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THE AFFECT OF CUSTOMER PERCEPTION'S ON THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN THE BANKING INDUSTRY

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ABSTRACT

The more recent developments of artificial intelligence (AI) and machine learning (ML) technologies are rapidly changing the customer perceptions of its usage in the banking industry. This paper gives background to various aspects of AI in banking industry, including its definition, the adoption of artificial intelligence in banking, the opportunities and challenges faced by banking institutions. This paper aims to investigate the customers perceptions of the artificial intelligence in the banking industry, whether it affects the adoption rate of AI enable technologies. Furthermore, the paper also examines the ethical aspects of AI usage from a banking customer's perspective.

The research was conducted using a quantitative method in an experimental context. An online survey divided into seven sections was developed and then distributed to participants over the age of 18 living in Europe. The research was empirically tested with 135 banking consumers. The results from the study develop a greater insight into consumer perceptions of AI adoption in banking across the three independent factors of awareness, trust and satisfaction. The results from the survey were analysed using SPSS. The findings have revealed new information to the existing research. The results indicate that satisfaction has a greater effect on the adoption rate of AI in the banking industry, than other variables such as trust and awareness. The researcher also highlights the key ethical concerns in relation to AI usage in the financial sector. The main limitation of this study was the scope of the quantitative data method. Therefore, for a more empirical analysis of this subject, in-depth interviews and observational studies should be conducted.

Key words: Artificial intelligence, technology adoption, banking, ethics, trust, awareness, satisfaction

Los desarrollos más recientes de las tecnologías de inteligencia artificial (IA) y aprendizaje automático (AM) están cambiando rápidamente la percepción que tienen los clientes de su uso en el sector bancario. Este artículo presenta diversos aspectos de la IA en el sector bancario, como su definición, la adopción de la inteligencia artificial en la banca, las oportunidades y los retos a los que se enfrentan las entidades bancarias. El objetivo de este documento es investigar la percepción que tienen los clientes de la inteligencia artificial en el sector bancario y si afecta a la tasa de adopción de las tecnologías que permiten la IA. Además, el documento también examina los aspectos éticos del uso de la IA desde la perspectiva del cliente bancario.

La investigación se llevó a cabo utilizando un método cuantitativo en un contexto experimental. Se elaboró una encuesta en línea dividida en siete secciones y se distribuyó a participantes mayores de 18 años residentes en Europa. La investigación se probó empíricamente con 135 consumidores de servicios bancarios. Los resultados del estudio permiten conocer mejor las percepciones de los consumidores sobre la adopción de la IA en el sector bancario a través de tres factores independientes: conocimiento, confianza y satisfacción. Los resultados de la encuesta se analizaron con SPSS. Los resultados han aportado nueva información a la investigación existente. Los resultados indican que la satisfacción tiene un mayor efecto en la tasa de adopción de la IA en el sector bancario que otras variables como la confianza y la concienciación. El investigador también destaca las principales preocupaciones éticas en relación con el uso de la IA en el sector financiero. La principal limitación de este estudio es el alcance del método de datos cuantitativos. Por lo tanto, para un análisis más empírico de este tema, deberían realizarse entrevistas en profundidad y estudios observacionales.

Palabras claves: Inteligencia artificial, adopción de tecnología, banca, ética, confianza, conciencia, satisfacción

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1. THE INTRODUCTION

1.1. Background

The background section will start with an introduction about the history of Artificial Intelligence and its current developments in the modern banking sector. Further on, this section will introduce the relationship between customers and AI in terms of their observed behaviours and attitudes. You as the reader should have a greater understand of the foundation of AI, and consumer behaviours.

The exponential growth of technology in recent decades has profoundly shaped the modern world as we see it today. Among these technological advancements, the integration of artificial intelligence in banking is crucial for enhancing efficiency, accuracy, and personalised customer experiences in the modern financial landscape (Ness et al., 2024). AI is not only seen in banking but all around us; in our homes, cinemas, educational centres and even tourist attractions (Boden, 2019). According to Anyoha (2017), the evolution of AI began between 1957 and 1974, when computers became more efficient, available, and cheaper, allowing for the storage of larger amounts of data. Since then, AI has been on a rollercoaster of successes and setbacks, thriving in the 1990s and 2000s in the absence of state investment and publicity. The early stages of its application in the 2000s was related to search engines for internet companies, gaming, data mining and mobile robotics. However, more recently, AI is widely used in diverse fields and processes, each with its own specific end goal (Eickhoff & Zhevak, 2023). According to report published by Deloitte AI Institute, recent artificial intelligence advances include sensation and discernment (the five senses), creativity (generative learning through reading, writing and arts) and congeniality (emotional intelligence) (Bechtel, 2021). The future of AI is extending beyond ‘human intelligence’ with the capabilities of revolutionising industries, changing our cultural norms and our ways of social interaction.

1.2. Research purpose

In response to the growing concerns related to the usage of AI, the purpose of this mono-method quantitative survey is to investigate the effect of customer perceptions towards AI adoption in the banking industry. The following factors of customer awareness, trust and satisfaction related to artificial intelligence adoption are measured statistically using linear regression models. Furthermore, this paper aims to shed a light on the ethical concerns raised by the increasing the usage of advanced technologies. To address the research gap surrounding the lack of awareness of 'AI ethics', the questionnaire applies descriptive statistical tools to measure customer's knowledge surrounding the application of ethical banking. Demographical data such as level of digital competency, age and gender were also examined to develop greater insight into the subject area.

1.3. Research question

The main aim of this research is to investigate the levels of awareness, trust, and satisfaction that affect customer adoption of artificial intelligence technologies. Therefore, the research question of this paper is:

What is the impact of awareness, trust, and satisfaction of AI technologies on the banking user's adoption levels?

2. LITERATURE REVIEW & THEORETICAL FRAMEWORK

2.1. Introduction of the literature review:

This literature review will focus on previous scholarly articles and studies aimed at answering the research question formulated prior to this theoretical framework. In the introductory section, the steps of how the literature review was conducted are discussed, including the key words used. The literature review is divided into subheadings which are related to the applications, the benefits, the challenges, and ethical aspects of artificial intelligence in the banking industry.

What once seemed imaginable is now a reality – The rapid adoption of artificial intelligence and machine learning technologies presents significant opportunities yet heightens the key risks and challenges in today's modern banking industry. For many banking institutions, artificial intelligence offers significant benefits including enhanced personalised products and services, greater decision-making, and process efficiencies due to increased automation (Ghandour, 2021). Further opportunities encompass areas such as improved security against cybercrime, reduced operational costs, and augmented risk and compliance management (Carsten et al., 2023). However, the adoption of advanced technologies presents several risks and challenges, including bias and data privacy concerns, lack of transparency, absence of regulatory and legal standards, and systematic risk. Despite these numerous drawbacks, the most salient issue from the perspective of humans and financial institutions is the ethical and moral dilemmas raised by implementing human-like technologies (Nowakowsi & Waliszewski, 2022).

The integration of AI in modern banking practices has raised numerous ethical considerations that are relevant to contemporary society. Previous studies highlight key issues which are related to mainly privacy, accountability, and bias (Rehman & Attaullah, 2023). These discussions are underpinned by a lack of ethical frameworks within the subject area. An ethical framework is defined as the collective interpretation of societal norms that dictate right from wrong (Resnik, 2020). Artificial intelligence, which can perform tasks that have traditionally relied on human intelligence, poses significant ethical concerns. This dissertation aims to investigate how banking customers perceive AI through their levels of awareness, trust, and satisfaction of AI in banking. It also highlights the concerns and issues raised using AI technology in banking, with a mention of the ethical dilemmas faced by banking institutions.

Whilst conducting the literature review, it was understood that this field is extremely novel, which led to limited access to previous research and studies. The constantly changing nature of AI to adapt to the wants and needs of the digital consumer makes this review subject to change. Moreover, as the topic being researched is considered an emerging technology, much of the literature reviewed pertains to further developments. As a result, there is a risk that this work may become obsolete or irrelevant in the future (University of Texas Libraries, 2022)

2.2. Method of the literature review:

Prior to conducting the literature study to answer to the research question, a search was conducted in all data bases using the resources offered by Comillas Pontifical University and Dublin City University. The relevant literature was researched using the online databases such as Web of Science, ResearchGate, EBSCOhost, Academic Search Complete, JSTOR, and so on. Multiple keywords were used in the initial search – they included “artificial intelligence”, “machine learning”, “fintech”, “banking institutions”. The primary search resulted in many different articles from all data bases. Following the filtration of all literature to only include articles which have been reviewed and published between 2019 and 2024, a large volume of articles which deemed irrelevant for the study purpose were excluded for further review. To reduce the number of articles further, the articles selected were filtered to the research area of “Business Economics”. This resulted in a refined selection of articles to allow for the next phase of abstract review to commence. The researcher evaluated and selected the articles which proved most applicable for the literature review, based on the analysis of their abstracts. It must be noted, while carrying out the review of previous studies, the researcher used online resources and webpages to further develop the arguments.

In essence, this literature review provided a profound insight into the previous research and studies conducted by individuals and larger corporations. Any of the data gathered in this literature review will enrich subsequent data collection methods for this paper. Some of the literary articles studied may be applied to support the results of the quantitative investigation carried out by the researcher in Chapter 5.

2.3. Definitions of key words used in the systematic literature review

Artificial intelligence: Artificial intelligence, denoted as AI, was a term invented by a former computer and cognitive scientist, John McCarthy (1977) (Manning, 2020). McCarthy was known essentially as the father of Artificial Intelligence as a result to his contributions and efforts since the early 1950s. It was defined by him as "the science and engineering of making intelligent machines" (Stanford University, 2020). It should be considered that due to the highly evolving nature and complexity of this technology, defining this term can prove quite challenging. In modern dictionary, the definitions focus on the computer's capabilities of imitation of human intelligence. The Oxford Dictionary (n.d.) illustrates the term as "the capacity of computer or other machines to exhibit or simulate behaviour; the field of study concerned with this". Similarly, Merriam-Webster (n.d.) gives the definition as "the capability of computer systems or algorithms to imitate intelligent human behaviour".

Machine learning: Machine learning is defined as a subfield of artificial intelligence, which was a term coined by Arthur Samuel (1959), a pioneer in the field of AI and former employee of IBM. In more simpler terms, machine learning is a "branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy" (*What is Machine Learning? | IBM*, n.d.) Machine learning and artificial intelligence are two terms which can be used interchangeably however, in essence AI is broader term in which machine learning can replicate a human's cognitive capabilities, Mitchell (1977) is the science that is "concerned with the question of how to construct computer programs that automatically improve with experience".

Banking institution: The definition of a "bank", according to the Oxford Dictionary (2008) is a commercial institution that provides various financial services, most notably its main function is to takes deposits and extend loans. Similarly, the International Monetary Fund define banks as "financial intermediaries" between depositors and borrowers. Its main functions include making loans, creating money through reserves, trading securities and interest payments. Banks also play a key role in the transmission of monetary policy which controls key economic factors such as growth and inflation rates (Gobat, 2012). In the face of contemporary societal transformations, the banking industry, whose historical origins can be traced back to ancient Babylon - recognised to as "the origin of banking" with its early practices in shrines and temples - continues to adapt to the dynamic financial landscape that has revolutionised modern banking practices (Grossman, 2010). Hence, many different types of banks exist specifying different purposes and catering to different sectors of the economy such as: traditional banks, commercial or corporate banks, investment banks, central banks, digital banks, neo banks[1], and so on.

Fintech: Fintech is an abbreviated term for financial technology, which describes the use of innovative technology to deliver improved services and offerings to customers in the financial sector (Cambridge Dictionary, n.d.). As of today, there are numerous definitions for the term due to the everchanging nature and rapid evolution of the financial industry. Despite extensive research into the exact meaning of the term, the neologism essentially describes the connection of the contemporary world – human intelligence learning, cloud computing, mobile technologies – and the business operations typical of the financial industry such as borrowings, transfers, withdrawals, and deposits (Gomber et al., 2017).

2.4. The adoption of AI in the banking sector

The increasing adoption of artificial intelligence and machine learning technologies has drastically transformed the way how financial institutions carry out their operations. For

[1] The fundamental difference between the terms "neobanking" and "digital banking" is that digital banks typically function as the online exclusive branch of a pre-existing established entity (known as a "traditional bank"). A neobank solely operates exclusively online – in the absence of a physical branch and operates as an independent institution (Aggarwal & Singh Narang, n.d.)

instance, JP Morgan Chase's in-house innovation, Omni AI, deploys AI and ML technologies at speed and scale to aid its data scientists and industry experts in finding and preparing data sets. It also provides access to training and testing models. The firm has deployed Omni AI at scale, by standardising its processes and providing greater security control due to increased access to highly sensitive financial and personal information (J.P Morgan, 2024)

Furthermore, a recent Evident AI Index was introduced in 2023. The index is a global standard benchmark of AI maturity providing insights across 4 key pillars: talent, innovation, leadership, and transparency (Evident Insights, 2023). According to the index, JP Morgan had the highest adoption rate of AI amongst the world's leading banks, with a ranking of 69.3. This is due to the firm's heavy investments in artificial intelligence and machine learning technologies across their R&D&i[2] department. The following banks that were ranked amongst the highest performing included Capital One (62.4), Royal Bank of Canada (51.7), Wells Fargo (42.2), and UBS (40.2) (Statista, 2024).

Based on a detailed SLR[3] by Kalyani & Gupta (2023), the most notable banking applications of AI and ML technologies encompass a range of areas, including customer-orientated services, credit scoring and risk management, microfinance, digital financial inclusion, fraud detection and cybercrime, bank risk assessment, management of NPAs[4] and financial consulting. Similarly, another study focused on the utilisation of AI in the banking industry identified three main themes: the theme of strategy which refers to the organisational value of applying AI systems; the theme of processes relating to data mining processes for forecasting, credit approval and risk analysis. Finally, the theme of customers covers the use of AI in marketing activities and improving banking services to enhance overall customer experience (Fares et al., 2022).

The banking and financial services sector is among the primary users of AI technologies, accounting for 18% of the global machine learning market share (Fortune

[2] Research, Development and innovation
[3] Systematic Literature Review
[4] Non-performing assets

Business Insights, 2023). Banks apply AI through different services providers, relying primarily on privately owned cloud-based ML services such as AWS[5], Microsoft Azure, and Google Cloud ML (Fernandéz, 2023). Meanwhile, some more established banks have developed their own in-house applications for artificial intelligence technologies.

More recently, following the release of the first GPT model in 2018 (Radford et al., 2018), there has been significant growth and increased acceptance of advanced AI models such as generative AI. GenAI is characterised as intelligence systems capable of generating novel outputs, encompassing text, image, audio, and video. These outputs are derived from the models' training data, often in response to an AI prompt[6] (Lorenz et al., 2023). In a prospective light, generative AI has the potential to transform how banking services operate, with the predicted annual value of its application to reach $340 billion. The optimistic outlook for developing artificial technologies considers the factors of enhanced productivity, greater scale up, improving employee experience, and so on (Kamalnath et al., 2023). However, despite the proliferation of more sophisticated AI systems, this has sparked widespread concern regarding its ethical challenges. These issues encompass themes such as data privacy, social justice, equality, and power usage (Chen et al., 2023). This study also applies some insight into the ethical aspects of AI to explore issues in AI adoption, however it mainly focuses on the levels of customer trust, awareness, and satisfaction.

2.5. The opportunities of AI application in the banking industry

The opportunities that emerging technologies such as artificial intelligence can provide banking institutions are merely endless. This is due to the constantly evolving nature of this technology and its rapid adoption in the financial sector, as well as other industries, such as education, healthcare, manufacturing, automotive. Nevertheless, numerous scholarly papers acknowledge the limitations of their research, and admit that current researchers and industry experts have not yet clarified of the strengths and weakness of

[5] Amazon Web Services
[6] An AI prompt is an specific set of instructions or commands inputted into an AI to generate an output which aligns to the user's intentions (Interaction Design Foundation, 2023)

artificial intelligence (Boukherouaa et al., 2021). Furthermore, industry experts suggest that the true potential of this technology is yet to be captured (Herweijer, et al., 2020). However, the outlook is positive, with an estimated $1 trillion in annual value creation potential for banks through using AI systems (McKinsey & Company, 2018/2020). This section of the paper summarises the most noteworthy benefits originating from the implementation of AI powered solutions in the banking industry under the following subheadings:

2.5.1. Risk and compliance management

With AI/ML advancing rapidly over the recent years, regulatory technology (Regtech)[7] is changing the ways in which financial institutions carry out compliance and reporting processes. Banks can leverage the use of regtech through the increased adoption of AI/ML technologies to reduce costs and improve compliance quality (Boukerouaa et al., 2021). A research article analysed the recent collapse of Silicon Valley Bank (SVB) in March 2023, attributing it to a classic bank run and the compliance failures in the bank. As a result, Hu & Wu (2023) highlight the need for adopting greater compliance systems, for example 'Financial Enterprise Control Intelligence' (FCEI). It allows banks to streamline regulatory compliance and risk management processes more effectively, through compliance reviews, risk analysis and risk exposures.

Financial institutions can utilise AI/ML systems to enhance fraud detection, this reduces the potential for financial losses. It also provides a safer, more secure banking environment for their customers. Additionally, AI can analyse vast streams of real time banking data to offer predictive insights and immediate responses to suspicious financial transactions. Such AI capacities curtail the inherent risk of human error and bias when dealing with complex databases (Aziz et al., 2023).

Risk management extends beyond fraud detection. Many research articles discuss how AI is transforming credit risk management in banking institutions. The use of AI/ML with alternative data sources, beyond financial capabilities, provides significant value

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[7] RegTech is a commonly recognised term for technologies that can be used by market participants to follow regulator and compliance requirements more effectively and efficiently (European Banking Authority, 2021)

for credit risk analysis. It enables an accurate assessment of client behaviours and loan repayment capabilities, potentially leading to economic growth and greater wealth distribution in our society (Widagdo et al., 2023)

2.5.2. Decision-making and problem solving

The advent of artificial technologies has significantly transformed the decision-making and problem-solving processes within the banking sector. By leveraging advanced technologies such as machine learning models into their operations, banks can improve their customer acquisition and enhance the customer life cycle which benefits the customer's overall banking experience (Sheth et al., 2022). Agarwal et al. (2021) illustrate the 5 main areas[8] which decision making can add the most value across the customer journey, enabling the automation of over 20 decisions per client lifecycle. A research article examining the usefulness of AI in decision making from the perspective of the Central Bank of Nigeria, highlights the importance of applying AI solutions across Nigerian banks. The study proves a stronger correlation (82%) between the use of AI and producing dispense error data than the current internet platform used by most Nigerian banks today. Subsequently, AI enhances the quality and quantity of decision-making based on the handling of customer complaints, with 60% of respondents agreeing their interests are protected when AI is used (Ibrahim & Nwobilor, 2020). A Harvard Business Review article discusses the clear value proposition of integrating machine learning to predict customer behaviours in the decision- making process. For example, banks could tailor their marketing strategies to target specific market segments. Additionally, AI can improve fraud detection by placing a hold on higher-risk transactions which thereby allows human auditors to make a conscious decision (Sigel, 2023).

2.5.3. Automation of repetitive tasks

AI-driven systems can be advantageous in automating repetitive, volume-intensive, and time-consuming tasks, particularly in the banking industry. In the case of the financial

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[8] 5 main areas of decision making across the customer lifecycle include customer acquisition, credit decisioning, monitoring and collections, deepening relationships and smart servicing.

industry, tasks such as issuing credit cards, updating lending details and detecting fraudulent transactions are deemed suitable for automation (KO, 2020). As a subfield of AI, machine learning mechanisms can streamline diverse and time-consuming banking processes, such as document verification and regulatory compliance checks, resulting in lower operational costs and enhanced efficiencies (OECD, 2021).

An article published by Deloitte (2020) highlights the accelerating adoption of Robotic Process Automation (RPA)[9], which enables organisations to reduce their operational and business process costs by up to 40%. McKinsey & Co study (2021) further highlights the widespread adoption of RPA technology in the banking sector. Specifically, over one-third of financial institutions have automated structured operational tasks, including client onboarding, regulatory compliance, loan approval processes, KYC, and fraud detection (Aleksandrovich, 2023). These structured repetitive tasks are designated for back-office and middle-office processes, such as loan processing, bulk transactions, credit risk management, and risk monitoring (Bhattacharya & Sinha, 2022).

2.5.4. Customer service skills

The banking sector has experienced a recent surge in the roll out of Generative AI (GenAI) applications. Numerous banks are leveraging the advanced technology to enhance their customer relations by providing more personalised and interactive products and services for the user. A study conducted by the National Bureau of Economic Research, analysed data from over 5,000 customer support agents. The findings prove AI has increased productivity by 14% for the average worker. The results were measured by the number of chats an agent can successfully resolve on an hourly basis (Byrnjolfsson, 2023). Consequently, financial institutions that integrate AI into their customer service operations will benefit from increased business productivity and efficiency, ultimately leading to greater long-term profits.

Research carried out by Indruasari et al. (2019) indicates that the deployment of AI is significantly transforming the banking experience through greater user interaction and

[9] RPA is also known as software robotics, which uses intelligent automative technologies to perform repetitive tasks of human workers e.g. extracting data, filing etc. (IBM, n.d.)

personalisation, optimisation of products, and customer relationship management. In particular, the rise of AI-powered chatbots signals a new era for customer service, offering clients with a user-friendly, 24/7 support channel for their queries (Margaret et al., 2023). According to Shevlin (2022), previous research shows that a significant majority of customers, up to 60%, opt for online agents over human counterparts when initiating services such as opening a current account. Furthermore, institutions deploying conversational AI technology[10] within their mobile banking apps tend to boast higher customer experience rating compared to those that do not integrate AI. In contrast, traditional brick-and-mortar banks grapple with the challenge of maintaining the accessibility of their physical branches amidst evolving consumer preferences.

2.5.5. Cost savings

Despite the high initial costs, the integration of artificial intelligence technologies (AI) holds significant promise for the long term cost benefits. Research carried out by Autonomous Next forecasts potential savings of approximately $447 billion for the industry by the year 2023 (Stellard, 2023). These cost savings extend beyond the operational processes, encompassing various core business functions. By leveraging AI technologies, banks can streamline their operations by reducing repetitive tasks through RPA and enhancing customer service through chatbots in customer service operations, as mentioned above (Rahmani & Zohuri, 2023). This leads to enhancing cost efficiencies, reducing labour costs, and fostering innovation through product development (Kaya, 2019). These activities drive overall profitability and sustainability, positively impacting the organisation.

Recent findings from Banco de España highlight the significant potential for AI to reduce costs, particularly in the area of regulatory compliance, where companies are currently facing escalating costs (Fernández, 2019). The paper underscores the adoption of AI by European authorities to boast operational productivity and achieve cost efficiencies across various domains such as micro prudential and macroprudential supervision[11], data

[10] Conversational AI technology: it refers to the technology used by companies, such as a chatbot or a digital aget, which the end user can speak to (IBM, n.d.)
[11] Micro prudential supervision refers to rules and acts applicable for the whole financial system, unlike micro-prudential policies which apply to specific financial firms (Serbanescu. 2022)

management and processing, and detection of financial crimes. For instance, the European Central Bank (ECB) pioneered a novel model which deployed AI to detect anomalies[12], thereby facilitating quality checks on the short-term interest rates of the euro zone (Acceornero & Boscariol, 2021). The model not only enhanced regulatory compliance but also yielded substantial cost savings for financial institutions.

2.6. The challenges of AI application in the banking industry

As the research proved in Chapter 2.5., there are a vast number of existing benefits that financial institutions can gain from the implementation of AI and ML technologies. However, alongside these benefits come notable challenges that must be addressed. These challenges encompass various aspects, including the quality and representativeness of data, the potential for bias inherent in selected datasets, and the suitability of chosen algorithms[13] (Ashta & Herrmann, 2021). Additionally, concerns regarding privacy and the looming threat of job displacement due to increased process automation further compound the complexity of AI integration within banking operations.

Many of the existing challenges present practical hurdles, however these are closely linked to the ethical implications which face banking institutions (Adaga et al., 2024) Therefore, it is necessary for researchers and industry experts to critically examine their ethical practices and policies to prioritise transparency and accountability across the industry. This will ensure responsible use of information for the long term sustainability and reputation of organisations in the evolving digital landscape.

This section of the paper outlines the key challenges faced by banks in adopting AI and ML technologies through their business operations. The main themes in the literature studied have identified by the researcher and are presented under the following sub-headings:

[12] Anomaly detection is the identification of irregularities in the data set that differentiate from the normal/standard model. In other words, it involves finding the outlier. (Quiroz-Vázquez, 2023)
[13] A choice of algorithms: an algorithm is a set of clearly defined instructions which are contained in AI systems.

2.6.1. Embedded bias and discrimination in AI

The explosion of AI technologies has led to several ethical dilemmas inherent in the novel AI technology, including concerns related to bias and discriminatory issues. A recent study by Gupta et al. (2023) develops on the three different types of bias that were introduced to the area of artificial intelligence: human bias, data-driven bias, and machine learning design bias.

Human bias can occur when individuals carry insights from past experiences, either consciously or subconsciously, hampering the design of experiments and data selection. This bias can also affect the frameworks implemented in the banking decision-making process, such as loan approvals and credit risk management.

Data-driven bias refers to the poor classification and sampling of data collected by AI machines, which could lead to discrimination and diversity issues for banking institutions. For example, the launch of the Apple-branded credit card partnered with Goldman Sachs was marred by a well-known case of biased data. The AI algorithm built within the system was able to find a proxy for gender, which resulted in limiting the credit for female users (Elsesser, 2019).

Lastly, the design framework for machine learning models could result in potential bias due to repeated processes in which AI cannot detect incomplete data, thus generating slightly biased and unfair results. Although less noticeable than human decision-making bias, studies highlight that AI may reflect the same biases that has historically existed in the mortgage market. The cases of discriminations against underprivileged mortgages homeowners such as Black, Latinx and low-income customers has resulted in reduced credit scoring and higher interest loans (Perry et al., 2023)

2.6.2. Transparency and explainability of AI systems

The principles of transparency, honesty and integrity are often outlined in several codes of conducts for organisations and regulatory bodies. These serve as a guide for banking institutions to overcome the challenges presented by the complex financial landscape (Adaga et al., 2024). Within this context, the concept of the “black box” emerges as a critical consideration in the deployment of AI and ML models. The term is used when referring to the unexplainable and often complex outputs generated by the machines (Boukherouaa et al., 2021). The black-box model is built directly from the data set by an AI algorithm. Consequently, most users are unable to interpret how the input variables were combined to reach a final decision or the output (Rudin & Radin, 2019). In simpler terms, the decision-making remains anonymous to the user. This lack of transparency raises concerns regarding accountability and trust in automated decision-making systems.

However, empirical studies, for instance an analysis on bankruptcy prediction carried out by Harvard Business School has demonstrated that black-box models can match the accuracy of white-box models in almost 70% of cases. Therefore, researchers have gathered information to prove that there is no trade-off between the accuracy and transparency when using the 'complicated' black box model (Candelon et al., 2023). To address the lack of transparency within these models, banks could adopt a hybrid model which combines both white-box and black-box models.

The opacity inherent in AI systems poses further challenges in establishing the levels of trust and veracity of machine-driven decisions (Mensah & Selorm, 2023). If the users in this case study are banking employees, they may be unable to comprehend how AI arrived at its conclusions. This lack of understanding could make them less likely to trust the AI's decisions, potentially leading to reduced efficiency and slower adoption of the technology. (Carsten et al., 2023).

Furthermore, Fenwick & Molnar (2022) highlight the need for AI and ML to rely less on predefined data sets and algorithms and more on human behaviour to carry out specific operational processes. By striving to replicate the workings of the human brain, AI systems can establish greater trust and comprehension among users regarding the outputs they produce. This in turn will make their application more ethical and human centric.

2.6.3. Data privacy and security concerns

The use of AI/ML systems in the financial sector raises security and privacy concerns due to the analysis of large data sets. A departmental paper published by the International

Monetary Fund, discusses the latest concerns arising from the risks inherent in the technology, with particular emphasis on the recent developments in GenAI. Among the range of risks outlined such as data leakage[14], they have the potential to reveal seemingly anonymous data through inference[15]. Furthermore, the ability of AI/ML systems to retrieve the user's personal information from the dataset even after it has been disposed of. This could lead to systems inadvertently disclosing classified information, directly or indirectly, and raising the stakes for further privacy breaches (Boukherouaa & Shabsigh, 2023). Additionally, the analysis of unstructured and unfiltered data could result in the machines revealing private customer information. The data exposure could potentially violate current regulations regarding customer data privacy such as GDPR (Gupta et al., 2023).

More specifically, GenAI is having significant impact in the cybersecurity industry with 75% of security professionals witnessing cyberattacks over the past 12 months (Fitzgerald, 2024). According to one security expert, the factors responsible for the significant increase in the number of cyberattacks observed recently encompass a range of technological developments, including GenAI, as well as more sophisticated AI techniques such as deepfakes and advanced phishing campaigns (Yampolskiy, 2024)

Therefore, to avoid the serious repercussions of privacy breaches, including customer mistrust and reputational losses (Bansal & Zahedi, 2015), financial institutions must prioritise customer experience, convenience, and trust. Banks should implement strict data protection measures, resolve any privacy concerns, provide clear and transparent information about their robust security measures, and offer customer support in e-banking operations (Aldboush & Ferdous, 2023).

Although there have been very few significant data breaches in banking institutions attributable to AI, the Equifax data breach in September 2017 compromised over 40% of the American population's Personally Identifiable Information (PII)[16] and financial

[14] Referring to data beyond private and personal information expanding to proprietary and sensitive financial sector data.
[15] Inference refers to the capacity of AI/ML technologies to depict an individual's identity from behavioural tendencies
[16] The following data was comprised: names, date of birth, SSN, driver's license and credit card numbers

information (Kost, 2023). This incident further highlights the need for continued vigilance and proactive measures to ensure security of sensitive data.

2.6.4. Regulatory and legal frameworks

One major concern within this domain is the inconsistent regulatory and legal frameworks governing the technologies such as artificial intelligence and machine learning. Raham et al. (2021) explore the challenges of artificial intelligence technologies in the Malaysian banking industry, recognising a lack of transparent and coherent guidelines from Bank Negara[17] in relation to the application of intelligent systems. The lack of explicit and comprehensive frameworks for AI explains why Malaysian banks are reluctant to adopt artificial intelligence.

Regulations for artificial intelligence technologies in financial institutions are still in the early stages of development. The researcher identified a significant gap in previous literature in this area. As argued by Boza & Evgeniou (2021), key reasons for this regulatory gap include the complex nature of AI, the greater number of stakeholders affected, difficulties in interpreting and implementing AI principles, and the vast range of available products and services, resulting in varying business models.

Although, there has been no implementation of a global standard for AI usage, many jurisdictions are actively working together to adopt a resolution on AI. In April 2024, the United Nations General Assembly adopted new non-binding measures on AI, asking countries to safeguard and protect data and to monitor the risks inherent in artificial intelligence (Li, 2024). Furthermore, The European Parliament reached a political agreement for an AI Act in December 2023, focusing on the regulation of identifiable risks for EU banking institutions (European Commission, 2023). In contrast, the US is unlikely to pass new federal legislation regarding AI in the coming years (Morini Bianzino et al., 2024). In October 2023, Joe Biden issued an Executive Order[18] to

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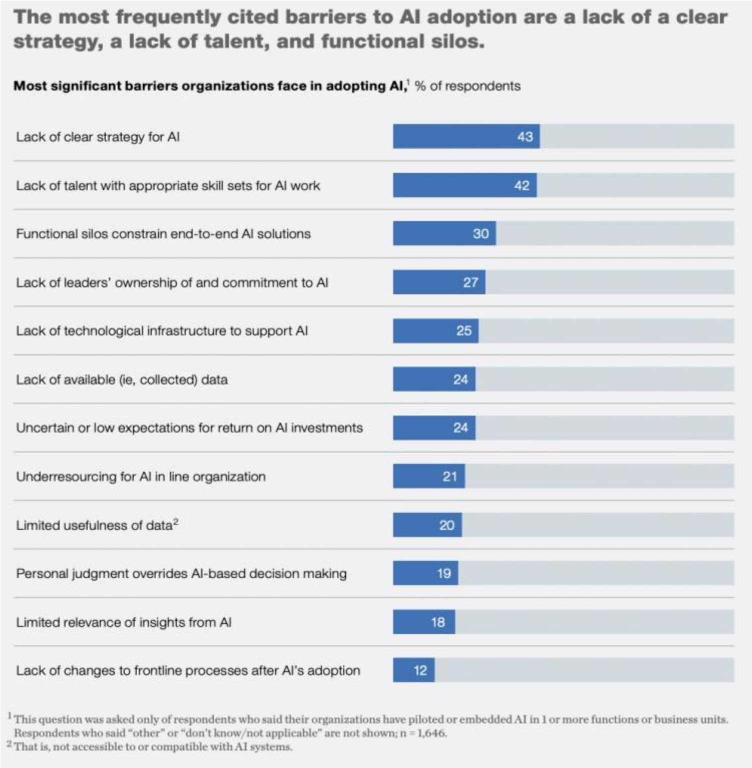
[17] Bank Negara is the Central bank of Malaysia (see here for further information: https://www.bnm.gov.my/introduction)
[18] The Executive Order: https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/

establish new standards for the safe, secure, and trustworthy use of AI (Biden Harris Administration, 2023). The rapid technological developments of AI have led to varying approaches in different jurisdictions. This has resulted in a regulatory gap in terms of artificial intelligent technologies. Financial institutions must comply with rigorous and precise regulatory frameworks established by governing bodies to ensure the most effective implementation in their operations (Boukherouaa et al., 2021).

2.6.5. Acquiring a robust information technology (IT) infrastructure

According to Biswas et al. (2020), banks are faced with two key obstacles when deploying AI technologies throughout their business operations. One of the top challenges in capturing value from AI is a lack of AI strategy. AI strategy refers to the planning for AI integration to ensure it aligns with and supports the ultimate goals of the organisation (Finio, 2023). According to a McKinsey Analytic AI frontier survey, 43% of survey respondents indicate a lack of a clear AI strategy as the most common barrier to AI integration. The second most common barrier for many banks is seen through a “weak core technology and data backbone”. The survey shows a quarter of the respondents cite a lack of technological infrastructure to support AI as the greatest challenge for technology integration (Webb, 2018). Therefore, organisations that depend highly on data and AI capabilities require its business leaders to define and execute an effective AI strategy through each level of the organisation. Leaders must apply an AI framework that includes each business layer, from organisational DNA (organisation, leadership, culture) to data enablers and data assets (human skills, privacy & ethics, AI portfolio), ultimately leading to a clearer vision and strategy aligning with the organisational goals (Kruhse-Lehtonen & Hofmann, 2020).

Figure 1: The most significant barriers to AI adoption



Source: Webb (2018)

In overcoming the core challenges that limit AI deployment, banks need to prioritise the training of AI and IT systems to ensure robust and high-quality data outputs that align seamlessly with the organisation's goals (Carsten et al., 2023). Given the financial industry's access to vast amounts of real-time data, it is crucial for banks to utilise data models that are entirely accurate, unbiased, and consistent. This is necessary to avoid compromising users' privacy and trust in IT systems.

In addition to the training of AI models, it is also necessary to provide training and up-skilling for employees in the field of AI. This is essential for ensuring seamless collaboration between personnel and machines (Biswas et al., 2018). One of the key challenges facing the banking industry is to ensure that they narrow the significant skills gap that is inevitable over the next five years, as AI makes changes to human skills required for specific tasks. It is estimated that 40% of the workforce will need to reskill in the next three years. Furthermore, there is a demand increase of 55% expected for all types of technological skills, from basic cognitive knowledge to advanced IT skills and programming (Lund & Hazan, 2018) (Tulchinsky, 2024).

Studies prove that organisations who adopt the incorrect and inappropriate technology may face the consequences of negative growth and higher risks. Consequently, this means that banks with weaker IT infrastructure, due to unsuitable adoption, may struggle to efficiently analyse real-time data across the different segments of the organisation (Biswas et al., 2018). However, despite the adoption barriers of acquiring a strong framework for technology, there has been recent progress with this domain, for instance in the development of MLOps[19]. To avoid ML failures, banks can effectively apply MLOps practices across the full life cycle of AI/ML model (data, model development, data model, productisation and scaling, live operations) (Lamerre et al., 2023). These specialised ML technologies enable data scientists to collaborate and improve the speed of delivery of data outputs by monitoring, validating, and regulating ML models (Soh & Singh, 2020).

2.6.6. Systemic risk

The risks of implementing AI in banking institutions is a major concern, due to the increased exposure to financial losses resulting from errors in AI technologies. This is inevitable in the context of commercial banking where there a high risk of error, as the loans in question are often worth millions of dollars (Carsten et al., 2023). Therefore, this heightened risk of potential errors in loan distribution could have serious repercussions for banks. In a single instance of system malfunction, Citibank's software system, which is supported by AI, mistakenly transferred $894 million to lenders associated with Revlon rather than the $7.9 million that was intended to be transferred in August 2020 (Stempel, 2022). This incident underscores the potential risks and challenges associated with the reliance on technology for wiring high valued payments.

There is increasing concern about the negative impact of AI applications on market stability. According to the World Economic Forum (2019), AI systems have the potential to amplify system-wide risks and undermine preestablished market defences. The WEF

[19] Machine learning operations, MLOps, for short, have been developed to address the problems of ML in relation to it's design process and ensuring its efficiency and productivity. (Kreuzberger et al., 2023)

have identified the most alarming risk arising from the implementation of AI applications as machine herding, which can result in fluctuations in market conditions and stability. This occurs through the destabilisation of the competitive positions of market players, and the generation of unexplained outputs which can cause humans to panic.

Additionally, the WEF cite another potential risk factor as humans' inability to interpret the market characteristics at any point in time, given their inherent complexities. This misinterpretation may result market players becoming disengaged from the market, leading to reduction in stock sales due to market inactivity. However, the AI machines do not consider the buyer's subjective evaluations, and therefore stock prices continue to fall, resulting in further economic damage (Svetlova, 2022). For instance, during unstable financial conditions, such as the Covid-19 outbreak in March 2020, which caused the fastest decline in global stock in history, studies indicate that the S&P Index had lost more than 34% of its value by August 2020 (Statista, 2022).

2.6.7. High investment costs

The findings from Chapter 2.5.5. of this paper support the affirmation that artificial intelligence (AI) can optimise cost efficiencies in the financial industry by increasing revenue and boosting staff productivity rates (Kaya, 2019). However, the initial cost expenses related to implementation of technology-intensive solutions has now emerged as a major cost concern for several banks. The cost of AI is determined by several factors, including the costs of hardware, software, labour, and training (Reilly, 2022).

Financial institutions have invested billions in deploying GenAI technologies. The banking industry alone contributed approximately 13.4% to the global expenditure for AI (Statista, 2023). According to a report released by International Data Corporation (2023), global expenditure for AI was expected to reach $154 million in 2023. Therefore, banks that are unable to invest in AI or upgrade their current IT support system due to cost restrictions may face long term bottlenecks in banking processes (Fernández, 2023).

2.7. The customer perceptions of AI in banking

The customer perceptions in the banking environment refer to how the client forms an opinion about banking and the products it offers through their banking services (Adefulu & Van Scheers, 2016). There are limited studies which have explored the impact of public perception of AI, which has resulted in a relatively widening research gap when it concerns customer attitudes and behaviours towards AI adoption. By optimising customer experience strategies and following the ethical use of AI, this study aims to investigate if banking institutions can enhance the user adoption through the variables under the following sub-headings:

2.7.1. Customer awareness of AI in banking

Adoption and use of digital banking services show a positive correlation with the level of awareness of customers towards AI-powered digital services (Noreen et al., 2023). In simpler terms, the greater the customer's awareness of AI technology, the greater the likelihood of their adoption of its services. According to Tulcanaza-Preto et al. (2023), the higher customer perception of factors relating to convenience in use, personalisation, trust, customer loyalty, and customer satisfaction, increases the customer AI-enabled experience. Thus, it is vital that banks focus on fulfilling the needs of customers perceptions to sustain their competitive advantage in the banking industry. Additionally, another study conducted on the Thai banking industry found the factors of trust, social norm, perceived usefulness and knowledge as influential in the adoption of AI technologies. The knowledge of using such technologies is a form of greater awareness and understanding (Noonpakdee, 2020).

However, despite the positive relationship between awareness and AI use, existing studies have demonstrated that there is a significant gap seen in this area. There is an insufficiency in public knowledge of artificial intelligence. As well as that there is a lack of understanding on how these technologies function (Nader et al., 2022). According to a recent survey conducted by UK Office for National Statistics (2023), only 17% of adults can recognise when they are using AI and a further 19% of adults can explain what AI is. The findings suggest a lack of awareness and understanding amongst the adult population, highlighting the need for greater education and more transparency, particularly in obsecure and complex environments such as the financial industry (Spargoli & Upper, 2018).

This discussion surrounding the awareness of AI technologies proposes the following hypothesis:
H1: Customer awareness has a positive effect on the adoption of AI enabled banking services.

2.7.2. Customer trust of AI in banking

As mentioned above, building trust is a key in helping banking institutions overcome the principal ethical questions of transparency, bias and fairness and accountability. Nevertheless, despite the recent developments in implementing more trustworthy AI solutions, there is still a prevailing concern around the trust inherent in consumers, with 35% remaining neutral, somewhat unlikely, and very unlikely to trust businesses using AI (Haan, 2023). In relation to loan applications, studies found customers who experienced higher trust when using AI-powered chat bots are more likely to share information (Zierau et al., 2021).

Furthermore, the level of perceived trust is linked to the customer's intentions to adopt mobile banking apps, which are most often powered by AI technologies (Rahman et al., 2021). These findings highlight the importance of fostering trust to enhance both the user's experience and banking performance. Therefore, these findings lead to the construction of the following hypothesis regarding customer trust levels:
H2: *Customer trust has a positive effect on the user adoption of AI enabled banking services.*

2.7.3. Customer satisfaction of AI in banking

Determining customer satisfaction levels is crucial to understanding how AI is perceived in the banking industry. AI in seen as a key application in the customer service area, like chatbots and virtual assistants. They offer prompt responses but may fail with complex queries, which leads to greater dissatisfaction in the technology (Huang & Rust, 2018) (Wirtz et al., 2018). Trust in AI is significant factor which also influences customer satisfaction (Devta, 2023). It is tied to transparency, fairness, and interpretability, thereby an increase in customer satisfaction occurs when the customer perceives that AI is making the decision in a fair and explainable manner (Baabdullah et al., 2019).

The current body of research indicates that policy makers should focus on variables such as perceived performance, visual appeal, communication quality and reputation to enhance overall customer satisfaction and boost user's confidence in accepting AI-enabled banking technologies (Alnaser et al., 2023). There is general positive feedback regarding customer satisfaction levels with AI chatbot services, as described by Ruan & Mezei (2022), who identifies reduced waiting times and perceived high quality of information as factors that directly affect satisfaction levels.

Lastly, the following construct regarding customer satisfaction was formed in relation to the final hypothesis:

H3: *Customer satisfaction has a positive effect on the user adoption of AI enabled banking services.*

2.8. The ethical questions of artificial intelligence in the role of the banks

As discussed in Chapter 2.6. AI presents significant challenges in the constantly evolving financial environment, particularly in relation to the ethical issues surrounding its development and widespread adoption. AI Ethics is defined as a "set of values, principles and techniques that employ widely accepted standards of right and wrong to guide moral conduct in the development and use of AI technologies". (Leslie, 2019).

Several scholarly articles identify three key issues surrounding ethics, focusing on transparency, the potential for embedded machine bias, and ensuring accountability (Mensah & Selorm, 2023). However, industry experts argue that these challenges can be overcome by the careful implementation and oversight of ethical business practices. Rees

& Müller (2023) and Enholm et al. (2021) have provided valuable insights into this topic. Ethical business practices and policies are implemented by those institutions who are socially responsible and more sustainable (Hurd, 2022). Rees & Müller (2023) highlight the repetitive theme across academic literature that there is a lack of effective and practical methods to deploying ethical AI. Moreover, Ahmed (2022) brings to light the potential harm caused misuse of data and private information (both personal and financial) which could result in unethical behaviour, jeopardising customer privacy and security.

2.8.1. Overcoming ethical concerns

Therefore, how can banking institutions mitigate the risks that question the moral interiority and ethical practices of AI technologies? Many scholars emphasise the importance of the pillar of trust which should be embedded in the customer's banking experience (Seaver et al., 2023). The construction an ethical framework could assist banks in overcoming these ethical barriers, extending beyond the mere protection of user's right's to the assurance of public trust and the prevention of harm in AI technologies. According to McLeod (2023), trust in ethics is defined as "an attitude we have towards people whom we hope will be trustworthy, where trustworthy is a property". Hurley et al. (2014) present data indicating that banks are among the least trusted organisations. Additionally, a survey conducted by HBR indicates a decline in public trust in business, media, and governing bodies. There was only 52% of respondents who expressed confidence and trust in the business's ability to act in the public interest (Harrington, 2017).

The question arises from these findings - how can banks overcome the lack of societal trust in their institutions? Banks need establish a trustworthy service by offering data-driven banking services that prioritise the improvement of data transparency through adhering to standard guidance and practice. They should also provide greater customer autonomy by allowing data sharing preferences and setting a high "opt-in" standard[20].

[20] As part of the EU data protection rules (EU GDPR), any company or organisation collecting and using personal information must ask for consent to data processing (https://europa.eu/youreurope/citizens/consumers/internet-telecoms/data-protection-online-privacy/index_en.htm)

Another researcher proposes the strategies of the implementing a culture of corporate digital responsibility (CDR), prioritising the responsible and ethical use of technical innovations to foster trust amongst shareholders (Jelovac et al., 2021). Tóth & Blut (2024) highlight the importance of implementing an AI accountability framework by providing managers with a CDR framework to help financial institutions navigate the complexities and ethical dilemmas that come with using technology. Thus, in theory these ethical business practices can have a positive impact on banking institutions by promoting a trustworthy brand and offering customers an enhanced range of products and services (Seaver et al., 2023)

The importance of adhering to general standards and guidance set by regulatory bodies in relation to the Ethics and AI is paramount to overcoming the issues embedded in AI/ML systems. The research presented in Chapter 2.6.4 addresses the challenge faced by the industry with a lack of coherent and structured legal frameworks in place regarding the implementation of AI/ML in the financial industry. The lack of coherence and transparency observed in regulatory bodies is also evident in the ethical guidelines, frameworks, and principles for AI, which scholars argue that the sudden rise in AI ethical principles is "useless", "meaningless" and "isolated" (Munn, 2022).

2.8.2. Ethical principles of AI

There has been a positive movement from international organisations, such as UNESCO, regarding the global movement of governing AI, following the organisation of the 2nd Global Forum on Ethics of AI. The "ten recommendations on the Ethics of AI" developed by UNESCO adopted in November 2023, aims to guide policymakers and shareholders on ensuring advanced technologies are deployed under strong ethical guardrails (Morandín-Ahuerma, 2023) (e.g., See Appendix for more details). According to Ramos, without these ethical guardrails, we are entering into a world inherited with "*real world biases and discrimination, fuelling divisions and threatening fundamental human rights and freedoms*" (UNESCO, 2023).

Furthermore, the High-Level Expert Group on Artificial Intelligence, established by the European Commission in June 2018, aims to promote trustworthy AI, and provide guidance on fostering and securing ethical AI through putting in place a standardised framework. The guidance is based on an approach founded by fundamental rights[21] that ensures development, deployment, and use of AI in a way that adheres to the following ethical principles (High-Level Expert Group on Artificial Intelligence, 2019).

1. Respect for human Autonomy
2. Prevention of harm
3. Fairness
4. Explicability

Similarly, PwC (2021) established nine ethical AI principles consolidated from more than 100 sets of ethical principles across various organisations (e.g., for further details, see Appendix). The principles encompass the general ethical considerations including accountability, data privacy, lawfulness and compliance, beneficial AI, human agency, safety, and fairness. These standards are more specific to ensuring interpretability and reliability when developing and deploying AI responsibly to real world problems.

Although ethics in AI is still developing in its early stages, 27% of companies incorporate ethical principles in their daily operations. However, only 21% of organisations apply an ethical framework for AI. Stanford scholars recently presented one of the first empirical investigations of AI ethics, which proves that many companies often “talk the talk” but rarely “walk the walk” with workers facing 3 key barriers for implementing ethical business practices[22] (Ali et al., 2023).

2.9. Theoretical framework

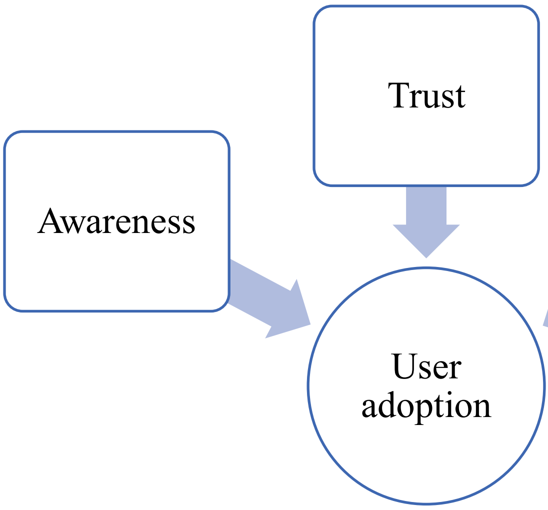
This study aims to measure three independent and one dependent variable. User adoption is noted as the dependent variable, as “awareness”, “trust” and “satisfaction” are anticipated to influence user adoption of AI technologies. To quantitatively measure

[21] There are 54 Articles under 7 subheadings of dignity, freedoms, equality, solidarity, citizen’s rights, justice and general provisions, in the Charter of Fundamental Rights of the European Union (2000) https://www.europarl.europa.eu/charter/pdf/text_en.pdf

[22] First, they struggle to have ethics prioritized in an environment centred around software product launches. Second, ethics are difficult to quantify in a context where company goals are incentivized by metrics. Third, the frequent reorganisation of teams makes it difficult to access knowledge and maintain relationships central to their work.

the concepts of customer behaviour, this study applied the operationalisation concept. The variables of awareness, trust and satisfaction cannot simply be observed and measured. Therefore, this process allows for the measurement of these concepts through indicators[23], assisting in the answering of the research question and testing of each hypothesis. The theoretical model is illustrated below in Figure 2:

Figure 2: Theoretical model



H1, H2 and H3 will be answered in the research by studying how AI technologies impact users' adoption, as per each dependent factor. The hypotheses attempt to seek a deeper understanding and provide an answer to the different aspects of the relationship between customer trust, awareness, and satisfaction on the adoption of AI technologies.

3. THE METHODOLOGY

The purpose of this chapter is to introduce the research methodology for this quantitative descriptive research approach employed in this paper, covering the research philosophy and approach, research design, data collection, and analysis techniques. The chapter begins with an explanation for the selected research approach, highlighting the principal

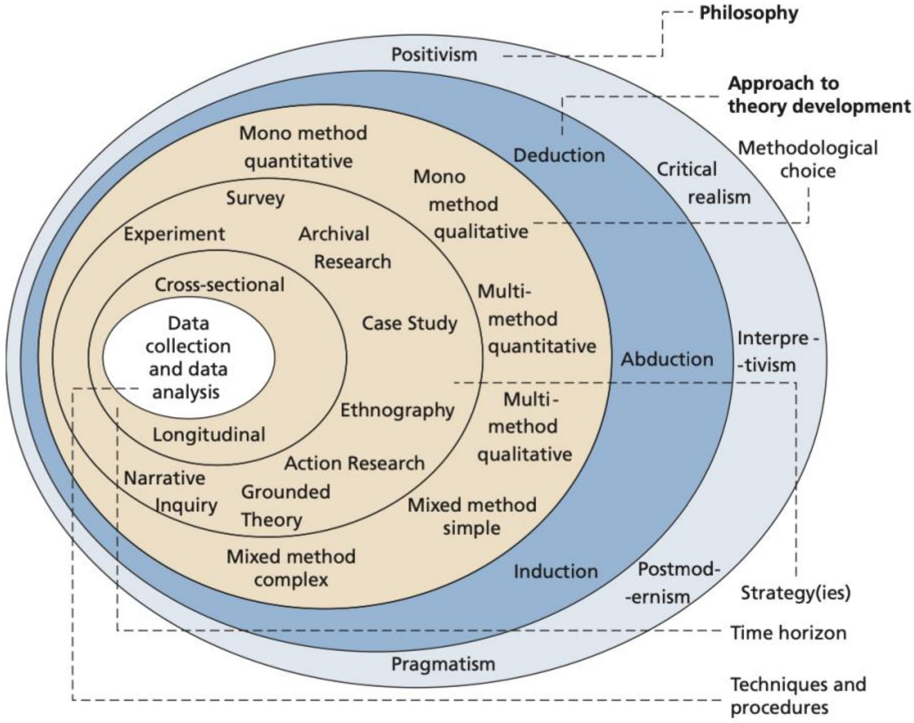
[23] Indicators include indexes, scales or typologies

assumptions and standards that focused on the research objectives. The following section describes the design process of the survey including its structure, types of questions, explaining the reasoning behind the choice. The data collection process explains the distributive methods used to gather responses, the time frame and the limitations of data collection including quality and ethical concerns. Finally, the analysis techniques explain the methods and instruments used for a statistical analysis of the data.

3.1. Research philosophy

Using the theoretical concept of the "research onion" originally proposed by Saunders in 2007. The research onion consists of distinct layers that need to be achieved when developing an effective research framework, which can be seen in Figure 3 below. Essentially, when conducting the research, Saunders et al. (2019) noted that when conducting research, one must move from the outer layer to the inner layer to construct an effective and focused research methodology.

Figure 3: The research onion



The first layer of the onion refers to the research philosophy. The research philosophy is the system of beliefs and profound assumptions related to the development of knowledge in a particular field (Saunders et al., 2019). During the knowledge development phase, the researcher makes numerous assumptions whether they are aware of these assumptions or not (Burrell & Morgan, 1979/2017). The main assumptions that are relevant to the research process include ontology (the study of reality), epistemology (the study of human knowledge) and axiology (the study of opinions). The researcher may be overwhelmed by the array of management philosophies, with the most common identified as positivism and interpretivism (Galliers & Sutherland, 1991).

For this research, a positivist approach was deemed most appropriate. Based on the ontological belief that reality is measurable and observable test hypotheses or make predictions about reality in a deductive manner (Tashakkori et al., 2020) (Hesse-Biber, 2017). Additionally, it views that only “factual” knowledge gained through observational methods, such as measurement, is trustworthy (Dudovskiy, 2024). One of main benefits of using this approach it is that is usually closely linked with “quantitative research”, which allows for efficient collection of a large volumes of data with clear and concise data methods for comparison (Clarke-Hagan et al., 2023). These factors played a key role in the selection process of the chosen research philosophy.

3.2. Research approach

The second outer layer of the onion relates to the research approach. Following Saunders's method, the research approach can be divided into three main categories: inductive, deductive, and abductive. The relevance of the hypotheses testing is what distinguishes the selection of each approach (Dudovskiy, 2024). According to Kim (2021), the deductive approach is most suitable for narrowing information from a general/common knowledge level to a more specific level. Therefore, this research approach analyses existing information, identifies a gap within the topic of interest, and then tests the hypotheses. For this reason, the deductive method was selected as the most appropriate research approach.

3.3. Research choice

The research choice can be divided into qualitative or quantitative research. Quantitative research refers to the collection of numerical and statistical data, which is often used in hypotheses testing, pattern identification and predictions. On the contrary, qualitative research provides an in-depth exploration of non-numerical data, which is expressed subjectively through words, images, and sounds (McLeod, 2024). A quantitative research strategy was chosen to facilitate a statistically rigorous and focused exploration of the relationship and attitudes of customers towards artificial intelligence in banking.

According to Verhoef & Casebeer (1997), the quantitative research approach is most suitable to determine the opinions, attitudes, and practices of a larger population. Due the extensive nature of the research, which necessitated the collection of a substantial volume of data for analysis, the quantitative research method was chosen. This data was examined from a broad perspective, with a subsequent narrowing of focus.

Quantitative research can be applied in various formats such as mono-method, mixed-method, and multi-method. Due to time constraints, budget limitations and the feasibility of the research, a mono-method approach was selected. The choice of the mono-method meant that only quantitative research was used throughout the study (Saunders et al., 2019). The researcher chose an online questionnaire as the research strategy, which will be discussed more in depth in the subsequent sections of this chapter.

3.4. Research strategies

The fourth layer of Saunders' onion is the research strategy which essentially is a plan of action on how to achieve a goal. The goal of this research is to answer the research question: *What is the impact of awareness, trust and satisfaction of AI technologies on the banking user's adoption levels?*

As mentioned above, the researcher adopted a survey strategy which allows for the collection of data that can be analysed using descriptive and inferential statistics (See Chapter 3.4.6 for further details). Furthermore, as outlined by Saunders et al. (2019), surveys offer an opportunity to investigate the relationships between variables and produce models of these relationships through graphs and other visual analytical tools. Similarly, Salant & Dillman (1994) state that survey research is useful for assessing a need, evaluating demand and examining impact. Therefore, this survey aims to measure various AI variables in relation to customer awareness, trust, satisfaction (the needs) and the impact of adopting these advanced technologies in the banking environment.

3.4.1. Survey design

To investigate the banking customer's attitudes and behaviours towards artificial intelligence, the researcher created an online survey using Microsoft Forms. The survey contained a mixture of the following types of questions used to collect data: dichotomous questions[24], questions based on the level of measurement[25], and contingency or filter questions[26] (Trochim & Donnelly, 2007). The survey used a mixture of these three types of questions. The final draft of the survey contained a total of 27 questions, broken down into seven different sections. The survey included 1 question for consent purposes, 11 general information and demographic questions, 2 questions about the benefits and challenges of AI in banking, 2 items measuring customer awareness of AI, 3 items measuring customers trust in AI, 3 items measuring customers satisfaction in AI, 1 item to measuring user adoption, and 6 questions relating to the ethical aspects of AI in banking. The questions measuring levels of awareness, trust, satisfaction, and adoption, consisted of 5-point Likert scales. They indicated 1 and 5 for strongly disagree and strongly agree, respectively. Table 1 provides a list of items for each variable and the previous studies used for each construct and item. The following items were included in the final draft of the survey. Other questions included in the measurement sections[27] of the survey included ranking questions, nominal and ordinal questions.

Table 1: Constructs and items of the questionnaire

Construct	***Item***	***Source***
Awareness	I am aware of the use cases of AI in the banking industry	(Muzaffar & Ahmed, 2023)
	I understand how AI is applied in the banking industry through NLP (Natural Language Processing), ML (Machine Learning), RPA (Robotic Process Automation), and Computer vision.	
Trust	I trust the use of AI in the banking industry to protect my personal data and information	(Muzaffar & Ahmed, 2023)
	I feel comfortable when using banking services that implement AI-powered solutions	

24 Yes/No questions
25 Nominal, ordinal, interval and ratio questions
26 Follow on questions; participant must answer the subsequent question if answered ‘yes’ or ‘no’.
27 Measurement sections of the survey: section 4, section 5 and section 6

	I feel banks are fully transparent in how they arrive at their decisions generated by AI	
Satisfaction	I believe the use of AI has positively impacted the banking industry	(Muzaffar & Ahmed, 2023)
	I am satisfied with the AI-based customer services provided by my bank	
	I would recommend a bank that implements AI rather than a “traditional bank” (branch only)	
Adoption	I feel the application of AI has improved my personal banking experience	(Muzaffar & Ahmed, 2023)

The first part of the self-reported survey provided a general description of the study and outlined important details regarding the collection and use of the personal data. All participants were informed about GDPR and gave their consent before to beginning the online questionnaire. Any participant who did not agree to give their consent to participate was directed to the end of the form.

The second segment gathered demographic information about the participants in terms of their age, nationality, gender, education and living situation. A closed question was included at the end of this section to filter out those who did not have a bank account. However, all 135 survey respondents were customers of one or more banking institutions.

The third section of the survey is relevant to the literature review of this study. In this section of the questionnaire, participants were asked to rank the benefits and challenges of using artificial intelligence technologies in the banking industry in order of importance. The benefits and challenges were formed using the data gathered from the literature review, which was conducted prior to formulating the research questionnaire.

The fourth, fifth, sixth and seventh sections of the questionnaire are relevant to the research question of this dissertation. The measurement sections of the survey were designed to measuring the following constructs: awareness, trust, satisfaction, and adoption. Each construct was based on the questionnaire previously administered by

Muzaffar & Ahmed (2023). However, only the relevant items from the previous research were included and adapted to suit the specific objectives of this study.

The final section of the self-report questionnaire aim is to study the ethical impacts The seventh section included questions regarding the ethical aspects of artificial intelligence and its application in the banking industry. Questions in this section included ranking questions, scenario-based questions, and net promoter score questions.

3.5. Time horizon

The fifth layer of the research onion relates to the time horizon of the survey. There are two types of time horizon: cross-sectional and longitudinal. As illustrated by Saunders et al. (2019), cross-sectional involves research that is collected over a specified period of period (known as ‘snapshots’), while longitudinal studies focus on a longer period of time (known as the ‘diary’ perspective).

According to research by Pandis (2014), the cross-sectional study is suited towards observational research, where outcomes are determined at the same point in time for each participant. It is the simplest and most common study design due to its temporal arrangement for both quantitative and qualitative data (Mardiana, 2020).

Unlike cross-sectional studies, which measure a specific moment in time, longitudinal research is suitable for collecting data which lasts beyond a single point in time over a long period of time. They are particularly useful for identifying changes, developments, or patterns in population’s demographics (Simkus, 2023).

According to Saunders et al. (2019), many cross-sectional studies employ the survey strategy, which aligns with the objectives of this research. In this regard, the researcher employed the cross-sectional approach, and sought to explain how different factors are related to user adoption levels through the distribution of a survey.

3.6. Data techniques and procedures

The final layer of the research onion relates to the techniques and procedures taken as part of the research. As described by Tengli (2020), the inner layer describes different aspects that the researcher has taken into account when collecting and analysing the data.

At this phase, the researcher is expected to distinguish between quantitative and qualitative. Primary data refers to first-hand data collected by the researcher, while secondary data is re-purposing of data collected by another subject for a specific reason (Dhudasia et al., 2021). Based on this research, both primary and secondary data sources were collected and analysed, in hope of seeking answers to the research question. For the primary research method, a structured questionnaire was developed and distributed to a population sample over the age of 18. Throughout this paper, the researcher uses secondary sourced data such as peer-review literature articles, books, conference papers, reports, and surveys. The purpose of using secondary research is to support the arguments of this paper. The majority of the secondary research presented in this paper is collected for the purposes of Chapter 2.

3.7. Data analysis

In the data analysis phase of the quantitative study, the researcher describes the methods used when analysing the data collected from the survey. According to Saunders et al. (2019) there are two ways of analysing data: thematic analysis and content analysis.

Thematic analysis is often used as the methodology for qualitative data analysis, which involves the process of identifying relevant themes or patterns within the data (Maguire & Delahunt, 2017). Due to its methodological approach, it is a very flexible way of conducting analysis and focuses on interpreting and making sense of the data (Clarke & Braun, 2013).

On the other hand, content analysis is more specifically applied to research using quantitative approach. Content analysis is defined as "the systematic, objective, quantitative analysis of message characteristics" (Neuendorf, 2017). It is more complex than thematic analysis and includes predictive regression analysis and structural equation models. For this research, different types of content analysis are presented in the results section, to illustrate the findings from the survey responses.

The main tool used for the content analysis is IBM SPSS ("Statistical Package for Social Sciences"). This is a software tool used for advanced statistical analysis of large data sets. Due to the size of the data set, a comprehensive analysis was carried out through descriptive statistics, contingency tables, and multiple linear regression analysis.

3.8. Research ethics

Research ethics refers to the set of ethical and moral rules that guide the research practice, to ensure the protection of human subjects in research (Castree et al., 2013). In order to ensure the research was ethically sound and adhered to the highest standard of integrity, the researcher followed the guidelines from Dublin City University. As part of the DCU research ethics guidelines[28] for conducting online surveys, the researcher completed the online data protection course available on the online moodle platform for DCU students. Additionally, the researcher followed the Data Protection Unit's recommendation to create the form using either Qualtrics or Microsoft Forms.

While the internet provides numerous benefits to researchers, it has also created many challenges in terms of maintaining human ethical standards. The ethical principles that should be followed in online research are essentially the same as those that should be followed in any research involving humans. These include respect for autonomy, justice and beneficence (Kitchin, 2007). More specifically Saunders et al. (2019) identify several ethical issues related to internet-mediated research, including deception, lack of

[28] See link to DCU Research Ethics Guidance: https://www.dcu.ie/researchsupport/research-ethics#tab-60061-3

respect and harm, respect for privacy, nature of participation and ability to withdraw, informed consent, data confidentiality, data analysis, data management and researcher safety.

Saunders et al. (2019) highlight the importance of ensuring that intended participants are aware of the research, the purpose of the research, how it will be used, its nature and the requirements for their participation. Therefore, prior to the survey, all participants were given a detailed introduction to the research project before giving informed consent to participate

3.9. Possible limitations

The main limitation for quantitative research methods is that it takes snapshots of a phenomenon, resulting in a less comprehensive analysis (Rahman, 2016). As mentioned by previous researchers, it provides an overall picture of the variables measured rather than the detailed descriptions that quantitative research provides. Therefore, this study may be limited by the depth of its findinga, however it does provide a clear and more concise answer to the objectives and research question.

Another possible limitation of this study is the number of participants in the survey due to time constraints. The study achieved a response from 135 participants, which is above the recommended threshold of 120. The survey research was limited to the timing guidelines for the completion date of the study. To ensure the researcher had sufficient time allotted to each part of the study, the timeframe for conducting the survey was 4 weeks. Consequently, this restricted the potential for obtaining a greater number of responses. It should be noted that a limited number of respondents can affect the robustness of statistical analyses and the reliability/validity of the survey findings (Jarrín González & Kayhan, 2024).

4. THE RESULTS

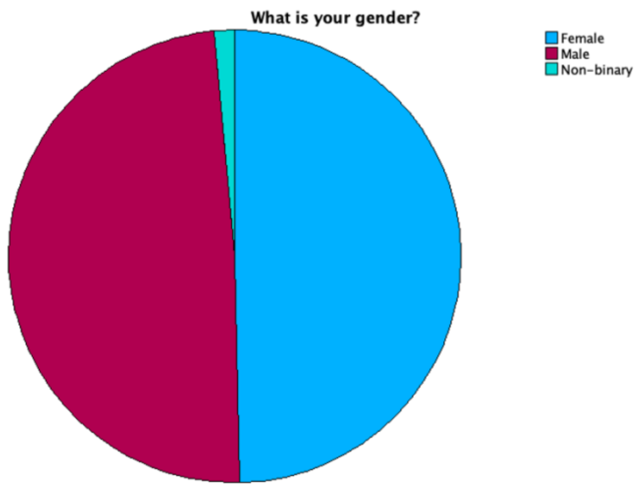
This chapter contains a description of the data collected from the questionnaire and an analysis of its results. The chapter begins with a descriptive analysis of the questionnaire summarising the demographic information gathered such as age and gender. The following section consists of a reliability analysis of the 3 variables studied – awareness, satisfaction, and trust. The testing of each hypotheses is carried out in Section 4.3 with linear regression analysis. The final section relates of the results is a frequency statistical test to analyse the ethical concerns related to this paper.

4.1. Demographic results

The demographic data from the survey reveals a diverse profile of the respondents. Among the 135 respondents, the gender distribution is strikingly equitable – with 67 identifying as female (49.6%) and 67 identifying as male (48.9%). There were 2 participants who identified themselves as non-binary (1.5%). Numerous studies have proven the importance of gender balance and gender perspectives, which enhances the scientific quality and relevant value of the research (The Research Council of Norway, 2014).

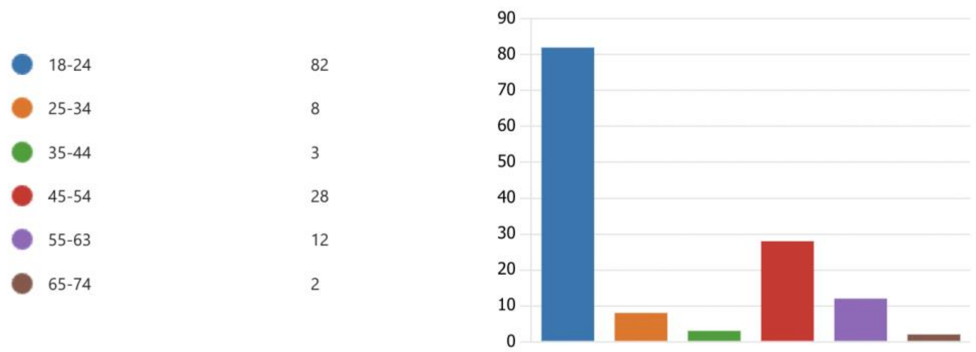
Figure 4: Descriptive statistics - gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	67	49.6	49.6	49.6
	Male	66	48.9	48.9	98.5
	Non-binary	2	1.5	1.5	100.0
	Total	135	100.0	100.0	



In terms of age, Figure 5 below illustrates the distribution of age between the 135 respondents. The graph shows that 82 respondents (60.74%) are in the 16-24 age group. This is the largest age group of respondents. The 25-34 and 35-44 age group are less represented with only 8 (5.92%) and 3 (2.22%) respondents respectively. The 45-54 age group is the second largest age group with 28 respondents, accounting for 20.74% of the total population. This suggests that there a wide range of different perspectives across different stages of life. The 65-74 age group is the least represented with only 2 participants (1.48%). It is important to note that individuals under the age of 18 were not able to participate in the study due to the sensitive nature of the topic of banking and artificial intelligence.

Figure 5: Descriptive statistics – age



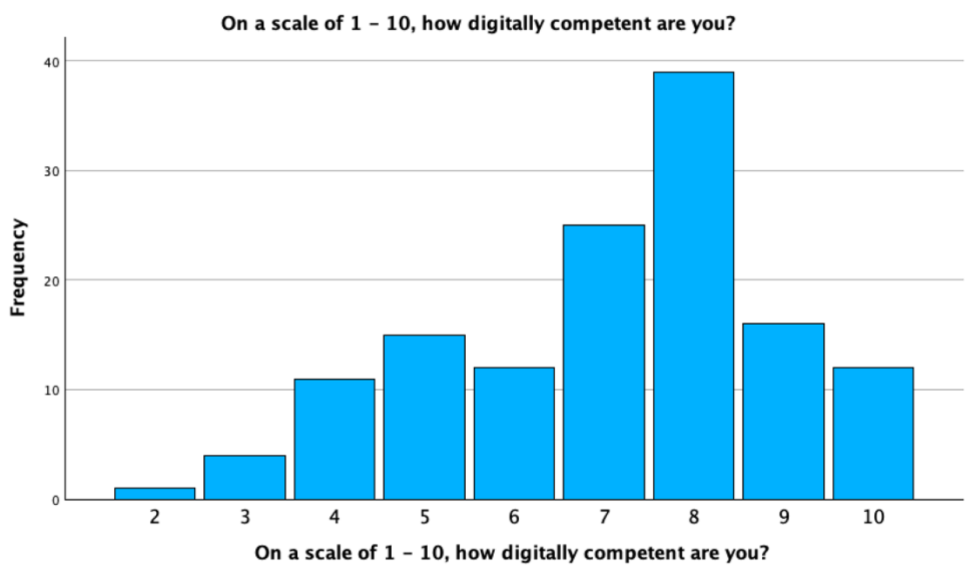
Finally, in terms of digital competency, the survey indicates varying levels of capability in relation to digital skills. The mean, also known as the average, is the total sum of values in a sample divided by the number of values in the sample (Hurley & Tenny, 2023). The mean level of digital literacy among the 135 survey participants is 7.08. The mode or most frequent score was 8, with 28.89% of respondents citing a significantly high level of digital competency.

Figure 6: Digital competency

Statistics

On a scale of 1 – 10, how digitally competent are you?

N	Valid	135
	Missing	0
Mean		7.08
Median		7.00
Mode		8



4.2. Descriptive statistics

As illustrated in the theoretical framework, the research model is conducted with both dependent and independent variables. Multiple linear regression analysis is applied to analyse the relationship between independent and dependent variables. Through the use of “estimation”, the value of the dependent variable is predicted based on the value of the independent variables (Ali & Younas, 2021). As statistically shown in the formula below, the relationship where the value of the independent variable x is associated with the dependent variable y:

$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + c$

where a is a constant term; b_1, b_2, b_3 are the correlation coefficients between the variables; c is the random error term (Sun, 2019). For this model, X_1, X_2, X_3 are the independent variables measured for the study: awareness, trust and satisfaction. The dependent Y variable is the user adoption to AI technologies in the banking industry.

Table 2 below shows the descriptive statistics, which are the minimum, maximum, mean and standard deviation of each of the independent variables: awareness, trust, satisfaction. The dependent Y variable is the level of adoption of AI technologies, which is also included in the analysis below. Based on the table, satisfaction has the highest mean equal to 3.189 and awareness has the lowest mean equal to 2.852.

Table 2: Descriptive statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Awareness AVG	135	1.0	5.0	2.852	1.1030
Trust AVG	135	1	5	3.00	1.044
Satisfaction AVG	135	1.0	5.0	3.189	.9441
Adoption AVG	133	1	5	2.92	1.225
Valid N (listwise)	133				

4.3. Multiple linear regression

Table 3 below provides a summary of the performance regression model's to explain the variance in the dependent variable – the user adoption of AI. The model summary includes R, R square, adjusted R Square and the standard deviation of error.

The R value is the simplest representation of the correlation between the dependent and independent variables. It indicates the strength and direction of the linear relationship between the predictors and the dependent variable. The model summary shows that the regression model has an R of 75.4%. This means that there is a strong correlation between the variables.

The R-squared value indicates the proportion of variance in the dependent variable that can be explained by the predictor variables. Although there are no specific guidelines, as a rule of thumb, Moore et al. (2013) illustrate that is the R-squared value < 0, the effect size is null or very weak, when 0.3 < r < 0.5, the effect size is null or very weak, when 0.5 < r < 0.7, the effect size is moderate, and when r > 0.7, the effect size is strong. Therefore, the regression model shows a moderately suitable fit to the data set, as indicated by the R-squared value of 0.568. Additionally, the adjusted R square indicates how well the data points fi the model in terms of the independent variables that actually affect the dependent variable, excluding unnecessary predictors (Dhakal, 2018). Hence, it provides a more accurate representation of the data model meaning the closer range of R^2 and the adjusted R^2 show a positive indication of the fit of the data model.

The standard error of the estimation is the measure the average deviation (dispersion) of the errors in the model (Watts, 2022). The better the model fits, the lower the value of the standard error of the estimation. Therefore, for the aggregated model of the 3 independent factors, the estimated values are on average of 0.814 units from the regression line. This indicates a suitable fit for the data model, highlighting that the results can be shown statically sound.

Table 3: Model summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.754[a]	.568	.558	.814

a. Predictors: (Constant), Satisfaction AVG , Trust AVG, Awareness AVG

b. Dependent Variable: Adoption AVG

The overall statistical significance of the models is supported by an F-statistic and a corresponding p-value, as shown in Table 4 below. The p-value < 0.001, which is less than the significance level of .05, indicates that the null hypothesis is rejected. According to Mesquita & Kostelijk (2022), this indicated that at least one of the independent variables has statistically significant influence on the dependent variable of user adoption of AI in banking. Further testing on the correlation analysis will reveal which variables are significant in affecting of AI adoption

Table 4: ANOVA tests

ANOVA[a]

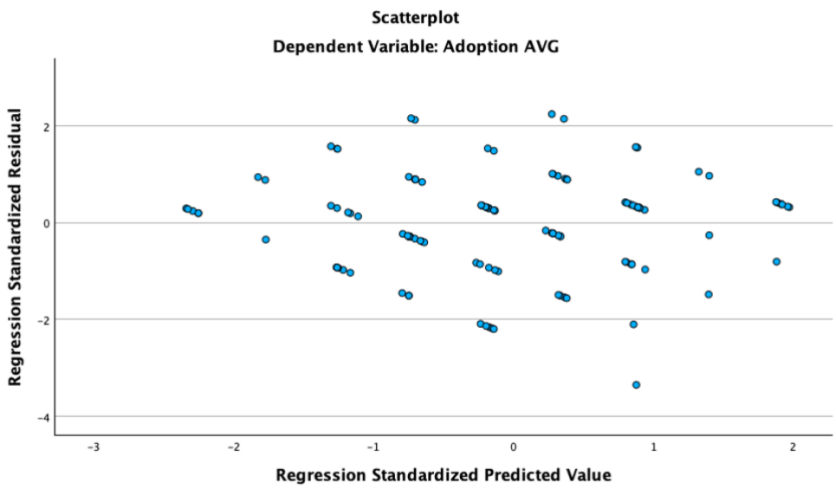
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	112.587	3	37.529	56.620	<.001[b]
	Residual	85.503	129	.663		
	Total	198.090	132			

a. Dependent Variable: Adoption AVG

b. Predictors: (Constant), Satisfaction AVG , Trust AVG, Awareness AVG

In regression analysis, the researcher must ensure that the assumptions of homoscedasticity and linearity are met. Linearity should be checked to ensure that there is a linear relationship between the dependent and independent variables. Homoscedasticity should ensure the data values for dependent and predicted values have equal variances (Saunders et al., 2019). Graph 3 suggests homoscedasticity, as the variance of residuals (errors) seem relatively uniform across the set of predicted values

Graph 3: Scatterplot



To detect multicollinearity in SPSS, the researcher should assess the degree of correlation between the dependent and independent using VIF (Variance Inflation Factor). The VIF scores should be > 1 and < 5, any value above 10 suggest high collinearity indicating the variable may not be necessary anymore (Marcoulides & Raykov, 2019). Based on the VIF values observed in Table 5, all values are well below 10, indicating thar the assumption of multicollinearity is not met. In this case, a change in one variable will not lead to a change in another variable, as they are independent from each other.

The results of the regression model are presented in Table 5 below The results of the regression model are presented in Table 5 below. The p-value (Sig.) is used to analyse the statistical significance of the independent variables. It indicates the degree to which the data fits the pattern predicted by the test hypothesis (Greenland et al., 2016). If the p-value is < 0.05, the null hypothesis that there is no relationship between two variables can be rejected. Instead, the alternative hypothesis can be accepted, which states that the independent variable has an effect on the dependent variable.

Table 5 shows that the p-value (Sig.) for awareness is 0.925, which is well above the threshold of 5% significance level. This indicates that there is no statistically significant relationship between customer awareness and adoption of AI-enabled banking services, which means that the alternative hypothesis is rejected:

H1: *Customer awareness has a positive effect on the adoption of AI enabled banking services* – **reject**

The results for the p-value for customer trust is 0.613. The p-value is notably greater than 0.05 meaning there is no evidence to support a statically significant relationship between customer trust and user adoption of AI in banking. Therefore, the decision is to reject the alternative hypothesis:

H2: *Customer trust has a positive effect on the user adoption of AI enabled banking services* – **reject**

The p-value for the third independent variable for customer satisfaction is less than 0.001, which is significantly less than $p < 0.05$. There is strong evidence that there is a positive relationship between customer satisfaction and their adoption of AI-enabled banking services. As a result, the alternative hypothesis is accepted:

H3: *Customer satisfaction has a positive effect on the user adoption of AI enabled banking services* – **accept**

While the findings support the third hypothesis (H3), there is insufficient evidence to show the significant positive effect of both variables of trust and awareness of AI on consumer adoption of AI-enabled banking services. In conclusion, it should be considered by banks to further explore the reasons behind the lack of trust and awareness of AI among users of their services.

Table 5: Coefficients

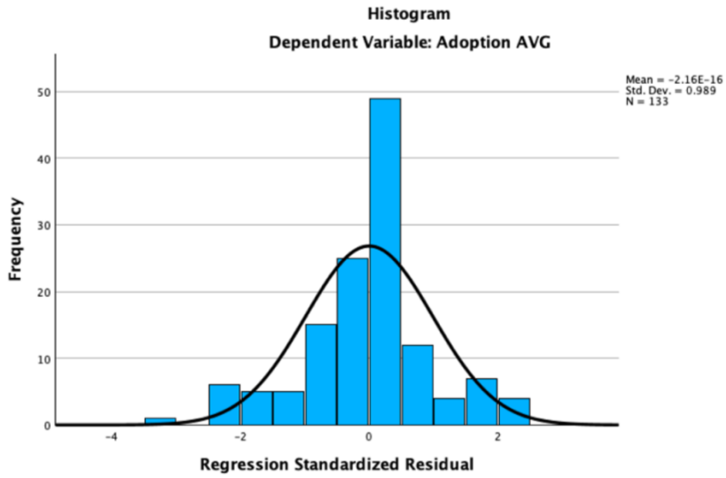
Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-.238	.272		-.874	.384	-.776	.301		
	Awareness AVG	.007	.078	.007	.094	.925	-.148	.162	.675	1.481
	Trust AVG	.040	.079	.034	.507	.613	-.116	.197	.736	1.359
	Satisfaction AVG	.948	.094	.733	10.117	<.001	.762	1.133	.637	1.571

a. Dependent Variable: Adoption AVG

The normality assumption was checked using the histogram as seen below in Graph 3. It can be observed that the regressions (errors) are normally distributed, although there is a slight skew to the left. Most of the values are centred between -2 and 2, which is the typical assumption for standardised results. However, there are some deviations from the standard of perfect normality, including some outliers on the left, resulting in a longer tail on the graph.

Graph 3: Histogram



4.4. Descriptive statistics - frequencies

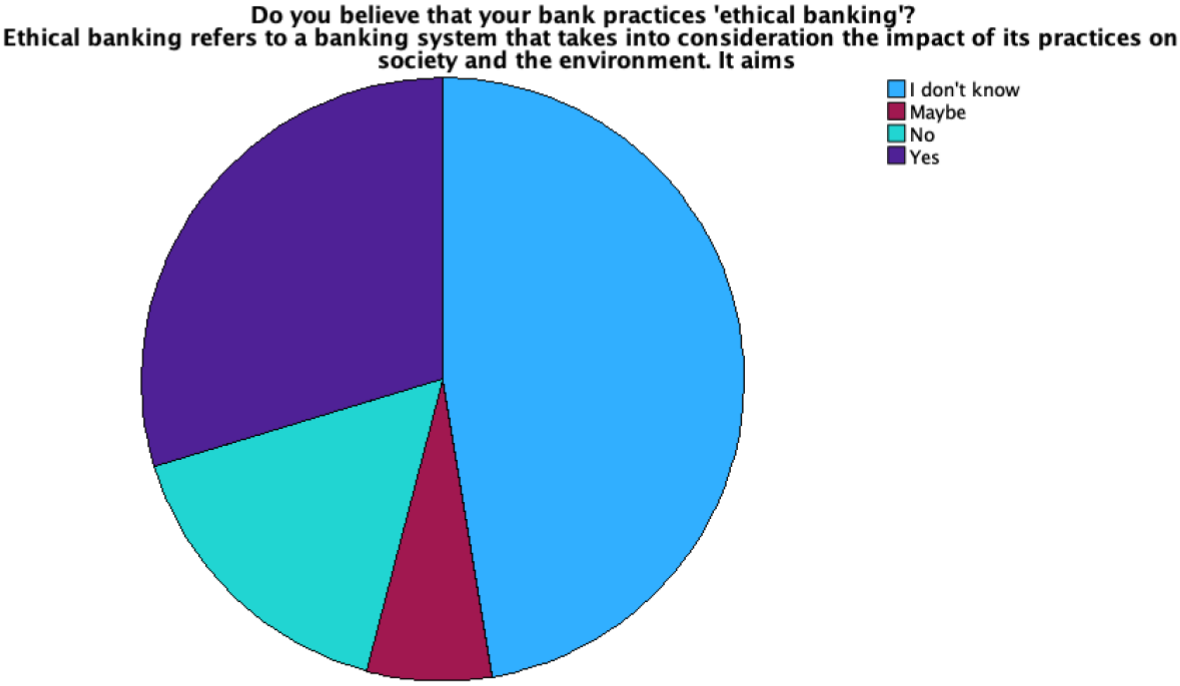
The ethical aspect of the research was statistically analysed using the descriptive statistics tool in SPSS. The research results show that almost 50% of banking customers do not know whether their bank is ethical. A further 9 respondents (6.7%) indicate that their bank may or may not be ethical with 22 participants (16.3%) responding that their bank is not ethical. These findings are consistent with the literature reviewed in Chapter 2, which suggests that there is a lack of awareness around AI. The lack of awareness is particularly evident in the area of 'AI ethics', with most studies focusing on the need to increase awareness through stronger guidelines and ethical frameworks (Pant et al., 2023).

Table 6: Frequencies

Do you believe that your bank practices 'ethical banking'? Ethical banking refers to a banking system that takes into consideration the impact of its practices on society and the environment. It aims

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	I don't know	64	47.4	47.4	47.4
	Maybe	9	6.7	6.7	54.1
	No	22	16.3	16.3	70.4
	Yes	40	29.6	29.6	100.0
	Total	135	100.0	100.0	

Graph 4: Pie chart


Do you believe that your bank practices 'ethical banking'?
Ethical banking refers to a banking system that takes into consideration the impact of its practices on society and the environment. It aims
I don't know
Maybe
No
Yes

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This dissertation has examined the complex influence of the customer perceptions of artificial intelligence in the banking industry. It has led to valuable insights into the impact of awareness, trust and satisfaction on the users' intention to adopt AI banking services. The variables were measured via a survey questionnaire distributed to adults over the age of 18, living in the European continent. The research findings found something new in addition to the existing research. This thesis proves that the adoption of AI-enabled banking is most strongly influenced by customer satisfaction. Meanwhile, factors like customer awareness and trust do not significantly affect the adoption levels of AI in the banking sector. Therefore, customers who do not trust AI applications in banking, as well those who lack awareness, are less likely to adopt AI banking services. Previous research has been carried out by Bedué & Fritzsche (2021), which addresses the slow rate of diffusion of AI due to insufficient user trust. Factors such as knowledge, transparency, explain ability, certifications and standards and guidelines were identified as the main determinants of trust in AI. Therefore, in order to foster user's trust in AI banking, banks should prioritise trust building through being more transparent, provide greater access to knowledge and complying with the main policies and standards.

The new findings from this research show that awareness is not statistically significant for user adoption of AI technologies in the banking industry. This part of the results is consistent with previous studies that have explored the public's understanding of AI. The study proves that many respondents were unable to identify the more complex AI technologies, such as NLP or computer vision (Nader et al., 2022). Many users struggle to describe and differentiate more technical terms. This has led to a limited or inferred understanding of AI (Bewersdorff et al., 2023). The survey responses produce the lowest mean value of 2.852 for the variable of user awareness of AI technologies in banking. Therefore, there is an apparent lack of awareness and knowledge of AI use and its relation to advanced terms such as NLP, ML, RPA and computer vision (See Table 1 for further details). Therefore, the financial industry needs to prioritize the ongoing awareness to assist customer understanding of AI and there increase the adoption of AI offerings.

This thesis presents something new to the current information on artificial intelligence in banking. The results prove that user satisfaction is the most important independent variable in relation to AI adoption in the industry. Although, there is limited research on user satisfaction with AI, the results show that there is a statistically significant relationship between the level of user satisfaction and adoption of AI. The limited existing literature also proves that customers who have high levels of satisfaction are more likely to adopt AI technologies, but this has only been studied in the services industries (Aguiar-Costa et al., 2022). Although some users may not experience high levels of trust or awareness of AI in banking, user satisfaction is a key driver of user adoption and acceptance of these technologies. The research findings are in line with other literature which proves that user satisfaction, along with other factors in customer behaviour and attitude[29], are significant to predicting user acceptance of artificial intelligence-based technologies (Alnaser et al., 2023).

To conclude on the ethical aspect of this paper, the research conducted a contextual review of the ethical implications of AI in the banking industry. Despite the existing research gap in this area, a number of existing studies suggest that there is an abundance of ethical implications surrounding the use of AI technology. Key ethical challenges of AI in the financial landscape that have emerged from existing research include transparency, bias and accountability. Furthermore, corresponding to this dissertation's findings, trust in banks is significantly low, proving the need for banks to prioritise improving transparency and increasing customer autonomy (Seaver et al., 2023) (Hurley, 2014).

The survey findings in relation to the level of ethical awareness surrounding the use of AI in banking is a topic that is limited in scholarly research area.The research findings prove that there is inadequate level of awareness with the terms AI and ethics,

[29] These factors include confirmation, perceived performance, visual attractiveness, communication quality, and corporate reputation

particularly prominent in the banking industry. Nearly half (47.4%) of the survey respondents were unaware if their bank carried out ethical business practices. Furthermore, the findings underscore the necessity for banks to prioritise the ethical guidelines and frameworks to enhance user awareness and trust thereby increasing overall satisfaction.

5.2. Recommendations

A possible recommendation for future research could be to investigate the different variables of customer perceptions towards AI. Due to the scope of the research, the findings are focused on banking user's levels of awareness, trust and satisfaction in relation to AI. However, other aspects such as perceived quality, perceived risk, customer engagement, perceived performance, perceived attractiveness and so on, could be applied to measure customer needs.

Another recommendation for this area would be to conduct a longitudinal study of customer behaviour and attitudes in relation to AI. Banks could observe how customer perceptions have evolved over a longer period, increasing their exposure and familiarity with AI tools. This study was focused to a limited time frame of a couple of weeks however further studies could reveal a more in-depth analysis over several months and years.

5.2.1. Recommendations for banking institutions

In light of the increasing integration of AI within the banking sector, fostering user trust has emerged as a critical challenge. As already proven, trust in banks using AI is significantly low. The results indicate the mean for user trust as 3.0, which is below the mean for the variable of user satisfaction of 3.2. Therefore, banks should prioritise the following activities to enhance user trust of AI, thereby increasing the likelihood of the user adopting these technologies.

Banks need to focus the development of Explainable AI systems, with the implementation of the hybrid black box and white box model. This improves transparency about the often opaque and unexplainable model outputs, making users more like to trust and adopt these technologies.

Furthermore, banks should adopt comprehensive ethical guidelines by following the guidance of regulatory bodies, as well as establishing their own frameworks that emphasise fairness, accountability, and transparency. By committing to ethical standards, banks can address the key ethical concerns (transparency, bias and fairness and accountability) and ensure their organisation operates within ethical boundaries. This will lead to increased trust among users.

As mentioned in the literature review, banks should promote a culture of Corporate Digital Responsibility, emphasising the responsible and ethical use of AI (jelovac et al., 2021). CDR involves prioritising the societal impact of AI to ensure that their use is for the greatest good and does not harm others. It generates a positive reputational brand thereby strengthening user trust.

5.2.2. Recommendations for public administration

Public administrations need to prioritise the ethical challenges posed by the increasing adoption of these technologies, evident in the banking industry. Regulatory bodies could apply the research findings which highlight the need for greater user trust and awareness of AI. Furthermore, the literature review highlights the current gap in regulatory guidance and frameworks for the implementation of AI.

Based on the researchers' recommendations, the launch of educational campaigns to inform the public about AI technologies, their benefits and limitations could be the most effective approach. Perhaps, introducing AI courses in educational settings such as high schools, could enhance public understanding and trust particularly from a younger age.

5.3. Practical limitations of the research

One limitation to this research could be the restricted scope of the sample population. As a result of time and resource constraints, haphazard sampling was used. Haphazard sampling, also known as convenience sampling, involves the selection of cases that are easiest to access, often without any obvious organisational principles (Saunders et al., 2019). Therefore, the sample of the study may not be fully representative of the target population. Due to timing issues, the study did not focus on a specific generation, which may indicate different levels of technological knowledge between different age groups. This may affect the applicability of the results.

Furthermore, the broad population was considered in this study which may result in geographical concerns. Out of the 135 survey respondents, the majority were Irish (n=116). The remaining participants included 7 British, 4 Spanish, 2 French, 1 German, and 4 individuals from other nationalities. The dominance of Irish participants could potentially limit generalisability, lead to sample bias and cultural bias, and reduce the diversity amongst the sample.

Another limitation of this study could be the self-reported questionnaire. Due to complex and technical nature of the terminology used for the survey might have affected participant's comprehension and responses. Terms like "natural language processing", "computer vision" are relatively new terms that could potentially be misunderstood by the respondents, leading to measurement errors. Furthermore, the wording of the questions and the layout of the survey can influence how truthfully participants respond to the items as users are incapable of clarifying any doubts they may have with the researcher.

5.4. Contribution to future knowledge

Although the term 'Artificial Intelligence' has been around since the 1950s, this study aims to complement the limited existing research in relation to customer behaviours towards AI. The knowledge surrounding AI in the banking industry is notably inadequate due to the dynamic and complex nature of the financial sector. The findings from this paper reveal that customer satisfaction is the most important factor in determining customer adoption of artificial intelligence in banking. However, surprisingly the variables of trust and awareness did not have a positive impact on the user adoption towards AI in banking. Banks should use these findings as a recommendation to focus on fostering trust between customers and AI. As well, banks should prioritise the user's awareness of AI technologies through improving public knowledge.

This thesis could be used by future researchers in order to expand on other variables that may affect the adoption rates of AI not only in the banking industry, but across other sectors leveraging these emerging technologies. A significant implication to this study was the novelty of the field, which resulted in a scarcity of pre-existing research and studies on the topic. There is a need for future researchers to develop and explore the customer perceptions and behaviours towards AI and how it affects aspects such as adoption, acceptance, knowledge and so on.

6. CHAT GPT STATEMENT

Declaración de Uso de Herramientas de Inteligencia Artificial Generativa en Trabajos Fin de Grado

ADVERTENCIA: Desde la Universidad consideramos que ChatGPT u otras herramientas similares son herramientas muy útiles en la vida académica, aunque su uso queda siempre bajo la responsabilidad del alumno, puesto que las respuestas que proporciona pueden no ser veraces. En este sentido, NO está permitido su uso en la elaboración del Trabajo fin de Grado para generar código porque estas herramientas no son fiables en esa tarea. Aunque el código funcione, no hay garantías de que metodológicamente sea correcto, y es altamente probable que no lo sea.

Por la presente, yo, Alexandra Murphy, estudiante de Grade en Administración y Dirección de Empresas con Mención en Internacional de la Universidad Pontificia Comillas al presentar mi Trabajo Fin de Grado titulado “The Affect of Customer Perception’s on the Adoption of Artificial Intelligence in the Banking Industry” declaro que he utilizado la herramienta de Inteligencia Artificial Generativa ChatGPT u otras similares de IAG de código sólo en el contexto de las actividades descritas a continuación:

1. Brainstorming de ideas de investigación: Utilizado para idear y esbozar posibles áreas de investigación
2. Revisor: Para recibir sugerencias sobre cómo mejorar y perfeccionar el trabajo con diferentes niveles de exigencia.

Afirmo que toda la información y contenido presentados en este trabajo son producto de mi investigación y esfuerzo individual, excepto donde se ha indicado lo contrario y se han dado los créditos correspondientes (he incluido las referencias adecuadas en el TFG y he explicitado para que se ha usado ChatGPT u otras herramientas similares). Soy consciente de las implicaciones académicas y éticas de presentar un trabajo no original y acepto las consecuencias de cualquier violación a esta declaración.

Fecha: 4 de junio

Firma: Alex Murphy

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8. APPENDICES

8.1. Appendix 1

The 10 Recommendations of the United Nations Educational, Scientific and Cultural Organization on the Ethics of Artificial Intelligence was adopted at the General Conference at its 41st session in Paris on November 23rd 202.

1. **Proportionality and do no harm**
   The use of AI systems must not go beyond what is necessary to achieve a legitimate aim. Risk assessment should be used to prevent harms which may result from such uses.

2. **Safety and Security**
   Unwanted harms (safety risks) as well as vulnerabilities to attack (security risks) should be avoided and addressed by AI actors.

3. **Right to Privacy and Data Protection**
   Privacy must be protected and promoted throughout the AI lifecycle. Adequate data protection frameworks should also be established.

4. **Multi-Stakeholder and Adaptive governance and collaboration**
   International law and national sovereignty must be respected in the use of data, meaning States can regulate the data generated within or passing through their territories. Additionally, participation of diverse stakeholders is necessary for inclusive approaches to AI governance.

5. **Responsibility and Accountability**
   AI systems should be auditable and traceable. There should be oversight, impact assessment, audit and due diligence mechanisms in place to avoid conflicts with human rights norms and threats to environmental wellbeing.

6. **Transparency and Explainability**

The ethical deployment of AI systems depends on their transparency and explainability. For example, people should be made aware when a decision is informed by AI. The level of transparency and explainability should be appropriate to the context, as there may be tensions between transparency and explainability and other principles such as privacy, safety and security

7. **Human Oversight and Determination**

   Member States should ensure that AI systems do not displace ultimate human responsibility and accountability.

8. **Sustainability**

   AI technologies should be assessed against their impacts on 'sustainability', understood as a set of constantly evolving goals including those set out in the UN's Sustainable Development Goals.

9. **Awareness and Literacy**

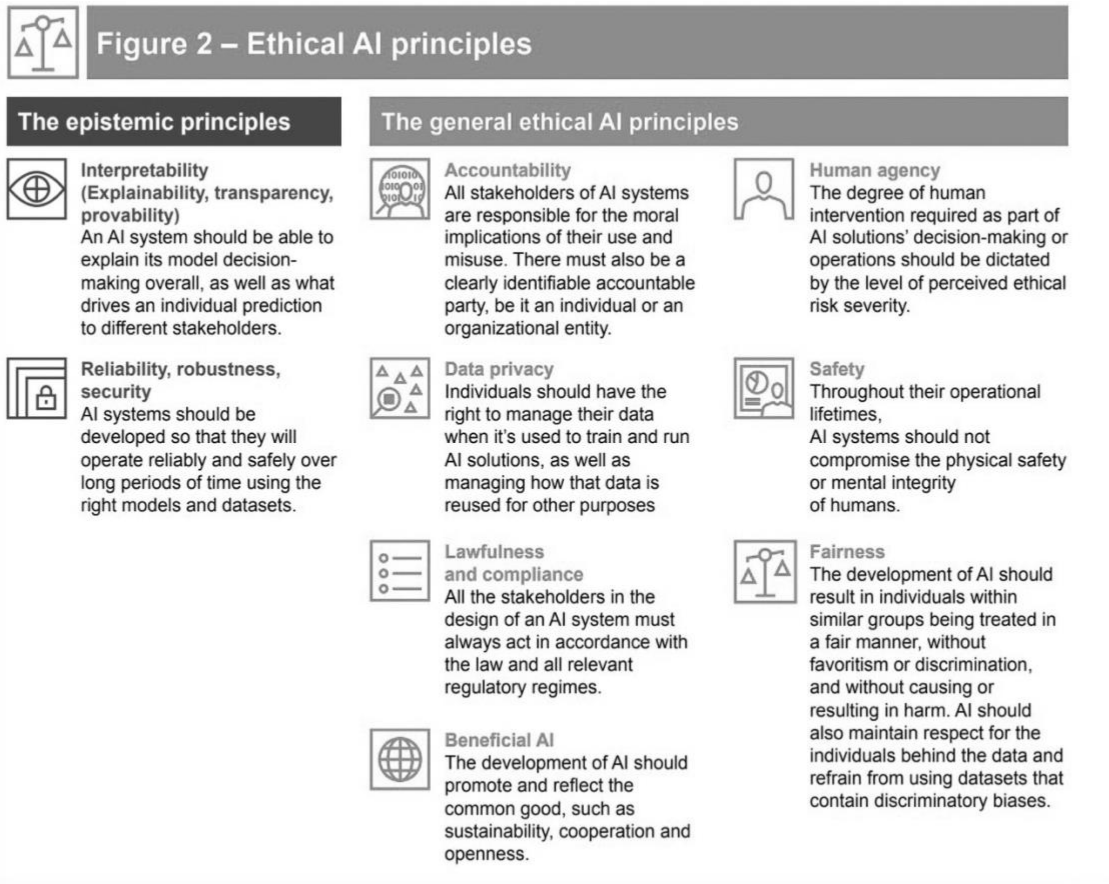
   Public understanding of AI and data should be promoted through open and accessible education, civic engagement, digital skills and AI ethics training, media and information literacy.

10. **Fairness and Non-Discrimination**

    AI actors should promote social justice, fairness, and non-discrimination while taking an inclusive approach to ensure AI's benefits are accessible to all

[Source: UNESCO, 2023]

8.2. Appendix 2



[Source: PwC, 2021]