		< 4 minimum wages	1.375*	0.453	0.03	0.09	2.66
	< 4 minimum wages	> 20 minimum wages	-1.533	0.554	0.058	-3.1	0.04
		10 - 20 minimum wages	-0.959	0.452	0.217	-2.24	0.32
		4 - 10 minimum wages	-1.375*	0.453	0.03	-2.66	-0.09

*. The mean difference is significant at the 0.05 level.

Table 10 – Multiple Comparison | Income – Indicators with Sig < 0.05

Regarding the state factor, for states where there is enough data to perform an ANOVA analysis, there are no significant differences in the behavior considering the locations where people live. The hypotheses have Sig. > 0.05, which means that, in the sample collected, and where it is possible to perform ANOVA, the location does not influence the digital investment broker adoption, people from different states have the same behavior.

Below is a summary table with the main differences between the categories of each of the variables. For the Gender factor, the main differences are in the Perceived Ease of Use (PEOU) and Information Offered (IO) constructs. For the Education factor, the main differences are in the Perceived Usefulness (PU), Subject Norm (SN) and Data Visualization (DV) constructs, and are between High School and the other categories, Master's Degree and University Degree. For the Income factor, the main differences are in the Information Offered (IO), Data Visualization (DV) and Digital Investment Broker Adoption (DIBA) constructs, and are between Social Class C (< minimum wages) and the other categories, Social classes A (> 20 minimum wages), B (10 - 20 minimum wages) and C (4 - 10 minimum wages).

Demographic Factor	Construct	Question	Main Differences
Gender	PEOU	PEOU3	Male x Female
		PEOU4	
	IO	IO2	
		IO3	
Education	PU	PU2	High School x Master's Dregree
	SN	SN3	High School x University Degree
	DV	DV1	High School x Master's Dregree High School x University Degree
		DV2	
		DV3	
Income	IO	IO1	Social Class D x Social Class A
			Social Class D x Social Class B
			Social Class D x Social Class C
		IO3	Social Class D x Social Class A
	DV	DV1	Social Class D x Social Class B
			Social Class D x Social Class C
	DIBA	DIBA2	Social Class D x Social Class A
		DIBA3	Social Class D x Social Class C

Table 11 – Summary of Differences by Demographic Factor

4.2. PLS-SEM

After the ANOVA analysis, the hypotheses were tested employing partial least squares structural equation modeling technique (PLS-SEM) using the SmartPLS software. Since this study adopted PLS-SEM, normal distribution of data is not required since this technique has some advantages in analyzing data that is not normally distributed (J. Hair et al., 2017, p. 445). All latent variables in the current study were the results of reflective indicators.

The diagram shown below, in Figure 15, introduces the research model designed in the SmartPLS. This model represents a set of relationships between variables, that is, hypothetical relationships, which allow explaining the behavior of a given population in relation to the investment broker adoption. The model presents 6 latent variables, represented by the blue circles: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Subject Norm (SN), Data Visualization (DV), Information Offered (IO) and Investment Broker Adoption (IBA).

The number inside the blue circles means how much the variance of the latent variable is being explained by the other latent variables. Latent variables are the variables that need others, that is, the manifest or observable variables, so that they can be explained. The path coefficients, which are the numbers on the arrows, explain how strong the effect of one variable is on another variable (Brito, 2022, p. 43; Hashmi et al., 2021, p. 13). Values that are close to one represent a stronger association and values thar are closer to zero represent a weak relationship (Hashmi et al., 2021, p. 13).

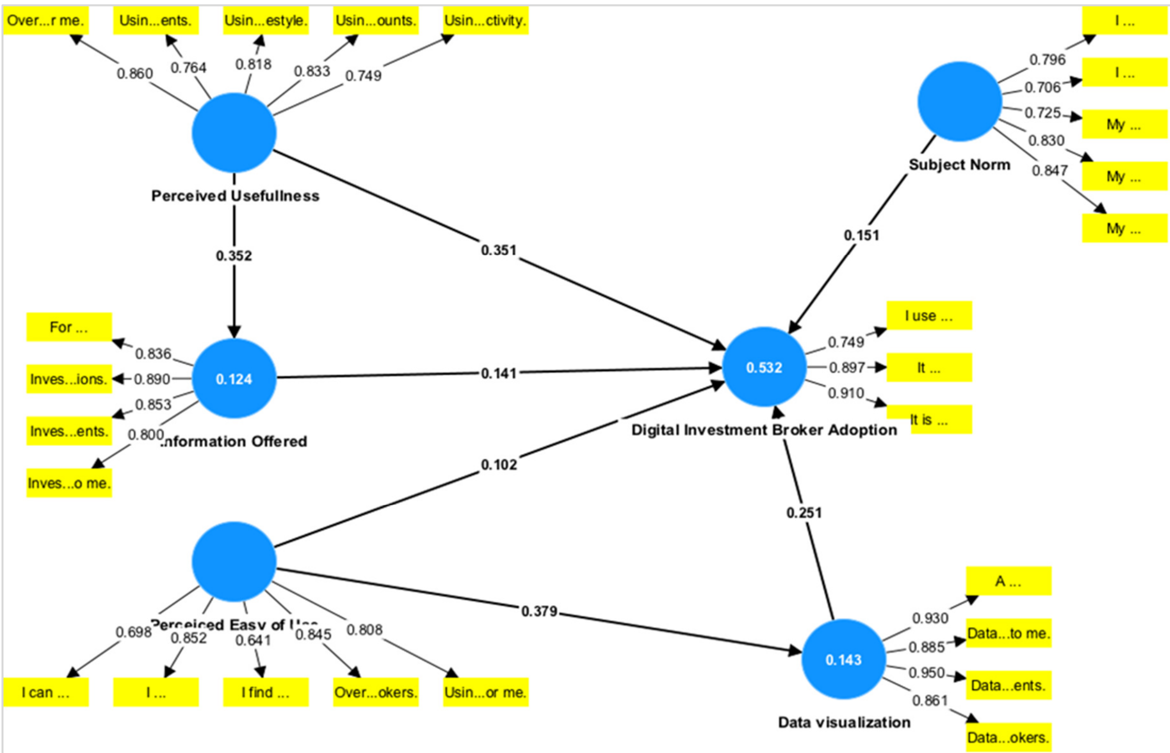

Figure 15 – Path Model | SmartPLS

In the research model design, the external loadings of each item are examined, and those that have loadings $\lambda < 0.6$ are removed and then the evaluation of the measurement model and structural model is made only with the remaining items identified below in the Table 12. So, the first three mentioned latent variables, Perceived Usefulness, Perceived Ease of Use and Subject Norm, are made up of five observed indicators, the Data Visualization and the Information Offered by four observed indicators, and the Digital Investment Broker Adoption by only three observed indicators.

Indicator	Notation	PU	PEOU	SN	IO	DV	DIBA
Using online investment brokers gives me more control over my financial investments.	**PU1**	0.764					
Using online investment brokers provides me with convenient access to my investment accounts.	**PU2**	0.833					
Using online investment brokers saves my time and allows me to do my investing activities quickly, saving my time and increasing my productivity.	**PU3**	0.749					
Using online investment brokers is compatible with my lifestyle.	**PU4**	0.818					
Overall, I find online investment brokerages useful for me.	**PU5**	0.860					
Using online investment brokers is easy for me.	**PEOU1**		0.808				
I feel comfortable using online investment brokers.	**PEOU2**		0.852				
I find all the content of online investment brokers understandable.	**PEOU3**		0.641				
I can use online investment brokers without asking for help, without any problem.	**PEOU4**		0.698				
Overall, I find it easy to use online investment brokers.	**PEOU5**		0.845				
My family and friends think I should use online investment brokers.	**SN1**			0.725			
I learn about online investment brokerages from my friends and family.	**SN2**			0.706			
I discuss online investment brokerages with my friends and family.	**SN3**			0.796			
My friends and family recommended online investment brokers to me.	**SN4**			0.830			
My friends, family and I share experiences and information about online investment brokers.	**SN5**			0.847			
Investment and financial market information is important to me.	**IO1**				0.800		
For me it is important to have accurate and up-to-date information about investments and the financial market.	**IO2**				0.836		
Investment and financial market information helps me in my financial investment decisions.	**IO3**				0.890		
Investment and financial market information improves my ability to plan my financial investments.	**IO5**				0.853		
Data visualization about financial investments is important to me.	**DV1**					0.885	
Data visualization about investment helps me understand my financial investments.	**DV2**					0.950	
A good data visualization about investment improves my experience using online investment brokers.	**DV3**					0.930	
Data visualization helps me to have a clear and understandable interaction when using online investment brokers.	**DV5**					0.861	
It is valuable for me to use online investment brokers.	**DIBA1**						0.910
It is important for me to use online investment brokers.	**DIBA2**						0.897
I use online investment brokers frequently.	**DIBA3**						0.749

Table 12 – Loadings

After having the research model designed, the reflective measurement model analysis was performed. Reflective measurement model analysis is basically a test of validity, which is the ability to measure what is proposed in a certain phenomenon, and a test of reliability, which is the ability to present measures faithful to reality (Gottems et al., 2018, p. 1; Hair, J. F. et al., 2011, p. 145)

The reliability tests used in the research are first the Cronbach's alpha and the composite reliability rho_c. According to Gottems et al. (2018, p. 1) the closer to 1, the greater the reliability of the indicators. Even the Cronbach's alpha is rather conservative and the composite reliability rho_c may be too liberal, they both assume the same threshold, with a lower limit of 0.7 being generally accepted, but which can be reduced to 0.6 in exploratory research. As an alternative, the consistent reliability coefficient rho_a has been proposed, which generally lies between the conservative Cronbach's alpha and the liberal composite reliability rho_c, and, therefore, it is considered an acceptable compromise between these two measurements (J. F. Hair et al., 2021, p. 77–78).

The reliability of the model was confirmed because all values of Cronbach's Alpha, composite reliability and consistent reliability of all constructs far exceeded the recommended minimum value with all the values above 0.8 and below 0.95, demonstrating that all the constructs have satisfactory reliability values, as shown in Table 13.

Construct	Notation	Cronbach's alpha	Consistent reliability (rho_a)	Composite reliability (rho_c)
Data visualization	DV	0.928	0.928	0.949
Digital Investment Broker Adoption	DIBA	0.817	0.858	0.890
Information Offered	IO	0.868	0.879	0.909
Perceiced Easy of Use	PEOU	0.833	0.867	0.880
Perceived Usefullness	PU	0.865	0.879	0.902
Subject Norm	SN	0.844	0.861	0.887

Table 13 – Reliability

The validity testing in the PLS-SEM analysis was determined by convergent validity and discriminant validity (Hair, J. F. et al., 2011, p. 146). Hair et al. (2016) and Müller et al. (2018) define convergent validity and discriminant validity as follows: convergent validity is the extent to which a measure is positively correlated with alternative measures of the same construct, and discriminant validity is the extent to which a construct is totally distinct from other constructs, which implies that a construct is unique and captures phenomena not represented by other constructs in the model.

The convergent validity at the construct level is commonly established by the average variance extracted (AVE), which is defined as the grand mean value of the squared loadings of the indicators associated with the construct, in other words, it is the sum of the squared loadings divides by the number of indicators (J. Hair et al., 2016, p. 114). The AVE represents how much of the variance of an indicator can be explained by the underlying factor (Müller et al., 2018, p. 9). According to Bagozzi and Yi (1988, p. 82) for it to be considered valid, AVE for all constructs must exceed the minimum value of 0.50. Thus, all the constructs of the research model showed sufficient convergent validity since they explained more than half of their indicators' variance, that is, all the constructs have AVE above 0.5 and so, the convergent validity of the model was confirmed by this criterion.

Construct	Notation	Average variance extracted (AVE)
Data visualization	DV	0.823
Digital Investment Broker Adoption	DIBA	0.731
Information Offered	IO	0.715
Perceiced Easy of Use	PEOU	0.598
Perceived Usefullness	PU	0.650
Subject Norm	SN	0.613

Table 14 – Convergent Validity

Regarding the discriminant validity, it is evidenced when indicators of distinct latent variables are not highly correlated (Müller et al., 2018, p. 9). The discriminant validity can be determined by the HTMT ratio (Heterotrait-Monotrait ratio) and by the Fornell-Larcker criterion. The HTMT approach is an estimate of what the true correlation between two constructs if they were perfectly reliable (J. Hair et al., 2016, p. 118). According to Henseler et al. (2015, p. 127), a threshold of 0.85 for HTMT is the most conservative, as it reaches the lowest specificity of all the conditions evaluated in their study. This means that it may indicate problems of discriminant validity in situations that higher thresholds would not indicate. Therefore, this limit of 0.85 for HTMT was adopted, and it is concluded that all HTMT values are below the limit value more conservative of 0.85, indicating that all constructs were distinct one from another, providing evidence of discriminant validity.

Construct	Notation	DV	DIBA	IO	PEOU	PU	SN
Data visualization	DV						
Digital Investment Broker Adoption	DIBA	0.649					
Information Offered	IO	0.479	0.530				
Perceiced Easy of Use	PEOU	0.419	0.544	0.351			
Perceived Usefullness	PU	0.614	0.714	0.380	0.629		
Subject Norm	SN	0.250	0.391	0.373	0.244	0.249	

Table 15 – Heterotrait-Monotrait ratio (HTMT)

For the Fornell-Larcker criterion to be validated the square root of the AVE must be greater than the correlation of the specific construct with all the other constructs of the structural model (Ramos, 2017, p. 14). As the square root for the constructs Data Visualization, Digital Investment Broker Adoption, Information Offered, Perceived Ease of Use, Perceived Usefulness and Subject Norm are 0.907, 0.855, 0.846, 0.773, 0.806 and 0.783, respectively, this condition is confirmed, thus confirming the discriminant validity by the criterion of Fornell-Larcker. The correlation of a specific construct with all the other constructs are identified below in the Table 16.

Construct	Notation	DV	DIBA	IO	PEOU	PU	SN
Data visualization	DV	1.000	0.581	0.445	0.379	0.550	0.235
Digital Investment Broker Adoption	DIBA	0.581	1.000	0.458	0.465	0.629	0.356
Information Offered	IO	0.445	0.458	1.000	0.309	0.352	0.333
Perceiced Easy of Use	PEOU	0.379	0.465	0.309	1.000	0.553	0.197
Perceived Usefullness	PU	0.550	0.629	0.352	0.553	1.000	0.225
Subject Norm	SN	0.235	0.356	0.333	0.197	0.225	1.000

Table 16 – Constructs Correlation | Fornell-Lacker Criterion

To evaluate collinearity of the formative indicators, the variance inflation factor (VIF) is often used (J. F. Hair et al., 2019, p. 10), and measures how much the variance of the estimated constructs is increased due to multicollinearity issues (Ramos, 2017, p. 14). High correlations among variables leads to a collinearity problem. So, the collinearity among the variables of the research model was assessed through Variance Inflated Factor (VIF) (Hashmi et al., 2021, p. 13). As the majority of the VIF values does not reach critical levels in any of the formative constructs, and are uniformly below the threshold value of 5, it is possible to conclude, that collinearity is not an issue for the estimation of the PLS path model (J. Hair et al., 2016).

To test the hypotheses and determine the associations between the variables, the path coefficients, which represent the direct effect of a variable on another variable were measured. When a path coefficient is close to 1 it means that the association is strong, and when a path coefficient is close to 0 it means that the association is weak (Lin et al., 2020, p. 13). To determine if the association between the variables is significant, bootstrapping was run to get the significance values. The commonly used and critical value for the tests is p value = 0.05 at significance level of 5% (Hashmi et al., 2021, p. 14–15). So, based on the p-values, the respective hypotheses were accepted or rejected.

Path coefficient values given in Table 17 show that data visualization exhibits a positive significant association with digital investment broker adoption ($\beta = 0.251$ and $p = 0.006$), information offered shows no significant association with digital investment broker adoption ($\beta = 0.141$ and $p = 0.155$), perceived ease of use shows a positive significant association with data visualization ($\beta = 0.379$ and $p = 0.001$) while it does not show a significant association with digital investment broker adoption ($\beta = 0.102$ and $p = 0.247$), perceived usefulness exhibits a positive significant association with both digital investment broker adoption ($\beta = 0.351$ and $p = 0.000$) and information offered ($\beta = 0.352$ and $p = 0.000$), and subject norm also show a positive significant association with digital investment broker adoption ($\beta = 0.151$ and $p = 0.014$).

Hypothesis | Path Coefficients	Original sample	Sample mean	Standard deviation	T statistics	P values
Data visualization -> Digital Investment Broker Adoption	0.251	0.264	0.092	2.729	0.006
Information Offered -> Digital Investment Broker Adoption	0.141	0.124	0.099	1.423	0.155
Perceiced Easy of Use -> Data visualization	0.379	0.373	0.119	3.177	0.001
Perceiced Easy of Use -> Digital Investment Broker Adoption	0.102	0.122	0.089	1.157	0.247
Perceived Usefullness -> Digital Investment Broker Adoption	0.351	0.349	0.096	3.649	0.000
Perceived Usefullness -> Information Offered	0.352	0.363	0.093	3.801	0.000
Subject Norm -> Digital Investment Broker Adoption	0.151	0.153	0.062	2.446	0.014

Table 17 – Hypothesis Testing | Path Coefficients

Path coefficient values of the hypothesis with specific indirect effects given in Table 18 show that data the perceived ease of use shows indirect positive significant association with digital investment broker adoption trough data visualization (β = 0.095 and p = 0.005), and the perceived usefulness does not exhibit a significant association with digital investment broker adoption trough information offered (β = 0.50 and p = 0.195).

Hypothesis | Specific Indirect Effects	Original sample	Sample mean	Standard deviation	T statistics	P values
Perceiced Easy of Use -> Data visualization -> Digital Investment Broker Adoption	0.095	0.093	0.034	2.803	0.005
Perceived Usefullness -> Information Offered -> Digital Investment Broker Adoption	0.050	0.044	0.038	1.296	0.195

Table 18 – Hypothesis Testing | Specific Indirect Effects

Assessing the structural model also includes the coefficient of determination (R-square) (J. F. Hair et al., 2019, p. 11). The R-square represents how much of the variance in an endogenous variable is explained by its antecedent constructs (Müller et al., 2018, p. 10), it is a measure of the model's predictive power and can range from 0 to 1, where higher values indicate greater explanatory power (J. F. Hair et al., 2019, p. 11; Lin et al., 2020, p. 16). For Lin et al. (2020, p. 16), R-square = 0.67 is strong, R-square = 0.33 is moderate, and R-square = 0.19 is weak. The coefficients of determination, R-square = 0.143, R-square = 0.532 and R-square = 0.124 represent a variability of 14.3%, 53.2% and 12.4% in data visualization, digital investment broker adoption and information offered respectively, explained by the independent variables. Digital investment broker adoption represents a moderate predicting value and, although data visualization and information offered represent weak predicting values, this does not necessarily indicate a problem. Good models can have a low R-square and a high R-square does not always indicate that the model is good (Jim Frost, 2019, p. 294). Jim Frost (2019, p. 295) believes that humans are hard to predict, and that studies that attempt to predict human behavior tend to have R-squared < 0.500.

Construct	R-square	R-square adjusted
Data visualization	0.143	0.136
Digital Investment Broker Adoption	0.532	0.513
Information Offered	0.124	0.117

Table 19 – R-square

So, based on the analysis above-mentioned, was possible to determine that six research hypotheses were supported, and three research hypotheses were not supported, as summarized in the table below.

	Hypothesis	Result
H1	Perceived Ease of Use -> Digital Investment Broker Adoption	Not supported
H2	Perceived Usefulness -> Digital Investment Broker Adoption	Supported
H3	Subject Norm -> Digital Investment Broker Adoption	Supported
H4	Data visualization -> Digital Investment Broker Adoption	Supported
H5	Perceived Ease of Use -> Data visualization	Supported
H6	Perceived Ease of Use -> Data visualization -> Digital Investment Broker Adoption	Supported
H7	Information Offered -> Digital Investment Broker Adoption	Not supported
H8	Perceived Usefulness -> Information Offered	Supported
H9	Perceived Usefulness -> Information Offered -> Digital Investment Broker Adoption	Not supported

Table 20 – Summary of Results | Research Hypotheses

The aim of this study is to better understand the factors that lead the individual investor to adopt a digital investment broker. For this purpose, it studied the effects of the following factors on predicting the customer’s intention to adopt digital investment brokers: perceived usefulness, perceived ease of use, subject norm, information offered and data visualization.

Contrary to expectations, the research results do not statistically prove that the Perceived Ease of Use (PEOU) factor plays an important role in influencing the decision to adopt the digital investment broker, not supporting H1, which is in disagreement with the previous literature (Alduais & Al-Smadi, 2022; Alhassany & Faisal, 2018; Almajali et al., 2022; Baber & Baki Billah, 2022; Bakri et al., 2023; Hayat et al., 2022; Matar & Alkhawaldeh, 2022; Purohit et al., 2022). Even if they believe the technology is simple to use, this may not influence their intention to adopt a digital investment broker. Okonkwo et al. (2022, p. 14) had the same result in his research, and he concludes that financial services require strong security to protect users’ information rather than ease of usage. Hence, users do not expect financial applications to be simple to use.

Nevertheless, the research results confirm that Perceived Usefulness (PU) factor in important in direct and positive influencing Fintech adoption, being consistent with expectations and previous studies (Alduais & Al-Smadi, 2022; Almajali et al., 2022; Baber & Baki Billah, 2022; Bakri et al., 2023; Hayat et al., 2022; Jangir et al., 2023; Matar & Alkhawaldeh, 2022; Okonkwo et al., 2022; Purohit et al., 2022). In the context of this research, it means that consumers will be more inclined to embrace a digital investment broker if it is useful for them. According to Okonkwo et al. (2022, p. 14), The use of technology is expected to boost the productivity and consumer work experience, the greater the usefulness of a technology product, the more willing users are to adopt it. In the context of this research, this means that users will adopt digital investment brokers if perceive them to contribute to their lives and work activities in a positive way. Also, the results confirm that the Perceived Usefulness (PU) factor is not positively and significantly associated with the information offered by the digital investment broker. However, the study cannot statistically prove that the Information Offered (IO) factor itself plays a role in influencing the decision to adopt the digital investment broker, either as a direct factor or as a moderating factor for the Perceived Usefulness Factor (PU) factor, being also misaligned with the literature review (Okonkwo et al., 2022). Thus, hypotheses H7 and H9 were also not supported, which state, respectively, that the information offered by the digital investment broker is positively and significantly associated with the intention of digital investment broker adoption and that the information offered mediate the positive, significant and indirect influence of the Perceived Usefulness (PU) in the intention of digital investment broker adoption.

Moreover, the results of this study related to the Subject Norm (SN) is in congruence with some studies (Alduais & Al-Smadi, 2022; Baber & Baki Billah, 2022; Purohit et al., 2022), which implies that customers may seek information from their referent groups to embrace new technology. The subject norm is positively and significantly associated with the intention of digital investment broker adoption. COVID-19 acted as a catalyst to create hype about digital financial services. Consumers grew more confident in the system and encouraged others to go digital financial services (Baber & Baki Billah, 2022, p. 37).

And finally, related to the Data Visualization (DV) factor, the research results confirm that the data visualization of the digital investment broker is positively and significantly associated with the intention of digital investment broker adoption, being aligned with the previous literature (Edu, 2022). Financial institutions are confronted with enormous volumes of financial data on a daily basis. Therefore, customers' financial transactions require emerging technologies to facilitate insight and knowledge creation from this data (Edu, 2022, p. 3). Also, it has been statistically proven through the research results that the perceived ease of use of digital investment brokers is positively and significantly associated with the data visualization of the digital investment broker, and, therefore, the data visualization also acts as a mediating factor since, the perceived ease of use positively, significantly and indirectly influences, through the data visualization, the intention of digital investment broker adoption.

5. CONCLUSION

Customers around the world are more skilled and active in the financial markets, having more access to sophisticated digital investment tools, such as digital investment brokers, which are considered as the financial service where financial transactions are conducted through application using complex software (Khvostenko et al., 2019, p. 411). This can be seen through the research survey, developed for this research, which had a sample collected from 279 surveys answered, with 126 (approximately 45%) of the 279 being answered by digital investors. It means that 45% of people already invest through digital investment brokers. This can be explained by its intrinsic characteristics that allow easy and quick access to investment services via the user's smartphone, notebook, or tablet. This demonstrates the importance that these digital services are gaining in the relationship between financial institutions and their customers.

The research survey was developed in two parts. The first part of the research survey made it possible to assess the sociodemographic profile of investors, and thereby address the first research objective: "identify the profile of clients who adopt the services of digital investment brokers". The respondents' sociodemographic profile shows the majority of the investors (almost 90%), are adults aged between 25 and 55 years old, people who are economically active and more likely to manage their own finances. Most of the investors are male, approximately 58%, and approximately 42% are female. The most of them have as the high education level University or Master's degree (over 95%). And as for their income, most of them have salaries in the range of 4 – 10 minimum wages (approximately 46%) and 10 – 20 minimum wages (approximately 27%).

The second part of the research was developed based on the literature review and on the developed research model, which was based on the Technology Acceptance Model (TAM) and the Unified Theory of Technology Acceptance and Use (UTAUT) adapted in order to incorporate other constructs. Nine research hypotheses were developed based on the following constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Subject Norm (SN), Data Visualization (DV), Information Offered (IO) and Digital Investment Broker Adoption (DIBA). So, based on the above-mentioned constructs and hypotheses, a research framework was developed to understand the factors that lead the adoption of a digital investment broker. The model aims to provide a comprehensive view of the main factors influencing the adoption intention. The data was collected throughout a survey, and for the exploration of the relationships among the dependent and independent variables in the model, the PLS-SEM was applied.

The main study results indicated that perceived usefulness, data visualization and subject norm have a significant positive impact on behavioral intention of digital investment broker adoption, thus, confirming hypotheses H2, H3 and H4. Also, the results indicate that perceived ease of use have a significant positive impact on data visualization, that the perceived usefulness have a significant positive impact on information offered and that the perceived ease of use positively and indirectly influences, through the data visualization, the intention of digital investment broker adoption, thus, confirming hypotheses H5, H8 and H6. These factors have been pointed out by the literature as relevant variables to financial technologies adoption, so our results suggest that these factors also contribute to digital investment broker adoption.

Based on this, it was then possible to address the second research objective: "identify whether the data visualization capabilities are important in digital investment broker adoption". The data visualization exhibits a positive significant association with digital investment broker adoption (β = 0.251 and p = 0.006). Also, this factor plays an intermediate role in digital investment broker adoption – the perceived ease of use positively and indirectly influences the intention of digital investment broker adoption, through the data visualization capabilities (β = 0.095 and p = 0.005).

However, the hypotheses H1, H7 and H9 could not be confirmed, which are, respectively, the perceived ease of use is positively associated with the intention of digital investment broker adoption, the information offered is positively associated with the intention of digital investment broker adoption, and the perceived usefulness positively and indirectly influences, through the information offered, the intention of digital investment broker adoption.

This allowed addressing the second objective of the research: "identify whether the information offered is important in digital investment broker adoption". The information offered shows no significant association with digital investment broker adoption (β = 0.141 and p = 0.155). Also, this factor does not play an intermediate role in digital investment broker adoption – the perceived usefulness does not exhibit a significant association with digital investment broker adoption trough information offered (β = 0.50 and p = 0.195).

The differences between the research results and previous studies can be explained based on that we are in the information age – we are immersed in an environment full of data and information updated in real time. The digital ascension has increased the amount and availability of data and information, so people may not be limited to looking for information in just one place and in just one way. The user has the possibility to consult an immense universe of data and information sources at a relatively low cost or even free.

And finally, after all the necessary analyses, it was possible to answer the research question: “What are the drivers for the adoption of a digital investment broker?”. As already explained before, digital investment broker refers to an online platform that allows investors to trade online and manage their investment portfolios using digital tools and resources. This type of platform has become increasingly popular in recent years, due to digital transformation and as more investors seek the convenience and flexibility of being able to manage their investments online. So, with the research results it was possible to identify that the drivers for the adoption of a digital investment broker are the perceived usefulness, perceived ease of use, the data visualization, and the subject norm, either through a direct positive or indirect positive association with the digital investment broker adoption factor.

Perceived usefulness refers to the degree to which users perceive a digital investment broker to be beneficial to them in achieving their investment goals, and this can include features such as real-time data access, advanced analysis tools and personalized investment recommendations. Perceived ease of use refers to how easy and intuitive users believe it will be to use a digital investment broker, and this might include factors such as the simplicity and user-friendliness of the interface, the ease of navigating different features, and the level of support and guidance provided to users. Data visualization" refers to the ability of a digital investment broker to provide users with clear and informative visualizations of investment data, and this might include features such as charts, graphs, and other interactive tools that allow users to easily understand trends, patterns, and other key insights. Subject norm refers to the degree to which users believe that adopting a digital investment broker is socially acceptable and in line with their peers' attitudes and behaviors and this might include factors such as social influence, peer pressure, and conformity to social norms.

Therefore, the more useful users perceive a digital investment broker, the easier users perceive a digital investment broker to be to use, the more effective a digital investment broker is at visualizing data and the more users perceive that adopting a digital investment broker is socially normative, the more likely they are to adopt it. By identifying the factors of perceived usefulness, perceived ease of use, data visualization, and subject norm, the study provides valuable insights into what motivates people to adopt digital investment brokers and how these factors might be leveraged to increase adoption rates.

5.1. CONTRIBUTIONS TO THE SCIENTIFIC AND BUSINESS COMMUNITY

Although TAM and UTAUT have been extensively used in the analysis of factors leading to a user's intention to adopt financial technologies, there are not many studies that specifically address digital investment brokers. Thus, this research is making a pioneering contribution to its evolution.

This research has mainly three theoretical implications. It used perceived usefulness and perceived ease of use, the key antecedents of TAM, and subject norm, also known as social influence, one of the key antecedents of UTAU, as potential predictors of digital investment broker adoption, a topic that has not yet been widely explored in financial behavior studies. The results revealed that perceived usefulness and subject norm have significant positive direct impact on behavioral intention of digital investment broker adoption and perceived ease of use significant positively but only indirectly influences, through the data visualization, the intention of digital investment broker adoption, so, somehow, they are significant predictors of digital investment broker adoption.

Furthermore, this research extends the literature by adapting TAM and UTAUT incorporating two cognitive constructs namely data visualization and information offered in the context of digital investment broker adoption. There is no clear evidence in the extant literature where these cognitive constructs have been studied in the context of digital investment broker adoption. The research results reveal that only the data visualization construct has a positive and significant impact on the decision to adopt a digital investment broker. So, the integration of data visualization and information offered in the extended research model has added knowledge in the existing literature. The new research model was developed with five predictors (perceived usefulness, perceived ease of use, subject norm, data visualization and information offered), which have given a new dimension to the understanding of users' decision to adopt digital investment broker. This study fills the theoretical gap and advances the literature on digital investment broker adoption with this new research model, applied in an emerging economy, namely Brazil.

This research has also some practical implications. It can also provide useful insights to the financial industry, the decision makers of digital investment brokers and other technology financial service providers, to enhance and maintain their customer base, to design and market its digital platforms to better serve investor needs and preferences, helping to achieve competitive advantage. Digital investment broker technology has potential to change the way people live, invest and manage their investment. So, the players in the digital financial investment market can improve the usability, the simplicity, and the data visualization of their e-services to facilitate and increase the digital investment broker usage.

5.2. Research Limitations and Future Research Proposals

Some of the limitations of the research is regarding the data collection that was done via online survey exhibit a self-report inventory, which presents the possibility for the respondents to misunderstand the questions or intentionally or unintentionally give wrong answers, may cause some bias. Also, the conclusions presented in this thesis are the result of an inherent limitation of academic research and the fact that it characterizes a certain context, in this case the context of Brazil. As 70% of the sample is from only one region of the country studied, the sample is not probabilistic and may affect the generalization of the results for other regions, or there may be some bias, although this does not disqualify the research results. Also, as the survey sample is restricted to Brazilians who possess internet access the study findings are not generalizable to the entire Brazilian population. In this perspective, this study has an exploratory nature, that is, it should not be generalized to other realities. Further data collection is encouraged to help overcome this limitation and it is recommended that future studies cover a wider geographical area.

There is also a limitation with regard to the research. The study has not considered the moderating role of any sociodemographic variable. Further research may assess the moderating role of these variables in the proposed model. Furthermore, it is also recommended that further studies include new variables in the research model, as well as develop qualitative research to obtain more information about the adoption of digital investment broker. Future studies should also consider objectively measuring individuals' financial indicators, such as the level of financial savings and the existence of debts and incorporate these measures in the analysis.

And the last limitation identified is with regard to the pandemic context of COVID-19, which may have an impact on the answers to the research survey, with consequences on the results obtained through it. The pandemic can have an impact on the economy of a country, on the personal finances of many families and consequently on the investment decisions of a population. Also, COVID-19 might have affected individual's both physically and mentally thus, influencing their survey answers.

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7. APPENDIX 1 – RESEARCH SURVEY STRUCTURE

ACADEMIC RESEARCH: The Drivers of Digital Investment Broker Adoption.

This form is part of an academic research carried out by the Master's in Information Management, with specialization in Business Intelligence at Universidade NOVA de Lisboa | Portugal. It intends to evaluate the factors for choosing a digital investment broker.

All data collected is anonymous and will only be used for its intended purpose, this academic research. Thus, ensuring the confidentiality of the data. Thank you for your contribution!

DEMOGRAPHIC DATA

Gender:

Male
Female
Other: __________

Age:

< 25 years old
25 - 45 years old
45 - 55 years old
> 55 years old

Academic Degree?

High School
University Degree
Master's Degree
Higher Education
Other: __________

Income:

< 4 minimum wages
4 - 10 minimum wages
10 - 20 minimum wages
> 20 minimum wages

State of residence in Brazil: __________

Do you invest through investment brokers?

Yes
No

THE DRIVERS OF A DIGITAL INVESTMENT BROKER ADOPTION

On a scale from 1 to 7, with 1 being "Strongly Disagree" and 7 being "Strongly Agree", rate your opinion regarding the following statements:

Using digital investment brokers gives me more control over my financial investments.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Using digital investment brokers provides me with convenient access to my investment accounts.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Using digital investment brokers saves my time and allows me to do my investing activities quickly, saving my time and increasing my productivity.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Using digital investment brokers is compatible with my lifestyle.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Overall, I find digital investment brokers useful for me.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Using digital investment brokers is easy for me.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I feel comfortable using digital investment brokers.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I find the content of digital investment brokers understandable.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

I can use digital investment brokers without asking for help, without any problem.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

Overall, I find it easy to use digital investment brokers.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

My family and friends think I should use digital investment brokers.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

I learn about digital investment brokers from my friends and family.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

I often discuss digital investment brokers with my friends and family.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

My friends and family recommended digital investment brokers to me.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

My friends, family and I share experiences and information about digital investment brokers.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

Investment and financial market information is important to me.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

For me it is important to have accurate and up-to-date information about investments and the financial market.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Investments and financial market information help me in my financial investment decisions.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Before adopting a digital investment broker, I want to know about the information it offers on investment and financial markets.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Investment and financial market information improve my ability to plan my financial investments.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Data visualization about financial investments is important to me.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Data visualization about financial investments helps me understand my financial investments.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

A good data visualization about financial investments improves my experience using digital investment brokers.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Before adopting a digital investment broker, I want to know about the data visualization they offer.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Data visualization helps me to have a clear understandable interaction when using digital investment brokers.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

It is valuable for me to use digital investment brokers.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

It is important for me to use digital investment brokers.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I use digital investment brokers frequently.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Digital investment brokers are not a waste of money and resources.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I don’t think digital investment brokers are meaningless.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I prefer investing through digital investment brokers to traditional banks.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Thank you so much for you contribution!

8. APPENDIX 2 – ANOVA | GENDER

Detailed ANOVA | Gender

		Sum of Squares	df	Mean Square	F	Sig.
PU1	Between Groups	2.331	1	2.331	1.986	0.161
	Within Groups	145.542	124	1.174		
	Total	**147.873**	**125**			
PU2	Between Groups	0.085	1	0.085	0.159	0.691
	Within Groups	65.86	124	0.531		
	Total	**65.944**	**125**			
PU3	Between Groups	1.29	1	1.29	1.296	0.257
	Within Groups	123.416	124	0.995		
	Total	**124.706**	**125**			
PU4	Between Groups	0.179	1	0.179	0.232	0.631
	Within Groups	95.29	124	0.768		
	Total	**95.468**	**125**			
PU5	Between Groups	0.213	1	0.213	0.251	0.617
	Within Groups	104.898	124	0.846		
	Total	**105.111**	**125**			
PEOU1	Between Groups	0.648	1	0.648	0.722	0.397
	Within Groups	111.225	124	0.897		
	Total	**111.873**	**125**			
PEOU2	Between Groups	1.736	1	1.736	2.049	0.155
	Within Groups	105.089	124	0.847		
	Total	**106.825**	**125**			
PEOU3	Between Groups	4.634	1	4.634	3.982	0.048
	Within Groups	144.295	124	1.164		
	Total	**148.929**	**125**			
PEOU4	Between Groups	14.689	1	14.689	8.984	0.003
	Within Groups	202.739	124	1.635		
	Total	**217.429**	**125**			
PEOU5	Between Groups	3.542	1	3.542	2.93	0.089
	Within Groups	149.887	124	1.209		
	Total	**153.429**	**125**			
SN1	Between Groups	1.229	1	1.229	0.458	0.5
	Within Groups	332.485	124	2.681		
	Total	**333.714**	**125**			
SN2	Between Groups	2.257	1	2.257	0.632	0.428
	Within Groups	442.544	124	3.569		
	Total	**444.802**	**125**			
SN3	Between Groups	0.193	1	0.193	0.072	0.789
	Within Groups	331.942	124	2.677		
	Total	**332.135**	**125**			
SN4	Between Groups	0	1	0	0	0.996
	Within Groups	428.857	124	3.459		
	Total	**428.857**	**125**			
SN5	Between Groups	0.014	1	0.014	0.005	0.945
	Within Groups	373.454	124	3.012		
	Total	**373.468**	**125**			
IO1	Between Groups	1.793	1	1.793	1.073	0.302
	Within Groups	207.199	124	1.671		
	Total	**208.992**	**125**			
IO2	Between Groups	15.009	1	15.009	9.562	0.002
	Within Groups	194.649	124	1.57		
	Total	**209.659**	**125**			
IO3	Between Groups	7.681	1	7.681	5.189	0.024
	Within Groups	183.534	124	1.48		
	Total	**191.214**	**125**			
IO4	Between Groups	0.455	1	0.455	0.209	0.649
	Within Groups	270.474	124	2.181		
	Total	**270.929**	**125**			
IO5	Between Groups	2.722	1	2.722	2.123	0.148
	Within Groups	158.992	124	1.282		
	Total	**161.714**	**125**			
DV1	Between Groups	0.108	1	0.108	0.114	0.736
	Within Groups	117.265	124	0.946		
	Total	**117.373**	**125**			
DV2	Between Groups	0.187	1	0.187	0.217	0.642
	Within Groups	107.114	124	0.864		
	Total	**107.302**	**125**			
DV3	Between Groups	0.055	1	0.055	0.071	0.79
	Within Groups	94.652	124	0.763		
	Total	**94.706**	**125**			
DV4	Between Groups	0.05	1	0.05	0.019	0.892
	Within Groups	333.379	124	2.689		
	Total	**333.429**	**125**			
DV5	Between Groups	0.219	1	0.219	0.205	0.652
	Within Groups	132.709	124	1.07		
	Total	**132.929**	**125**			
DIBA1	Between Groups	0.403	1	0.403	0.417	0.52
	Within Groups	119.637	124	0.965		
	Total	**120.04**	**125**			
DIBA2	Between Groups	0.991	1	0.991	1.015	0.316
	Within Groups	121.049	124	0.976		
	Total	**122.04**	**125**			
DIBA3	Between Groups	0.011	1	0.011	0.006	0.936
	Within Groups	203.418	124	1.64		
	Total	**203.429**	**125**			
DIBA4	Between Groups	8.37	1	8.37	2.093	0.15
	Within Groups	495.789	124	3.998		
	Total	**504.159**	**125**			
DIBA5	Between Groups	0.994	1	0.994	0.389	0.534
	Within Groups	316.721	124	2.554		
	Total	**317.714**	**125**			
I prefer investing through digital investment brokers to traditional banks.	Between Groups	0.105	1	0.105	0.044	0.834
	Within Groups	295.102	124	2.38		
	Total	**295.206**	**125**			

9. APPENDIX 3 – ANOVA | AGE

Detailed ANOVA | Age

		Sum of Squares	df	Mean Square	F	Sig.
PU1	Between Groups	3.247	3	1.082	0.913	0.437
	Within Groups	144.626	122	1.185		
	Total	**147.873**	**125**			
PU2	Between Groups	0.959	3	0.32	0.6	0.616
	Within Groups	64.985	122	0.533		
	Total	**65.944**	**125**			
PU3	Between Groups	1.872	3	0.624	0.62	0.603
	Within Groups	122.834	122	1.007		
	Total	**124.706**	**125**			
PU4	Between Groups	3.358	3	1.119	1.482	0.223
	Within Groups	92.111	122	0.755		
	Total	**95.468**	**125**			
PU5	Between Groups	0.184	3	0.061	0.071	0.975
	Within Groups	104.927	122	0.86		
	Total	**105.111**	**125**			
PEOU1	Between Groups	0.519	3	0.173	0.19	0.903
	Within Groups	111.354	122	0.913		
	Total	**111.873**	**125**			
PEOU2	Between Groups	1.536	3	0.512	0.593	0.621
	Within Groups	105.29	122	0.863		
	Total	**106.825**	**125**			
PEOU3	Between Groups	1.889	3	0.63	0.523	0.668
	Within Groups	147.039	122	1.205		
	Total	**148.929**	**125**			
PEOU4	Between Groups	3.233	3	1.078	0.614	0.607
	Within Groups	214.196	122	1.756		
	Total	**217.429**	**125**			
PEOU5	Between Groups	1.609	3	0.536	0.431	0.731
	Within Groups	151.819	122	1.244		
	Total	**153.429**	**125**			
SN1	Between Groups	2.565	3	0.855	0.315	0.814
	Within Groups	331.149	122	2.714		
	Total	**333.714**	**125**			
SN2	Between Groups	10.398	3	3.466	0.973	0.408
	Within Groups	434.404	122	3.561		
	Total	**444.802**	**125**			
SN3	Between Groups	20.311	3	6.77	2.649	0.052
	Within Groups	311.824	122	2.556		
	Total	**332.135**	**125**			
SN4	Between Groups	0.937	3	0.312	0.089	0.966
	Within Groups	427.921	122	3.508		
	Total	**428.857**	**125**			
SN5	Between Groups	17.146	3	5.715	1.957	0.124
	Within Groups	356.322	122	2.921		
	Total	**373.468**	**125**			
IO1	Between Groups	0.775	3	0.258	0.151	0.929
	Within Groups	208.217	122	1.707		
	Total	**208.992**	**125**			
IO2	Between Groups	0.205	3	0.068	0.04	0.989
	Within Groups	209.454	122	1.717		
	Total	**209.659**	**125**			
IO3	Between Groups	2.357	3	0.786	0.508	0.678
	Within Groups	188.857	122	1.548		
	Total	**191.214**	**125**			
IO4	Between Groups	6.711	3	2.237	1.033	0.381
	Within Groups	264.217	122	2.166		
	Total	**270.929**	**125**			
IO5	Between Groups	1.425	3	0.475	0.362	0.781
	Within Groups	160.289	122	1.314		
	Total	**161.714**	**125**			
DV1	Between Groups	1.175	3	0.392	0.411	0.745
	Within Groups	116.198	122	0.952		
	Total	**117.373**	**125**			
DV2	Between Groups	0.243	3	0.081	0.092	0.964
	Within Groups	107.058	122	0.878		
	Total	**107.302**	**125**			
DV3	Between Groups	0.683	3	0.228	0.295	0.829
	Within Groups	94.023	122	0.771		
	Total	**94.706**	**125**			
DV4	Between Groups	8.105	3	2.702	1.013	0.389
	Within Groups	325.323	122	2.667		
	Total	**333.429**	**125**			
DV5	Between Groups	4.761	3	1.587	1.51	0.215
	Within Groups	128.168	122	1.051		
	Total	**132.929**	**125**			
DIBA1	Between Groups	0.934	3	0.311	0.319	0.812
	Within Groups	119.106	122	0.976		
	Total	**120.04**	**125**			
DIBA2	Between Groups	1.211	3	0.404	0.408	0.748
	Within Groups	120.829	122	0.99		
	Total	**122.04**	**125**			
DIBA3	Between Groups	0.541	3	0.18	0.109	0.955
	Within Groups	202.887	122	1.663		
	Total	**203.429**	**125**			
DIBA4	Between Groups	2.903	3	0.968	0.236	0.871
	Within Groups	501.256	122	4.109		
	Total	**504.159**	**125**			
DIBA5	Between Groups	14.193	3	4.731	1.902	0.133
	Within Groups	303.521	122	2.488		
	Total	**317.714**	**125**			
I prefer investing through digital investment brokers to traditional banks.	Between Groups	12.868	3	4.289	1.853	0.141
	Within Groups	282.339	122	2.314		
	Total	**295.206**	**125**			

10.APPENDIX 4 – ANOVA | EDUCATION

Detailed ANOVA | Education

		Sum of Squares	df	Mean Square	F	Sig.
PU1	Between Groups	4.116	2	2.058	1.761	0.176
	Within Groups	143.757	123	1.169		
	Total	**147.873**	**125**			
PU2	Between Groups	3.505	2	1.753	3.453	0.035
	Within Groups	62.439	123	0.508		
	Total	**65.944**	**125**			
PU3	Between Groups	1.401	2	0.701	0.699	0.499
	Within Groups	123.305	123	1.002		
	Total	**124.706**	**125**			
PU4	Between Groups	2.486	2	1.243	1.644	0.197
	Within Groups	92.983	123	0.756		
	Total	**95.468**	**125**			
PU5	Between Groups	1.338	2	0.669	0.793	0.455
	Within Groups	103.773	123	0.844		
	Total	**105.111**	**125**			
PEOU1	Between Groups	0.285	2	0.143	0.157	0.855
	Within Groups	111.588	123	0.907		
	Total	**111.873**	**125**			
PEOU2	Between Groups	1.205	2	0.602	0.701	0.498
	Within Groups	105.621	123	0.859		
	Total	**106.825**	**125**			
PEOU3	Between Groups	3.047	2	1.523	1.284	0.281
	Within Groups	145.882	123	1.186		
	Total	**148.929**	**125**			
PEOU4	Between Groups	0.013	2	0.007	0.004	0.996
	Within Groups	217.415	123	1.768		
	Total	**217.429**	**125**			
PEOU5	Between Groups	0.542	2	0.271	0.218	0.805
	Within Groups	152.887	123	1.243		
	Total	**153.429**	**125**			
SN1	Between Groups	2.982	2	1.491	0.554	0.576
	Within Groups	330.732	123	2.689		
	Total	**333.714**	**125**			
SN2	Between Groups	0.021	2	0.01	0.003	0.997
	Within Groups	444.781	123	3.616		
	Total	**444.802**	**125**			
SN3	Between Groups	16.163	2	8.082	3.146	0.047
	Within Groups	315.972	123	2.569		
	Total	**332.135**	**125**			
SN4	Between Groups	7.073	2	3.537	1.031	0.36
	Within Groups	421.784	123	3.429		
	Total	**428.857**	**125**			
SN5	Between Groups	1.783	2	0.891	0.295	0.745
	Within Groups	371.686	123	3.022		
	Total	**373.468**	**125**			
IO1	Between Groups	6.287	2	3.144	1.907	0.153
	Within Groups	202.705	123	1.648		
	Total	**208.992**	**125**			
IO2	Between Groups	3.762	2	1.881	1.124	0.328
	Within Groups	205.897	123	1.674		
	Total	**209.659**	**125**			
IO3	Between Groups	0.628	2	0.314	0.203	0.817
	Within Groups	190.586	123	1.549		
	Total	**191.214**	**125**			
IO4	Between Groups	1.002	2	0.501	0.228	0.796
	Within Groups	269.926	123	2.195		
	Total	**270.929**	**125**			
IO5	Between Groups	1.926	2	0.963	0.741	0.479
	Within Groups	159.789	123	1.299		
	Total	**161.714**	**125**			
DV1	Between Groups	12.272	2	6.136	7.181	0.001
	Within Groups	105.101	123	0.854		
	Total	**117.373**	**125**			
DV2	Between Groups	12.365	2	6.182	8.01	<.001
	Within Groups	94.937	123	0.772		
	Total	**107.302**	**125**			
DV3	Between Groups	13.834	2	6.917	10.52	<.001
	Within Groups	80.872	123	0.657		
	Total	**94.706**	**125**			
DV4	Between Groups	4.293	2	2.146	0.802	0.451
	Within Groups	329.136	123	2.676		
	Total	**333.429**	**125**			
DV5	Between Groups	6.017	2	3.008	2.916	0.058
	Within Groups	126.912	123	1.032		
	Total	**132.929**	**125**			
DIBA1	Between Groups	4.026	2	2.013	2.134	0.123
	Within Groups	116.013	123	0.943		
	Total	**120.04**	**125**			
DIBA2	Between Groups	1.114	2	0.557	0.566	0.569
	Within Groups	120.926	123	0.983		
	Total	**122.04**	**125**			
DIBA3	Between Groups	7.128	2	3.564	2.233	0.112
	Within Groups	196.3	123	1.596		
	Total	**203.429**	**125**			
DIBA4	Between Groups	16.505	2	8.252	2.082	0.129
	Within Groups	487.654	123	3.965		
	Total	**504.159**	**125**			
DIBA5	Between Groups	1.968	2	0.984	0.383	0.682
	Within Groups	315.747	123	2.567		
	Total	**317.714**	**125**			
I prefer investing through digital investment brokers to traditional banks.	Between Groups	4.044	2	2.022	0.854	0.428
	Within Groups	291.163	123	2.367		
	Total	**295.206**	**125**			

11.APPENDIX 5 – ANOVA | INCOME

Detailed ANOVA | Income

		Sum of Squares	df	Mean Square	F	Sig.
PU1	Between Groups	3.733	3	1.244	1.053	0.372
	Within Groups	144.14	122	1.181		
	Total	**147.873**	**125**			
PU2	Between Groups	0.549	3	0.183	0.341	0.795
	Within Groups	65.395	122	0.536		
	Total	**65.944**	**125**			
PU3	Between Groups	1.016	3	0.339	0.334	0.801
	Within Groups	123.69	122	1.014		
	Total	**124.706**	**125**			
PU4	Between Groups	2.895	3	0.965	1.272	0.287
	Within Groups	92.573	122	0.759		
	Total	**95.468**	**125**			
PU5	Between Groups	0.63	3	0.21	0.245	0.865
	Within Groups	104.481	122	0.856		
	Total	**105.111**	**125**			
PEOU1	Between Groups	3.474	3	1.158	1.303	0.277
	Within Groups	108.399	122	0.889		
	Total	**111.873**	**125**			
PEOU2	Between Groups	0.647	3	0.216	0.248	0.863
	Within Groups	106.179	122	0.87		
	Total	**106.825**	**125**			
PEOU3	Between Groups	1.338	3	0.446	0.369	0.776
	Within Groups	147.59	122	1.21		
	Total	**148.929**	**125**			
PEOU4	Between Groups	2.36	3	0.787	0.446	0.72
	Within Groups	215.069	122	1.763		
	Total	**217.429**	**125**			
PEOU5	Between Groups	1.337	3	0.446	0.358	0.784
	Within Groups	152.091	122	1.247		
	Total	**153.429**	**125**			
SN1	Between Groups	10.605	3	3.535	1.335	0.266
	Within Groups	323.109	122	2.648		
	Total	**333.714**	**125**			
SN2	Between Groups	26.794	3	8.931	2.607	0.055
	Within Groups	418.007	122	3.426		
	Total	**444.802**	**125**			
SN3	Between Groups	8.245	3	2.748	1.035	0.38
	Within Groups	323.89	122	2.655		
	Total	**332.135**	**125**			
SN4	Between Groups	21.483	3	7.161	2.145	0.098
	Within Groups	407.374	122	3.339		
	Total	**428.857**	**125**			
SN5	Between Groups	16.907	3	5.636	1.928	0.129
	Within Groups	356.561	122	2.923		
	Total	**373.468**	**125**			
IO1	Between Groups	22.934	3	7.645	5.013	0.003
	Within Groups	186.058	122	1.525		
	Total	**208.992**	**125**			
IO2	Between Groups	9.952	3	3.317	2.026	0.114
	Within Groups	199.707	122	1.637		
	Total	**209.659**	**125**			
IO3	Between Groups	15.519	3	5.173	3.592	0.016
	Within Groups	175.695	122	1.44		
	Total	**191.214**	**125**			
IO4	Between Groups	5.828	3	1.943	0.894	0.446
	Within Groups	265.1	122	2.173		
	Total	**270.929**	**125**			
IO5	Between Groups	4.891	3	1.63	1.268	0.288
	Within Groups	156.823	122	1.285		
	Total	**161.714**	**125**			
DV1	Between Groups	11.335	3	3.778	4.347	0.006
	Within Groups	106.038	122	0.869		
	Total	**117.373**	**125**			
DV2	Between Groups	5.661	3	1.887	2.265	0.084
	Within Groups	101.641	122	0.833		
	Total	**107.302**	**125**			
DV3	Between Groups	3.243	3	1.081	1.442	0.234
	Within Groups	91.464	122	0.75		
	Total	**94.706**	**125**			
DV4	Between Groups	12.464	3	4.155	1.579	0.198
	Within Groups	320.964	122	2.631		
	Total	**333.429**	**125**			
DV5	Between Groups	9.026	3	3.009	2.962	0.035
	Within Groups	123.903	122	1.016		
	Total	**132.929**	**125**			
DIBA1	Between Groups	8.633	3	2.878	3.151	0.027
	Within Groups	111.406	122	0.913		
	Total	**120.04**	**125**			
DIBA2	Between Groups	10.121	3	3.374	3.678	0.014
	Within Groups	111.918	122	0.917		
	Total	**122.04**	**125**			
DIBA3	Between Groups	14.833	3	4.944	3.199	0.026
	Within Groups	188.595	122	1.546		
	Total	**203.429**	**125**			
DIBA4	Between Groups	14.116	3	4.705	1.171	0.324
	Within Groups	490.043	122	4.017		
	Total	**504.159**	**125**			
DIBA5	Between Groups	7.022	3	2.341	0.919	0.434
	Within Groups	310.692	122	2.547		
	Total	**317.714**	**125**			
I prefer investing through digital investment brokers to traditional banks.	Between Groups	24.305	3	8.102	3.649	0.015
	Within Groups	270.902	122	2.221		
	Total	**295.206**	**125**			

12.APPENDIX 6 – ANOVA | STATE

Detailed ANOVA | State

		Sum of Squares	df	Mean Square	F	Sig.
PU1	Between Groups	8.692	9	0.966	0.805	0.613
	Within Groups	139.181	116	1.2		
	Total	**147.873**	**125**			
PU2	Between Groups	5.022	9	0.558	1.062	0.396
	Within Groups	60.923	116	0.525		
	Total	**65.944**	**125**			
PU3	Between Groups	8.722	9	0.969	0.969	0.469
	Within Groups	115.984	116	1		
	Total	**124.706**	**125**			
PU4	Between Groups	5.498	9	0.611	0.788	0.628
	Within Groups	89.97	116	0.776		
	Total	**95.468**	**125**			
PU5	Between Groups	2.489	9	0.277	0.313	0.969
	Within Groups	102.622	116	0.885		
	Total	**105.111**	**125**			
PEOU1	Between Groups	9.821	9	1.091	1.24	0.277
	Within Groups	102.052	116	0.88		
	Total	**111.873**	**125**			
PEOU2	Between Groups	12.326	9	1.37	1.681	0.101
	Within Groups	94.499	116	0.815		
	Total	**106.825**	**125**			
PEOU3	Between Groups	5.712	9	0.635	0.514	0.862
	Within Groups	143.217	116	1.235		
	Total	**148.929**	**125**			
PEOU4	Between Groups	10.562	9	1.174	0.658	0.745
	Within Groups	206.867	116	1.783		
	Total	**217.429**	**125**			
PEOU5	Between Groups	9.796	9	1.088	0.879	0.546
	Within Groups	143.632	116	1.238		
	Total	**153.429**	**125**			
SN1	Between Groups	21.706	9	2.412	0.897	0.531
	Within Groups	312.008	116	2.69		
	Total	**333.714**	**125**			
SN2	Between Groups	53.605	9	5.956	1.766	0.082
	Within Groups	391.196	116	3.372		
	Total	**444.802**	**125**			
SN3	Between Groups	24.613	9	2.735	1.032	0.419
	Within Groups	307.522	116	2.651		
	Total	**332.135**	**125**			
SN4	Between Groups	34.161	9	3.796	1.116	0.357
	Within Groups	394.696	116	3.403		
	Total	**428.857**	**125**			
SN5	Between Groups	25.586	9	2.843	0.948	0.487
	Within Groups	347.882	116	2.999		
	Total	**373.468**	**125**			
IO1	Between Groups	34.808	9	3.868	2.576	0.01
	Within Groups	174.184	116	1.502		
	Total	**208.992**	**125**			
IO2	Between Groups	8.977	9	0.997	0.577	0.814
	Within Groups	200.681	116	1.73		
	Total	**209.659**	**125**			
IO3	Between Groups	12.49	9	1.388	0.901	0.527
	Within Groups	178.725	116	1.541		
	Total	**191.214**	**125**			
IO4	Between Groups	9.47	9	1.052	0.467	0.894
	Within Groups	261.459	116	2.254		
	Total	**270.929**	**125**			
IO5	Between Groups	9.035	9	1.004	0.763	0.651
	Within Groups	152.679	116	1.316		
	Total	**161.714**	**125**			
DV1	Between Groups	6.81	9	0.757	0.794	0.623
	Within Groups	110.563	116	0.953		
	Total	**117.373**	**125**			
DV2	Between Groups	3.319	9	0.369	0.411	0.927
	Within Groups	103.982	116	0.896		
	Total	**107.302**	**125**			
DV3	Between Groups	6.498	9	0.722	0.95	0.486
	Within Groups	88.208	116	0.76		
	Total	**94.706**	**125**			
DV4	Between Groups	18.166	9	2.018	0.743	0.669
	Within Groups	315.263	116	2.718		
	Total	**333.429**	**125**			
DV5	Between Groups	8.644	9	0.96	0.896	0.531
	Within Groups	124.284	116	1.071		
	Total	**132.929**	**125**			
DIBA1	Between Groups	14.931	9	1.659	1.831	0.07
	Within Groups	105.109	116	0.906		
	Total	**120.04**	**125**			
DIBA2	Between Groups	18.102	9	2.011	2.245	0.024
	Within Groups	103.938	116	0.896		
	Total	**122.04**	**125**			
DIBA3	Between Groups	21.664	9	2.407	1.536	0.143
	Within Groups	181.765	116	1.567		
	Total	**203.429**	**125**			
DIBA4	Between Groups	36.351	9	4.039	1.002	0.443
	Within Groups	467.808	116	4.033		
	Total	**504.159**	**125**			
DIBA5	Between Groups	19.386	9	2.154	0.838	0.583
	Within Groups	298.329	116	2.572		
	Total	**317.714**	**125**			
I prefer investing through digital investment brokers to traditional banks.	Between Groups	31.425	9	3.492	1.535	0.144
	Within Groups	263.781	116	2.274		
	Total	**295.206**	**125**			

13.APPENDIX 7 – CORRELATIONS OF INDICATORS | SMART PLS

		PU1	PU2	PU3	PU4	PU5	PEOU1	PEOU2	PEOU3	PEOU4	PEOU5	SN1	SN2	SN3	SN4	SN5	IO1	IO2	IO3	IO4	IO5	DV1	DV2	DV3	DV4	DV5	DIBA1	DIBA2	DIBA3	DIBA4	DIBA5
PU1	**1**	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PU2	**2**	0.602	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PU3	**3**	0.490	0.591	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PU4	**4**	0.459	0.614	0.498	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PU5	**5**	0.563	0.615	0.520	0.670	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PEOU1	**6**	0.349	0.413	0.419	0.402	0.426	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PEOU2	**7**	0.401	0.479	0.526	0.401	0.520	0.662	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PEOU3	**8**	0.240	0.318	0.323	0.270	0.272	0.400	0.411	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PEOU4	**9**	0.222	0.153	0.393	0.180	0.110	0.370	0.412	0.420	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PEOU5	**10**	0.256	0.288	0.416	0.246	0.307	0.539	0.624	0.433	0.715	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SN1	**11**	0.392	0.270	0.074	0.294	0.299	0.115	0.184	0.322	0.175	0.211	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SN2	**12**	0.024	-0.024	-0.105	0.130	0.121	-0.053	-0.006	0.120	-0.064	-0.060	0.383	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SN3	**13**	0.051	0.119	0.003	0.151	0.094	0.147	0.101	0.253	0.114	0.149	0.374	0.460	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SN4	**14**	0.182	0.093	-0.030	0.184	0.143	0.100	0.097	0.209	0.083	0.014	0.548	0.581	0.547	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SN5	**15**	0.155	0.053	0.082	0.103	0.186	0.130	0.092	0.169	0.028	0.110	0.387	0.574	0.679	0.664	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IO1	**16**	0.317	0.199	0.326	0.351	0.347	0.280	0.306	0.179	0.082	0.146	0.149	0.203	0.126	0.167	0.310	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IO2	**17**	0.055	0.060	0.214	0.160	0.207	0.246	0.264	0.251	0.158	0.200	0.161	0.172	0.105	0.109	0.283	0.582	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IO3	**18**	0.144	0.111	0.147	0.259	0.289	0.247	0.159	0.115	0.064	0.174	0.240	0.209	0.234	0.211	0.423	0.574	0.710	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IO4	**19**	0.036	-0.006	0.167	0.146	0.097	0.208	0.183	0.244	0.237	0.198	0.192	0.191	0.210	0.175	0.225	0.286	0.406	0.318	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IO5	**20**	0.225	0.136	0.365	0.278	0.299	0.222	0.246	0.162	0.186	0.223	0.212	0.177	0.141	0.211	0.396	0.488	0.632	0.741	0.526	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DV1	**21**	0.311	0.409	0.307	0.373	0.398	0.297	0.295	0.211	0.200	0.279	0.232	0.106	0.224	0.256	0.141	0.418	0.254	0.430	0.301	0.473	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DV2	**22**	0.375	0.470	0.412	0.365	0.506	0.267	0.321	0.192	0.192	0.252	0.214	0.075	0.164	0.198	0.115	0.344	0.227	0.318	0.326	0.444	0.827	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DV3	**23**	0.401	0.511	0.343	0.354	0.486	0.354	0.311	0.168	0.183	0.294	0.258	0.042	0.172	0.194	0.119	0.294	0.167	0.278	0.270	0.349	0.757	0.887	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DV4	**24**	0.139	0.137	0.151	0.151	0.110	0.180	0.243	0.236	0.124	0.113	0.237	0.197	0.173	0.284	0.281	0.305	0.400	0.377	0.544	0.430	0.343	0.425	0.395	1.000	0.000	0.000	0.000	0.000	0.000	0.000
DV5	**25**	0.372	0.440	0.354	0.472	0.375	0.288	0.323	0.235	0.244	0.263	0.290	0.057	0.116	0.114	0.062	0.310	0.233	0.274	0.522	0.456	0.630	0.737	0.734	0.472	1.000	0.000	0.000	0.000	0.000	0.000
DIBA1	**26**	0.500	0.402	0.380	0.466	0.500	0.308	0.435	0.180	0.242	0.277	0.315	0.184	0.247	0.148	0.218	0.308	0.255	0.301	0.313	0.365	0.474	0.533	0.474	0.340	0.588	1.000	0.000	0.000	0.000	0.000
DIBA2	**27**	0.496	0.487	0.401	0.509	0.646	0.408	0.414	0.290	0.136	0.267	0.338	0.208	0.285	0.291	0.342	0.381	0.303	0.390	0.266	0.419	0.512	0.476	0.488	0.209	0.489	0.727	1.000	0.000	0.000	0.000
DIBA3	**28**	0.217	0.268	0.179	0.364	0.397	0.329	0.399	0.181	0.221	0.365	0.191	-0.029	0.214	0.043	0.215	0.330	0.222	0.349	0.134	0.254	0.333	0.279	0.277	0.148	0.332	0.573	0.492	1.000	0.000	0.000
DIBA4	**29**	0.303	0.244	0.132	0.325	0.260	0.176	0.213	0.051	0.144	0.176	0.143	0.256	0.150	0.073	0.170	0.152	0.056	0.167	0.068	0.134	0.203	0.206	0.288	0.158	0.346	0.451	0.282	0.277	1.000	0.000
DIBA5	**30**	0.233	0.216	0.103	0.414	0.228	0.125	0.225	0.018	0.054	0.171	0.183	0.098	-0.010	0.085	0.081	0.205	0.253	0.303	0.115	0.270	0.136	0.088	0.066	0.166	0.229	0.286	0.238	0.106	0.383	1.000

14.APPENDIX 8 – DESCRIPTIVE STATISTICS | SMART PLS

Name	No.	Type	Missings	Mean	Median	Scale min	Scale max	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
PU1	0	MET	-	6.254	7.000	2.000	7.000	2.000	7.000	1.083	2.102	-1.546	0.000
PU2	1	MET	-	6.611	7.000	2.000	7.000	2.000	7.000	0.723	12.365	-2.814	0.000
PU3	2	MET	-	6.421	7.000	1.000	7.000	1.000	7.000	0.995	7.272	-2.347	0.000
PU4	3	MET	-	6.484	7.000	3.000	7.000	3.000	7.000	0.870	3.685	-1.924	0.000
PU5	4	MET	-	6.556	7.000	1.000	7.000	1.000	7.000	0.913	13.091	-3.171	0.000
PEOU1	5	MET	-	6.254	7.000	3.000	7.000	3.000	7.000	0.942	1.282	-1.280	0.000
PEOU2	6	MET	-	6.270	7.000	3.000	7.000	3.000	7.000	0.921	0.584	-1.121	0.000
PEOU3	7	MET	-	5.357	5.000	2.000	7.000	2.000	7.000	1.087	-0.186	-0.189	0.000
PEOU4	8	MET	-	5.476	6.000	1.000	7.000	1.000	7.000	1.314	0.177	-0.766	0.000
PEOU5	9	MET	-	5.857	6.000	3.000	7.000	3.000	7.000	1.103	-0.103	-0.752	0.000
SN1	10	MET	-	4.714	5.000	1.000	7.000	1.000	7.000	1.627	-0.143	-0.423	0.000
SN2	11	MET	-	4.183	4.000	1.000	7.000	1.000	7.000	1.879	-1.041	-0.268	0.000
SN3	12	MET	-	4.706	5.000	1.000	7.000	1.000	7.000	1.624	-0.727	-0.359	0.000
SN4	13	MET	-	4.095	4.000	1.000	7.000	1.000	7.000	1.845	-0.963	-0.111	0.000
SN5	14	MET	-	4.516	5.000	1.000	7.000	1.000	7.000	1.722	-0.966	-0.268	0.000
IO1	15	MET	-	6.008	6.000	1.000	7.000	1.000	7.000	1.288	2.928	-1.639	0.000
IO2	16	MET	-	6.103	7.000	2.000	7.000	2.000	7.000	1.290	1.719	-1.564	0.000
IO3	17	MET	-	6.214	7.000	2.000	7.000	2.000	7.000	1.232	2.428	-1.732	0.000
IO4	18	MET	-	6.024	7.000	1.000	7.000	1.000	7.000	1.466	2.870	-1.830	0.000
IO5	19	MET	-	6.286	7.000	2.000	7.000	2.000	7.000	1.133	4.320	-2.042	0.000
DV1	20	MET	-	6.468	7.000	1.000	7.000	1.000	7.000	0.965	8.526	-2.509	0.000
DV2	21	MET	-	6.460	7.000	1.000	7.000	1.000	7.000	0.923	9.385	-2.519	0.000
DV3	22	MET	-	6.579	7.000	1.000	7.000	1.000	7.000	0.867	13.465	-3.058	0.000
DV4	23	MET	-	5.476	6.000	1.000	7.000	1.000	7.000	1.627	0.313	-0.993	0.000
DV5	24	MET	-	6.310	7.000	2.000	7.000	2.000	7.000	1.027	2.334	-1.588	0.000
DIBA1	25	MET	-	6.198	6.000	3.000	7.000	3.000	7.000	0.976	0.872	-1.187	0.000
DIBA2	26	MET	-	6.198	7.000	3.000	7.000	3.000	7.000	0.984	0.618	-1.118	0.000
DIBA3	27	MET	-	5.857	6.000	2.000	7.000	2.000	7.000	1.271	0.076	-0.926	0.000
DIBA4	28	MET	-	5.603	7.000	1.000	7.000	1.000	7.000	2.000	0.649	-1.415	0.000
DIBA5	29	MET	-	6.048	7.000	1.000	7.000	1.000	7.000	1.588	3.719	-2.089	0.000