Behavioral Finance in Fintech: Biases & Opinions

Evidence from the Portuguese market

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Abstract

Title: Behavioral Finance in Fintech: Biases & Opinions.

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Fintech has become a worldwide and continuously growing phenomenon, yet fintech adoption has still not reached its full potential. The customer value proposition is now the core of development of any platform, and it is necessary to implement tools and measures that improve the experience. As such, the present thesis proposes the introduction of Behavioral Finance into modern fintechs as a provider of an enhanced customer engagement and increased value. The behavioral finance tool is described as an abstract algorithm, based on the concepts and methodologies of the subject, then tested via a two-part survey. The first part aims to understand the impact of two drivers behind the adoption of fintechs, namely behavioral biases and pre-conceived opinions. It is found that, on average, opinions have a positive impact on the likelihood of fintech adoption, whereas behavioral biases, despite present in the population, are not statistically significant in the engagement decision. In addition, past usage had a positive influence on the future usage, and this expected use had a positive influence in the future recommendation of the technology. The second part aims to study whether the introduction of the behavioral finance tool impacts the decision of adoption. It is found that, on average, future usage and future recommendation increase with the insertion of the algorithm, but the increase is not statistically significant. Furthermore, market perception of adoption is above 70%, indicating a possible opportunity.

Abstract (Portuguese Version)

Título: Behavioral Finance in Fintech: Biases & Opinions.

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Palavras-Chave: Adoção; Fintech; Finanças Comportamentais; Preconceito; Opinião.

Fintech tornou-se num fenómeno mundial, e de crescimento constante, mas a sua adoção ainda não atingiu o seu potencial. Hoje em dia, o valor para o cliente é o centro de desenvolvimento de qualquer plataforma, tomando-se necessário implementar ferramentas e medidas que melhorem a sua experiência. Como tal, a presente tese propõe a introdução de Finanças Comportamentais nas fintechs modernas como uma ferramenta que permite fornecer uma experiência superior e adaptada ao cliente. A ferramenta de finanças comportamentais é descrita como um algoritmo abstrato baseado nos conceitos e metodologias da disciplina, e seguidamente testada, através de um questionário de duas partes. A primeira parte tem como objetivo estudar o impacto de dois fatores determinantes para a adoção das fintech, nomeadamente, os comportamentais irracionais e as opiniões pré-concebidas. Constatou-se que, em média, as opiniões têm um impacto positivo na probabilidade de adoção das fintech, embora os vieses, apesar de presentes na população, não são estatisticamente significativos na decisão de utilização. A utilização passada tem uma influência positiva no uso futuro, sendo que o último influencia positivamente a recomendação futura da tecnologia. A segunda parte visa analisar se a introdução da ferramenta afeta a decisão de adoção da tecnologia. Verifica-se que, em média, o uso futuro e a recomendação futura aumentam com a inserção do algoritmo, mas o aumento não é estatisticamente significativo. Ademais, a perceção de adoção do mercado supera os 70%, indicando uma possível oportunidade.

I. Index

II. Introduction

"In addressing the challenges and risks that financial innovation may create, we should also always keep in view the enormous economic benefits that flow from a healthy and innovative financial sector. The increasing sophistication and depth of financial markets promote economic growth by allocating capital where it is most productive."

(Ben Bernanke, Chair US Federal Reserve, New York, 15 May 2007)

FinTech has become a name of focus for the past few years, combining two major fields: Finance and Technology. Its spontaneous character, innovative solutions and massive investment have conquered the hearts of many, but worldwide adoption is still far. As organizations, fintechs provide the much-needed enhancement and disruption of the financial system, with groundbreaking concepts and ideas, the most known being Bitcoin, customer value propositions, like the gamification of financial operations, business models, like peer-to-peer lending, tools, for instance robo-advisors, and technologies, such as distributed ledgers. Every day individuals are surrounded by an infinity of raw data with algorithms prepared to analyze it, and it is now crucial to open arms and minds to the next step of the technological revolution. The financial system was previously seen as bureaucratic and slow-moving, but in today's fast-paced society, institutions and markets must make an effort to keep up.

On a macroeconomic level, fintech has been driven by the exponential technological innovation seen in the past three decades, by demographics, as younger generations crave technology on all aspects of their lives, by talent, fleeing from older and pre-established organizations to new entrepreneurial ventures on all segments, and by trust, essentially due to the World Financial Crisis of 2008. Microeconomically, fintech drivers are equally meeker yet more complex – here, simplicity is key, and when combined with intuitive design and gamification, it becomes exponentially more powerful; however, the driver in common: trust. Here, trust refers to the customer's willingness to share their personal data and preferences with an online platform, not knowing who or what's on the other side of the screen.

An increasingly developed society will have a more active technological component; as such, it is perceived that one of the key aspects to the development of a country is the adoption of technologies, as opposed to a closed mentality, filled with bureaucracy and inefficiency. In

Portugal, the overall adoption of fintechs is still quite quaint, and specifically in the Savings & Investments sector, only a small percentage of consumers have experienced the technology.

Therefore, the concept of this thesis is the proposal of a Behavioral Finance tool that could enhance the financial knowledge of the individual, in addition to increasing its attractiveness for the customer and the overall functionality of a robo-advisory type of platform, such as Betterment. The concept is presented as abstract, since behavioral finance has endless possibilities, but the idea arises from the current developments in softwares and other various solutions among fintechs and incumbents. The examples given were speculative, while based on existing advances in the technology not yet available in the country, relating, in the Savings subsection, to the spending and saving habits of the individual, and in the Investments subsection, to the his personal preferences.

Behavioral Finance focuses on the psychological factors behind an individual's financial decisions. Here, the traditional *homo economicus* ceases to exist, as the "normal investor" is not always rational as financial assumption would state. This quasi-new field assumes investors are human: they don't always make the optimal choice, they make mistakes, they are flawed. As the subject is the investor, the final customer, it is deemed crucial to understand the circumstances and elements behind his cognitive reasoning.

Nowadays, the introduction of Behavioral Finance tools has become increasingly adopted, as it provides the customer with a deeper experience into the world of finance, while allowing a more meaningful understanding of the ecosystem, as well as thorough and tailored experience. As of now, in investment platforms, this type of tools uses the investors' risk profile, age, income, and expectations to provide investment recommendations based on such assumptions. However, in savings platforms, these tools are much more rudimentary, regarding solely generalized saving, expense tracking and budget tracking. This thesis proposes the further advancement of this technology, to test the possibility of integrating existing products and services, of more advanced markets, in Portugal. As such, this Behavioral Finance tool is used as a complimentary tool to fintechs, namely in the role of a "personal advisor", tailored to the specific needs and preferences of a given individual.

Robo-advisory has become prominent for the past five years, with the development of algorithms that include, not only investor risk preferences, but also ethical and industry preferences. It's advancement has been undeniable, and according to Vincent et al. (2015), the portfolios managed by robo-advisors worldwide are valued at over $200 billion – furthermore, it is expected that by 2020, this number rises and the total amount of assets under management will account for *circa* 10% of the wealth management industry.

Thus, this thesis is divided into two main parts: Part I focuses on the usage of fintechs in general, and studies two of the potential drivers of adoption of such technologies, namely behavioral biases and pre-conceived opinions; Part II attempts to investigate if the introduction of the behavioral finance tool – henceforth described as an algorithm based on customer behavioral, cognitive and personality traits – would encourage the adoption of the fintech, and its endorsement to colleagues, aiming to enhance the customer's experience while using a robo-advisory type of platform, as well as serve as a financial education mechanism, by providing tailored insights. Hence, three research questions are proposed:

i. Are there biases and pre-conceived opinions regarding fintechs?

ii. Do they influence the adoption of fintechs?

iii. Would the addition of a behavioral finance tool influence the customer's choice?

The following section will discuss the research that has been previously conducted on the respective fields. In order to study the analysis of biases, the works of Kahneman (2015) and Pompian (2006) use used as primary sources, as both authors thoroughly investigate the impact of mental prejudices and misconceptions in the financial decision-making process. Additionally, in order to assess the impact of opinions, the Technology Acceptance Model (TAM) was used a basis – here, the work of Chuang, Liu & Kao (2016) was consulted, as the authors tested the model in fintech adoption. In addition, previous work has been conducted on the adoption of fintechs, namely by Belanche, Casaló and Flavián (2019), who examined the adoption of fintech with the introduction of Artificial Intelligence, Fulk, Grable, Kruger and Watkins (2018), who researched the types of customers of robo-advisory platforms, and Woodyard ang Grable (2018), who explored the differences among robo-advisors and traditional advisors. However, no previous research was found that studied the impact of both variables, biases and opinions, on the adoption of a new technology.

Section IV presents the methodology used to conduct the aforementioned analysis on a sample of 427 entries from Portuguese respondents, based on the research of Xiao and Porto (2019) and Woodyard et al. (2018). Section V exhibits the findings of the conducted analysis, evidencing the results of the presence of biases and opinions, as well as their impact on fintech adoption. In addition, it further presents the results of the introduction of the behavioral finance tool and its impact on the decision to embrace the technology. Section VI includes the concluding remarks, as well as the limitations of this analysis and the further possibilities for future research.

III. Literature Review

III.A. Fintech

III.A.1. Definition of Fintech

Mainstream society is now dominated by technology. Nowadays, people find themselves searching for the simplest and effortless solutions to even the most menial tasks, and that is when technology kicks in. Something as simple as a money transfer can be done from the comfort of home, in a seamless and virtually costless click. From the invention of the Automated Teller Machine (ATM) in 1967, to the recent developments in Distributed Ledgers, Schindler (2017) argued that technology is vital to innovation. The emergence of financial technology is a widely discussed topic, and there is no universal consensus. Arner, Barberis and Buckley (2016) stated that finance and technology have been connected for centuries, and that developments in either industry tend to be mutually beneficial – perhaps because technology allows the dispersion of information that is necessary for financial advancement, while the advancement of the financial services allows for better investments.

Alt, Beck and Smits (2018) traced the introduction of technology in banking as "Banking IT", in the 1960s, which referred to the digital systems created to facilitate the flow of information within the organization, and on a later stage, outside. On the other hand, Lee and Shin (2018) argued that the contribution for the technological development of the contemporary financial system landscape came in the 1990s, with the diffusion of the internet – the authors believed it was the creator of e-finance, the bundle of technologies that allowed services such as banking, trading and insurance to be done online –, where the information craze drove innovation to reduce the human interaction and labor, and to switch it for powerful algorithms and generalized automation (allowing less costly and time-consuming transactions). According to Hochstein (2015), the term "Fintech" can be traced as far back as the 1990s, where it was used by the predecessor of Citigroup for the Financial Services Technology Consortium, which aimed to share the technologies among market players. However, throughout the several authors, one element appears to be consensual: one of the most used neologisms in the past decade, referring to the usage of technology in finance, typically referred to as "fintech", "Fintech" or "FinTech", had its origin around the 2008 Global Financial Crisis (GFC) (Alt and Puschmann, 2012; Alt, Beck and Smits, 2018; Arner et al., 2016; Gomber, Koch and Siering, 2017; Lee et al., 2018). In its most generalized characterization, this new-found industry employs technology in finance. Schindler (2017) stated that fintech innovations are not the first to use technology as a driver, but they are the first innovations to have such a massive volume to create an independent segment of the financial sector; furthermore, it is this tech-savvy personality that furthers the excitement of the public: the possibility of new and improved services and products. Fintech has grown exponentially, and it comes in all shapes and sizes: money transfers and payments, assorted algorithms, cryptocurrencies, insurance, cyber-security and regulation, among many others.

According to Lee et al. (2018), the powerful combination of the GFC with the existing financial and mobile technology, internet advancements, social media and networks, artificial intelligence, and big data analytics originated the "fintech phenomenon". The authors elaborated their rationale by explaining the impact of the internet in the banking sector, referring to the improvements in data transmission, the cost reduction of online stock trading and brokerage and the adoption of the smartphone, allowing the easy and instantaneous accessibility of banking information and various transactions.

Alt et al. (2012) presented a different view on the subject, stating that the creation of fintech as we know it was due to four drivers: (1) the repercussions of the Global Financial Crisis, which forced financial entities to hold high capital requirements, precluding smaller and riskier investments and imposing the direct identification of profitable products/services; (2) the changes in banking customer behavior, as the increased usage of digital channels is not only expected, but also its transparency towards the consumer, leading to a better informed generation; (3) the integration of high-tech hardware into day-to-day life, such as smartphones and tablets, leading to a craze of software dissemination; (4) the emergence of non-banks, which strived with the creation of new business models and value propositions that were not offered by their incumbents. These drivers dynamized an otherwise bureaucratic and obsolete industry, shifting the focus from the organization to the customer.

However, Arner et al. (2016) presented a more political and macroeconomic point of view, stating that the consequential market conditions of the Global Financial Crisis paved the way to new entrants and new technologies, namely: (1) the tarnished public perception of the financial institutions; (2) the deeper regulatory scrutiny, into the critical actions and methods of organizations; (3) the political demand for a wider range of services and products, as well as the decline of the monopoly of the dynasty banks; and (4) the economic conditions that followed this downturn, specifically the soaring unemployment rates and the lack of accessibility to lending and credit. The crisis originated a shift in the money flow, from financial institutions to tech-based companies, combining previous financial leaders and recent graduates with innovative ideas to flourish. Schindler (2017) deepened the analysis on the drivers of the fintech era, by subdividing the issue into supply and demand factors. The author appointed four main supply factors: the increase and development of technology, the stricter regulations following of the financial crisis, the macroeconomic and industry shift – all previously mentioned by Arner et al. (2016) –, and the “innovation spiral”, the series of innovations that follow an initial substantial one. On the demand side, the key aspects on which the author focused on were: the lack of product/service adoption, an important factor here introduced, relating to the fact that customer adoption and retention play an extensive role in the development of an industry or organization; demographics, previously explained by Alt et al. (2012), referring to the youthful mindset of the newer generations, as well as the increasingly higher technological adoption viewed on all age groups; and finally, once again, regulation, discussed also by Alt et al. (2012) and Arner et al. (2016), as the new and stricter guidelines to banking management and investment. Higgins (2019) exemplified the power of demographics on his research vis-à-vis the adoption of the debit card in Mexico, from 2009 to 2012, exhibiting that acceptance was required from both sides of the market in order to provide a pure disruption, and that nowadays, in the fintech era, a massive wave of customer adoption could create a consequential shock, invoking the idea of the “innovation spiral”, and dramatically increase the implementation of the technology on both the supply and the demand side.

Gomber et al. (2017) argued that these organizations, most of which originated in the IT sector, and not on the financial sector, use their expertise not only to solve existing challenges, but also to compete with the established financial services providers, by providing innovative products and services, hence conquering new markets and segments. In 2018, the same authors discussed the pillars of this new industry, attributing it to the massive amount of capital available for investment in financial innovation, to the different products and services offered by the startups and to the enhanced business models and value propositions.

The digitalization of the financial sector opens the door to countless opportunities, but also threatens the incumbents, forcing them to “sink or swim” – this analogy applies as, in the face of this adversity, pre-established companies must find their way of integrating technology, or they become obsolete, which will ultimately lead to their demise. Accordingly, Alt et al. (2012) stated that traditional financial institutions tend to support and connect amongst themselves but resist the real IT/tech solution. Lee et al. (2018) further explained that banks are focused on traditional models, with new interfaces with the customer, while fintech startups manage to unlock and create value in new ways, largely related to data science. Hence, fintech is presented not just as a threat to pre-existing traditional banks, but it is also a huge opportunity for them to adopt new demographics and niches, as they present different business models, different value propositions and different cultures. They strive on data-driven solutions, specific customer segments, seamless and transparent operations and, most importantly, innovation. Dapp et al. (2014) further stressed that fintechs tend to have a technological background, as opposed to a financial background, and that the future of the industry is reliant upon the enhancement of technologies such as mobile services and data processing, as this development could facilitate the adaptability of both current and new softwares.

III.A.2. Fintech Ecosystem

KPMG's Pulse of Fintech stated that investment in Europe in the first half of 2019 was mostly focused on larger deals among more mature organizations, such as Payments and Borrowings, translating into the investor's current preference in consolidated businesses and industries to early stage startups, invoking the need for scaling and strengthening. Fintechs and incumbents have continued to develop mutually beneficial relationships via open banking and open data, allowing incumbents to learn from startups about new technologies and to improve their systems, mainly in the customer experience segments, and fintechs to further explore the value in big data, namely in customer management, digital identity management, preferences, rights and consents. Globally, the Deal Count, the Total Investment Value, the Angel/Seed Investment and Early Stage Venture Capital have declined, whereas Later Stage Venture Capital increased in the past year. However, in Europe, while the landscape is quite similar, the Total Deal Value also increased.

EY (2015) distinguished between two types of fintechs: "disrupted" and "invented". A "disrupted" service was described as a pre-existent service that has now been challenged by a fintech, which provides a new, and more tech-savvy way, of accessing similar products, but with more simplicity, accessibility and lower cost. Opposing, an "invented" service was defined as one that simply did not exist before, such as peer-to-peer lending or mobile payments, which may refer to a specific niche of customers, or something that is industry wide. Furthermore, the organization defined four distinct categories of fintechs: 1) Money & Payments, which includes Online Foreign Exchange, Overseas Remittances and Non-Banks to transfer money; 2) Savings & Investments, including Peer-to-Peer Platforms for investments, Equity or Rewards Crowdfunding, Online Investments & Investment Advice, Online Budgeting & Financial

Planning and Online Stockbroking & Spread Betting; 3) Borrowings, including once again Peer-to-Peer platforms, now for lending; 4) Insurance.

According to EMEA Fintech Disruptors (2019), from 2018 to 2019, the fintechs' ability to achieve larger scales and customer reach decreased by approximately 20 percentage points, from 65% to 45%, while gaining customer trust, by doubling the initial low level of 15% to 30%, ultimately translated into an overall driving adoption of *circa* 35%. In the Wealthtech segment, the landscape has mostly been described as fast-paced, moving into a later stage of development, and driven by countless applications of data science. In this subsector, there was a significant increasing in funding, fueled by massive deals conducted by challenger banks.

Choi and Phan (2006) stated that the creation of startups depended on supply factors and demand factors of a given financial ecosystem. On the supply side, the authors attributed the driving force to the labor dynamism, due to the previous experience of recently unemployed bankers, willing to create a new venture and become independent. On the demand side, the authors argued that the driver was the market availability for technological innovation, meaning the gaps in the industry that could be solved by the introduction of new technologies.

Based on this work, Haddad (2019) posed a question regarding the distribution of financial innovation across the world – here, the author found that the workforce had a positive impact on entrepreneurship, but that this impact depended on both the qualifications of a given individual and the geographical region, as they tended to be more concentrated around "hubs"; at the same time, the easier access to investment also played a key role, pointing to the fact that, not only do startups require considerable amounts of investment, but they also need a constant support in order to provide a more stable growth environment. As such, the author asserted that the location of the startup should reflect a careful ponderation of the aforementioned factors, in addition to the macroeconomical, political, and socio-demographic conditions.

From 2005 to 2015, according to CrunchBase, 10 fintech startups were created in Portugal, awarding the country the 49th position in the worldwide ranking. According to the Portugal FinTech Report 2019, there are now over 100 fintech startups within the ecosystem, which is divided as quite evenly. Among the top 30 Portuguese organizations, there are two small majorities, of 17% of Lending & Credit and Insurtech, whereas Personal Finance accounts for 10% and Capital Markets & Wealth Management account for 7%.

III.A.3. Fintech Adoption

Gomber et al. (2017) referred to the fact that fintechs are usually from an IT background, and that they are increasingly growing within the financial industry, "stealing" customers from the traditional market players, for three reasons: 1) its offer of new products and services, that were either not offered by incumbents, or that did not fulfil the customers' needs; 2) its innovative technology and business models have allowed them new opportunities, whether in different markets, unexplored segments and customer value propositions and original infrastructures; 3) its tech-savviness makes them more capable of dealing with the fast-paced and ever-changing environment and society that we live in today – hence, they are very agile.

EY (2015) defined fintechs as organizations with the open-mind and creativity to design new business models, as well as the technology to disrupt the financial industry as a whole. The organization stated that these companies owe their success to their easiness to use, focusing on design principles like customer-centered value proposition, easy onboarding, simple and intuitive interface, simple and customizable products, with no penalties or commitments. Here, traditional institutions are at a disadvantage, as they are subjected to many constraints, such as strict regulations, outdated softwares and pricing guidelines. In 2015, EY's Global Fintech Adoption Index stated that the average adoption, for the studied markets, was *circa* 15.5%. In order of usage, Money Payments and Transfers (17.6%), Investments (16.7%), Insurance (7.2%) and Borrowing (5.6%). Of the non-users, over half stated that they didn't use fintechs because they didn't know they existed. In Savings & Investments, the most used was Online Stockbroking & Spread Betting, followed by Online Budgeting & Planning, and finally Online Investments. As expected, younger generations were more likely to use these kinds of technologies. For the youngest demographic, ages 18 to 34, *circa* 23% expected to be using two or more fintechs within six months, meaning that in the near future, almost 50% of the adopters would be between 25 and 34 years old. Carlin, Olafsson and Pagel (2017) corroborated similar results while studying the adoption of fintechs in Iceland, stating that the lowest usage rates were found for individuals born between 1946 and 1964, or Baby Boomers, followed by individuals born between 1965 and 1980, or Generation Xers, and finally, the biggest adopters, Millennials, born between 1981 and 1996. In 2019, EY's FinTech Global Adoption Index showed a different landscape: adoption in the 27 studied markets was, on average, 67%. This methodology evaluated the responses of 27 countries, counting each market as one vote. However, this approach presented limitations due to the distinct cultures, development and technological advancement – as such, these results were not deemed adequate for extrapolation to the general market, nor to Portugal. By cultural, infrastructural and geographical proximity, based on Hofstede Insights, the countries to consider for comparison were Spain, Italy and France, entailing an average fintech adoption index of, approximately, 47%, which was still deemed abnormal for this country. Investment platforms descended from second to third most used, and Savings platforms from third to fourth most used, while Money Payments & Transfers continued to lead the chart, and with Insurance platforms climbing from fourth to second most used in the last four years; Borrowings continued to be the least used throughout the analyzed period.

EY (2019) stated that the fintech adoption due to an improved interface or differentiation and innovation of products and services, was becoming less common, since incumbents have proven to become more competitive and have developed new approaches to customer attraction and retention, from easy setup to lower costs. However, one factor was still deemed quite an anchor to non-adoption: trust. Non-adopters preferred to stay with the incumbents as they did not trust fintechs, such that in several markets, like France or Japan, incumbents exploit this lack of trust to build their own fintech solutions and retain customers with their existing brand.

Also, word-of-mouth was vital for fintech adoption: 30% of adopters and 35% of non-adopters admitted to taking advice from those around them, while social media spread brands and products easily, by facilitating peer-to-peer conversations. 23% of non-adopters appear to be "lost" as they felt underserved by incumbents but were not aware of new solutions. Adopters revealed uncertainty when sharing their personal data with non-financial organizations: 38% of adopters would share them with traditional banks, 31% with fintechs and 23% with non-financial institutions, meaning that there is still a considerable gap, namely in the trustworthiness of fintechs, hence presenting an opportunity for incumbents and challengers. Even though they are quite agile when developing solutions for the market, fintechs lack the trust of customers to take them onto their lives, which is something that incumbents already have. The research similarly argued that there are opportunities in Investments and Savings, mainly due to low adoption rates in key demographics, namely women, customers in rural areas and customers with fewer education.

III.A.4. Robo-Advisory

Gai et al. (2017) stated that the current big trend in fintech is data analysis, such that data analytics softwares and artificial intelligence are being developed at overwhelming speeds in order to create the next big tool in information management and value creation, proving the ever-growing complexity and availability of unstructured data. The robo-advisor was then described as the bundle of functions, building algorithms that allow the automatization of financial investment and planning, hence excluding human judgement errors and biases, using theories developed over decades, such as Markowitz Mean-Variance Portfolio Theory (Gai et al., 2017; Gomber et al., 2018; Phoon and Koh, 2018; Sironi, 2016; Tertilt and Scholz, 2018). Phoon et al. (2018) highlighted that incumbents are held back by archaic technological systems and hierarchies, stricter regulations, and cost structures, deeming it much harder to improve performance at a pace that is consistent and challenging to the new technologies. Jung, Dorner, Glaser and Morana (2018) further stated that robo-advisors are now replacing traditional wealth managers, and Gomber et al. (2018) argued that they disintermediate markets that were previously controlled by traditional players. Phoon et al. (2018) traced their conception after the financial crisis, like many other fintechs, highlighting that these were rudimentary: they provided low-cost and low-risk solutions in a turbulent time for the financial industry, by combining few allocation assets (mainly ETFs), automatic rebalancing and passive management, hence reducing transaction costs. The authors considered that robo-advisory is still developing, but that there is much potential, due to the scalability and low-cost structure of the business, as well as the possibility for future customization. Here, and also stated by Gomber et al. (2017), there are possibilities of tailoring needs and solutions based on retirement planning, tax harvesting or real estate benefits. Maxfield (2017) argued that Wealthfront and Betterment are the most progressive in their field, the first having introduced college savings plans for young parents, and the second having developed 401(K) solutions for businesses.

According to Tertilt (2018), robo-advisors are less thorough when onboarding, providing less tailored solutions and less insights as to personal investment needs, biases and preferences – it is considered both an opportunity and a risk for incumbents. Baker and Dellaert (2018) further analyzed the implication, as opportunity and risk, for regulators, due to the transparency of the service, the human error in the construction of the softwares and the inherited fear of lack of privacy and security when dealing with financial data. Hence, Phoon et al. (2018) suggested that the creation of complex algorithms could lead to an increasingly higher adaptation of the robo-advisor to the customer, by analyzing customer saving and spending behavior, assets and liabilities or expectations; plus, they could introduce concepts and methodologies from other fields, such as behavioral finance. Fulk et al. (2018) further stated that, besides the lack of flexibility from only having ETFs (or sometimes equities), being passively managed, and rudimental tailoring, the lack of human interaction may be a factor of exclusion for the adoption of these technologies. Ruf et al. (2016), quoted by Jung et al. (2018), argued that key factors of the success of a robo-advisor are “quality of service”, “trust” and “information asymmetry”, asserting that these have just as a significant impact as the investment advice.

III.B. Behavioral Finance

III.B.1. Definition of Behavioral Finance

Sargent (1993) defined two clauses for rationality in the investor: the first is, when faced with new data, the information is assimilated in a correct way and the investor’s beliefs will be adjusted; the second is, when faced when a decision, the investor will make the choice on the basis of maximization of expected utility. The concept was first introduced by Simon (1957), and it is the key to behavioral finance. Bounded rationality has been previously studied by a wide panoply of authors, such as Barber and Odean (2001), DeBondt (2010), Kahneman and Tversky (1979) and Thaler (2016).

Statman (1999) traced the origin of standard finance to four contributions: Markowitz’s Mean-Variance Portfolio Theory; Modigliani and Miller’s Theory of Investment; Sharpe, Lintner and Black’s Capital Asset Pricing Model; and Black, Scholes and Merton’s Option Pricing Model. Antony (2019) further stated that classical finance thrives on complex mathematical models, with many conditions and assumptions, to answer even more complex questions. Financial theory dictates that the investment decision is purely based on rationality towards wealth maximization, with no regard for the individual, whereas the author defended that the decision is made based on experience and perception, which is guided by the psyche. Coined in the 19th century, the *homo economicus* is the basis of most economic and financial models, assuming agents are rational, self-interested and pursue the maximization of their wealth. However, the reality is that agents are subjects of emotion, intuition and cognitive error.

Hence, Behavioral Finance attempts to explain how investors make their decisions, or better yet, the irrationality behind them. According to Ricciardi (2000), behavioral finance combines concepts and ideas from various disciplines, namely Finance, Psychology and Sociology, in order to understand the decision-making process of the “normal” investor. De Bortoli et al. (2019) explained that the discipline arises from neoclassical economics, creating theories and methodologies to explain the real-life irrational behavior of the aforementioned *homo economicus*. Frankfurter et al. (2002) argued that Behavioral Finance is now being integrated into modern Finance, by studying new methodologies and theories, without changing its core. Subrahmanyam (2007) defended that while the mathematical approach brought objectivity and rigor to Finance, it also left many occurrences unexplained. As such, the author supported the development of behavioral theories, as they portray human behavior, while recognizing that even these may encompass lacunae if the subjects don't present that behavior.

Statman (2014) further compared traditional finance to behavioral finance, evidencing four key aspects: 1) rationality *versus* normality of agents; 2) efficiency of financial markets; 3) portfolio design following mean-variance portfolio theory or behavioral portfolio theory; 4) asset pricing theory and its determinants. De Bondt (2010) pointed to the fact that behavioral finance is pragmatic, as it does not make strong and unrealistic assumptions, such as rational agents, optimal pricing of assets or lack of information asymmetry. Avgouleas (2015) exemplified this pragmatism with the Efficient Market Hypothesis (EMH), by explaining that its two main assumptions were challenged by Behavioral Finance: this subject accounts for "anomalies" in the pricing of an asset, such that it does not fully reflects its true value, and for limited arbitrage opportunities, due to market restrictions, such as inefficiencies and transaction costs. Antony (2019) stated that, for decades, in order to understand the drivers behind human behavior, social studies were anchored to the Expected Utility Theory. However, two distinct schools of thought were created: Festinger's Theory of Cognitive Bias, where one's behavior was driven by one's mind, including emotions, conducts and perception, and Kahneman and Tversky's Prospect Theory, where individuals perceived profit and loss in opposite manners, meaning they behaved as risk-averse towards gains, and risk-seeking towards losses.

Shefrin and Statman (1984) explored investor's choices towards stock picking, arguing that emotions and cognitive errors had a significant impact on the individual's preference. Later, Statman (2014) argued that experienced investors have learned to circumvent these factors as to avoid mistakes, whereas unexperienced investors have yet to learn the true influence of cognitive errors and emotions, in addition to trusting inaccurate information. The author claimed that emotions should be taken into account when making the investment decision, as they mostly complement rationality, and emphasize the previous mistakes made. As such, rational investors are portrayed as utilitarians, while customers appear to be more complex, measuring their wealth and well-being in a utilitarian, expressive and emotional frame. From this triple benefit structure, Shefrin and Statman (2000) created the Behavioral Portfolio Theory (BPT), where investors were not just recommended an optimal mean-variance portfolio, but created and adjusted the portfolio to their specific goals, in a pyramid-like structure, gradually increasing risk and reward – hence, the risk of the portfolio is described as the probability of failure to reach or complete a goal, such that the investors tend to be less risk-averse towards high standard deviations. However, Klontz et al. (2017) stated that such behavioral finance theories, developed by academics, are in experimental stages and real-world application is far.

III.B.2. Biases & Opinions

Frankfurter et al. (2002) argued that Behavioral Finance intends to teach agents how to control their emotions and to not become victims of cognitive errors. Pompian (2006) thus defined behavioral biases as "systematic errors in judgement", inconsistent with economic theory, subdividing them into cognitive biases and emotional biases. Mitroi and Oproiu (2014) argued that agents are irrational, as their human nature overcomes their logic, education and experience, and Mitroi (2014) further instigated that if such biases are significantly regular, quantifiable and predictable, it is possible to exploit them as arbitrage opportunities.

Pompian (2006) described overconfidence as the cognitive bias originated in the overestimation of probabilities and excessive trust in incomplete information, ultimately translating into poor judgement and poorer competencies. The appointed implications of this type of biased behavior in investors are underdiversification of portfolios, underestimation of risk and overestimation of asset value. Based on this description, the author further subdivided overconfidence into prediction overconfidence and certainty overconfidence. Barber and Odean (2001) demonstrated the effect of overconfidence when trading, concluding that men tended to be more overconfident than women, rendering a higher trading frequency, higher transaction costs and overall worse performance over the long term. Confirmation Bias, as the name indicates, presents the cognitive bias responsible for the continuous search for information that confirms and supports one's preferences, beliefs and decisions, while disregarding the information that contradicts them. Pompian (2006) refered to it as a variation of the Selection Bias, where subjects, or data points, are previously screened and selected as opposed to being randomized, creating distortions in the analysis, and consequently, in the final results. Hence, the sought confirmation creates an intrinsic need to ignore information that disproves the individual's beliefs. Agnew et al. (2008) researched the role of gender and framing in an investment context and found that women tended to be more influenced by biases regarding conflicting information. Cognitive Dissonance Bias arises from the inconsistency between contradictory beliefs. Developed by Festinger (1957), the Cognitive Dissonance Theory stated that incongruity between beliefs causes significant mental discomfort and anxiety. Ricciardi et al. (2000) argued that individuals are able to reduce this dissonance by either changing their beliefs, or by rationalizing their behavior. Pompian (2006) further noted that this bias leads to poor investment decisions, driven by herding behavior, holding or reinvesting in losing positions and disregarding essential information that contradicts the investor's preferences. Status Quo Bias constitutes an emotional bias, wherein individuals irrationally make the decision that prolongates the status quo, entailing mental inertia. Pompian (2006) argued that this bias is frequently discussed along with the Endowment Effect, where an investor tends to attribute more value to a given asset if he has possession over it, and with the Loss Aversion Bias, a subcategory of the aforementioned Prospect Theory, wherein the agent presents a greater need to avoid losses than to pursue gains. Regret Aversion Bias has an emotional background, and it renders investors unable to rationally make decisions out of regret. Pompian (2006) claimed that regret aversion arises from two distinct types of error: the error of commission, where a wrong action is perpetrated, or the error of omission, where the simple lack of action leads to a missed opportunity. The bias causes agents to question beliefs and past engagements, which could ultimately lead to herding or conservative investment behavior, holding winning or losing positions for too long or preference for seemingly better companies with lower returns.

Davis (1986) first introduced the Technology Acceptance Model (TAM) in order to understand how technological systems, and their user-based characteristics, influenced their adoption, and it rested on three key principles: attitude, intention and externalities. The individual's attitude towards the new technology was described as a proxy of his opinion of the technology itself: subcategorized into Perceived Usefulness (USEF) and Perceived Easiness of Use (EOU), the first component measures one's belief that the new technology will improve his day-to-day life and overall well-being, whereas the second component measures the perceived degree to which the technology will be of simple implementation and functionality. The behavioral intention assesses the individual's intent to use the given technology, by reconciling attitude and behavior. The externalities refer to variables that impact the decision to adopt the technology that do not depend on the previous measures, such as demographics and personality traits. Chuang et al. (2016) tested the model on the adoption of fintechs in factory engineers in Taiwan, and determined that the trust, convenience and easiness to use had positive effects on the intention of usage, and that customer's opinion of fintechs was the most important driver on the adoption of the fintechs. Belanche et al. (2018) conducted a similar analysis, focusing on the adoption of robo-advisors in the United States, United Kingdom and

Portugal, concluding that both perceived usefulness and perceived ease-of-use had positive effects on attitude, whereas only perceived ease-of-use had a significant effect on intent.

III.C. Financial Education

According to Baker and Ricciardi (2018), financial planning and investing is considered overwhelming and intimidating, leading to a lack of adoption in the general population. The appointed causes for this irrational anxiety were the lack of education and the lack of experience. The authors recommended the study of these matters, as they lead the way to the individual's financial well-being, and do not depend on the knowledge of financial markets and investment strategies, or behavior and personality, as problems may arise from this lack of knowledge regarding biases and decision-making processes.

Financial innovation in markets appears to have its perks and its downsides, and it is becoming increasingly more complicated and sophisticated, with a wide panoply of products, services, and providers. The fact that customers don't understand basic financial concepts, which are crucial to the decision-making process and financial well-being, is a worldwide concern, that has been around for decades, affecting individuals of all gender, age, race, education and wealth. As such, the concept of personal finance was introduced as a mix of economics, finance and management, pursuing to provide individuals with basic foundations of money allocation, while giving them the tools to disregard, or disprove, negative influences, and concentrate on positive ones, whether they are internal or external. Schuchardt et al. (2007) affirmed that personal finance covers financial statements, debt, insurance, risk and return, taxes and retirement, among others. However, it must also help clarify values and goals, distinguish between wants and needs, and recognize the limits of financial resources – as such, it goes beyond simple operations and concepts, and nowadays, several tools are available for individual needs and preferences; besides, despite the common misuse of financial education as "financial literacy", Coben (2003) defined it not just as the theoretical knowledge, but also the practical knowledge and the decision-making skills. Hira (2009) stated that a considerable amount of the literature in finance is mostly focused on the financial markets and corporate finance, such that personal finance is overshadowed by the big market players and regulators. However, the author argued that customers are the primary players responsible for the correct operation of the financial markets.

IV. Data & Methodology

The data used to conduct the analysis presented on this thesis was collected via survey. The survey is original, adapted to younger demographics, and based on the works of Kahneman (2016) and Pompian (2006). The survey contained a total of 30 questions, divided into four distinct subsections. The survey was distributed on a subset of exclusively Portuguese respondents, from all regions, qualifications and areas, for a period of 30 days, having the sole restriction of age, due to the little significance of answers of individuals below the age of 15. In the original database, an extra demographic control was included, the Portuguese region of living, but it was ultimately excluded due to the lack of significant data in all categories but one, the South. The survey (see Appendix) was distributed via Google Forms, allowing a wider online dispersion and further response variability. The softwares used to conduct the analysis were MS Excel, for data viewing and plotting, and Stata, for covariances and regressions. The total number of responses was 464 – however, due to missing answers on variables and controls, the final number of valid responses decreased to 427. Table 1 presents the demographics:

	Frequency	Percentage	Cumulative
Gender			
Female	251	58,78%	58,78%
Male	176	41,22%	100,00%
Age			
15 - 29	227	53,16%	53,16%
30 - 44	65	15,22%	68,38%
45 - 59	100	23,42%	91,80%
60 +	35	8,20%	100,00%
Profession			
Student	206	48,24%	48,24%
Worker	187	43,79%	92,04%
Inactive	34	7,96%	100,00%
Education			
Highschool or Below	140	32,79%	32,79%
Bachelor's Degree	129	30,21%	63,00%
Master's Degree or Above	158	37,00%	100,00%
Area			
Commerce, Industry & Tourism	69	16,16%	16,16%
Education, Services & Administration	151	35,36%	51,52%
Sciences & Engineering	81	18,97%	70,49%
Finance & Economics	93	21,78%	92,27%
Others	33	7,73%	100,00%
Total	427	100,00%	

Table 1 – Demographics, by total number, by percentage and by cumulative percentage.

The survey was designed picturing a robo-advisory platform, and the examples given in the survey are those of an algorithm already being applied on current robo-advisors, or of easy implementation. However, the term “robo-advisor” was not included throughout the survey as it was a possibility that respondents could subconsciously create unrealistic ideas and expectations of the platform and its components, which could ultimately translate into biased answers. Furthermore, the questionnaire was divided in four distinct sections, the first three regarding Period I, before the introduction of the Behavioral Finance tool, and Period II, after the introduction of the Behavioral Finance tool.

Section I of the survey intended to collect data regarding the presence of behavioral biases on the respondents. Five distinct biases were selected for this study: Overconfidence Bias, a crucial irrationality that leads to recklessness and unrealistic expectations when investing; Status Quo Bias, an emotional response, highly correlated with Loss Aversion, that drives the prolonged hold of familiar assets and improper portfolio diversification; Regret Aversion Bias, a complement of the aforementioned bias, where the investor fears regretting a decision, and is thus perplexed; Confirmation Bias, a mental veil over undesired information that could jeopardize an investment or a series of investments; and Cognitive Dissonance Bias, a powerful driver for herding behavior and, complementing the previous bias, rationalization of poor decisions. Following the work of Pompian (2006), the questions proposed for each bias, and respective coding, are presented on Table 2 (see Appendix).

Section II of the survey presented a simplified explanation of fintech, with current and easily identifiable examples of the technology. Subsequently, the past usage of a fintech, and its category, was inquired, followed by questions of opinion. Five key elements were established, namely Utility, Necessity, Innovativeness, Attractiveness and Trustworthiness. Following the Technology Acceptance Model, the Perceived Usefulness (PU) was tested by the variable “util”, whereas the Perceived Ease-Of-Use (PEOU) was tested by the variable “atract”. In addition, three variables are tested: “neces”, in order to measure the level of perceived necessity of such technology; “innov”, in order to quantify the perceived level of innovation of fintechs as a service; and “trust”, in order to evaluate the level of trust of the customers in these technologies. Consequently, the past usage of fintechs was tested not only against behavioral biases, but also against pre-conceived opinions of the technologies. Finally, the section was concluded when asked the possibility of future usage and future recommendation of fintechs.

Section III deepened the focus into Savings & Investments fintechs, analyzed independently, beginning with an explanation, and each followed by questions on its previous knowledge of existence, its previous usage, and accordingly, its future usage and future recommendation to friends, family and/or coworkers.

Section IV introduced the concept of Behavioral Finance in a simplified manner, explaining the founding sciences and possible applications. Moreover, figurative examples of its possible usage in each type of fintech were present to aid the respondents in the creation of a more concrete image of what the field could entail, the Behavioral Finance tools. Hence, previously described as Period II, for Savings and Investments fintechs, an example was proposed, and the opinion and potential usage was tested. Finally, for each of the subcategories, and following the work of Wichman et al. (2006), a question of expected use of the technology was proposed, in order to test the likelihood of the adoption – this question aimed to project the possible usage of the platform beyond the subjective views and opinions of each individual.

An initial analysis was conducted, in order to investigate relevant proportions and correlations. In order to test the significance of the general biases and the general opinions, two variables were created – $bias$ and $opin$ – as the arithmetic average of its five constituents. As such, correlations were tested between each bias, and between each opinion. In total, the study included 37 variables, and their description is in Table 3 (see Appendix).

Afterwards, following the methodology of Xiao et al. (2019) and Woodyard et al. (2018), a series of regressions were computed. Here, the logit model was used due to the binary outcome of the dependent variable, in addition to following the agreement in the reviewed literature. Therefore, the initial regressions were computed, in order to test the effects of each bias on the past usage of fintechs, plus a regression with the average bias. Furthermore, the same regressions were run for each opinion, and for the average opinion. Lastly, a regression was computed to analyze the joint effect of biases and opinions on the past usage of fintechs, controlling for demographics.

$$puse = \alpha + \beta \, bias_i + \varepsilon$$
$$puse = \alpha + \beta \, opin_i + \varepsilon$$

$$puse = \alpha + \beta \, bias + \varepsilon$$
$$puse = \alpha + \beta \, opin + \varepsilon$$
$$puse = \alpha + \beta_1 \, bias + \beta_2 \, opin + \varepsilon$$

Next, the future usage of fintechs was regressed against the past usage of fintechs, followed by a regression of future recommendation upon the future willingness to use.

Subsequently, the focus was shifted to the Savings & Investment fintechs, each one explored individually. Once again, the regressions analyzed the relationship between the future engagement of such platform and its previous usage.

$$sav\_fuse = \alpha + \beta\, sav\_puse + \varepsilon$$
$$inv\_fuse = \alpha + \beta\, inv\_puse + \varepsilon$$

On the second period, after the introduction of the Behavioral Finance tool, the respondent's opinion was studied on three levels: utility, necessity and trustworthiness. Here, two of the previously used measures were not considered: attractiveness is not quantifiable as it is merely speculative, and innovativeness is perceived as a given, since the technology is new. Once again, in order to test the significance of the generalized opinion, a new variable is created, as an arithmetic average of its three constituents. Hence, the relationship between the future usage of the platform and the new opinions based on the insertion/addition of the Behavioral Finance tool was tested, controlling for demographics.

$$bf_{sav_{fuse}} = \alpha + \beta\, bf_{sav_{opin}} + \varepsilon$$
$$bf_{inv_{fuse}} = \alpha + \beta\, bf_{inv_{opin}} + \varepsilon$$

$$bf_{x_{frec}} = \alpha + \beta\, bf_{x_{fuse}} + \varepsilon$$
$$bf_{x_{frec}} = \alpha + \beta\, bf_{x_{opin}} + \varepsilon$$
$$bf_{x_{frec}} = \alpha + \beta_1\, bf_{x_{fuse}} + \beta_2\, bf_{x_{opin}} + \varepsilon$$

Lastly, in order to test the general market perception, the perceived usage was applied as a measure of optimism, meaning as the proxy to general market acceptance of the new technology. As such, for Savings and Investments fintechs:

$$perc_x = \alpha + \beta\, bf_{x_{opin}} + \varepsilon$$
$$perc_x = \alpha + \beta\, bf_{x_{fuse}} + \varepsilon$$
$$perc_x = \alpha + \beta\, bf_{x_{frec}} + \varepsilon$$
$$perc\_x = \alpha + \beta_1\, bf_{x_{opin}} + \beta_2\, bf_{x_{fuse}} + \beta_3 bf_{x_{frec}} + \varepsilon$$

V. Findings & Discussion

1. Part I: Biases vs. Opinions

Section I of the survey aimed to test the presence of behavioral biases. The first bias, the Status Quo Bias, appeared to affect a staggering majority of the population surveyed, namely 82.20% of all respondents. As previously explained, this bias affects an individual's choices, in the sense that the individual is lead to choose the path of least resistance: in this case, when faced with two choices, between a certain gain of €5.000 versus an 80% probability of a €7.000 gain, biased individuals answered they would prefer the first option, even if the second option would give them a higher expected return, of €5.600. In addition, the emotional component of the bias is linked to loss aversion, furthering the need to choose the riskless option, as opposed to the rational one, with the highest expected return. While it appeared to be more proportionally more predominant in women – biased responses in women account for 86.45% of female answers, while biased responses in men account for 76.14% of all male answer –, the results are homogeneous throughout all other demographic subsets.

The second bias, Overconfidence Bias, refers to the increased, and irrational, sense of conviction and belief in one's intuition, skills and abilities. Here, once again there was a significant amount of biased responses. When asked how much control they have over their investment, biased individuals responded "some to a significant amount of control", while unbiased individuals acknowledged they have little if any control over them. The responses showed, once again, that this bias was not only quite common, affecting 76.35% of all respondents, but also that they affected women and men differently. In the case of overconfidence, like previous research shows, this bias tends to affect more the males than the females. Here, over 80% of men appeared to be biased, in comparison to the 73% of biased women. Additionally, the proportion of biased responses was lower for working respondents and for respondents between the ages of 30 – 44, while higher, at 90.32%, for respondents in the Finance & Economics area.

The third bias, Regret Aversion Bias, refers to the basic instinct to avoid taking on decisive actions in situations of stress, causing delayed losses and sub-optimal results; here, the "hanging on" to past mistakes and expectations acts as a drawback for future investment opportunities. For the presented question, the unbiased answer would be the one that would state that investing in Company A or Company B would be indifferent, as the expected risk and the expected return would be the same: the fact that a company is previously known or established should have no influence on the choice, as the expected outcome would be the same. Answers from the survey suggested that 200 of the 427 respondents present this bias: more specifically, over 75% of biased responses, stating that, as investors, respondents would feel safer by following the strategy of an institutional investor, causing a herding behavior. Women appeared to be more prone to present this bias by 7 percentage points, which once again, follows the logic of status quo and loss aversion, in addition to a higher risk tolerance and overconfidence by men. In addition, the presence of the bias was less pronounced in the Finance & Economics area, presenting only 35% of biased responses, whereas it increased by the respondents age, leading up to 60% of biased answers in the 60+ age category.

The fourth bias, Confirmation Bias, is quite self-explanatory: an individual seeks to get confirmation on his rationale and his decisions. In this case, after investing in a company that announces both a failure in an existing product and a new product, biased individuals will seek the confirmation that their investment was good by noticing first the new product launch, whereas unbiased individuals will take notice of the existing problems and analyze if the investment in such company is worth continuing. Survey responses suggest that 49% of individuals presented the bias, it being more present in women by 7 percentage points. Throughout controls, responses were homogeneous except for the 60+ category, where biased answers accounted for only 37% of all responses.

Finally, the fifth bias, the Cognitive Dissonance Bias, refers to the impending conflict in the individual's mind when presented with new information after the decision is made. In this case, after buying a computer, respondents are asked what they would do: unbiased individuals would further research the features of another computer and ponder their decision, while biased individuals would relieve the tension in their minds by giving "mental excuses" to their poor judgement – here, the presented scenarios would be to consider doing the research, but ultimately deciding not to follow through, or to think "if I had to do it again, I might buy the other computer". A total of 35% of respondents presented this bias, it being similarly distributed between both genders; however, the 30 – 44 respondents presented a 50% recurrence of biased answers, and individuals with high education levels present over 40% of biased answers.

The correlations between biases, presented in Table 4 (see Appendix), show that most correlations were deemed not statistically significant. However, a weak positive correlation between the Status Quo Bias and the Regret Aversion bias, significant at a 1% significance level, was discovered – this relationship indicated that the regret aversion one may experience, and possible inaction, was correlated to one's need for the maintenance of the status quo, or vice-versa. Moreover, at a 5% significance level, a weak negative correlation was found between the Cognitive Dissonance Bias and the Regret Aversion bias, pointing that regret aversion would cause the biased individual to abstain from making a decision out of regret, whereas the cognitive dissonance would force the conflict to be resolved by taking action.

As aforementioned in the Technology Acceptance Model, the utility of the platforms was studied across the respondents. Hence, in a scale from 1 to 5, the average perceived utility of fintechs was 3.76, indicating a good principle for the development of such platforms. Male respondents appointed a higher utility in fintechs by *circa* 0.3, while the youngest generation, between 15 and 29 years old, and similarly the students and the individuals with higher education levels, appointed a higher classification, of approximately 4.00. The highest average utility score was found in the Finance & Economics area respondents, of 4.24, pointing to the fact that the individuals in the fintech adjacent areas find a greater value in it. Necessity presents a lower average, of 3.43, with a similar tendency throughout the controls as Utility. Higher scores were given by younger and more educated individuals, and the highest score was found, once again, within respondents of Finance & Economics. Innovativeness presented the highest average among the five variables, of 3.82. It showed a clear decreasing trend in age, and a clear increasing trend in education. Once again, individuals in the financial area were the ones with the most positive review of the characteristic, and no significant difference was found between genders. Attractiveness presented similar results to those of Necessity, with an average of 3.56. A slight increase, of *circa* 0.1, was verified between male and female respondents, while a decreasing relationship was observed between the variable and the individual's age, reaching a low of 3.00 at the eldest age group; in addition, the variable presented a positive correlation with the respondent's education level, and high scores for individuals in the Finance & Economics area, as well as in the Sciences & Engineering area. Lastly, Trustworthiness was the lowest scored of the variables, with an average of 3.18 – the formerly observed tendencies were similarly verified, decreasing with age and increasing with education, with the highest value in the Finance & Economics subcategory, of 3.40. Table 5 (see Appendix) presents the correlation matrix between the analyzed opinions: all correlations were deemed statistically significant, and all were strong positive correlations – however, the strongest correlations were those of Attractiveness and Innovativeness, explaining the rationale behind the creation of such fintechs, where innovation and creativity drive the customer experience and the desirability of the platforms, and Attractiveness and Utility, describing the customer's point of view, wherein a useful platform is also perceived as more attractive. Furthermore, the correlations between

Trustworthiness and all other opinion variables were the weakest, emphasizing the previous conclusions, where trust is still the least acknowledged characteristic of fintechs.

Subsequently, respondents were asked about their past usage of a fintech. The majority of respondents had not used a fintech in the past, accounting for approximately 60% of surveyed individuals. The number of individuals who had used a fintech in the past was 172: 162 respondents had used a Transfers & Payments platform; 35 respondents had used a Savings & Investments Platform; 11 respondents had used an Insurance fintech; and 2 respondents had previously used a Borrowings fintech. Past users were equally distributed among male and female respondents, as well as among individuals of all areas; however, usage was more common among inactive population, meaning unemployed and retired respondents, than students or workers, as well as among individuals with Master's or above educational levels, while lower among individuals with a Bachelor's degree. Age-wise, the least acceptant category was the 60+, with 25% of respondents having used a fintech; next, the 40 – 59 segment, with 34% of individuals previously adopted the technology; the youngest generation was the second most receptive to these platforms, with over 40% adoption of respondents; and the biggest users of the technology were those between the ages of 30 and 44 years old, with approximately 57% of respondents having used a fintech in the past.

Based on the past usage of fintechs, a t-test analysis was conducted on the means of each bias, and average bias, and the means of each opinion, and average opinion – Table 6 (see Appendix) presents the p-values. Results showed that, in biases, for users and non-users, there is no statistically significant difference between the means – as such, it is argued that the presence of the biases does not impact the decision of fintech adoption, meaning that none of the biases have a significant impact in the choice to use or not a new technology. However, the Cognitive Dissonance bias presented a p-value of 0.0761, deeming it the most impactful, yet only at a 10% significance level. Figure 1 (see Appendix) presents the difference in means.

Furthermore, tests between opinion show opposite results: for each opinion, the mean for users and non-users was deemed statistically significant, implying that there is a clear difference of opinions among those who have used a fintech and those who have not. On average, opinions of past fintech users were approximately 10% higher than those of non-users. The highest opinions related to the Utility and the Innovativeness aspects of the platforms, whereas the lowest scoring opinion was Trustworthiness, indicating that, on average, the usage of fintechs provides a good customer experience, such that the customer's opinion increased. Figure 2 (see Appendix) presents the described results.

In order to verify these results, a regression was computed after the transformation of the variables, *bias* and *opin*. These averages were tested as predictors of attitude for past usage of fintech. The results are shown in Table 7, wherein it is observed that, once again, the average bias was deemed not statistically significant, whereas the average opinion was deemed statistically significant, conducting a positive effect on the logistic probability of past usage of fintechs.

Past Usage of Fintechs

Bias	-0.569 (0.479)		-0.797 (0.493)
Opin		**0.500***** (0.112)	**0.517***** (0.113)

Table 7 – Results of logistic regression, testing the effects of Average Bias and Average Opinion on the Past Usage of Fintechs. Standard Deviation in parentheses. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Furthermore, the regression was tested for demographic controls: by age, three of the four segments showed similar results, except for the individuals between 30 and 44 years old, where no statistically significant results were found; and by profession, all categories showed statistically significant positive results for opinions only. Individuals with the lowest education level showed no statistically significant results, whereas the ones with a bachelor's degree are positively influenced by opinions – moreover, individuals with the highest education level are positively influenced by opinions, but also, at a 5% significance level, are negatively influenced by mental biases. By area, Education & Services and Commerce & Tourism presented positive statistically significant coefficients for opinions, whereas other areas produced no statistically significant results. Finally, despite the fact that women tended to be, on average, more affected by cognitive biases, these did not influence the decision of fintech adoption, opinion was the driver – however, men were influenced by both: biases were more statistically significant, and more impactful than opinions, as the presence of their presence negatively influenced the choice of adoption of a fintech, as opposed to the lighter positive influence of opinions. The possibility of future usage was tested against its past usage, producing a positive statistically significant coefficient, meaning that an individual that has previously been a user of the technology is more likely to use it again in the future. Similar results were found regarding future recommendation: a similar statistically significant coefficient implying an increased likelihood of endorsement of the technology given the willingness to use it in the future – the results are presented on Table 8 (see Appendix).

Savings fintechs were previously used by approximately 15% of respondents, and their willingness to start using, or reuse, this technology was positively influenced by the past usage. Similar results were found throughout the controls, indicating that the previous adoption of the fintech had a statistically significant positive impact on the possible future adoption – here, the Finance & Economics area was the least impactful, with a lower positive coefficient, and significant only at a 5% significance level. Investments fintechs showed analogous results, evidencing that the customer's attitude and mentality influence both fintech subcategories in a similar manner.

Subsequently, the Behavioral Finance tool was introduced: as previously explained, the tool was merely exemplified in a clear and concise manner based on the available products in other markets. For Savings fintechs, the example given was the introduction of smart savings, by introducing an algorithm that could track the saving and spending habits of the customer and hence give a tailored advisory into the optimized saving periods and amounts. For Investments fintechs, the example given was of an investment preference algorithm, not just goal and risk based, but also on personal likes and dislikes, towards assets, companies or industries. Once again, opinions were evaluated on three parameters, Utility, Necessity and Trustworthiness, and further transformed into an arithmetic average.

After the introduction of Behavioral Finance, the opinions of Savings and Investments fintechs were collected and analyzed. Utility was the highest scoring measure, at 3.94, followed by necessity, with a 3.76 value, and trust, the lowest scoring opinion, was a feeble 3.22. Investments fintechs showed lower averages on all measures. Once again, a t-test was used to test the difference in means of savings opinions and investments opinions. Utility and Necessity show a statistically significant difference in the average opinions between subsectors, whereas no statistical difference was found in the average Trustworthiness of the categories – Table 9 (see Appendix) presents the results. Subsequently, regressions were computed to test the future usage based on the opinion. Savings were positively influenced by all three measures, Necessity being the least significant. Using the average opinion, the results stand: the opinion is a statistically significant driver for the future adoption of the fintech. Controlling for demographics, all but one category demonstrated the same results – in Other areas, the coefficient was not significant. Furthermore, future recommendation was regressed against opinion and future usage, both measures being deemed statistically significant, usage having a greater impact on the likelihood of endorsement than one's opinion of the technology. Table 10 (see Appendix) presents the results. Investments regressions showed that, separately, all opinions are deemed to have a positive, and statistically significant, impact on the future adoption of such a fintech; however, when jointly regressed, necessity was deemed not statistically significant. Averaged, opinion had a statistically significant positive impact on the likelihood of future engagement of the technology – the analysis by controls showed a similar landscape throughout, with the lowest coefficient for Students, and the highest coefficient for individuals aged between 30 and 44 years old. Moreover, future endorsement of the fintech was regressed against opinion and future usage, deeming both variables positive and statistically significant, and as previously observed, the adoption of the technology has a greater impact on the likelihood of recommendation – Table 11 (see Appendix) presents the results for future usage and endorsement regressions. Table 12 (see Appendix) presents the difference in means, via t-test, of future use and recommendation, based on the introduction of the tool, where no significant results were found.

Finally, in order to test the generalized market perception of the technology, the perceived likelihood of usage was surveyed among respondents. Here, the likelihood of usage by other users was regressed against one's opinion, one's possibility of future usage and one's possibility of future recommendation. For Savings fintechs, the average perceived usage was 3.69. When regressed separately, all three variables are deemed statistically significant, and having a positive impact on the perception of the technology; however, when combined, only future recommendation was deemed statistically significant, at a 5% significance level – results are shown in Table 13 (see Appendix). Gender and age controls showed no significant results, whereas profession presented different findings, at a 5% significance level: for students, opinions were the only significant driver, but workers follow the generalized trend of recommendation.

For Investments platforms, the findings were similar, for an average perceived usage of 3.60: singular regressions showed positive, and statistically significant results, for the three variables, while the joint regression deemed only future endorsement of the technology to have a significant positive impact in the likelihood of higher perceived generalized adoption – results are shown in Table 14 (see Appendix). The finding stood true for students and workers, as well as individuals with bachelor's degree or lower levels of education – however, at a 5% significance level, for individuals aged between 15 and 44 years old, endorsement was the driver, whereas for individuals between the ages of 45 and 59, own opinion is the driver. Gender-wise, females showed consistent results with those of the general population, though males presented no statistically significant results.

VI. Conclusion

"Financial markets are a real game. They are the arena of fear and greed."

(Wood, A. (1995) in "Behavioral Finance and Decision Theory in Investment Management")

The adoption of fintechs has become a topic of extensive research in the past years, in order to understand the drivers, both supply and demand. Several methodologies have been proposed and used by a number of authors, who have found that, on average, the youngest segments of the population tend to present more potential for future growth of the industry – Carlin et al. (2017) concluded that the adoption of fintechs was the lowest for Baby Boomers, followed by Generation Xers and finally Millennials. In addition, the works of Belanche et al. (2019), Fulk et al. (2018) and Woodyard et al. (2018) similarly studied the adoption of fintechs across various demographics, such as culture, income and behavior. Hence, the purpose of the thesis was to study the presence of biases and pre-conceived opinions in the population, and whether these have an impact on the adoption of fintechs, namely in the Savings and Investments segment – and furthermore, whether the introduction of a Behavioral Finance-based algorithm would incentivize the adoption of the technology.

The Status Quo bias and the Overconfidence bias were found to be the most common biases, affecting the majority of respondents of the survey, namely over 70%. The first bias presented itself as the need for prolongation of the current situation at the cost of possible higher returns, and it was found to be more present in women, and in individuals with higher educational levels, while presenting a negative relationship with age. The second bias, on the other hand, entailed the irrational excessive conviction in the individual's capabilities and intuition, and it was discovered to be more common among men. Furthermore, by age, overconfidence affected respondents in a convex trend, affecting young and old respondents more than middle aged respondents, in addition to being highly pronounced in individuals of the Finance & Economics area. Barber and Odean (2001) state that due to unfounded intuition, bad timing and underdiversification, overconfidence had a sizeable impact on portfolios worldwide, more pronounced in male investors. The Regret Aversion Bias and the Confirmation Bias were found on approximately half of the surveyed population, affecting more females, and presenting, once again, a convex relationship with age. Regret Aversion was described as the irrational fear of the decision-making process that lead the individual unable to choose in the face of uncertainty, affecting more individuals of lower education levels and being the least pronounced in the respondents of Finance & Economics. The Confirmation bias was described as the search for information that supports the individual's choices and beliefs, being more present in those of higher education levels, and in the Finance & Economics area. Finally, Cognitive Dissonance was the least encountered bias in the sample, defined as the mental discomfort caused by contradictory beliefs and actions, affecting *circa* 35% of respondents – here, the individuals between the ages of 30 and 44 were the most affected, in addition to those of higher education levels. It was found that, despite present throughout the population, on average, biases did not impact the decision of fintech adoption – except for the male and the highest educated demographics, where the presence of biases had a positive and statistically significant influence in the likelihood of fintech adoption.

Additionally, five opinions were tested: Utility, Necessity, Innovativeness, Attractiveness and Trustworthiness. Separately, all opinions were deemed statistically significant in the choice of usage; however, when jointly tested, Utility and Innovativeness were the most impactful, and statistically significant drivers on the adoption of the technology, whereas necessity was not perceived as a requirement for the use of fintechs. As previous research showed, trust was the lowest scoring parameter, evidencing the conservative mentality and the skepticism in full computer-based platforms. Moreover, the opinions of past users of fintechs were higher, and statistically different, from the opinions of non-users. Past users of the technology also showed a significant willingness to reuse the technology, as well as recommend it to others.

Subsequently, imagining the scenario of the Behavioral Finance tool being inserted into a robo-advisory type of platform, the opinions about Utility, Necessity and Trustworthiness were collected, along with the willingness to use and to recommend the technology. The average utility slightly increased, whereas the other two measures showed similar averages, meaning that the introduction of such an algorithm was recognized as useful but would ultimately not be sufficient to drive the adoption of the technology. Finally, in order to obtain an unbiased and personal view of this augmentation, the perceived likelihood of usage was studied for both Savings and Investments subcategories, where it was found that one's future recommendation of the technology was the driver for higher likelihood of general adoption.

In conclusion, the answers to the proposed questions in the beginning of this thesis:

i. The research demonstrated the presence of both behavioral biases, and strong pre-conceived opinions regarding fintechs, in the surveyed sample. Overconfidence and Cognitive Dissonance were more established in men, whereas Regret

Aversion, Status Quo and Confirmation were more established in women. Past users of fintechs have a significantly higher opinion of the technology, and on average, male respondents displayed greater opinions than female respondents.

ii. However, in general, only opinions are statistically significant, and positive, drivers on the adoption of fintechs, with the exception of the male and the highest educated respondents, where both biases and opinions were significant, biases having a negative impact on the decision.

iii. Despite the perceived increase in utility, the addition of the behavioral finance tool was not statistically significant to influence the customer's adoption choice.

Thus, it is possible to argue that robo-advisors present an advantage and a solid opportunity for customers, as the initial capital requirements are, on average lower, and due to the reduced fees and transaction costs, for similar investment assets, they could theoretically outperform human advisors – furthermore, the insertion of a tool that could potentially increase the financial knowledge of users would be beneficial. Nowadays, the foundations have been built do develop such technologies, only market adoption is necessary from both institutions and customers.

VI.A. Limitations

The thesis presented limitations in the demographics, as the sample was not statistically representative of the Portuguese population – a large majority of the surveyed were from the southern and more provincial areas, which could influence the results, as more cosmopolite regions tend to be more tech-savvy and open-minded. In addition, a key demographic segment, of individuals aged between 30 and 44 years old, were underrepresented in the final dataset, and as a key group of potential users of the technology, it would be interesting to take a closer look. Moreover, limitations also apply to the nature of the survey, as it was entirely dependent on the respondents, entailing human error, translated into inconsistencies in the answers that could lead to distortions in the analysis. Thus, further research on this topic could be done with a broader and more inclusive sample of the Portuguese population. Also, it would be of interest to study other drivers of the adoption of the technology, or other areas beyond Savings and Investments. Moreover, following the thought-provoking result of biases influencing the adoption decision of men, and not women, it would be quite interesting to understand the depth of the biases themselves, and the depth of influence over the decision to use the technology.

VII. References

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VIII. Appendix

Table 2 – Surveyed questions, responses and coding for presence of bias.

Status Quo Bias Which of the following would you choose?	
An 80% probability of winning €7.000, with a 20% probability of winning €0.	0
A 100% probability of winning €5.000.	1
Overconfidence Bias How much control do you believe you have in picking good investments?	
Absolutely no control.	0
Little, if any, control.	
Some control.	1
A significant amount of control.	
Regret Aversion Bias Imagine you decided to invest €1.000 on the stock market and you've narrowed down your choice between two companies: Company A and Company B. They have equal risk and payoff. Company A is a big and well-known company, while Company B has performed well but is still hasn't caught public attention. In which of the companies would you most likely invest?	
I would feel indifferent between investing in Company A or Company B because they give the same expected return for the same risk.	0
I will most likely invest in Company A because I feel safe following many institutional investors. If Company A declines in value, I won't be the only one caught by surprise, and with so many professionals investing here, I could hardly blame myself for poor judgement.	1
I will most likely invest in Company A because if I invested in Company B and it failed, I would feel foolish. Few well-known investors invest here, and I would regret going against their informed consensus only to discover that I was wrong.	
Confirmation Bias Suppose you invested in a company after much careful research. Now, imagine they have a press release stating a problem with its main product. The second paragraph, however, describes a new product they might release later this year. What are you more likely to do?	
I will typically notice the problem with the main product and do some research on it.	0
I will typically notice the new product and do some research on it.	1
Cognitive Dissonance Bias Imagine you recently bought a new computer, XPTO, and you're very happy with it. One day, your friend tells you "did you know the competitor brand, COOL, was giving out free Anti-Virus protection when you bought your computer?". You're initially confused: you didn't know, you would have liked to have it, so you may wonder, was getting this a bad decision? You begin to second-guess yourself. Most likely, what will you do next?	
You go online and see the several specs, wondering if you should've bought computer COOL.	0
You keep playing on your computer and think "If I had to do it again, I may have bought computer COOL. Even though I don't have the anti-virus, I'm still happy with my purchase".	1
You think about doing some additional research on computer COOL, but you decide not to. The computer was a big, important purchase, and you've been so happy with it that discovering an error in your purchase leaves you feeling uneasy, so it's better to just put this to rest and enjoy the computer.	

Table 3 – Variables and Description.

Variables	Meaning
bias_sq	Status Quo Bias 0 - “Not Present”; 1 - “Present”
bias_ovc	Overconfidence Bias 0 - “Not Present”; 1 - “Present”
bias_rav	Regret Aversion Bias 0 - “Not Present”; 1 - “Present”
bias_conf	Confirmation Bias 0 - “Not Present”; 1 - “Present”
bias_cgd	Cognitive Dissonance Bias 0 - “Not Present”; 1 - “Present”
bias	Average Bias (continuous variable)
util	Fintechs are considered “Useful” 1 - "Completely Disagree"; 2 - "Disagree"; 3 - "Neither Agree Nor Disagree"; 4 - "Agree"; 5 - "Completely Agree"
neces	Fintechs are considered “Necessary” 1 - "Completely Disagree"; 2 - "Disagree"; 3 - "Neither Agree Nor Disagree"; 4 - "Agree"; 5 - "Completely Agree"
innov	Fintechs are considered “Innovative” 1 - "Completely Disagree"; 2 - "Disagree"; 3 - "Neither Agree Nor Disagree"; 4 - "Agree"; 5 - "Completely Agree"
atract	Fintechs are considered “Attractive” 1 - "Completely Disagree"; 2 - "Disagree"; 3 - "Neither Agree Nor Disagree"; 4 - "Agree"; 5 - "Completely Agree"
trust	Fintechs are considered “Trustworthy” 1 - "Completely Disagree"; 2 - "Disagree"; 3 - "Neither Agree Nor Disagree"; 4 - "Agree"; 5 - "Completely Agree"
opin	Average Opinion (continuous variable)
puse	Past Usage of Fintechs 0 - “No”; 1 - “Yes”
fuse	Future Usage of Fintechs 0 - “No”; 1 - “Maybe”; 2 - “Yes”
frec	Future Recommendation of Fintechs 0 - “No”; 1 - “Maybe”; 2 - “Yes”
sav_ex	Knowledge of Existence of Savings Fintechs 0 - “No”; 1 - “Yes”
sav_puse	Past Usage of Savings Fintechs 0 - “No”; 1 - “Yes”
sav_fuse	Future Usage of Savings Fintechs 0 - “No”; 1 - “Maybe”; 2 - “Yes”
sav_frec	Future Recommendation of Savings Fintechs 0 - “No”; 1 - “Maybe”; 2 - “Yes”
inv_ex	Knowledge of Existence of Investment Fintechs 0 - “No”; 1 - “Yes”
inv_puse	Past Usage of Investment Fintechs 0 - “No”; 1 - “Yes”
inv_fuse	Future Usage of Investment Fintechs 0 - “No”; 1 - “Maybe”; 2 - “Yes”
inv_frec	Future Recommendation of Investment Fintechs 0 - “No”; 1 - “Maybe”; 2 - “Yes”
bf_sav_neces	After Behavioral Finance Tool, Savings Fintechs are considered “Necessary” 1 - “Not At All”; 2 - “Not Really”; 3 - “Indifferent”; 4 - “A Little”; 5 - “Very Much”
bf_sav_util	After Behavioral Finance Tool, Savings Fintechs are considered “Useful” 1 - “Not At All”; 2 - “Not Really”; 3 - “Indifferent”; 4 - “A Little”; 5 - “Very Much”
bf_sav_trust	After Behavioral Finance Tool, Savings Fintechs are considered “Trustworthy” 1 - “Not At All”; 2 - “Not Really”; 3 - “Indifferent”; 4 - “A Little”; 5 - “Very Much”
bf_sav_opin	After Behavioral Finance, Average Savings Fintech Opinion (continuous variable)
bf_sav_fuse	After Behavioral Finance Tool, Future Usage of Savings Fintechs 0 - “No”; 1 - “Maybe”; 2 - “Yes”
bf_sav_frec	After Behavioral Finance Tool, Future Recommendation of Savings Fintechs 0 - “No”; 1 - “Maybe”; 2 - “Yes”

Table 3 – Variables and Description (continued).

Variables	Meaning
bf_inv_neces	After Behavioral Finance Tool, Investment Fintechs are considered "Necessary" 1 - "Not At All"; 2 - "Not Really"; 3 - "Indifferent"; 4 - "A Little"; 5 - "Very Much"
bf_inv_util	After Behavioral Finance Tool, Investment Fintechs are considered "Useful" 1 - "Not At All"; 2 - "Not Really"; 3 - "Indifferent"; 4 - "A Little"; 5 - "Very Much"
bf_inv_trust	After Behavioral Finance Tool, Investment Fintechs are considered "Trustworthy" 1 - "Not At All"; 2 - "Not Really"; 3 - "Indifferent"; 4 - "A Little"; 5 - "Very Much"
bf_inv_opin	After Behavioral Finance, Average Investments Fintech Opinion (continuous variable)
bf_inv_fuse	After Behavioral Finance Tool, Future Usage of Investment Fintechs 0 - "No"; 1 - "Maybe"; 2 - "Yes"
bf_inv_frec	After Behavioral Finance Tool, Future Recommendation of Investment Fintechs 0 - "No"; 1 - "Maybe"; 2 - "Yes"
perc_sav	After Behavioral Finance Tool, Generalized Perception of Possible Usage of Savings Fintechs 1 - "Very Unlikely"; 2 - "Unlikely"; 3 - "Indifferent"; 4 - "Likely"; 5 - "Very Likely"
perc_inv	After Behavioral Finance Tool, Generalized Perception of Possible Usage of Investment Fintechs 1 - "Very Unlikely"; 2 - "Unlikely"; 3 - "Indifferent"; 4 - "Likely"; 5 - "Very Likely"

Table 4 – Correlation Matrix, measuring the correlations between biases: Status Quo, Overconfidence, Regret Aversion, Confirmation and Cognitive Dissonance. P-Values in parentheses. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Correlation Matrix

	bias_sq	*bias_ovc*	*bias_rav*	*bias_conf*	*bias_cgd*
bias_sq	1,0000				
bias_ovc	0,0003 (0,9945)	1,0000			
bias_rav	**0,1300**** (0,0071)	0,0034 (0,9443)	1,0000		
bias_conf	0,0781 (0,1071)	0,0184 (0,7041)	0,0623 (0,1986)	1,0000	
bias_cgd	-0,0864 (0,0744)	0,0137 (0,7782)	**-0,1044*** (0,0311)	-0,061 (0,2083)	1,0000

Table 5 – Correlation Matrix, measuring the correlations between opinions: Utility, Necessity, Innovativeness, Attractiveness and Trustworthiness. P-Values in parentheses. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Correlation Matrix

	Utility	*Necessity*	*Innovativeness*	*Attractiveness*	*Trustworthiness*
Utility	1,0000				
Necessity	**0,7910***** (0.0000)	1,0000			
Innovativeness	**0,8054***** (0.0000)	**0,7261***** (0.0000)	1,0000		
Attractiveness	**0,8319***** (0.0000)	**0,7660***** (0.0000)	**0,8302***** (0.0000)	1,0000	
Trustworthiness	**0,6960***** (0.0000)	**0,7127***** (0.0000)	**0,6804***** (0.0000)	**0,7173***** (0.0000)	1,0000

Table 6 – T-Test analysis, for individual and average Biases, and individual and average Opinions, for the difference in means for past users and non-users of fintechs. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Biases				Opinions			
Status Quo Bias	Past Usage = 0	Average	0,8431	Utility	Past Usage = 0	Average	3,5216
		Std Dev	0,3644			Std Dev	1,1461
	Past Usage = 1	Average	0,7907		Past Usage = 1	Average	4,1105
		Std Dev	0,4080			Std Dev	1,1570
	p - value		0,1655		p - value		**0,0000*** **
Overconfidence Bias	Past Usage = 0	Average	0,7608	Necessity	Past Usage = 0	Average	3,2314
		Std Dev	0,4274			Std Dev	1,1000
	Past Usage = 1	Average	0,7674		Past Usage = 1	Average	3,7151
		Std Dev	0,4237			Std Dev	1,1003
	p - value		0,8742		p - value		**0,0000*** **
Regret Aversion Bias	Past Usage = 0	Average	0,4706	Innovativeness	Past Usage = 0	Average	3,6902
		Std Dev	0,5001			Std Dev	1,2368
	Past Usage = 1	Average	0,4651		Past Usage = 1	Average	4,0174
		Std Dev	0,5002			Std Dev	1,0567
	p - value		0,9118		p - value		**0,0047** **
Confirmation Bias	Past Usage = 0	Average	0,4863	Attractiveness	Past Usage = 0	Average	3,3765
		Std Dev	0,5008			Std Dev	1,1187
	Past Usage = 1	Average	0,5000		Past Usage = 1	Average	3,8256
		Std Dev	0,5015			Std Dev	1,0889
	p - value		0,7814		p - value		**0,0000*** **
Cognitive Dissonance Bias	Past Usage = 0	Average	0,3922	Trustworthiness	Past Usage = 0	Average	3,0078
		Std Dev	0,4892			Std Dev	0,9306
	Past Usage = 1	Average	0,3081		Past Usage = 1	Average	3,4302
		Std Dev	0,4631			Std Dev	0,9858
	p - value		0,0761		p - value		**0,0000*** **
Average Bias	Past Usage = 0	Average	0,5906	Average Opinion	Past Usage = 0	Average	3,3655
		Std Dev	0,2075			Std Dev	0,9901
	Past Usage = 1	Average	0,5663		Past Usage = 1	Average	3,8198
		Std Dev	0,2064			Std Dev	0,9663
	p - value		0,2348		p - value		**0,0000*** **

Table 8 – T-Test analysis, for Future Usage and Future Recommendation, for the difference in means for past users and non-users of fintechs. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Future Attitude			
Future Usage	Past Usage = 0	Average	0,9255
		Standart Deviation	0,6005
	Past Usage = 1	Average	1,8140
		Standart Deviation	0,4591
		p - value	**0,0000*** **
Future Recommendation	Past Usage = 0	Average	1,1529
		Standart Deviation	0,6492
	Past Usage = 1	Average	1,8430
		Standart Deviation	0,3956
		p - value	**0,0000*** **

Table 9 – T-Test analysis, for individual and average Opinions, after the introduction of the Behavioral Finance tool, for the difference in means for Savings and Investments fintechs. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Post- Behavioral Finance Opinions			
Utility	Savings	Average	3,9391
		Standart Deviation	0,9425
	Investments	Average	3,7002
		Standart Deviation	0,9490
		p - value	**0,0002*** **
Necessity	Savings	Average	3,7564
		Standart Deviation	0,9576
	Investments	Average	3,6042
		Standart Deviation	0,9643
		p - value	**0,0209***
Trustworthiness	Savings	Average	3,2295
		Standart Deviation	0,9611
	Investments	Average	3,1897
		Standart Deviation	0,9758
		p - value	0,5482
Average Opinion	Savings	Average	3,6417
		Standart Deviation	0,8348
	Investments	Average	3,4980
		Standart Deviation	0,8662
		p - value	**0,0138***

Table 10 – Results of logistic regression, testing the effects of Average Opinion and Future Usage on the Future Recommendation of Savings Fintechs, after the introduction of the Behavioral Finance tool. Standard Deviation in parentheses. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Post- Behavioral Finance Savings Fintech Recommendation

Opinion	**2.345***		**1.623***
	(0.196)		(0.235)
Future Usage		**3.613***	**2.932***
		(0.242)	(0.263)

Table 11 – Results of logistic regression, testing the effects of Average Opinion and Future Usage on the Future Recommendation of Investments Fintechs, after the introduction of the Behavioral Finance tool. Standard Deviation in parentheses. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Post- Behavioral Finance Investments Fintech Recommendation

Opinion	**1.842***		**0.958***
	(0.161)		(0.211)
Future Usage		**3.976***	**3.420***
		(0.262)	(0.277)

Table 12 – T-Test analysis, for Future Usage and Future Recommendation, for the difference in means for Savings and Investments fintechs, based on the introduction of the Behavioral Finance tool. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Savings				**Investments**			
Future Usage	Pre-BF	Average	1,2295	Future Usage	Pre-BF	Average	1,1124
		Std Dev	0,6308			Std Dev	0,6439
	Post-BF	Average	1,2623		Post-BF	Average	1,1920
		Std Dev	0,6439			Std Dev	0,6322
	p - value		0,4525		p - value		0,0686
Future Recommendation	Pre-BF	Average	1,2623	Future Recommendation	Pre-BF	Average	1,1148
		Std Dev	0,6179			Std Dev	0,6117
	Post-BF	Average	1,2248		Post-BF	Average	1,1733
		Std Dev	0,6175			Std Dev	0,5957
	p - value		0,3756		p - value		0,1569

Table 13 – Results of logistic regression, testing the effects of Average Opinion, Future Usage and Future Recommendation on the Perceived Usage of Savings Fintechs. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Perceived Usage of Savings Fintech

Opinion	**0.578*****			0.284
	(0.119)			(0.159)
Future Usage		**0.659*****		-0.0246
		(0.155)		(0.234)
Future Recommendation			**0.882*****	**0.654***
			(0.164)	(0.257)

Table 14 – Results of logistic regression, testing the effects of Average Opinion, Future Usage and Future Recommendation on the Perceived Usage of Investments Fintechs. Significance at 0.1% (***), Significance at 1% (**), Significance at 5% (*).

Perceived Usage of Investments Fintech

Opinion	**0.419*****			0.168
	(0.113)			(0.144)
Future Usage		**0.524*****		-0.283
		(0.155)		(0.247)
Future Recommendation			**0.849*****	**0.941*****
			(0.167)	(0.266)

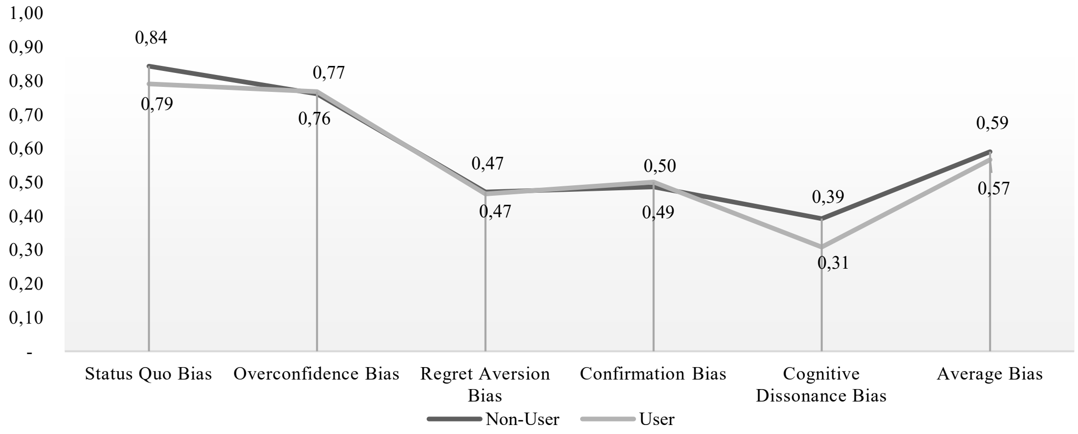

Figure 1 – Difference in means, for each individual bias and average bias, based on the past usage of fintechs.

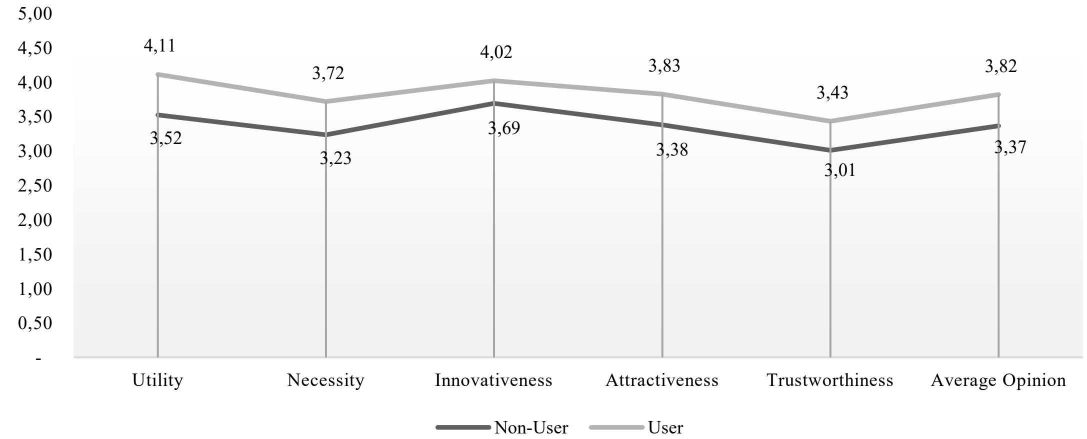

Figure 2 – Difference in means, for each individual opinion and average opinion, based on the past usage of fintechs.

Will Behavioral Finance be your Best Friend in FinTech?

Hello! My name is Daniela Francisco and I am a masters student at Católica Lisbon School of Business & Economics. In order to complete my Masters in Finance program, I am currently writing my dissertation, researching the usage of Savings & Investment FinTechs in Portugal and the customers' reaction to the introduction of Behavioral Finance tools. As such, I'd like to ask for your help in my research. Are you ready?

Personal Information

Gender

- ○ Female
- ○ Male

Age

- ○ 15 - 29
- ○ 30 - 44
- ○ 45 - 59
- ○ 60 +

Region

- ○ North
- ○ Center
- ○ Lisbon Metropolitan Area
- ○ South
- ○ Islands

I am...

- ○ Studying
- ○ Working
- ○ Unemployed
- ○ Retired

I'm pursuing a...

- ○ Highschool Diploma
- ○ Bachelor's Degree
- ○ Post-Graduate Degree
- ○ Master's Degre
- ○ PhD, MD

My area of studies is...

- ○ Arts
- ○ Commerce
- ○ Education & Humanities
- ○ Finance & Economics
- ○ Industry & Transportation
- ○ Medical & Pharmaceutical
- ○ Tourism & Hospitality
- ○ Science & Engineering
- ○ Services & Administration

Education

- ○ 9th Grade
- ○ 12th Grade
- ○ Bachelor's Degree
- ○ Post-Graduate Degree
- ○ Master's Degree
- ○ PhD, MD

Sector of Activity

- ○ Arts
- ○ Commerce
- ○ Education & Humanities
- ○ Finance & Economics
- ○ Industry & Transportation
- ○ Medical & Pharmaceutical
- ○ Tourism & Hospitality
- ○ Science & Engineering
- ○ Services & Administration

Part I: A Quick Survey

Which of the following would you choose?

- ○ A 100% probability of winning €5.000
- ○ An 80% probability of winning €7.000, with a 20% probability of winning €0.

How much control do you believe you have in picking good investments?

- ○ Absolutely no control
- ○ Little if any control
- ○ Some control

○ A fair amount of control

Imagine you decided to invest €1.000 on the stock market and you've narrowed down your choice between two companies: Company A and Company B. They have equal risk and payoff. Company A is a big and well-known company, while Company B has performed well but is still hasn't caught public attention. In which of the companies would you most likely invest?

○ I will most likely invest in Company A because I feel safe following many institutional investors. If Company A declines in value, I won't be the only one caught by surprise, and with so many professionals investing here, I could hardly blame myself for poor judgement.

○ I will most likely invest in Company A because if I invested in Company B and it failed, I would feel foolish. Few well-known investors invest here, and i would regret going against their informed consensus only to discover that I was wrong.

○ I would feel indifferent between investing in Company A or Company B because they give the same expected return for the same risk.

Suppose you invested in a company after much careful research. Now, imagine they have a press release stating a problem with it's main product. The second paragraph, however, describes a new product they might release later this year. What are you more likely to do?

○ I will typically notice the new product and do some research on it.

○ I will typically notice the problem with the main product and do some research on it.

Imagine you recently bought a new computer, XPTO, and you're very happy with it. One day, your friend tells you "did you know the competitor brand, COOL, was giving out free Anti-Virus protection when you bought your computer?". You're initially confused: you didn't know, you would have liked to have it, so you may wonder, was getting this a bad decision? You begin to second-guess yourself. Most likely, what will you do next?

○ You go online and see the several specs, wondering if you should've bought computer COOL.

○ You keep playing on your computer and think "If I had to do it again, I may have bought computer COOL. Even though I don't have the anti-virus, I'm still happy with my purchase".

○ You think about doing some additional research on computer COOL, but you decide not to. The computer was a big, important purchase, and you’ve been so happy with it that discovering an error in your purchase leaves you feeling uneasy, so it's better to just put this to rest and enjoy the computer.

Part II: Enter FinTech

Right now you're probably wondering: "What is a FinTech?"

I'll give you a little help then: in a simplified manner, a FinTech is a software, like a website or a mobile app, that allows you to do all sorts of financial transactions. Some FinTechs can combine several categories, but we currently divide them into four categories: Money Transfers & Payments, like Paypal or Revolut; Savings &

Investments, like Seedrs or Stash; Insurance, like BIMA or Lemonade; and Borrowings, like Funding Circle or Lending Club.

Do you currently or in the last 6 months use any fintech?

- ○ Yes
- ○ No

Which kind of fintechs?

You can choose more than one!

- ○ Money Transfers & Payments
- ○ Savings & Investments
- ○ Borrowings
- ○ Insurance

What is your opinion regarding these services?

	Completely Disagree	Slightly Disagree	Neither Agree Nor Disagree	Slightly Agree	Completely Agree
Useful	○	○	○	○	○
Necessary	○	○	○	○	○
Innovative	○	○	○	○	○
Attractive	○	○	○	○	○
Trustworthy	○	○	○	○	○

Will you continue using these kinds of services?

- ○ Yes
- ○ No
- ○ Maybe

Do you recommend them to family, friends or coworkers?

- ○ Yes
- ○ No
- ○ Maybe

Part III: Savings & Investments

This next section will focus on the Savings & Investments sector of FinTech. As the name indicates, it refers to the services that allow you to save and invest your money online. I will further subdivide it into 2 sub-sectors: Savings platforms can range from simple budget tracking apps, to online deposits, or from integrated spending tracking to expense sorting; Investment platforms can range from investment advice websites to mobile stock trading, or from crowdfunding platforms to robo-advisors.

A. Savings

Are you aware of the existence of platforms that allow you to save your money?

- ○ Yes
- ○ No

Have you ever used one of these platforms?

- ○ Yes
- ○ No

Would you continue or start using them?

- ○ Yes
- ○ No
- ○ Maybe

Would you recommend them to friends and family?

- ○ Yes
- ○ No
- ○ Maybe

B. Investments

Are you aware of the existence of platforms that allow you to invest your money?

- ○ Yes
- ○ No

Have you ever used one of these platforms?

- ○ Yes
- ○ No

Would you continue or start using them?

- ○ Yes
- ○ No
- ○ Maybe

Would you recommend them to friends and family?

- ○ Yes
- ○ No
- ○ Maybe

Part IV: Behavioral Finance

Now you're wondering: "What is Behavioral Finance?" So I'll help again: Behavioral Finance is the science that combines Finance, Psychology and Sociology. It studies the investors and their decisions, meaning how they invest their money, what do they invest it in and why in that. Behavioral Finance can be used in many scenarios:

for example, by studying your habits, it can give you suggestions of things you may like to purchase, or to teaching you how to break the bad ones, like overspending on sweets; or by studying how much of an adventurer you are, it can suggest safer or riskier investments, according to your risk tolerance. Now imagine they are available...

A. Savings: the platform inserted the BF tool and is now able to study your spending habits. This means it could track in which months you spend more and in which months you spend less, teaching you and helping you to save more according to you, and not just give you a plain approach, or teach you where you spend more or less, and where you can cut some of the spending.

How much do you believe this tool is necessary?

	1	2	3	4	5	
Not At All	○	○	○	○	○	Very Much

How much do you believe this tool helps you?

	1	2	3	4	5	
Not At All	○	○	○	○	○	Very Much

How much do you trust this tool with your data and personal preferences?

	1	2	3	4	5	
Not At All	○	○	○	○	○	Very Much

Would you use the platform?

○ Yes
○ No
○ Maybe

Would you recommend it to friends and family?

○ Yes
○ No
○ Maybe

B. Investments: the platform inserted the BF tool and is now able to study your investment preferences. This means it would give you suggestions of portfolios where you'd be more comfortable investing, for example: in sports clothing companies like Nike and Adidas, or in companies that are socially responsible, like Starbucks or Disney; in lower risk-reward portfolios, with more stable bonds, or in higher risk-reward, with more volatile stocks.

How much do you believe this tool is necessary?

	1	2	3	4	5	
Not At All	○	○	○	○	○	Very Much

How much do you believe this tool helps you?

	1	2	3	4	5	
Not At All	○	○	○	○	○	Very Much

How much do you trust this tool with your data and personal preferences?

	1	2	3	4	5	
Not At All	○	○	○	○	○	Very Much

Would you use the platform?

○ Yes

○ No

○ Maybe

Would you recommend it to friends and family?

○ Yes

○ No

○ Maybe

Final Question!

How likely do you believe other people would use them in Savings Platforms?

○ Very Unlikely

○ Unlikely

○ Maybe

○ Likely

○ Very Likely

How likely do you believe other people would use them in Investment Platforms?

○ Very Unlikely

○ Unlikely

○ Maybe

○ Likely

○ Very Likely

You're done!

Thank you for your participation in my research study!

Once more, if you have any doubts or just plain curiosity, don't hesitate to contact me!