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AI-Powered Personalization: A Behavioural Economics Perspective in Marketing

Maria Beatriz Fernandes de Castro Carreira

MSc in Business Administration

Supervisors:
PhD, Renato Jorge Lopes da Costa, Assistant Professor with Habilitation,
ISCTE-Instituto Universitário de Lisboa

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BUSINESS
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Department of Marketing, Strategy and Operations

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Resumo

Com a constante evolução da Inteligência Artificial nos últimos anos, o potencial para a incorporação desta tecnologia em diversas áreas tem acompanhado essa tendência. Esta incorporação tem levado ao aumento da eficiência, produtividade e crescimento. Na atualidade, o e-commerce e o marketing online têm sido utilizados como nunca antes, com a Inteligência Artificial a desempenhar um papel importante nesta evolução e otimização.

Esta investigação tem como objetivo analisar como pode haver uma integração dos princípios e teorias da economia comportamental nas estratégias de personalização da IA. Este estudo também pretende avaliar e compreender melhor o panorama atual da personalização potenciada por IA no marketing, bem como investigar o impacto que a personalização da IA tem no comportamento do consumidor. Para alcançar as conclusões necessárias para responder a estas questões, estas três matérias foram investigadas em profundidade, numa primeira instância através da revisão da literatura e, posteriormente, através das entrevistas realizadas via abordagem qualitativa.

Através das entrevistas, foi possível avaliar que as principais razões pelas quais esta integração seria um sucesso se devem à opinião geral de que a IA e a melhor compreensão do comportamento do consumidor são um ativo para qualquer empresa, levando a uma melhoria dos resultados gerais. Por outro lado, as principais razões pelas quais esta integração seria mal-sucedida seriam a falta de conhecimento e know-how dos profissionais de marketing, assim como as falhas que ainda ocorrem com esta tecnologia, como a não entrega dos resultados esperados.

Palavras-chave: Inteligência Artificial, Marketing, Personalização, Economia Comportamental

Classificação *JEL*:

M310 – Marketing
O320 – Management of Technological Innovation and R&D

Abstract

With the ever-growing evolution of Artificial Intelligence in recent years, the potential for this technology to be incorporated in various different fields has been accompanying the trend. This incorporation has led to increasing efficiency, productivity and growth. In today's day and age, e-commerce and online marketing have been utilized as never before, with Artificial Intelligence playing a big role in this evolution and optimization.

This investigation aims to analyse how there could be an integration of behavioural economics principles and theories into AI personalization strategies. This study also intends to assess and better understand the current landscape of AI-Powered personalization in Marketing, as well as investigate the impact that AI personalization has on the consumer behaviour. In order to reach the conclusions needed to answer said questions, these three matters were investigated in depth, on a first instance through the literature review, and later through the interviews conducted via the qualitative approach.

Through the interviews it was possible to assess that the main reasons on why this integration would be a success was due to the general opinion that AI and the better understanding of the consumer behaviour is an asset to any company, leading to an improvement of overall results. On the other hand, the main reasons why this integration would be unsuccessful would be the lack of knowledge and know-how of the marketing professionals and the malfunctioning that still occurs with this technology, ultimately not delivering the expected results.

Keywords: Artificial Intelligence, Marketing, Personalization, Behavioural Economics

JEL Classification:

M310 – Marketing

O320 – Management of Technological Innovation and R&D

General Index

Index of Tables

Index of Figures

List of Abbreviations

AI – Artificial Intelligence

AIUI – AI User Interfaces

AIVAs – Artificial Intelligence Voice Assistants

BE – Behavioural Economics

CBB – Compulsive Buying Behaviour

CMs – Customer Models

CRM – Customer Relationship Management

DCO – Dynamic Creative Optimization

DM – Decision Maker

DSSs – Decision Support Systems

EY – Expected Utility

FOMO – Fear of Missing Out

IoT – Internet of Things

ML – Machine Learning

NLP – Natural Language Processing

RSs – Recommendation Systems

SEO – Search Engine Optimization

SERP – Search Engine Result Pages

TIME – Theory of Interactive Media Effects

Chapter 1 - Introduction

1.1. Contextualization

There is no denying that we are now in the era of unprecedented technological advancements. Along with this evolution, there has been a conversion of both artificial intelligence (AI) and marketing, with this intersection causing a paradigm shift and redefining the dynamics of consumer engagement.

The evolution of AI seems to be leading to a bigger interaction between machines and humans, where the lines between real physical space and digital virtualized networks will become blurrier. This also translates to a broader usage of this technology in various different industries like in agriculture, autonomous driving, education, financial industry, governance, intelligent robotics, manufacturing, healthcare industry, retailing industry and security (Lu, 2019).

The usage of personalization has been a tool utilised by marketers in order to improve their job and the relationship with its customers. Although this technology isn't new, there are still some challenges. Therefore, understanding the processes required to conduct personalised marketing would be useful. For most scholars and marketers there are several terms to illustrate the personalization process like segmentation, profiling, filtering, tailoring, targeting, customization, mass customization, mass personalization and one-to-one marketing, while for practitioners, there is the consideration of topics like location diagnosis, tailoring the content of the message, tailoring the product and fitting the visual layout of the message to the data terminal equipment (Vensanen & Raulas, 2006).

For Montgomery and Smith (2009), personalization is an important component when it comes to interactive marketing strategies that will adapt itself and improve with the evolution of the internet. With that in mind, there are three problems that ought to be addressed and enhanced in the future such as Privacy, Adaptive Web Design and Computation. Regarding Privacy, this problem stems from the fact that this attribute could be viewed as an invasion of privacy that could be solved by applying the term of Sufficiency. Although this could be a viable solution, the line between what is sufficient information and what is a violation of privacy is still very blurred. For Personalization using adaptive web design, since this generates an anticipation of the objectives the user has, making inferences of their goals based on the observed actions, could be a more effective solution. Finally, the computational issues are related to the inference of potential statistical algorithms in real-time decision environments.

There seems to be many discussions on how this evolution will have repercussions in different areas like consumer behaviour, competition, and labour market, and how this could translate to issues of inequality and unemployment. Nevertheless, there is still little to no empirical studies regarding the subject of Machine Learning algorithms, which may lead to misinterpretation or an exaggeration of the consumers behavioural biases. The importance of these studies lies in understanding how these developments can both benefit and mitigate the problems of new technologies (Abrardi et al., 2022).

Additionally, the evolution of the Behavioural Economics scope also means that there will likely be alterations in basic neoclassical economic paradigm and its implications in consumer's choice behaviour. According to Etzioni (2011), this progression in BE, thanks to the various sociological and psychological studies, translates in new findings such as choice behaviour not being based on any deliberations, both intuitive choices and those subjected to deliberations are strongly affected by norms and emotions, that are in turn influenced by cultural and social factors and cognitive biases (BE) are frequently observed and reported in instances where reasoning occurs. These conclusions could lead to new ways in which Behavioural Economics could be implemented in various fields, such as Marketing, and its potential in expanding its reach.

Ultimately, the aim of this thesis is to delve into the intricate nexus of AI-Powered personalization through the lens of behavioural economics while also exploring the alliance between cutting-edge technology and the insights offered by behavioural economics principles.

1.2. Problem Discussion

While investigating, doing research, and reading different articles and journals, it was detected that despite the growing adoption and prominence of AI-Driven personalization in marketing, there was still a need to delve deeper into this area.

The term personalization has been defined by several scholars, with a more generalised definition being formulated by Chandra et al. (2022), as a strategic approach involving the processes of acquiring knowledge, aligning and providing products and services in order to meet the unique needs of customers. This way, customers have an improved satisfaction since there is a reduction in disorientation and better decision quality. Even though the focus of this research is about the personalization of ads and publicity, it is important to mention the phenomenon of mass customization. In a brief and concise way, for Tseng et al. (2017) mass customization has as a goal to provide products and services tailored to individual customer needs, combining the efficiency of mass production. This approach emphasises the importance of offering uniquely designed products and services by treating each customer as an individual, achieved through process agility, flexibility, and integrating the entire product life cycle.

For Zhang and Sundar (2019), the two terms of personalization and customization have been hand in hand when describing the process of tailoring content for consumers. However, they differ when it comes to the source of tailoring, since personalization involves tailoring driven by the system, while customization involves tailoring done by users. In continuance, customization can be done by action route and the cue route through the theory of interactive media effects (TIME). According to this theory, in the action route, affordances prompt users to take actions, such as actively selecting options to customise an online service according to their preferences. This way, the engagement fosters in the user a sense of agency and self-determination, which ultimately enhances their involvement. As for the cue route, the mere existence of affordances or outcomes indicating the impact of these affordances, implies the probability for user action, even in the absence of actual user behaviour at the moment of decision-making. Through this theory, it is expected that customization likely affects user behaviours and psychology through both routes.

In more practical terms, personalization is viewed as a designed process aimed at tailoring a pertinent, individualised interaction to improve the customer experience. It integrates the utilisation of artificial intelligence (AI) and machine learning (ML) within the domain of cognitive and social psychology. Recently, there has been significant expansion in the body of literature focused on personalization research, and the field is gaining momentum thanks to its multidisciplinary nature, even though, despite of the exponential growth in personalization research, a comprehensive review is lacking to bring together the fragmented literature (Chandra et al. 2022).

According to Kopalle et al. (2021), although there have been many studies conducted related to AI in different contexts globally, the quick spread and fast development of these technologies will likely lead to a customised offering, translating in a need of further examination of the role of AI technologies in marketing. For that reason, there is still a need in understanding how the integration of behavioural economics principles could enhance the effectiveness of AI-powered personalised marketing strategies. This way, it would become easier to understand the connection between behavioural biases and AI personalization and ultimately optimise the marketing efforts.

1.3. Research Objectives and Questions

Taking in consideration what was mentioned earlier, there are several objectives that have been set with the intention of better answering the research problem. The main objective has been established as understanding how there could be an integration of behavioural economics principles into AI personalization strategies. Regarding more specific objectives, these have been settled as assessing the current landscape of AI-Powered personalization in Marketing and investigating the impact of AI personalization on consumer behaviour.

Upon analysing and studying the subject at hand, these are the questions that could be used to aid in the answering of the research problem:

RQ1) How does AI-powered personalization influence consumer decision-making processes and choices?

RQ2) How do businesses implement AI personalization in their marketing strategies, and what are the challenges they face?

RQ3) What are the key principles of behavioural economics that can be integrated into AI personalization strategies?

RQ4) How can these principles be effectively incorporated into AI-powered personalization algorithms and systems?

RQ5) What benefits arise from integrating AI with behavioural economics?

1.4. Investigation Structure

In order to achieve the proposed objectives, the dissertation is presented with the following structure: Chapter 1, being the introduction, presents the contextualization, the problem discussion, research objectives and questions and the investigation structure. For Chapter 2, the literature review will be an exposition and comprehension of various themes of interest such as Behavioural Economics, Consumer Attitudes and Behaviours, Artificial Intelligence, Artificial Intelligence in Marketing and the Relation between these topics.

Following the literature review, in Chapter 3 the theoretical approach will consist of a discussion and further analysis of the research questions and objectives for this research. For Chapter 4, the methodology is thoroughly addressed by encompassing the research model, a detailed presentation of the chosen approach for this study while also outlining the specific data analysis methods utilised. Additionally, the content of this approach is elucidated, providing a comprehensive understanding of the instruments employed in the data collection process.

In Chapter 5, the result presentation and discussion, findings and results are addressed, confirming the pivotal research questions and if they align with the initial objectives. Following the presentation of results, there is a critical discussion that provides a comprehensive analysis of the collected data. This integrated approach allows for a coherent exploration of how the previously introduced topics interconnect and influence each other. By merging the presentation of results with a thorough discussion, this section aims to not only answer the research questions but also to offer a nuanced understanding of the intricate relationships between the variables under examination. Finally, in Chapter 6 there is the conclusion of this study as well as the limitations and recommendations for future research in this topic.

Chapter 2 - Literature Review

2.1. Behavioural Economics

As defined by Mullainathan & Thaler (2001, p.1), Behavioural Economics is "the combination of psychology and economics that investigates what happens in markets in which some of the agents display human limitations and complications". According to Camerer (1999, p.1), the objective of behavioural economics "is to suggest mathematical alternatives with firm psychological foundations to rationality assumptions" while as for Rabin (1998, p.660) "the goal of psychological economics is to investigate behaviourally grounded departures from these assumptions that seem economically relevant".

When compared to Mainstream Economics, Behavioural Economics seems like an entirely different school of thought, since its ideologies are less narrow, mechanical, individualistic, rigid, separate, and intolerant, giving its study a more personal and realistic approach (Tomer, 2007). According to Rabin (1998), researchers in both areas of economics and psychology were sceptical about connecting these two concepts as they believed it would be unrealistic. More recently, the incorporation of more realistic human notions and behaviours in economic models have improved massively its study in the last decade, as the more realistic the assumptions made, the better is the outcome of the investigation.

Because of this, in more recent years, economists have started to deepen their understanding of what it means to not be a classical rational consumer, and to better understand the various variables that would influence their behaviour. Economists like Herbert Simon have contributed to this study by introducing the concepts of Bounded Rationality and Satisficing, while Amartya Sen came up with the concept of Capability-Concept and Joseph Stiglitz with Information

Paradigm. All these concepts have helped with analysing how people react to notions like trust, tendency to succumb to temptation, inconsistency, norms, and many others (Berg, 2014).

According to Kahneman (2003), one of the most influential behavioural economists, there could be a more precise study in economics when combining intuitive choices and reasoning, debunking the allegations of classical economics supporters that it is not possible to analyse non rational behaviour, as it is unpredictable. By utilising an intuitive/reasoning model it is easier to predict what a person would do. According to Laibson and List (2015), the field of Behavioural Economics not only embraces the core assumptions of modern economics but aspires to evolve and refine those ideologies and make them more empirically accurate. This field studies how individuals attempt to choose the best option and also the situations when they fail to do so, despite their efforts.

With the expansion of the knowledge in Behavioural Economics, the questions on whether this matter will significantly change the way we look at neoclassical economic paradigm, when it comes to consumer choice and behaviour, remains. But utilising this new paradigm of BE in the study of various different economic models will only enrich the study as it could provide more reliable predictions, lay the foundation for more complete policies, and generate more absolute explanations for the given information. (Etzioni, 2011). As pointed out by Hepburn et al. (2010), even though behaviour does not always fit the standard economics models, the empirical evidence from behavioural economics serves as a compelling reminder of the importance of humility in economic modelling. It plays down the necessity of using models of human behaviour that are precise and suitable for a specific context, and conversely ensures that policy recommendations are well-founded and effective.

2.1.1. Behavioural Economics Theories and Concepts

Aforementioned, the field of behavioural economics utilises some of the traditional economic assumptions, while incorporating psychological aspects, in order to not only explain and predict behaviour, but also to pave the way for new policies. According to Laibson and List (2015), this requires an adoption and refinement of three core principles of economics, being optimization (individuals always try to choose the best feasible option), equilibrium (individuals try to choose the best feasible option when dealing with others) and empiricism (models need testing with data).

Several authors have gathered what they consider to be the assumptions and principles of behavioural economics. Laibson & List (2015) also huddled six principles of behavioural economics, that encompass the main ideas and subject matters of this field. As the first principle, they identified that people always try to choose the best feasible option but are not always successful. As mentioned by Hernandez-Cervantes (2022), this is a different perspective when in comparison with neoclassical economics, as the models in this field would assume that the agent always chooses the best option among all others, the so called "*Homo economicus*". The second principle suggests that people mind about how their circumstances compare when looking at reference points, meaning that for an individual it matters whether they are losing or gaining when considering a certain reference point. Moreover, losses are more meaningful and hold more weight for individuals compared to gains, as the suffering is about twice as much as the benefit from a gain of the same magnitude. For the third principle, there is an understanding that people have self-control problems. Again, this is a different perspective when in comparison with traditional economic models, since in these, there is no gap between a person's intentions and actions. Regarding the fourth principle, it states that even though people generally care more about their own payoff, there is also a concern with other people's payoffs, even individuals outside of our family. For the fifth principle, it claims that even when market exchange ceases to matter when looking at psychological factors, many psychological factors matter even in markets. Finally, in principle 6, by limiting people's choices, it could potentially protect them from their behavioural biases but in practice, the intervention of third parties (heavy-handed paternalism) has mixed opinions and is usually unpopular.

Table 2.1 - The Six Principles of Behavioural Economics

Six Principles of Behavioural Economics	
1st Principle: People try to choose the best feasible option, but they sometimes don't succeed	Nagel (1995); Miravete (2003); Agarwal et al., (2013); Hernandez-Cervantes (2022)
2nd Principle: People care (in part) about how their circumstances compare to reference points	Kahneman & Tversky (1979); Thaler (1980); Kahneman, Knetsch & Thaler (1990); Tversky & Kahneman (1991); List (2003); Hussain & List (2012)
3rd Principle: People have self-control problems	Laibson (1997); Read & Van Leeuwen (1998); O'Donoghue & Robin (1999); Ashraf, Karlan & Yin (2006); Giné, Karlan & Zinman (2010); Beshears et al., (2013); Augenblick, Niederle & Sprenger

	(2014); Kaur, Kremer & Mullainathan (2015); Schilbach (2015)
4th Principle: Although we mostly care about our own material payoffs, we also care about the actions, intentions, and payoffs of others, even people outside our family	Güth, Schmittberger & Schwarze (1982); Andersen et al., (2011)
5th Principle Sometimes market exchange makes psychological factors matter even in markets	Lamont & Thaler (2003)
6th Principle: In theory, limiting people's choices could partially protect them from their behavioural biases, but in practice, heavy-handed paternalism has a mixed track record and is often unpopular	Gruber & Kőszegi (2001); Madrian & Shea (2001); Johnson (2004); Thaler & Sustein (2008)

Source; Laibson & List (2015)

When looking at the different theories that are part of this field of studies, there are a few that are deemed more important and that have a higher appearance in several different articles. The theory of bounded rationality is perhaps the one that is more times mentioned and analysed by authors, as it pertains to the recognition that in practical economic scenarios, individuals often utilise various decision-making shortcuts, or heuristics, that may cause them to diverge from the predictions outlined in expected utility theory (Dold, 2023); it is the assumption that agents are not completely rational and instead possess restricted cognitive capabilities (Hernandez-Cervantes, 2022); it proposes that individuals face both physiological and psychological limitations, which consequently means that it is essential to account for these constraints in the information processing capabilities of decision-makers (Qi et al., 2023).

To better understand and to corroborate the theory above mentioned, there are several concepts that are important to mention. One of these concepts that is linked to the theory of Bounded Rationality is called Mental Accounting, first coined by Thaler, that explains that people handle money differently depending on various factors such as the money's origins and intended use. According to Thaler (1999), mental accounting is the array of mental processes employed by individuals and households to structure, assess and manage financial endeavours and have three components that should receive the most attention. The first component captures the perception and experience of outcomes, as well as the decision-making process and its subsequent evaluation, the second one entails assigning activities to particular accounts where both the sources and destinations of the funds are categorised in both tangible and mental accounting frameworks, and finally, the third component concerns to how often accounts are assessed and what Read et al. (1998) termed as "choice bracketing".

The concept of choice overload vividly illustrates humans' bounded rationality. This term, also known as "overchoice", denotes a heightened inclination to adhere to the default option in decision scenarios featuring numerous alternatives. Here, the default option represents the choice that ensues if the decision maker (DM) refrains from actively selecting any alternative (Buturak & Evren, 2017). On the other hand, there is also a concept for when there is a lack of information, called limited information or knowledge, where Thaler and Sustein (2008) highlight experience, accurate information and timely feedback as pivotal factors that empower individuals to make sound decisions.

Furthermore, Thaler & Sustein (2008) created the concept of nudge, that can be defined as any element of the choice architecture that influences people's behaviour in a predictable manner, without eliminating any options or significantly altering their economic incentives. So, nudges involve the intentional modification and design of people's decision-making environments, the manner in which these choices are presented or framed, in order to guide individuals in a particular direction. This concept of nudging has been widely embraced in public policy, due to its potential to steer behaviour effectively, as referred to by Schmidt & Engelen (2020).

Behavioural economics deduces that individuals are boundedly rational actors, possessing limited capacity to process information. While extensive research has focused on understanding how available information influences decision quality and outcomes, a recent line of research has delved into scenarios where individuals actively avoid information altogether. The term of Information Avoidance concerns to situations where people willingly choose to not obtain knowledge that could be easily accessed, also denominated as Active Information Avoidance (Golman et al., 2017). Even though information avoidance can be a strategic choice, it often provides immediate hedonic benefits by shielding individuals from the negative psychological effects associated with acquiring certain information. However, this short-term benefit may yield negative consequences in the long run, as it deprives individuals of valuable insights for decision-making and crucial feedback for guiding future behaviour.

The Prospect Theory was first developed by psychologists Daniel Kahneman and Amos Tversky as a way of trying to explain various responses to risky decisions that consistently deviated from the traditional notions of rational decision-making that were encapsulated in Von

Neuman and Morgenstern’s (1944) expected utility (EY) theory (Loomes, 2010). One of the most influential papers on Prospect Theory by Kahneman & Tversky (1979) supports the claim that even though most people obey the axioms of Expected Utility Theory, also known as Rational Choice Theory, there are several categories of decision scenarios wherein preferences consistently defy these claims, leading them to believe that the Prospect Theory is a more accurate descriptive model. As part of Kahneman and Tversky’s development of this theory, there was a concept that was created, called the Framing Effect. According to the authors, choices can be presented or framed in different lights, both positive and negative, which ultimately influences the decision-making process. For Gosling and Moutier (2019), if individuals are presented with options offering the same expected value but differing in certainty, when influenced by the framing effect, they tend to be more inclined to choose the risky option when it is presented as a potential loss rather than a potential gain.

An equally mentioned and utilised Behavioural Economics theory is the Dual-System theory, that alludes that there are times where our judgements and decisions don’t usually abide with the formal notions of rationality. This theory assumes that there are two different processing modes, with type 1 being fast, intuitive, relatively unconscious, and automatic, while type 2 is a slower, controlled, reflective and deliberative thinking process (Frankish, 2010).

According to Kahneman (2011), system 1 is the cognitive domain where heuristics, or mental shortcuts, are comprised, and it is also accountable for the biases, or systematic errors that persist when we make decisions. One of the most well-known heuristics is the availability heuristic and stated by Tversky & Kahneman (1974) it acts as a cognitive shortcut when the likelihood of an event is deemed higher merely because it can be readily recalled or brought to mind, or as defined by Siegrist (2021) it is a concept utilised to explain the differing perceptions of hazards among people, yet it has not been used to account for the variations in risk perception at an individual level. Another more general heuristic is the affect heuristic, where, according to Finucane et al., (2000), individuals may evaluate the risks and benefits of hazards by looking at a conjunction of positive and negative emotions linked to those hazards. This heuristic is deemed more efficient than analytical processing, which, consequently, anticipates that individuals facing time constraints lean more towards relying on affect, as efficiency holds greater significance compared to those not under time pressure.

Another more impetuous heuristic that is highly influential in consumer behaviour is scarcity. According to Lee & Seidle (2012), this term is used when there is an insufficiency of product supply or time of availability, and in general, this translates to more positive evaluation by the consumers. The impact that this perceived scarcity has on the consumer’s perceived value has been thoroughly studied, showing consistently that it positively influences both the preference for a product and its perceived desirability, thereby affecting purchase intentions and behaviour. Supporting these findings, Eisend (2008) demonstrated that advertising that emphasises scarcity leads to a heightened perception of value, which consequently boosts purchase intention.

Even though there are several heuristics and biases that originate from quick impressions, the automatic characteristics of system 1 is also based in a human aversion to change. This can be denoted by the creation of habits, the repetition, and the automatic behavioural patterns (Duhigg, 2012). The term Status Quo Bias, characterises an individual's inclination to resist changes and uphold the present situation, only changing behaviours if the incentive to do so is strong. As stated by Godefroid et al. (2023), this biased preference can be detrimental, since there could be another alternative that would improve the way things are done, therefore hindering progress.

Upon revisiting System 1, it becomes evident that it operates on impulses and faces limitations in processing information. This effect is originated when individuals display excessive optimism, a phenomenon known as the overconfidence effect and it occurs when individuals' subjective confidence in their abilities surpasses their actual objective performance, sometimes leading to issues such as excessive risk-taking (Pallier et al., 2002).

Another meaningful and highly discussed concept in Behavioural Economics is the sunk-cost fallacy, which, according to Haita-Falah (2017), in normative economic theory, should be ignored as they are irrelevant for future marginal payoffs. However, this idea doesn't depict reality, since people tend to consider historical costs. Therefore, the sunk-cost fallacy (bias) is the irrational behaviour of "wasting" good money, after there was a loss of money, with an example being sticking to a bad investment, just because there was a previous investment of time and money. Because this is a bias, these bad decisions could also translate to the opposite behaviour of prematurely abandoning a profitable investment, because there was a previous loss.

The temporal dimension is an important domain in Behavioural Economics, as there are biases towards the present and future for people. According to the time-discounting theories, the events occurring in the present are more heavily weighted than future ones, like people's preference with receiving less money now, over more in the future (Frederick et al., 2002). This theory is commonly known as Hyperbolic Discounting and, as specified by Hepburn et al. (2010), it refers to an application of time-declining discount rates to trade-offs in between present and future consumption. These preferences may lead to plans that are inconsistent over time, offering a potential explanation for behaviours such as procrastination, addiction, insufficient saving, and other perplexing human behaviours commonly observed.

Unlike the traditional economic perspective of *Homo Economicus*, which assumes that individuals make decisions solely based on rational self-interest, in Behavioural Economics there is a recognition that human choices are influenced by factors beyond individual cognition and emotion. In addition to these dimensions, BE acknowledges the significant role of social forces in shaping decision-making processes as individuals, naturally social beings, are influenced by and embedded within social environments when making decisions. This domain is part of the social dimension, where there are various explanations as to why there is a discrepancy between the actual behaviour of an individual and the one predicted by a model (Bridge, 2010).

In this social dimension, the anchoring heuristics is one of the most thoroughly investigated behavioural biases. First introduced by Slovic (1967), but later studied and analysed more in depth by Tversky & Kahneman (1974), the anchoring effect refers to the tendency of decision makers to be overly influenced by the first piece of information they receive, leading to biased judgments. According to Furnham & Boo (2010), this heuristic suggests that this bias occurs when individuals fail to make adjustments from an initial starting point, causing their final judgements to gravitate towards that starting point during deliberation.

Another crucial social phenomenon studied and analysed in the field of Behavioural Economics is the informational influence or descriptive norm called Social Proof. According to Roethke et al. (2020), social proof serves as a social influence strategy signalling product popularity and demand. When faced with uncertainty, individuals often rely on social proof for guidance in their actions and, for that reason, companies capitalise on this tendency by leveraging social proof to demonstrate widespread adoption, particularly in situations where uncertainty is prevalent. In E-commerce platforms there is a strategic incorporation of social proof cues to alleviate user apprehensions and bolster trustworthiness. This phenomenon can lead to herd behaviour, as pointed out by Cialdini et al. (1999), since there is an indication that individuals from collectivist cultures are more likely to comply when provided with information about how others behave, whereas individuals from individualist cultures are more inclined to comply when presented with information about the individual's past behaviour.

2.1.2. Consumer Attitudes and Behaviour

The definition of Consumer Behaviour is considered as the entire process of looking for, buying, using and disposing of a product or service that is expected to satisfy their needs. This definition also includes how single or multiple individuals make decisions on how to spend their available resources on consumable goods or services. The analysis of consumer behaviour also goes deeper, as it delves into the emotions behind these decisions, like why, how or when they buy it (Schiffman et al., 2013).

The origins of consumer behaviour research go back to the 1960's with the introduction of two broad paradigms, the positivistic and the non-positivistic. While the positivistic paradigm includes the economic and behavioural cognitive that assumes the world is a rational, ordered place, where rationalism is a fundamental in this perspective, the non-positivist paradigm emphasises a more interpretive and postmodern perspective, where it is given more importance to individual experience and the unique and shared cultural realities, translating in a non-existent single common world view (Pachauri, 2001).

Consumer Behaviours are more commonly associated when an individual performs the act of buying a product or service. But this action entails a lot more when it comes to researchers. Understanding the way consumers act is a valuable asset when it comes to deciding which products to produce, to campaign and what to discontinue (Ajzen, 2008).

Naturally, consumer behaviour studies represent an important field not only to marketers, but to all of us. According to Sethna & Blythe (2019), understanding the thought process behind a purchasing decision is of the utmost importance as it aids in the managing of every aspect of the exchange process, while for Asiegbu (2012), a consumer is a psychological being who thinks, perceives, and learns, driven by motives, personality, and attitudes, with these psychological factors influencing consumer behaviour, and with marketers aiming to influence or capitalise on them.

Also mentioned by Asiegbu (2012), there is an increasing need for marketing strategists to better understand their customers' attitudes towards their companies' products, services, and delivery systems, all of these crucial to both services and goods marketeers when designing strategies. Moreover, attitudes are based on the beliefs consumers hold about the attributes or features of the products they evaluate, with these attributes often forming the foundation for developing marketing strategies. Additionally, attitudes are primary drivers of behaviour, making them highly relevant to marketers seeking to understand why consumers choose to buy or not buy their products.

When looking more closely at how consumers behave and why they shop, it is important to acknowledge certain behavioural phenomena that have been increasing ever since the introduction of the internet and social media. As mentioned by Saibaba (2022), with the increasing adoption of technology, today's consumers have an array of opportunities to explore different products and services, compare features across brands, read reviews from users and experts, and take advantage of attractive offers and discounts available at any given time. This accessibility to both smartphones and social media, combined with the fear of missing out on online rewards and heighted impulsiveness, has led to an increase of nefarious shopping patterns, contributing to the rise of compulsive buying disorders.

According to Dinh & Lee (2022), FOMO, or the fear of missing out, is a well-recognized and significant concept in consumer behaviour, particularly within the realm of social media marketing. Previous research describes FOMO as a psychological phenomenon linked to the anxiety individuals experience when engaging with social media platforms and it is characterised by the fear that others might be having better experiences or receiving greater rewards, which drives people to use social media as a means to fulfil their needs, making it a powerful consumerism motivator. Additionally, Hussain et al., (2023) describe FOMO as a psychological phenomenon where individuals experience anxiety or fear about being excluded from events or experiences that their peers are enjoying, possibly leading to compulsive buying behaviour (CBB), where individuals make impulsive purchases in an effort to keep up with their peers or avoid missing out on perceived opportunities.

Another behavioural phenomenon that has been observed recently has been the younger generation's preference for a simplification of not only websites or app design, but also language. According to Djamasbi et al., (2016), there has been substantial evidence supporting this claim, as Generation Y tends to be more impatient, preferring short passages of text which ultimately affects their ability to process information. Additionally, Djamasbi et al., (2016), indicated that the preference for image-based communication, meant that one way to enhance the effectiveness of text-based communication was through structuring the information so it would be easily understood in brief glances and facilitate a more visual search.

In order to better understand these phenomena, it is important to measure the user experience as a way of analysing, evaluating and ultimately improving the design of these websites and apps. As indicated by Albert & Tullis (2013), user experience metrics are used to evaluate and measure certain episodes, phenomena or situations, which not only add valuable insights to the design and evaluation process, but also aid in the decision-making process. These metrics can help denote whether there has been an improvement in the user experience, realising if money has been saved or increased, finding patterns or inefficiencies or gaining new perceptions on how to better understand the consumer.

2.2. Artificial Intelligence

Artificial intelligence has been around and a reality for many years, but only recently it gained popularity amongst various fields. This ascent in traction has been mainly due to the fact that there has been the creation of new AI approaches, the now widely available and cheap computer force and also the availability of Big Data that has been increasing substantially in the past few years (Overgoor et al., 2019).

There are several definitions of what AI is, with its mainstream definition, as said by one of the pioneers of AI, Marvin Minsky, giving machines the ability to perform tasks that require human intelligence. This simple rationale has evolved, with the premise now being to enable machines not only to perform repetitive human tasks, but also be able to develop human-like intelligence (Jiang et al., 2022).

For Kumal et al. (2021) the definition of AI resides in "the science of training machines to perform human tasks, by processing large amounts of data and recognizing patterns in the data through the use of an assortment of technologies such as machine learning, natural language processing, and so on", while according to Russel & Norvig (2010), artificial intelligence not only aims to understand intelligent entities but also to create them. For Legg & Hutter (2007), the junction of various different definitions of intelligence leads them to a concept that encompasses the ability of an individual agent to acquire, profit and adapt from the different environments and objectives it possesses.

Despite all of these definitions and notions of what AI and intelligence is, there is still some difficulty to state precisely all of its nuances, leading ultimately to misunderstandings, confusion and misuse. So, a more specific and restrictive definition could be more adequate, so not to make assumptions, as "machines that mimic human intelligence in tasks such as learning, planning, and problem-solving through higher-level, autonomous knowledge creation" (De Bruyn et al., 2020, p.93).

The utilisation of AI in today's industries pertains to allowing problems that would previously be dealt with by humans' intelligence, now could be solved with the help of computerised and mechanical solutions. Thus, the adoption of AI and Machine Learning (ML) has been rising, in order to aid employees when attending customers, to forecast what are the customer demands and to enable simple questions to be answered by bots (Campbell et. al, 2020).

According to Campbell et. al (2020), the definition of Machine Learning is “an application of AI that provides systems the ability to automatically learn and improve from experience without being explicitly programmed”, while for Zhou (2021) is “the technique that improves system performance by learning from experience via computational methods”.

Even though AI is the technology that is typically defined as the one that allows machines to learn from standardised behaviour and execute human-like tasks, Machine Learning is an important aspect of this revolution in Marketing, as it supports the performance of AI. (Campbell et al., 2020).

2.2.1. Artificial Intelligence in Marketing

The definition of Marketing AI is linked to the making of the optimal decision with the available information, and so a more concise definition could be “the development of artificial agents that, given the information they have about consumers, competitors, and the focal company, suggest and/or take marketing actions to achieve the best marketing outcome” (Overgoor et al., 2019).

The usage of AI in Marketing has been evolving rapidly since there are various benefits of its utilisation. With the increase of the usage of computers and online shopping, the access to big data, the minor computing costs and the evolution of the machine learning algorithms and models, there has been an application of this technology in various areas of marketing (Huang & Rust, 2020).

According to Campbell et al. (2020), the usage of AI in Marketing offers many potential applications in various stages of the marketing process. This way, the authors recognize that there are several stages in the marketing process, nine to be more precise, and there are numerous ways in which Artificial Intelligence can be useful in each of them. In a first stage, there is a need of analysing the environmental situation that could affect the stakeholders and the organisation. In this phase, AI can help with the simplification of the understanding of large data sets, recognize abnormalities in the market and the recommendation of systems to help identify plausible future events. The second stage pertains to the understanding of the way market’s function and the customers behaviours and attitudes, and so the way in which AI could aid is by identifying the shifts in the behaviour of the competitor, assessing if the customers are satisfied and content and estimate the demand of the product.

The third stage relates to a more technical aspect of marketing, the segmentation, targeting and positioning, with AI coming in hand by classifying into the different segments, estimating the probability of a positive response to promotions, improving their targeting of ads and recommendation of products and brands. Stage four concerns the planning of the direction to take and the more long-term objectives, with AI aiding by providing a digital customer service via chatbots, the estimation of the receptivity of the consumers to the price shifts and promotions and identifying the most likely to purchase.

With stage five comes the development of the product strategy, and by identifying the gaps in the market for a new product development, creating a more customised product and assisting with the design and production of products that would be customised to isolate consumers, AI would be very useful. By stage six, there is a development of the pricing strategy, with AI assisting in the estimation of consumer price elasticity at both an individual and collective level, provisioning dynamic pricing and detecting anomalies. With stage seven, comes the development of channels and the logistics strategy, with the prediction and improvement of the distribution, inventory, and store display and layouts process being a way for AI to assist the process.

Developing the communication and the influence strategy is what comes next, in stage eight, with AI being of usage in creating ads that take in consideration content and that are individualised, as well as an optimization of ad placement. Finally in stage nine there is a planning of metrics and implementation of control, with the aid of AI in assisting in the prediction of expected revenues and profit and the outcome of the correct actions, while also diagnosing what could be done to improve.

Table 2.2 - The nine stages of the marketing process

The nine stages of the marketing process	
Stage 1: Analysing the current situation	Entails grasping the macro-level environmental factors that could impact the organization, its marketing strategies and its stakeholders
Stage 2: Understanding markets and customers	Involves acquiring insights into microenvironmental factors that directly influence the company such as market share dynamics, demand for products/ categories, and customer attributes encompassing needs, desire, behaviours, attitudes, brand preferences and purchasing habits

Stage 3: Segmenting, targeting, and positioning	Entails cultivating insights into customer segments and aiding in targeting and positioning strategies
Stage 4: Planning direction, objectives, and marketing support	Involves formulating extended-term goals and corresponding short-term objectives to bolster overarching strategies
Stage 5: Developing product strategy	Involves the development of the range of products offered by a company
Stage 6: Developing pricing strategy	Centers on devising pricing strategies aimed at optimizing sales
Stage 7: Developing channels and logistics strategy	Involves making decisions regarding logistics, distribution, and inventory management
Stage 8: Developing marketing communication and influence strategy	Centers on delivering targeted promotions to customers at opportune moments
Stage 9: Planning metrics and implementation control	Entails identifying, monitoring, and taking necessary action based on performance metrics

Source: Campbell et all., (2020)

There are some areas with the potential to benefit massively when integrating AI in their operations. According to a McKinsey & Co. study (2018), the areas that could improve substantially with this execution are Marketing and Sales. The close relationship with customers and massive data gathering, gives these industries a privileged position in analysing and using this information for personalised and accurate suggestions.

The utilisation of AI in the creative processes in marketing is one area with massive potential. According to Pagani & Wind (2024), the usage of AI on creativity in marketing is transformative, as AI not only boosts individual creativity, but improves marketing performance, as a new instrumental tool, a gateway to explore innovative ideas and a method for breaking down the creative process itself. Ultimately, the integration of AI into marketing, automates routine tasks, enabling marketers to shift their focus toward strategic and innovative thinking, conduct more in-depth data analysis, and serve as a catalyst for creativity in content creation.

The various different software's and technologies that allow this personalization are vast and constantly evolving. From predictive analytics tools, recommender systems, search engine optimization, dynamic creative optimization, AI-driven chatbots offering real-time customer support, all these automating and tailored processes are helping marketers enhance efficiency and boost customer satisfaction. According to Verma et al., (2021), AI-driven chatbots, powered by Natural Language Processing (NLP), have significantly enhanced customer experiences by enabling seamless and personalised interactions, while Machine learning (ML) algorithms efficiently process vast amounts of data, allowing businesses to make informed decisions. With AI playing a crucial role in analysing customer behaviour, including habits, preferences, and purchasing patterns, in Customer Relationship Management (CRM), AI User Interfaces (AIUI) have streamlined operations and improved customer engagement.

Moreover, AI and the Internet of Things (IoT) have transformed traditional retail into smart stores, improving both the shopping experience and supply chain management. Beyond physical stores, AI also powers online businesses, driving personalised services and operations, with recent advancements in AI even leading to machines being capable of tracking human senses—sight, hearing, taste, smell, and touch—further showcasing the technology's potential in enhancing human interactions (Verma et al., 2021).

Another highly employed technology is Search Engine Optimization (SEO), which according to Almukhtar et al., (2021), is the process by which a website or web page is optimised to increase the volume and quality of organic traffic from search engines, meaning that in order to have a successful SEO, there needs to be an improvement in a page's chances of ranking higher on search engine results pages (SERP). With Google being the most famous search engine, SEO would be the process of improving your website's ranking on Google and other search engines, increasing its visibility to more users, expanding your business, and establishing your company as a leader in the industry.

Recommender systems fall under the broader categories of information retrieval and natural language processing techniques. In e-commerce, recommendation systems are crucial as they enhance profitability by helping users discover relevant products, leading to increased sales, a mutually beneficial model for both sellers and buyers. These recommender systems are applied in various domains beyond e-commerce, such as suggesting movies to users, curating personalised news feeds, and recommending new music (Harinath & Kumaran, 2015).

When it comes to remarketing, as defined by Isoraite (2019), it is a process that allows advertisers to target consumers who are already familiar with their businesses, by tracking past visitors to a website. With this strategy it is possible to re-engage visitors who may have left the site without taking action, by encouraging them to return and complete a purchase or utilise the service they offered. Additionally, according to Arya et al., (2019), this vast amount of data and consumer’s personality, buying behaviour and online activity, allied with the advanced computer technology not only enhances their brand experience, but fosters their sense of attachment to the brand.

Based on Kumar et al., (2021), the availability and evolution of the digital world has made its consumers more aware and qualified to use these technologies, meaning that their demand for effective and functional solutions for the problems they face is a requirement. This increase in the importance of the utilisation of technology, has meant that there are new technologies that have been created and utilised more than ever. These new technologies are Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT) and blockchain. Although these technologies are still considered new age, their adoption by the mainstream population is due to happen in the future.

As described by Akter et al., (2021), today's customers are more demanding than ever, seeking speed, convenience, and flexibility with every purchase. The expectation of a seamless experience, whether shopping in-store or online with the ability to pick up online orders in-store, even after hours, increasing exponentially. Showrooming is increasingly common, with customers using mobile phones to find better prices online while examining products in-store, additionally demanding faster delivery, the so-called "express delivery". In order to meet these expectations, retailers must adapt and refine their multichannel strategies.

According to Hajdas et., al (2022) with the shift towards a seamless consumer journey in the retail industry, driven by a customer-centric approach and influenced by the technological advancements, widespread use of mobile phones and the rise of consumer expectations, has meant that marketing channels are becoming increasingly interconnected, leading more companies to adopt omni-channel strategies. With the usage of these strategies, the main challenge for retailers is how to fully integrate these channels while optimising the customer experience, allowing for a smooth and interchangeable use of various marketing platforms.

Omnichannel is a modern retail strategy aimed at enhancing the customer shopping experience by addressing the limitations of the multichannel approach. It responds to changing consumer habits, where customers frequently switch between online and offline stores and increasingly rely on digital devices like smartphones and tablets. By coordinating multiple channels and customer touchpoints, omnichannel retailing seeks to provide a seamless, integrated experience that optimises both customer satisfaction and channel performance, while considering the impact of channel integration on customer behaviour and purchasing decisions (Hickman et al., 2020).

For that reason, as defended by Pereira et., al (2022), in the global multi-trillion dollar fashion industry that faces challenges related to social and environmental sustainability, as well as the shift towards digital, customer-centric operations, the shift to Decision Support Systems (DSSs) is essential, more recently with fashion recommendation systems (RSs) that have been developed based on customer models (CMs) that include basic customer data, such as body measurements, along with additional inputs like clothing features and usage context. With these systems it is possible to reduce information overload, offering personalised services that help customers make better decisions, as researchers emphasise the importance of considering personality and emotions in fashion e-commerce.

This can also be integrated in retail online stores with an omnichannel approach allowing grocers to leverage AI algorithms and advanced analytics tools to automate and enhance various processes, enabling features like quick, cashier-free checkouts, in-store navigation, and personalised promotions. As online shopping adoption grows across Europe, implementing an omnichannel strategy is crucial for grocers' future success, as developing mobile apps for online shopping, offering home delivery, or curb side pickup options, significantly enhances convenience for shoppers (Neurauter, 2022).

Although many retailers have recognized the importance of omnichannel strategies, according to Shi et al., (2020), there remains a significant gap between customer expectations and the omnichannel capabilities that retailers currently offer, with most omnichannel customers not being effectively served, as companies struggle to address specific customer needs with their existing channel setups. Additionally, many retailers have established multichannel platforms, such as web, mobile, physical stores, and social media, but continue to operate them in isolated business processes, with the overall quality of the customer experience being the key factor influencing shopping intentions and determining the success of omnichannel strategies.

When looking at how this personalization and seamless customer experience can be obtained, according to Baardman et al., (2021), dynamic creative optimization (DCO) has become one of the solutions to guarantee the maximisation of revenue while addressing constraints such as minimising ad fatigue, ensuring retargeting, and maintaining user diversity. This stems from the core challenge for advertisers of not merely displaying the right product to each user, but also showing the right creative to match individual preferences, while simultaneously reaching a broad audience that remains engaged. Even though this technology is evolving, currently, DCO is carried out using heuristic and rule-based approaches defined by the advertiser, leading to ads that are not fully personalised but are tailored to broader customer segments that the advertiser has divided the campaign into.

But regardless of this breakthrough in the marketing field, this type of development could bring both positive and negative implications. When looking at the way humans react to this technology, there could be some divergent responses. Although AI could, for example, improve a salesperson's capabilities by having those standard responses that fit every customer, when a customer knows that they are talking to a bot, this could become uncomfortable and inconvenient (Davenport et al., 2019).

Bearing this in mind, this type of reactions and limitations need to be studied and analysed in order to understand the most effective way in which we can implement this AI powered marketing strategies. The need for more research on how AI could be utilised to solve marketing problems is ever more growing, as the only way in which a marketing team could be successful would be to be better equipped in knowing how to apply a Marketing AI solution (Overgoor et al., 2019).

This type of limitation was also addressed by Santoro et al., (2024), that pointed out that some challenges associated with AI-driven growth-hacking strategies, such as the need to experiment through trial and error in order to understand what works and what doesn't work, ultimately leading to more effective and fruitful strategies, the need to maintain human input and aid creativity, rather than substituting it and the need to have more extensive data so that AI can obtain better results and reach more accurate decisions. Moreover, some of the other challenges related to the implementation of AI, according to Rosa et al., (2022), are the associated high costs of these technologies to the companies and the loss of relationships with human and customer.

2.3. Relation between consumer behaviour and Artificial Intelligence

With the evolution of AI, there is a natural relation between this technology and the way consumers behave. Its application in Marketing means the discovery of new ways of making it more efficient. AI is now used as a way to not only dissuade and influence costumers when it's time for them to conduct their purchases, but also to aid them while they are visiting websites. But the evolution of how consumers behave, influenced by the advancements in AI, meant that the conventional marketing strategies were no longer effective in the understanding of human behaviour. (Jain et al., 2024)

According to Anayat et al. (2023), with globalisation and Industry 4.0, technological fields like the Internet of Things (IoT) and artificial intelligence (AI) are increasingly penetrating markets and shaping the business landscape. AI, in particular, is emerging as a pivotal force in driving the fourth industrial revolution, the so-called Industry 4.0. The introduction of AI-based innovations into markets is significantly transforming consumer behaviour and, in this AI-driven environment, consumers' decision-making processes are evolving accordingly.

The integration of artificial intelligence has the potential to transform the dynamics of customer-business interactions. Companies are increasingly turning to AI technologies fuelled by data analytics to navigate persistent margin challenges, shorter strategic cycles, and rising customer demands, translating in a shift that redefines how firms engage with their clientele by offering opportunities for enhanced customer-brand connections (Ameen et al. 2021).

According to Jain et al. (2024), businesses are able to excel by enhancing personalization, targeting, segmentation, and automating marketing tasks, consequently leading to greater efficiency and accuracy. Because of this rapid expansion the need for a higher level of comprehension due to its application to critical tasks, has been necessary.

As stated by Evans & Ghafourifar (2019), when looking at it in more specific terms, these advancements in AI can lead to an enhancement of the customer experience with the new gain knowledge of these customers preferences and their shopping patterns. With this information, retailers can then use this technology in several ways like the AI-powered chatbots, customer insights and content generation, and personalize services based on past preferences and purchases (Ameen et al. 2021).

The attempt to continue searching and innovating to improve the way we manage and stimulate Consumer Behaviour is ever more important, as it is the aim of marketers to influence the way consumers make independent decisions, ultimately influencing the way society behaves (Hawkins & Mothersbaugh, 2016, as cited in Olan et al., 2021).

In today's day and age, the level of influence that AI has in the consumer choice is very high. Websites like Netflix and Amazon use this technology to make suggestions to the consumer based on their preferences, while other programs like the ones used in autonomous cars, use this technology to drive the car, as well as predict the preferable route and driving style (André et al. 2017).

But with this evolution, also comes some disadvantages. Although this evolution in AI means an improvement in efficiency, productivity and quality of decision making, there is also a risk of structural unemployment, a rise in inequality, the surfacing of new undesirable industrial structures and a risk of job polarisation (Abrardi et al., 2022).

Looking at more specific usages of AI, there is an ever-growing adoption of Artificial Intelligence Voice Assistants (AIVAs) by consumers. According to Dellaert et al., (2020), even though the usage of this technology has the potential of being more interactive and helpful, not much is known about how the decision processes in verbal dialogs can differ from verbal environments. This shift can have consequences, like the trade-offs between autonomy and efficiency. Despite not much being known about this novel technology, according to P&S

Intelligence (2020), the global market for voice assistants generated $1,723.6 million in 2019 and is projected to reach $26,872.6 million by 2030.

According to Dwivedi et al., (2021), there are several expected benefits such as the cost reduction, the streamlined customer interactions and the increase in flexibility, but on the other hand, other problems might arise, such as trust issues among customers. The lack of human interaction and the additional endeavours required from consumers might influence negatively their overall experience as stated by Malle et al., (2015).

Chapter 3 - Theoretical Approach

Following the Literature Review previously elaborated, there were several topics in need of further investigation. For that reason, five research questions were created as a way to tackle these inquiries throughout the chapter.

The automation and facilitation for consumers in the fields of Artificial Intelligence and data analytics has been an ever more reality, leading to an emergence of micro-targeting marketing practices. This approach in marketing has led to more satisfied consumers, since their choice process is facilitated, more efficient and practical. As pointed out by André et al. (2017), the standard economic perspective of utility theory, the evolution of these technologies should aid consumers in getting better options that cater to their needs, while having lower search costs and higher utility derived from their choices. By providing marketers the ability to deliver the right product and/or service, the consumer will be relieved from the hurdle of having to choose, allowing them to save up in searching costs and other possible difficult trade-offs.

Even though this is a known reality, there is still some aspects of the conjunction of these two topics that are still not so well understood like how these AI-based shopping experiences can lead to a shift in how consumers perceive the quality of service, adapt their commitment to the relationship, and assess their overall experience empowered by AI (Jarrahi, 2018). However, given the rapid development of AI, and consequently its growing usage, researchers recognize the necessity for up-to-date empirical evidence in this domain. This recognition led to the formulation of the first research question:

(Q1) How does AI-Powered personalization influence customer decision-making processes and choices?

Following the reasoning above, the implementation of these strategies is still under evaluation. According to Ameen et al. (2021), companies are increasingly adopting AI technologies enabled by data analytics to address ongoing margin pressures, shorter strategy cycles, and heightened customer expectations. These AI advancements hold promise in enhancing the customer experience, by improving companies' understanding of customer preferences and shopping behaviour.

In accordance with Asaju (2024), the future of AI in marketing personalization is evermore growing. With the advancement in AI models, there will be an assimilation of diverse data streams, leading to an enhancement in their predictions of consumer behaviour. Consequently, brands will craft hyper-personalised encounters, blurring the boundaries between marketing and authentic customer rapport even more. In the same way, Bi et al. (2024), also states that with AI models advancing and integrating novel data streams, brands can generate hyper-personalised experiences, dimming the distinction between marketing efforts and authentic customer connections.

As stated by Evans (2019), the strategic deployment of AI technologies across various crucial customer touchpoints can thus yield substantial advantages for companies, potentially leading to heightened customer satisfaction. According to Solis (2017), previous studies indicate that in the retail industry, AI implementation can target the top 1% of customers, who hold a value 18 times higher than average customers for retailers. This is accomplished through highly personalised interactions and increased engagement, utilising contextual and behavioural data.

This transition to personalised marketing empowers brands to cultivate stronger bonds with consumers, nurturing engagement, brand allegiance, and ultimately, a formidable competitive advantage. Insights from Customer Relationship Management (CRM) data, purchase history, demographics, and prior interactions are invaluable for understanding customer preferences. Meanwhile, browsing behaviours, content consumption, and time allocation on specific pages provide essential hints about customer interests (Craig et al., 2024).

As claimed by Okorie et al., (2024), in order for brands to harness advantages from AI-driven personalization, there must be a prioritisation of trust and ethical data handling with their customers. The complexity and opacity of many AI algorithms often obscure how consumer data shapes personalised experience, leading to feelings of distrust and manipulation. Transparency regarding AI's role in personalization is essential for fostering consumer trust and ensuring ethical practices by brands.

As AI personalization advances in the future, the responsibility falls on brands to uphold its positive impact, nurturing trust and cultivating a personalised marketing environment that benefits all stakeholders. While AI-powered personalization is undeniably influential, it introduces ethical considerations and challenges to address. Thus, responsible implementation becomes essential for brands seeking to harness personalization's advantages while maintaining trust and adhering to ethical data practices (Reis et al., 2024).

According to Babatunde et al., (2024), it's imperative for companies to remain updated on evolving regulations and establish thorough data collection and usage protocols. In navigating this landscape, traditional marketing metrics may necessitate adjustment, and the creation of new metrics could be essential. Embracing this evolving future, both brands and consumers can benefit from the potential of AI-driven personalization in marketing.

For that reason, the second research question was created:

(Q2) How do businesses implement AI personalization in their marketing strategies, and what are the challenges they face?

In recent years, both behavioural economics and artificial intelligence (AI) have experienced rapid expansion as areas of study. As stated by Aoujil (2023), Behavioural Economics seeks to integrate insights from psychology, sociology, and neuroscience with traditional economic theory to unravel the intricacies of human decision-making within complex economic contexts. Meanwhile, AI strives to develop intelligent systems capable of emulating human cognitive functions like learning, problem-solving, decision-making, and language comprehension.

According to Königstorfer & Thalmann (2020), even though the utilisation of AI in Behavioural Economics is still relatively a novel subject, due to being an interdisciplinary subject (with an intersection in various fields such as computer science, mathematics, psychology, and economics), a lot of progress has been made in recent years. Because of this integration into sub-fields like finance and advertising, several scholars have created algorithms capable of anticipating consumer behaviour, projecting stock market trajectories, and discerning and mitigating human biases (Huang & You, 2023).

Moreover, AI has facilitated the development of behavioural simulations, offering valuable perspectives on how diverse economic, regulatory, and behavioural elements might influence both consumers and organisations within a market setting. The potential uses of AI in behavioural economics are extensive and diverse, leading to a promising and optimistic future for the field (Banal-Estanol & Micola, 2011). Hence the second research question was developed:

(Q3) What are the key principles of behavioural economics that can be integrated into AI personalization strategies?

The way these principles are integrated in the personalization algorithms and systems is crucial. According to Sadeghian & Otarkhani (2023), with the rise of digital devices, a new field called digital nudging has been created. This field explores techniques for nudging behaviour within digital contexts, integrating big data analysis, smart technologies, and Artificial Intelligence algorithms. As stated by Gao & Liu (2022), with this newfound attention in the digital realm, as individuals face significant choices in online interactions, such as e-commerce and e-government platforms, it is crucial for practical policy reasons to encourage informed decision-making in digital environments.

While personalised nudging offers opportunities for enhanced effectiveness in nudging programs, such as those in public policy, health, and sustainability, it also poses considerable challenges. According to Mills (2022), personalised nudging may jeopardise universality, crucial for consistent policy frameworks and social cohesion, undermine transparency in areas like law and regulation, and increase the risk of compromising data privacy.

After Susser & Grimaldi (2021), described a field of automated influence, with a spotlight on targeted advertising, digital nudging, and recommender systems, it was possible to pinpoint four primary worries associated with automated influencing such as privacy, autonomy, economic harm and epistemic harm. Moreover, Von Der Weth et al. (2020) suggests that researchers clarify that while personalization boosts the efficiency of data-powered digital nudging, it may also undermine users' privacy and autonomy.

As indicated by Schmauder et al. (2023), it's crucial to emphasise that although AI-generated nudges may yield desired results, a significant issue arises due to the absence of a precise understanding of human cognitive processes. As a result, predicting potential unintended side effects from these nudges becomes challenging. Additionally, in accordance with Sabolev & Lesic (2022), certain users might exhibit heightened sensitivity towards personalised digital nudging practices and be susceptible to harm due to their characteristics, such as age, health, and wealth, alongside situational factors like time constraints or distressing life events. With the survey of these possibilities, my fourth research question was formulated:

(Q4) How can these principles be effectively incorporated into AI-powered personalization algorithms and systems?

Beyond these behavioural principles being integrated successfully, the outcomes of their application are of the utmost importance. There are various ways in which they can be integrated to help better navigate technological aspects of businesses, such as Decision Support Systems. As claimed by Arnott & Gao (2019), various theories of decision-making have been crucial to decision support systems, as Behavioural Economics better helps comprehend human decision-making.

There are several areas and topics within Decision Support Systems research that could greatly benefit from Behavioural Economics as a foundational theory. There is a predominant focus on heuristics and biases in current DSS research, however, there is a growing utilisation of dual-process theory, while prospect theory and nudging are emerging as increasingly referenced theories. Therefore, Decision Support Systems researchers should recognize that Behavioural Economics extends beyond mere heuristics and biases, with theories and methodologies such as dual-process theory, prospect theory, and nudging offering substantial potential for advancing Decision Support Systems research (Arnott & Gao, 2019).

Other terms and theories related with behavioural economics have also been an object of study. As noted by Ingendahl et al. (2021), there is a noticeable increase in research attention towards subtle adjustments in choice architecture, known as nudging, which exert significant influence on consumer behaviour. As per Demarque et al. (2015), the better understanding of these matters, in the particular context of shaping consumer choice behaviour, can lead online retailers to employ these nudges to steer customers towards purchasing particular products.

According to Ingendahl et al. (2021), despite the growing relevance of the application of nudging in more practical settings, there is still little research on whether the effectiveness of these nudges is influenced by the consumer's personality. Thus, a more in-depth study could help identify potential challenges in implementing certain nudges for specific subgroups, while also demonstrating how nudging interventions could be tailored to individual personalities to maximise their influence on consumer behaviour. Consequently, examining whether a specific personality trait moderates the effect of nudging would provide additional insights into the reasons behind the effectiveness of nudges in influencing compliance. These promising outcomes of the integration of AI with BE and future possibilities lead me to my fifth research question:

(Q5) What benefits arise from integrating AI with Behavioural Economics?

Chapter 4 – Methodology

4.1. Research Model

Research requires a thorough examination of a subject, often with the goal of uncovering new information or achieving a deeper comprehension. According to Bell and Waters (2018), research aims to gather and analyse data in order to seek answers to questions, and it is composed of three stages: the elaboration of a question, the data collection to answer said question and the presentation of a final answer.

In this study, there is an exploratory aspect, as there is still a lot left to explore regarding Marketing and the influence AI has on its optimization. Moreover, the specific association of Behavioural Economics with AI-personalised ads is still not well explored. After incessantly researching on this topic, I believe this is the first investigation delving into the junction of Behavioural Economics notions with AI personalization strategies and the possible outcomes of this association.

Following these considerations, it was decided that a qualitative approach would be the most suitable method for this investigation, as it places a greater emphasis on understanding the phenomena. As explained by Hennink et al. (2020), qualitative research is a methodological approach that enables thorough examination of individuals' experiences through specific research techniques, making it possible to uncover issues from the viewpoint of study participants and comprehend the meanings and interpretations they attribute to behaviours, events, or objects. While the response rate and participation in interviews were satisfactory, its essential to be mindful of the limitations of this investigation. The reliance on a relatively small sample size, which leads to broad generalisations, and the gaps in the literature review were anticipated limitations taken into account from the beginning.

Table 4.1 - Relationship between literature review, the objectives and the research questions

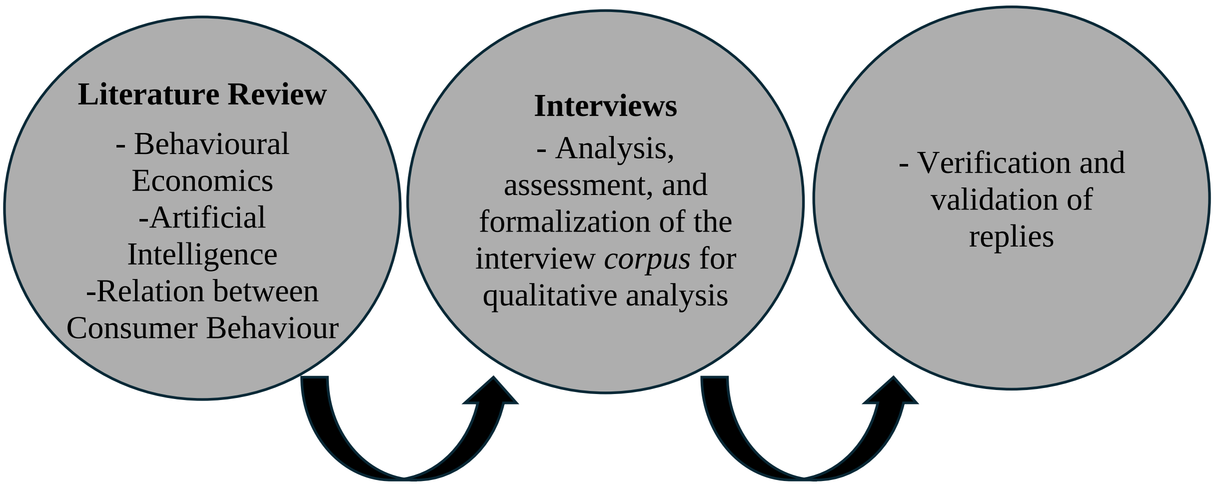
Objectives	Research Questions	Literature Review
Investigating the impact of AI personalization on consumer behaviour	(RQ1) How does AI-Powered personalization influence customer decision-making processes and choices?	Malle et al., (2015); André et al., (2017); Jarrahi (2018); Evans & Ghafourifar (2019); Dwivedi et al., (2021); Olan et al., (2021); Ameen et al., (2021); Abrardi et al., (2022)
Assessing the current landscape of AI-powered personalization in Marketing	(RQ2) How do businesses implement AI personalization in their marketing strategies, and what are the challenges they face?	Solis (2017); Evans (2019); Davenport et al., (2019); Overgoor et al., (2019); Huang & Rust (2020); Campbell et al., (2020); Kumar et al., (2021); Ameen et al., (2021); Asaju (2024); Bri et al., (2024); Babatunde (2024); Craig et al., (2024); Okorie et al., (2024); Reis et al., (2024)
Understanding how there could be an integration of behavioural economics principles into AI	(RQ3) What are the key principles of behavioural economics that can be integrated into AI personalization strategies?	Banal-Estanol & Nicola (2011); Königstorfer & Thalmann (2020); Hernandez-Cervantes (2022); Aoujil (2023); Huang & You (2023); Dold (2023); Qi et al., (2023)

personalization strategies	(RQ4) How can these principles be effectively incorporated into AI-powered personalization algorithms and systems?	Von Der Weth et al., (2020); Susser & Grimaldi (2021); Mills (2022); Gao & Liu (2022); Sabolev & Lesic (2022); Otarkhani (2023); Schmauder et al., (2023)
	(RQ5) What benefits arise from integrating AI with Behavioural Economics?	Demarque et al., (2015); Arnott & Gao (2019); Ingendahl et al., (2021)

Source: Self-Elaborated

In conclusion, this investigation unfolded through four distinct phases. Initially, a thorough review of relevant literature was conducted, with a collection of the existing information on the subject matter; following this, the theoretical framework was translated into practical observation, with the objective of ensuring the utmost reliability in the results; subsequently, fieldwork was undertaken, involving data collection through interviews and lastly, the gathered interview data underwent qualitative analysis.

Figure 4.1 - Research Model



Source: Self-Elaborated

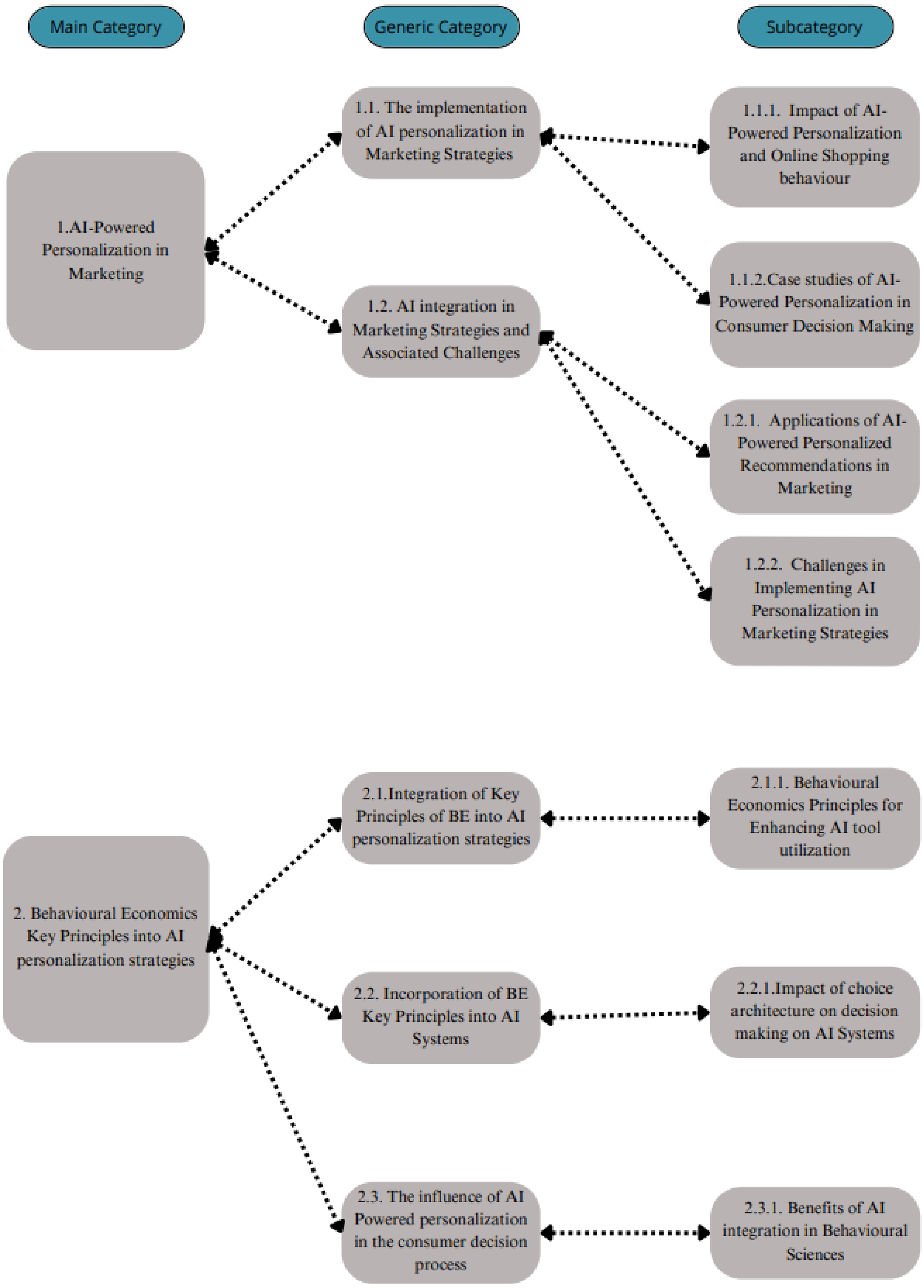
4.1.1. Data Collection Method

For methodological purposes, the data was collected through the realisation of one-to-one semi-structured interviews using a non-probabilistic convenience sample, selected based on the availability and accessibility of the participants (Manuel Da et al., n.d). The target interviewees were selected based on the know-how on the matter in study and the job performed in the same area, whether they were individuals with medium to high decision-making authority and strategic expertise within the organisation or connected to the field in an academic perspective. The aim was to understand and analyse the knowledge and expertise of the respondents and have a broader sample of opinions.

As stated by Vilelas (2020), a study requires 15 to 20 interviews to achieve an acceptable degree of reliability. After conducting 11 interviews, a noticeable repetition of ideas emerged, so in consideration of this and Vilelas' criterion, the interviews were concluded after 15 sessions. Nevertheless, despite meeting the recommended number of interviews, it is important to interpret the study's conclusion with caution due to the small sample size.

As mentioned previously, semi-structured interviews were chosen as the data collection method. The approach was selected in order to avoid restricting participants to a predefined script, thereby encouraging more detailed responses and capturing a wider range of information. The research adopted a pragmatic or inductive approach, focusing not on establishing true or false conclusions, but on analysing various phenomena and facts to enable comparisons and explore correlations.

Figure 4.2 - Categorization and Codification of the interview for qualitative analysis



Source: Self-Elaborated

Based on Bardin (2018), content analysis involves three phases, starting with pre-analysis, which entails organising and systematising ideas from the interviews, followed by the exploration of the material, where the content is coded and categorised, and finalised by the treatment and interpretation of the results. For this investigation, content analysis of the interview data was conducted using MAXQDA 24.4. This tool is a professional software for qualitative data analysis, facilitating not only the transcription and analysis of interviews, but also the categorization of pertinent data using codes.

4.1.2. Interview's procedure

A crucial stage of the research involved planning the interview and developing the corresponding script. The interview script was structured into two sections: the first consisted of 1 question designed to characterise the sample, while the second comprised questions aimed at achieving the study's primary objective. This objective focuses on understanding how there could be an integration of behavioural economics principles into AI personalization strategies while also addressing the current landscape of AI personalization in marketing, the advantages and obstacles of said utilisation and the relevance it poses for future applications.

In order to conduct said interviews, the participants were contacted through the LinkedIn app and website or through email, requesting them to participate in a research project focused on the possible integration of behavioural economics principles into AI personalization strategies, with the aim of improving the marketing efforts. The conduction of the interviews was achieved by using Zoom or telephone platforms.

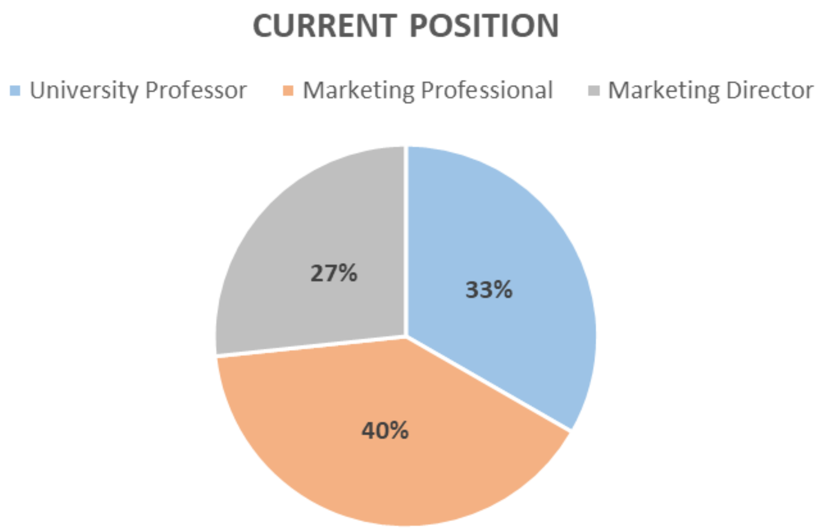
The interviews were conducted from May 16, 2024, to June 18, 2024, each lasting approximately 20 minutes and all being recorded. Confidentiality of personal data was strictly maintained in each interview and made clear to the interviewees in the beginning. In all interviews the objective of the investigation and a brief overview of the topic of Behavioural Economics was explained by means of contextualization and clearing of possible misunderstandings. For data analysis purposes, all 15 audio interviews were meticulously transcribed, with all of them being translated to English.

4.2. Sample Characterization

For the formation of the sample of this study, the participants were picked from a specific population, based on their knowledge on the matter at hand and the level of expertise working on the field. Since the aim of this study is to analyse various opinions and inputs from professionals in the area of Marketing, the common denominator for all the interviewees is their connection to this field. Therefore, in order to conduct the sample characterization, the parameters sector of activity, current professional activity, years of experience and dimension of the organisation were considered, while parameters like gender were dismissed due to the confidentiality agreement done in the beginning of the interviews.

When looking at figure 4.3, it is possible to denote that the majority of the interviewees current position within the company is of marketing professional (40%), followed by university professor with 33% and finally 27% of the respondents being marketing directors.

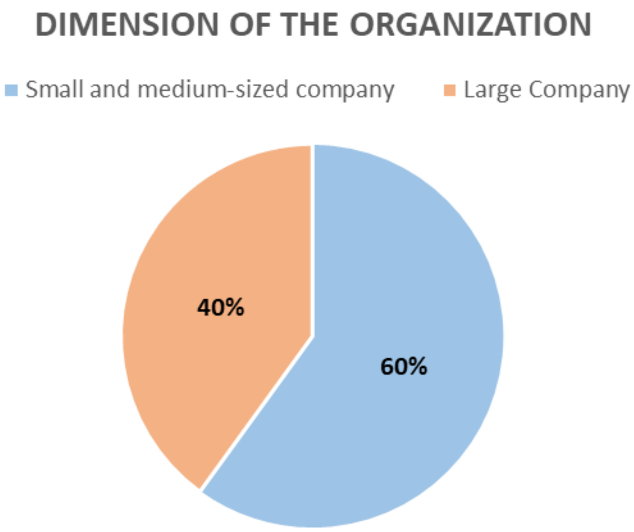
Figure 4.3 - Interviewees Current Position within the Company



Source: Self-Elaborated

As per seen in figure 4.4, out of the respondents not working in the academic field, about 60% of the interviewees are currently working at a small and medium-sized company, while around 40% are working at a large company.

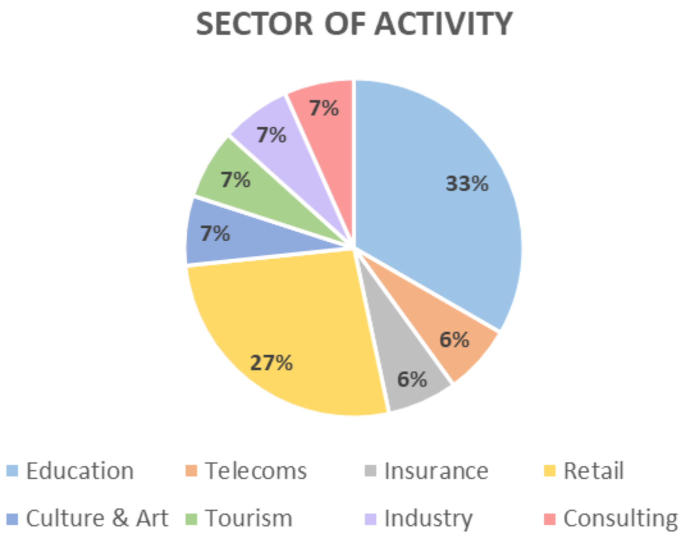
Figure 4.4 - Dimension of the Organization



Source: Self-Elaborated

Regarding the companies' sector of activity, in figure 4.5 it is possible to identify that 33% of interviewees were in the education sector, 27% were in the retail sector, the consulting, industry, tourism and cultural and art sectors all had 7% and finally the insurance and telecoms sectors had 6% of interviewees working.

Figure 4.5 - Companies' Sector of Activity

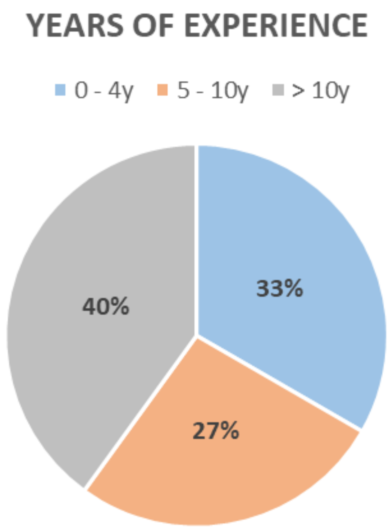


Source: Self-Elaborated

Pertaining the years of experience working in the Current Position, it is evident in table 4.6 that about 40% of the respondents have more than 10 years of experience, 33% have between

5 to 10 years of work experience and around 27% have less than 4 years of experience working in the field of marketing.

Figure 4.6 - Years of Experience working in the field



Source: Self-Elaborated

Chapter 5 - Data Analysis and Discussion

In this chapter, we will analyse the data collected from interviews and discuss it in relation to the literature reviewed in Chapter 1. Specifically, our focus will be on the integration of Behavioural Economics in AI personalization strategies while also assessing the current landscape of AI-Powered personalization in Marketing and its impact on consumer behaviour. Ultimately, the aim is to make the understanding of the connection between behavioural biases and AI personalization easier as well as optimise the marketing efforts.

5.1. The implementation of AI Personalization in Marketing Strategies

For this investigation, the first research category focused on looking more closely at AI-Powered personalization in Marketing and how its implementation has been made in a more strategic perspective. This involved looking at how impactful this personalization was when it came to consumer behaviour and shopping patterns as well as how this implementation could aid marketers when it came to reaching the right audience.

In table 5.1 it is possible to denote the various answers given by the interviewees regarding the impact this personalization had on the consumers and their decision-making process when utilising websites and apps as well as how this personalization helped marketers maximise its potential. As mentioned by André et al., (2017); Evans & Ghafourifar (2019); Ameen et al., (2021) with the evolution of AI it is possible to enhance the customer experience by utilising knowledge from previous preferences and shopping patterns, therefore catering more efficiently to their needs. As denoted in table 5.1, the majority of the respondents recognized that AI personalization in marketing, impacted greatly the consumers by showcasing ads derived from previous searches, preferences and purchases on websites and apps. Furthermore, this personalization enables companies to improve their websites and apps, influencing the overall experience and expectations of consumers. As pointed out by some respondents this personalization leads to greater consumer engagement throughout the consumer journey, which can ultimately lead to an improvement in sales and commitment to the brand as defended by Jarrahi (2018); Evans & Ghafourifar (2019); Ameen et al., (2021). Another factor deriving from the influence of AI personalization in marketing strategies is the improvement in targeting, segmentation and recommendation of ads, identified by the respondents as reaching the right audience. This consequently leads to greater efficiency and accuracy, while also augmenting the probability of a positive response to promotions as defended by Campbell et al., (2020); Ameen et al., (2021); Jain et al., (2024).

As denoted by Campbell et al., (2020), during the marketing process there is a need in developing the channels and the logistics strategy, as well as a utilisation of AI to plan metrics and implementation of control. This supports the element that was considered by some of the interviewees as the utilization of AI aids with a better usage of key words for add recommendation in websites and apps, leading to a more positive outcome not only for the consumers but also the marketers. According to authors Dinh & Lee (2022); Saibaba (2022); Hussain et al., (2023), the rise of technology and social media has led consumers to become more impulsive and less thoughtful behind the purchasing process, supporting the consideration given by two of the interviewees that noted that the personalization in marketing has led to impulsive behaviours in consumers.

Finally, the increase in brand visibility with the utilisation of AI in ads and websites was mentioned by one of the interviewees and supported by Campbell et al., (2020) who denotes that using this technology not only reaches the right audience but also allows the diffusion of the right ads and promotions to consumers.

Table 5.1 - Impact of AI-Powered Personalization and Online shopping behaviour

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Having ads related to previous shopping and search history	1.1	1.1.1	9	1,3,4,5,6,7,11, 12,15
Greater consumer engagement throughout the customer journey	1.1	1.1.1	4	2,9,10,15
Impact the right target audience	1.1	1.1.1	4	2,8,11,15
Usage of better keywords for add recommendation	1.1	1.1.1	3	9,13,14
Makes the consumer more impulsive	1.1	1.1.1	2	13,14
Increases brand visibility	1.1	1.1.1	1	13

Source: Self-elaborated

As described by Akter et al., (2021), the modern customers are increasingly demanding speed, convenience, and flexibility with every purchase, with the expectation of a seamless experience, whether it being shopping in-store or online with the ability to pick up online orders in-store, even after hours increasing exponentially. As it can be seen in table 5.2, for that reason the interviewees were asked to give examples where personalization affected the way people shop and make choices in order to understand where this personalization holds the most impact.

The majority of respondents used the example of online fashion retail stores as defended by Pereira et al., (2022) that fashion as an ever-growing industry, allied with the social and environmental sustainability and the shift towards digitalization customer-centric operations, made it the ideal candidate for the implementation of Decision Support Systems.

Hajdas et al., (2022) explained that the transition to a seamless consumer journey in the retail industry, motivated by a customer-centric approach, influenced by the technological advancements and diffused with the use of mobile phones and the rise of consumer expectations, has meant that marketing channels are becoming increasingly interconnected, leading more companies to adopt omni-channel strategies. From table 5.2 it is possible to denote that, a significant number of interviewees answered online grocery shopping apps and websites, as defended by Neurater (2022), that this personalization in retail online stores with an omnichannel approach that allows grocers to leverage AI algorithms to automate and enhance various processes, significantly enhances convenience for shoppers.

Considering the personalization in social media and similar online platforms, Hickman et al., (2020); Akter et al., (2021); Hajdas et al., (2022); Pereira et al., (2022) explained that with the evolution of technology, increasing demand of consumers, and rampant usage of mobile phones, the integration of marketing channels in these platforms is the new norm, with some of the respondents stating this as a very common example of personalization in their customer journey.

The recommendation of products and content based on individual preferences and ultimate shaping of consumers decisions, noted by André et al., (2017), in online streaming platforms and services was mentioned by 2 of the interviewees, while only a singular respondent mentioned online travel agencies and engines.

Table 5. 2 - Case Studies of AI-Powered Personalization in Consumer Decision Making

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Online fashion retail stores	1.1	1.1.2	7	5,6,7,9,11,14,15
Online Grocery Shopping apps and websites	1.1	1.1.2	5	1,3,4,6,13
Sponsored ads on social media	1.1	1.1.2	3	8,10,15

Streaming services or platforms	1.1	1.1.2	2	2,12
Online travel agencies and engines	1.1	1.1.2	1	2

Source: Self-Elaborated

5.2. AI integration in Marketing Strategies and associated challenges

The second research category focused on understanding how businesses implement AI personalization and the challenges they face in the process. Not only are both aspects critical for maximising AI's potential in marketing, but also gaining insights into effective AI personalization strategies and addressing the obstacles involved are essential for businesses to fully leverage this technology. For that reason, interviewees were asked to name examples on how businesses are doing this integration in order to promote their services or products.

Table 5. 3 - Applications of AI-Powered Personalized Recommendations in Marketing

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Product Engine Recommendation	1.2	1.2.1	8	4,5,8,9,11,12, 13,15
Remarketing	1.2	1.2.1	7	1,2,3,6,7,10,14
Search Engine Optimization	1.2	1.2.1	3	7,13,14
Dynamic creative optimization	1.2	1.2.1	2	2,7
Recommendations of keywords for ad design	1.2	1.2.1	1	2
Recommendations of platform design	1.2	1.2.1	1	7

Source: Self-Elaborated

As per seen in table 5.3, the most mentioned tool utilised by the respondents was product engine recommendation as it was pointed out that this technology aids marketers to reach the right audience, therefore increasing efficiency and customer satisfaction. This perspective is corroborated by Harinath & Kumaran (2015), who claim that recommender systems are paramount to boost profitability through helping users discover the right products, translating in a beneficial scenario to both sellers and buyers. Related to this system, is the strategy that implements it, with remarketing being indicated as the most prominent and effective. As denoted by Isoraite (2019) and Arya et al., (2019), this marketing strategy allows marketers to re-engage not only visitors of their website but also consumers familiarised with their business, culminating in enhanced brand experience and ultimately matching the interviewees responses of an effective marketing strategy. As it can be seen, three interviewees mentioned Search Engine Optimization as another beneficial tool in enhancing the marketing efforts, by allowing a website or webpage to be more visible, therefore maximising the online traffic that is directed towards it, as defended by Almukhtar et al., (2021). The personalization in ads and content showcased to consumers can also be obtained in real-time and automatically with advanced programmatic advertising that looks at data based on viewer's demographics, behaviour and location. Two of the respondents mentioned Dynamic Creative Optimization as another tool that enhances the performance of campaigns since it optimises the creative elements based on what are the preferences of the target audience as stated by Baardman et al., (2021). The usage of AI in order to better recommend the keywords that should be employed when creating an ad was mentioned by one of the interviewees, while another one stated that it could be utilised when designing platforms and websites, therefore being in accordance with Campbell et al., (2020); De Bruyn et al., (2020) and Jiang et al., (2022).

Table 5. 4 - Challenges in implementing AI Personalization in Marketing Strategies

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Difficulties in showcasing ads that are aligned with the consumers interests and needs	1.2	1.2.2	7	1,5,7,10,11,14, 15
Lack of knowledge on this subject among professionals	1.2	1.2.2	6	2,3,6,7,13,15

Insufficient humanization, sentiment and emotion	1.2	1.2.2	5	4,8,9,11,13
Legal and ethical issues	1.2	1.2.2	5	4,5,12,14,15
High implementation costs	1.2	1.2.2	4	1,2,7,13
Resistance from companies in implementing these technologies	1.2	1.2.2	4	6,7,13,15
Deficiency in the accuracy of the information displayed	1.2	1.2.2	3	2,3,8
Malfunctioning and bugs	1.2	1.2.2	1	10

Source: Self-Elaborated

Various authors such as Malle et al., (2015); Overgoor et al., (2019); De Bruyn et al., (2020); Dellaert et al., (2020); Dwivedi et al., (2021); Okorie et al., (2024) and Babatunde et al., (2024) alerted that despite the various benefits of the implementation of AI in marketing, there are always associated challenges and difficulties. Looking at table 5.4, the majority of the participants responded that a big challenge associated with the showcase of ads to consumers is that many times these are not aligned with the real customers preferences, oftentimes showing content that is either too repetitive or no longer relevant. This inefficiency with AI could be a result of the lack of technology and experimentation in this field as denoted by Santoro et al., (2024) and also due to the shift between a consumer's decision process happening in real time situations versus it happening in a digital setting, with the machine not understanding different nuances and basing its decision on programmed logic and past data as pointed out by Dellaert et al., (2020). Furthermore, the interviewees addressed the lack of knowledge among various marketing professionals on this subject, with this being a barrier in the implementation, understanding and efficient usage of AI in marketing strategies. This idea is supported by Overgoor et al., (2019) that mentions that a team's success depends on its ability to effectively implement AI-driven solutions and De Bruyn et al., (2020) stating that despite the various different definitions of AI, there still remains a lot of confusion, misunderstandings and misuse, make it challenging for its users. A large number of respondents recognized that the insufficient humanization, sentiment and emotion leads to not only a disengagement from the consumers, but also to less authentic and impactful campaigns and ads, as supported by Malle et al., (2015); Davenport et al., (2019); Dellaert et al., (2020); Dwivedi et al., (2020); Okorie et al., (2024); Reis et al., (2024) and Santoro et al., (2024).

The legal and ethical issues were mentioned by various respondents, as there is still a grey area regarding the field of AI, with these respondents questioning the limits of its usage and the parameters in which it stops being ethical. This claim is defended by Okorie et al., (2024), that states that in order for brands to fully leverage the benefits of AI-driven personalization, there must be a prioritisation in building trust and handling the customers data ethically, having transparency as a priority. Moreover, the high implementation costs associated with adopting AI in companies, makes it a challenge to dynamize this type of technology and apply it to strategies, as per said by Rosa et al., (2022). Equally, four interviewees mentioned the resistance from companies in implementing these technologies and keeping up to date with these trends, due to feelings of mistrust and misinformation, with Babatunde et al., (2024), claiming that it is imperial for companies to stay informed about evolving regulations and protocols in order to stay updated. According to Santoro et al., (2024), the need for trial and error in order to experiment, leading to better and more effective results, is essential, aligning with some respondents stating that there is still a deficiency in the accuracy of the information displayed, leading to errors and faults and also supporting the claim of another interviewee that mentioned the malfunctioning and bugs associated with the usage of this technology.

5.3. Integration of Key Principles of Behavioural Economics into Artificial Intelligence personalization theories

The third research category of this investigation pertains to understanding how there could be an integration of various key principles of behavioural economics into Artificial Intelligence personalization theories and in that way potentialize them. In order to garner this information, the interviewees were asked if they could name behavioural economics theories that they thought were beneficial in marketing or that they were already using. That way it would be possible to analyse the potential use of Behavioural Economics in AI and marketing and later understand its applicability.

Table 5.5 - Behavioural Economics Principles for Enhancing AI tool utilization

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Combination of various theories	2.1	2.1.1	9	2,4,5,6,7,8,9,13, 15
Loss Aversion	2.1	2.1.1	3	1,3,12
Sunk Cost Fallacy	2.1	2.1.1	3	1,10,11
Prospect Theory	2.1	2.1.1	3	3,6,14
Social Proof	2.1	2.1.1	2	1,15
Rational Choice Theory	2.1	2.1.1	1	14
Nudge Theory	2.1	2.1.1	1	15
Heuristics	2.1	2.1.1	1	15

Source: Self-Elaborated

When looking at table 5.5, it is possible to better understand, in summary, the respondents' opinions on the various different types of behavioural economics theories. According to Königstorfer & Thalmann (2020), although the intersection between AI and Behavioural Economics is still a novel subject, a lot of progress has been made and, with that evolution, the creation of algorithms capable of anticipating consumer behaviour have been growing in various sub-fields as defended by Huang & You (2023). As it can be seen, the majority of the respondents answered that they couldn't name just a singular theory or concept and that the combination of various ones made the strategies more effective and successful, also pointing out that with the evolution of AI, it would be possible to better develop behavioural simulations and ultimately better understand organisations and consumers in a market setting as defended by Banal-Estanol & Micola (2011). When looking at the loss aversion theory, we can see in table 5.5, that 3 out of the totality of the respondents answered that this was a crucial concept, when combining it with artificial intelligence personalization theories, since, according to Laibson & List (2015) losses tend to carry greater significance and impact for individuals compared to gains, as the pain from a loss is roughly twice as intense as the pleasure derived from an equivalent gain. Equally, 3 interviewees mentioned the sunk cost fallacy, that pertains to when individuals keep investing in a decision, project, or endeavour due to the cumulative past investments (time, money, effort) that cannot be recovered, instead of basing their decisions on potential future benefits and costs, as defended by Haita-Falah (2017). An also important theory that was noted by the respondents and is intrinsically related with the previous one was Prospect Theory, that explains how people make decisions under conditions of risk and uncertainty, unlike traditional economic theories where there is an assumption that people are fully rational, as referred by Kahneman & Tversky (1979) and Loomes (2010).

According to Roethke et al., (2020), when faced with uncertainty, individuals tend to rely on social proof to guide their actions, with companies taking advantage of this tendency by using social proof to showcase widespread adoption, especially in situations where uncertainty is high. This can be used online by influencing people's decisions based on testimonials, product reviews, follower accounts as it was mentioned by two respondents. As demonstrated by table 5.5, one respondent mentioned rational choice theory, with this theory stating that there is an assumption that individuals make decisions by carefully considering all available options to maximise their utility or benefit as described by Kahneman & Tversky (1979), while one respondent mentioned the nudge theory, as the concept of nudging allow individuals to be steered to a desired direction as defended by Thaler & Sustein (2008); Schmidt & Engelen (2020) and Sadeghian & Otarkhani (2023). Heuristics are mental shortcuts or rules of thumb that people use to make decisions and solve problems more quickly and efficiently. One interviewee mentioned this concept of Behavioural Economics, as instead of engaging in a thorough analysis of all available information, heuristics allow individuals to focus on a few critical factors to make judgments more easily, as affirmed by Slovic (1967); Tversky & Kahneman (1974); Finucane et al., (2000); Eisend (2008); Furnham & Boo (2010); Kahneman (2011); Lee & Seidle (2012) and Siegrist (2021).

5.4. Incorporation of Behavioural Economics Key Principles into AI Systems

The fourth research category of this investigation centred on understanding how having small changes in the way choices are presented could affect someone's decisions when utilising computer programs or apps. That way it would make it possible to better understand what factors could influence, either positively or negatively, people's perception of an ad or website.

Table 5. 6 - Impact of choice architecture on decision making on AI systems

Text	**Generic Category**	**Subcategory**	**Times mentioned**	**Interviewees**
User experience pertaining the good practices in websites and apps such as payment methods, after sales and delivery experience and logistics	2.2	2.2.1	6	1,2,4,5,6,12
Simplification of the website and app design	2.2	2.2.1	5	2,5,7,9,11
Aligning the website and app layout considering metrics analysis	2.2	2.2.1	4	3,4,8,15
Overexposure to ads	2.2	2.2.1	3	7,9,14
Having an app or mobile friendly website	2.2	2.2.1	2	7,10
Usage of video and images	2.2	2.2.1	2	11,13
Application of behavioural biases in the design of websites and apps	2.2	2.2.1	1	2

Source: Self-Elaborated

Table 5.6 provides an overview of the interviewees' opinions on the relevance of these changes and details, with the most considered answer among the interviewees, 6 out of 15, being the overall experience while using a website or app. The various answers presented, pertained to the payment method options, the after sales experience like adequate products or services recommendations, careful monitoring of the shipment process, efficient and timely delivery and logistics associated, as defended by Asiegbu (2012) and Albert and Tulli (2013).

The simplification of the website and app design was the next most answered response, with the respondents emphasising how the layout of all the apps and websites features made it easier and more intuitive to navigate it, therefore making it more likely for them to complete a purchase, an opinion also shared by Djamasbi (2016).

According to Albert & Tullis (2013) and Babatunde et al., (2024), the utilisation of metrics in order to better understand and analyse consumers behaviour online is crucial and this view was outlined by 4 out 15 interviewees who stated that this utilisation of metrics analytics such as the screen mapping of where people show the most interest or pay more attention, utilisation of words, terms or references to something that is trendy and on vogue at the time and adaptation to the target age groups, was a pivotal factor for decision making. Some respondents mentioned the overexposure to ads as having a negative impact when utilising computer programs or apps, stating that it caused feelings of discomfort, anger and annoyance, leading them to abandon the website or app more quickly, as noted by Davenport et al., (2019) and Campbell et al., (2020). With the evolution of internet and e-commerce, the ever-growing utilisation of apps websites on cell phones seems logical, with 2 respondents stating that having an app or mobile friendly website could be the difference between finalising a purchase or revisiting the brands online outlet, as defended by Hajdas et al., (2022). Two other interviewees indicated that the utilisation of video and images, meant that the consumer would be more engaged and drawn to the website and app, as this is more attractive and entertaining, as stated by Djamasbi (2016). A singular respondent mentioned that the application of behavioural biases in the construction of websites and apps could lead to better results and outcomes.

5.5. The influence of AI Powered Personalization in the consumer decision process

The fifth and last general research category of this investigation aimed to understand to what extent leveraging AI's advanced data analysis capabilities alongside insights from Behavioural Economics, would make possible the design of interventions that effectively account for cognitive biases and natural decision-making tendencies. AI's ability to process vast amounts of data, identify patterns, predict outcomes, and provide real-time feedback would only enhance the impact of Behavioural Economics, allowing for the continuous testing, refining, and personalization of decision environments but also ensure that interventions are both more targeted and effective.

Table 5.7 - Benefits of AI integration in Behavioural Sciences

Text	Generic Category	Subcategory	Times mentioned	Interviewees
Automation of processes and simplification of repetitive tasks	2.3	2.3.1	13	1,4,5,6,7,8,9, 10,11,12,13, 14,15
Enhancement of consumer insights and ad personalization through data utilisation	2.3	2.3.1	7	1,2,3,8,11,13, 15
Fosters greater creativity	2.3	2.3.1	7	3,5,6,7,10,12, 13
More effective application of cognitive biases and psychological and economic theories in advertising	2.3	2.3.1	5	1,2,3,11,15
Easier access to information	2.3	2.3.1	4	1,3,13,14

Source: Self-Elaborated

Table 5.7 presents the main benefits and advantages of the respondents when utilising Artificial Intelligence in their daily lives, while also establishing a connection to potential applications of Behavioural Economics. The automation of processes and simplification of repetitive tasks was the most unanimous answer, with 13 out of 15 interviewees mentioning that this functionality was one of the key advantages when using AI for the completion of activities, as supported by Campbell et al., (2020) and Pagani & Wind (2024). The rise of Artificial Intelligence has translated into an easier and more thorough access to information and details of consumers, leading to a more enhanced customer experience and personalised services as mentioned by Evans & Ghafourifer (2019); Ameen et al., (2021); Jain et al., (2024) and Pagani & Wind (2024). This notion was signalled by 7 interviewees, who highlighted that the integration of Behavioural Economics in these inputs could lead to greater results and an even more optimised outcome. With the same number of responses, the idea that implementing AI in everyday usage leads to greater creativity as defended by Pagani & Wind (2024). The respondents defended that utilising AI helped aid their creative process by enhancing their own ideas or helping generate others, ultimately leading to better and more engaging results. The advantages of using AI in advertising with customers being more demanding and companies utilising this newfound data, has led to a redefinition of customer-business dynamics, as identified by Ameen et al., (2021). This concept was mentioned by 5 respondents who highlighted that the integration of AI in this field translates to a more efficient application of cognitive biases and psychological and economic theories in advertising, once again establishing a new opportunity for the application of B.E theories and concepts. The insight that AI utilisation means having an easier access to information, as stated by Campbell et al., (2020), was shared by 4 interviewees, who observed that not only it saved time but also provided more complete and trustworthy information, while also emphasising the importance of curating information.

Chapter 6 - Conclusion

6.1. Final Considerations

Taking in consideration the previous analysis of data gathered from both interviewees and the considerations done by researchers regarding the topics of Artificial Intelligence, Marketing and Behavioural Economics, this final chapter aims to summarise the pivotal findings of this investigation. The topic of Artificial Intelligence has been studied for many years, but in today's day and age, this field has gained traction and more attention. Equally, the topic of Marketing has been gaining popularity amongst researchers with the evolution of social media and e-commerce demanding the optimization of this field. Additionally, the topic of Behavioural Economics has been attracting interest in the scientific field, as it has immense potential for application in various different fields.

Primarily, the first research question of this investigation intended to understand how the personalization powered by AI, influences consumers decision-making processes and choices. In order to get a clear understanding of this matter, the interviewees were asked not only about how AI personalization affected the way people make decisions when shopping online or using apps, but also to give more practical examples of situations where this happens. From the interviews conducted it was possible to infer that 60% of the respondents believed that this recommendation was effective, as usually it was possible to denote that they would have ads related to previous shopping and search history patterns, therefore making the ads they receive more adequate. A percentage of 27 respondents believe that this personalization leads to a greater consumer engagement throughout the customer journey, while the same percentage supports that it helps reach the right target audience. Only about 13% considered that this technology makes the consumer more impulsive, since the ads are more targeted and personalised, and about 7% of the interviewees acknowledged that it could increase the brand visibility. Overall, this personalization allows consumers to improve targeting, engagement, drives impulsive buying, and boosts brand visibility.

When looking at the answers given by the respondents about the examples where it is noticeable the influence of this AI-driven personalization in the customer behaviour, the vast majority of the interviewees, about 53%, mentioned online fashion retail stores. All of these respondents indicated that their personal experiences with online retail fashion stores provided adequate recommendations and options that positively influenced their clothing purchases. About a third of the respondents alluded to online grocery shopping apps and websites, stating that these websites allowed them to go through previous purchased items and be informed about new ones that fit their personal preferences. Some of the interviewees, about 20%, mentioned as an example the sponsored ads when utilising social media, while 13% mentioned the recommendation seen in streaming services or platforms. Only about 7% indicated the recommendations utilised in online travel agencies and engines.

The goal of the second research question was to understand how businesses are able to implement AI personalization in their marketing strategies and what are the challenges they face in doing so. In order to garner these answers, the interviewees were asked to give examples of how businesses are using personalised recommendations to promote their products or services, with the majority of the respondents, about 53%, stating that product engine recommendations are the most common example, since this technology assists marketers reach the right audience and consumers by discovering the right products, leading ultimately to more efficiency and customer satisfaction. About 47% of the interviewees indicated that remarketing was a relevant example since this strategy enables marketers to re-engage with visitors and recurrent consumers, while only 20% of the respondents referenced the technology of search engine optimization. Roughly 13% of interviewees highlighted the usage of Dynamic Creative Optimization, while 7% picked the example of utilising AI personalization to aid in the recommendation of keywords for ad design. Also, about 7% of the interviewees, opted for utilising this technology to assist in recommendations of platform design.

In order to further delve into this research question, the respondents were asked to indicate what are the challenges and obstacles that businesses face while trying to implement AI personalization in their marketing strategies, with the highest percentage of respondents, about 47%, mentioning the difficulties that this technology has in showcasing ads that are aligned with the consumers interests and needs, highlighting the display of ads that are their irrelevant or that no longer make sense to the user. The difficulties when handling these technologies and lack of knowledge on the subject was the next most common answer, with 40% of the respondents mentioning that many marketing professionals lack the know-how and expertise to handle and maximise the potential of this technology. About a third of the interviewees noted that the lack of humanization associated with this technology was still a barrier for both professionals and consumers, with also a third of the respondents mentioning the legal and ethical issues that arise when handling personal data of the consumers. The high implementation costs associated with the integration of this technology in businesses was referenced by 27%, which was also the same percentage of respondents that mentioned the resistance from companies in implementing these technologies. Only about 20% of the interviewees noted the deficiency in the accuracy of the information presented when utilising AI, and, lastly, 7% of the respondents indicated the malfunctioning and bugs as a constraint when using this technology.

In line with the purpose of this investigation, the third research question was designed to explore how there could be an integration of various key principles of behavioural economics into Artificial Intelligence personalization theories and concepts. To enable the gathering of this information, the interviewees were asked to name behavioural economics theories that they deemed appropriate when in conjunction with marketing theories, with the vast majority of the respondents, 60%, stating that they utilised and thought the best way to potentialize its utilisation was by combining various theories and concepts. The theory of loss aversion was mentioned by a fifth of the interviewees, with the sunk cost fallacy and the prospect theory also being mentioned the same amount of times. The social proof concept was highlighted by 13% of the respondents, and lastly the rational choice theory, the nudge theory and heuristics were all mentioned by 7% of interviewees.

Considering the investigation's purpose to also explore how can these behavioural economics principles be effectively incorporated into AI-powered personalization algorithms and systems, the fourth research question was formulated with the interviewees being inquired to give examples on how changes in choice presentation could impact someone’s decision process when utilising programs or apps. The great majority of the respondents, 40%, stated that the user experience pertaining to good practices such as the payment methods, the after sales and delivery experience and the logistics when utilising an app or websites was the most influential aspect and was directly correlated with the user’s final decision or impression. About a third of the respondents mentioned the simplification of the website and app design, while 27% of the interviewees highlighted the alignment of the website and app with metrics analysis. The overexposure to ads having a negative effect on consumers opinions on a website or app was remarked by 20% of the respondents, while 13% pointed out that having an app or mobile friendly website would positively impact the consumer. The same percentage of 13% of the interviewees highlighted that using videos and images attracts customers visually and finally about 7% of the respondents referenced that the application of behavioural biases in the design of apps and websites would be beneficial and garner positive results.

Taking into account the investigation’s aim to also examine what are the benefits that arise from the integration of AI with Behavioural Economics, making it possible to better design effective interventions that account for cognitive biases and decision-making tendencies, the last and fifth research question was created and it garnered information by inquiring the respondents what are the main benefits that could be extracted when utilising AI, with the overwhelming majority of the respondents, about 87%, mentioning the automation of processes and simplification of repetitive tasks. About 47% of the interviewees highlighted the enhancement of consumer insights and ad personalization through data utilisation, with the same percentage of respondents mentioning the amplification of creativity. About a third of the respondents referenced how the utilisation of AI translated into a more effective application of cognitive biases and psychological and economic theories in advertising and lastly around 27% of the interviewees noted the easier access to information.

Altogether, taking in consideration all of the content reviewed and analysed throughout this investigation, it is apparent that the study of Artificial Intelligence has deepened in recent years, with its integration into marketing strategies becoming increasingly prevalent. Similarly, Behavioural Economics has gained significant attention from researchers, making this investigation a timely exploration of three emerging fields.

This study had the aim to delve into the intricate nexus of AI-Powered personalization via the lens of behavioural economics while also exploring the link between cutting-edge technology and the insights offered by behavioural economics principles, resulting in the five research questions indicated in the Methodology chapter. The research model of this investigation was shaped by its exploratory nature, which required one-on-one semi-structured interviews. This approach allowed interviewees the flexibility to go beyond the interview script, therefore enabling the collection of more in-depth information than would be possible with structured interviews. However, it is important to note that the sample size is too small to allow for broad generalisations or extrapolated conclusions.

As a result, the major takeaways from the first research question that intended to understand how the personalization powered by AI influences consumers decision-making processes and choices, was that this personalization was effective and an important influencer, with multiple industry platforms being vessels of said influence.

For the second research question, it was possible to denote that businesses effectively implement AI personalization in their marketing strategies by leveraging various supporting technologies. However, the main challenges identified include the technology's occasional inefficacy in displaying relevant ads to consumers and the lack of expertise and knowledge among professionals in managing these tools.

In view of the third research question, that aimed to understand how there could be an integration of key principles of Behavioural Economics, the significant finding was that combining multiple theories proved to be the most effective approach, with interviewees also highlighting several theories and concepts they considered relevant.

From the fourth question, which intended to explore how these behavioural economics principles could be effectively incorporated into AI Powered personalization algorithms and systems, the primary conclusions indicated that the presentation of choices to consumers significantly impacts decision-making, with the overall user experience and best practices on websites being crucial, along with the simplification of the website or app.

Considering the fifth research question, that sought to examine the benefits of the integration of AI with Behavioural Economics are, the key observations revealed significant advantages from this combination, with the most notable benefits including the simplification of repetitive tasks and automation processes, as well as enhanced consumer insights derived from data utilisation.

6.2. Theoretical and Practical Implications

As previously mentioned, the intersection between Behavioural Economics, Marketing and AI is a relatively new area in literature, with additional studies being necessary to fully understand its possible impact on organizations, including how these consumer-centred marketing strategies can be more effective. Numerous questions in this field remain open, with this study being possibly helpful in clarifying some of these issues, offering guidance and proposing new directions for future research.

Furthermore, this study can help current and future marketing professionals reflect on ways in which these strategies can be integrated in businesses and improve their performance. Marketeers may evaluate their approach towards the strategies, considering both benefits and challenges shared by the interviewees

6.3. Limitations

This investigation was based on a review of existing literature and the primary data was gathered from interviews. The main limitation of this research is the small sample size of the interviewees. Even though the findings align with previous studies done on the subject, caution is advised when extrapolating results from the interview data. Additionally, it is important to emphasise that this is an exploratory study, and due to the limited sample size, the findings should not be generalised or considered representative.

6.4. Suggestions for Future Research

The topic of Artificial Intelligence and its effects on daily life has gained significant attention recently. Furthermore, the marketing landscape has been rapidly evolving, driven by the growth of e-commerce and social media. For that reason, the addition of Behavioural Economics, aims to potentialize the usage of both these topics, thus my recommendation would be to further focus on this area of study.

The first recommendation addresses the primary limitation of this research, the small sample size and, for that reason, I consider that it would be advantageous to expand the study in order to include a significantly larger sample size. Another suggestion is to further explore the topic of Behavioural Economics across different sectors, as it would be beneficial for the field to see the extent of its potential. Additionally, although Artificial Intelligence has been studied more thoroughly over the past years, I still find the continuation of the study of this field crucial.

Lastly, my final recommendation pertains to the study and investigation of the improvements and suggestions made by the interviewees about what they would like to see implemented and updated in the field of Artificial Intelligence, that is on Annex B.

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Annex A – Interview Script

1) Tell me a bit about your career path in the area of marketing.

2) How do you utilize AI tools in your day-to-day work and how do they affect it?

3) How is AI-powered personalization affecting the way people make decisions when they're shopping online or using apps?

4) Can you give any examples where AI-powered personalization has changed the way people shop or make choices?

5) Can you give examples of how businesses are using personalized recommendations to promote their products or services?

6) What are the challenges and obstacles that businesses are facing while trying to implement AI personalization in their marketing strategies?

7) What are the Behavioural Economics factors that could be used to improve the utilization of AI tools?

8) Can you give examples of how small changes in the way choices are presented could affect someone's decisions in computer programs or apps?

9) What are the benefits that you extract from the usage of AI?

10) What advancements do you envision in how computers offer suggestions to individuals, and what factors do you hope companies will take into account when utilizing AI to tailor recommendations in the future?

Annex B – Interviewees envisioning of the future of AI

Strengthening ethical principles in AI use is essential, especially in handling consumer data. Serious regulations should ensure respect for consumer preferences, transparency, and legal compliance, prioritizing citizens' rights and ethical standards.
Companies will need to adapt their websites and information-sharing strategies to keep up with younger audiences who search via social media, AI chats, voice, and images rather than traditional search engines. New AI-driven tools, like the ability to search directly from video content, mean that brands will no longer control how their information is presented. This shift poses a challenge, not due to companies lagging, but because the technology is advancing so quickly.
Collecting consumer data on habits and interests can improve ad relevance and reduce overexposure, allowing fewer but more targeted ads. However, companies need to obtain user consent to access this data and use it ethically. Since AI lacks inherent ethical principles, human oversight is essential to ensure responsible data usage.
Charging for access could reduce platform clutter by limiting casual users. Additionally, platforms should allow users to set specific roles (e.g., digital marketing specialist) for more relevant interactions.
To enhance platform evolution, it's crucial to refine the quality of information available by eliminating misinformation. If incorrect claims persist, AI may propagate these errors due to a lack of individual curation, relying instead on collective input.
Improvements in technology will lead to a more omnichannel experience, where tools can analyse consumer behaviour across various platforms, both online and offline. This would allow a machine to provide seamless assistance, informing customers about product availability and streamlining their shopping experience, making it feel like a conversation, even though it’s automated.
Adding a human component to AI is challenging, and ultimately, users must exercise their own awareness. Some companies are already creating private AI models, allowing secure analysis of confidential data—something they wouldn’t do with public tools like ChatGPT or Google.
Ads should respect user preferences by using skips as feedback. If a user repeatedly skips an ad after the mandatory few seconds, it indicates a lack of interest, and the ad should stop being shown to them. This would improve user experience.

Audio offers a unique, less visually demanding way to engage, with a sense of intimacy that affects how information is processed neurologically. As investments in audio grow, there’s still significant potential to explore its integration in various contexts.
There's both curiosity and concern about technology's power to deceive our senses, potentially altering our perception of reality and relationships. While more recommendation options can be overwhelming, the goal should be to create recommendations that are personalized and contextually relevant, respecting human limits in processing information.