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Banking and Artificial Intelligence:
The Impact on the "Invisibles" and the Future of Financial Services

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Abstract

This thesis examines the impact of artificial intelligence implementation in financial services on traditionally excluded segments, also referred to as the "invisibles," in relation to financial inclusion and technological transformation. As banks increasingly adopt AI-based solutions, a crucial question emerges as to whether these new digital advances will extend financial services to additional segments of society or deepen inequalities even further. This study adopts a mixed-method approach consisting of quantitative regression analysis and fuzzy-set Qualitative Comparative Analysis (fsQCA) to examine complex interrelationships between AI adoption, user attributes, and financial inclusion outcomes. A cross-sectional survey study on 200 banking users was conducted, split between AI-based services and conventional bank channels customers, and it ivestigated psychological drivers of technology adoption such as trust in technology, perceived ease of use, and personal innovativeness, alongside demographic indicators of vulnerability, beyond regular Technology Acceptance Model (TAM) variables, to capture persistent engagement. The findings show that consumers of AI services present an increased engagement compared to those of traditional banks, and this attitude persists after controlling for demographic factors as well. Therefore, challenging previous TAM assumptions, traditional psychological indicators revealed poor explanatory capabilities, implying that the value stemmed from digital services transcends individual psychological obstacles. The fsQCA study identified multiple equifinal outcomes to successful digital adoption, suggesting that financial inclusion can be achieved through numerous configurations and not just one ideal solution, underlining the importance of adaptive and customized solutions in banking. Moreover, this research contributes to stakeholder theory, showing how AI adoption can provide shared value to various customer segments while achieving ESG targets on financial inclusion, highlighting how successful technology adoptions must move beyond efficiency-driven implementations toward approaches ensuring accountability, algorithmic fairness, and digital inclusion and accessibility for excluded individuals. This thesis concludes that while AI has unprecedented ability to provide financial inclusion, realizing this potential requires active effort, inter-disciplinary collaborations, and governance frameworks in support of stakeholder welfare rather than short-term measures of efficiency. With critical crossroads facing the financial sector, today's decisions in AI deployment

will determine whether advances in technology will be an engine of financial empowerment or an inhibitor solidifying dominant gaps deeper.

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Chapter I: Introduction

In today's financial services landscape, artificial intelligence is emerging as a transformative force rewriting at unprecedented speed institutions' distribution of services, risk management, and customer engagements dramatically. The application of AI to banking channels is transforming financial services to a degree never seen before, with algorithmic trading and portfolio management being driven by robo-advisors, AI-powered credit scoring, and chatbots being critical features of modern financial ecosystems (Vuković et al., 2025). Such paradigm change promises greater operational efficiency, reduced cost, increased predictive ability, and customer satisfaction through the ability to process large sets of information at unmatched speed and precision. However, with digital tools increasingly being embraced by financial institutions, a critical question arises: who can help those people who always remained invisible to mainstream financial services? "Invisibles" in financial services are those who have traditionally remained outside mainstream banking services' coverage due to circumstances such as economic marginalization, lack of information about credit history, minimal knowledge of technology, geographic remoteness, or institutional exclusion (Park & Mercado, 2018; Vuković et al., 2025). These segments are estimated to approach 1.4 billion adults, as stated by the World Bank, and are likely to remain further excluded while the financial landscape is being redesigned by fast transforming digitalization. The paradox lies in AI technology presenting great possibilities towards democratization of financial services and access to excluded communities, while at the same time potentially increasing digital exclusion and further widening social inequities

Financial services have seen a revolutionary change over the last decades from branch-based to digitalized data-driven ecosystems. In the late 20th century, internet banking represented a catalytic agent to initiate the process towards digitalization, however the trend attained significant momentum towards the 2000s with the rise of online banking and payments through mobile phones. Today, AI as represents further steps towards this process change and act as a disruptive phenomenon to radically transform financial operations and decision-making approaches (Vuković et al., 2025). Machine learning algorithms, deep learning systems, natural language processing (NLP), and robotic process automation (RPA) are increasingly being implemented on all banking activities. Adoption of AI is automating repetitive tasks as well as empowering data-driven decisions, improving decision-making and risk management procedures and radically

transforming financial services' competitive environment. The underlying motivators for this AI transformation are grounded upon promises to boost operational efficiency, cost reduction, improved predictive intelligence, and superior customer experience management, as AI technology's ability to process high volumes of information quickly and with greater accuracy, compared to human capacity, allows more accurate decisions in risk assessment and proactive risk monitoring (La Croce, 2023; Vuković et al., 2025).

However, this transformation is driven by both opportunity and competition. The emergence of agile modern FinTech players and neobanks has amplified customer expectations about seamless digital services and digital excellence to the point of forcing traditional banks to renew and reinvest at very fast rates to compete successfully and maintain profitability in the current landscape (Digital Banking Trends 2025, 2025). However, with these promises, a critical paradox emerges: while AI has the power to catalyze breakthrough performance gains, it creates at the same time new risks when not monitored properly (Vuković et al., 2025). This trade-off between transparency and accuracy is an exemplification of how complex "black-box" models can achieve superior predictive performance but are difficult to interpret, explain, and trust, which has generated significant controversy and regulatory interest in the context of explainable AI (XAI) (Ahern, 2021; Arner et al., 2020; Vuković et al., 2025).

Despite the fast pace at which financial institutions are being digitalized, many people still remain underserved or excluded from mainstream financial services. As services are transferred to digital formats, not all customers are able to cope with these transformations and some segments are thus rendered "invisible" and left further behind in the process. Economic vulnerability has been correlated with digital exclusion since individuals who are socioeconomically weaker and less educated are further likely to lack access to technology and digital literacy, creating what researchers refer to as a "digital divide." Financial inclusion barriers arise from structural and digital challenges. The structural barriers are characterized by residence in rural or disadvantaged locations with poor banking access. The digital barriers are represented by non-ownership of mobile platforms, poor internet coverage, insufficient digital literacy, and lack of confidence when using digital tools (Kling et al., 2020; Fazal et al., 2023). However, it is crucial to recognize that vulnerability to financial services is neither permanent nor necessarily an intrinsic characteristic of the individual per se, yet contextual and can be constructed by service design and delivery decisions (SERVSIG, 2020). Even traditionally non-vulnerable consumers can become vulnerable

when service settings are not suited to their needs, as financial service providers can inadvertently exacerbate vulnerability or create "invisible" customers by failing to accommodate to users' requirements. Common issues include explicit or implicit bias against specific demographics, accessibility barriers in service delivery (such as websites or applications inaccessible to people with disabilities or non-native speakers), standardized service procedures that disadvantage those with fewer resources or less knowledge, and channel assumptions that all customers engage in identical manners (SERVSIG, 2020). Therefore, the industry must actively recognize and address these "invisible" populations—customers who are overlooked or underserved in the drive toward high-technology banking solutions.

As we navigate the multifaceted context of challenges and possibilities, this research aims to discover AI-driven banking services' impact upon vulnerable or "invisible" customers compared to traditional ones. The study employs a mixed-method approach by combining quantitative analysis and comparative qualitative examination to achieve a comprehensive understanding of this phenomenon.

We will address three main research questions:

RQ1. *"Does service type (AI or traditional) impact customers' adoption and engagement levels?"* This question examines whether customers using AI-based banking services demonstrate different adoption patterns, satisfaction levels, or engagement compared to users of traditional banking services.

RQ2. *"How do key psychological drivers influence adoption and use of banking services?"* This question focuses on psychological factors such as technology trust, perceived ease of use, and individual innovativeness, investigating whether these factors significantly affect adoption and engagement across different customer segments.

RQ3. *"Do psychological factor interactions with adoption and engagement depend on service type or user attributes?"* This question explores potential interaction and moderation effects, examining whether psychological drivers play different roles depending on service type or user characteristics, particularly for vulnerable groups.

The future of the financial sector will undoubtedly be shaped by artificial intelligence but whether it will be inclusive or exclusive of the "invisibles" is determined by decisions undertaken today. This research is a contribution to this crucial debate by investigating intricate interactions between AI adoption, user attributes, and financial inclusion outcomes. By integrating empirical

analysis and recommendations for banks and policymakers, it aspires to discover the paths of AI-driven financial services that can benefit society as a whole. By understanding how different populations interact with AI-enabled financial services, we can aim at a future where technology innovation is the key to financial inclusion and never a barrier to it. The implications are big and diverse: success can extend financial services' benefits to excluded segments while failure can deepen current disparities and create new facilitators of digital exclusion. The responsibility to ensure the desirable outcomes lies with all stakeholders in the financial system, tasked to design and develop the future of the baking landscape.

This research is a contribution to this necessary effort, offering findings and recommendations to inform responsible AI design and deployment towards financial services. As we enter this turning point for banking and financial history, decisions we make regarding AI will have lasting impacts for financial inclusion and social equity. It is therefore absolutely necessary that we approach this transformation with thoughtful consideration regarding its implications for all population segments, particularly those who have suffered exclusion or lack of access to financial services. The journey towards inclusive AI for financial services is hard and iterative, and will require constant effort, continued learning, and responsive strategies to changing technology and shifts in social demand. By doing high-quality research, informed policy work, and responsible innovation, we can work towards a future where AI is a financial empowerment resource and source of opportunity for all to access and benefit fully.

Chapter II: Literature Review

The application of artificial intelligence (AI) to banking sectors is transforming financial services to an unprecedented degree. Algorithm trading and robo-advisory services to AI-driven credit scoring and chatbots, AI technologies are transforming banks' ways of working and providing value to customers (Vuković et al., 2025). However, such innovations with great potential for efficiency and customisation pose important questions over inclusion and ethics. A particular concern is the impact on the "invisibles": individuals who have historically been invisible to formal financial systems because they were economically vulnerable, lacked credit history, or were excluded from digital opportunities, therefore, making sure that AI-led innovation includes these populations, rather than leaving them behind, presents a core challenge. This chapter will delve in an in-depth literature review of AI in banking with a focus on financial inclusion and vulnerable consumers' well-being. It will review the development of AI in financial services, examine the obstacles faced by the "invisibles," and address theoretical approaches like transformative service research that centers on consumer well-being. Additionally, it will further discuss the varieties of AI technologies utilized in banking sectors and their strategies (such as personalisation and cost efficiency), the fine balance between innovation and inclusion, and the ethical concerns arising from automation, accountability, and fairness. Finally, inclusive AI practice examples from empirical studies will be examined, including Environmental, Social, and Governance (ESG) frameworks and stakeholder theory in directing ethical and inclusive AI adoption.

II.I AI and the evolution of financial services

Financial services have undergone a transformative development over the last decades, from conventional branch-centric models to digitalized, big-data-driven ecosystems. Internet banking in the late 20th century began the process of digitalizing financial services, but the process gained momentum in the 2000s with the emergence of online banking and mobile payments. Today, AI represents the next step in this evolutionary process and has been classified as a distruptive phenomenon transforming financial operations and decision-making (Vuković et al., 2025). AI technologies such as machine learning algorithms, deep learning, natural language

processing (NLP), and robotic process automation (RPA) are finding increasing deployment across banking functions, as they enable automated scoring of credits, detection of frauds, algorithmic trading, customer service via chatbots, robo-advisory investment solutions, and more (Ranković et al., 2023; Vuković et al., 2025). Integration of AI is not only automating routine activities but it also is empowering data-driven insights that optimize decision-making and risk management. Industry surveys indicate that almost 80% of financial institutions around the world are already implementing some form of AI, with investment in AI set to double over the coming years, reaching an estimated $97 billion by 2027 with a compound annual growth rate of nearly 30% (Vuković et al., 2025; U.S. Department of the Treasury, 2024). Moreover, a recent study on 600 bank leaders identified 78% of banks implement generative AI in at least one use case, with key areas of focus including risk & compliance (32% of cases) and customer engagement (26%) (U.S. Department of the Treasury, 2024). The underlying causes driving this transition are the promise of improved operational efficiency, reduction in costs, improved predictive tasks with higher precision, and better customer experiences, as AI technology has the ability to process large sets of data faster and with higher precision than human capabilities in areas such as risk evaluation, making it possible to make more accurate decisions around lending, as well as monitor risks better proactively (La Croce, 2023; Vuković et al., 2025). Thus, the motivation behind this AI-driven transformation is a result of opportunities and challenges in the banking sector. On the one hand, AI promises more personalization, greater efficiency, and a decrease in service-related costs, since AI-driven automation is capable of making procedures less labor- and time-intensive (e.g. loan administration, fraud identification) with great cost savings paired with faster service resolution. On the other, banks are facing pressure both when it comes to competition, as well as regulatory challenges that require digital innovation, as the emergence of agile FinTech startups and neobanks has raised expectations among customers for smooth digital experiences (Digital Banking Trends 2025, 2025). Therefore, in response and to remain competitve, conventional banks need to innovate fast, providing the 24/7, mobile-first services demanded by technology-prone consumers. This pressure has only increased as mobile banking became the key gateway for interactions: in Europe, for instance, 85% of online banking users make use of a mobile app at least four times per month (Digital Banking Trends 2025, 2025). In addition, banks face thin interest margins and cost constraints, pushing them to embrace AI as a means for process efficiency and cost reduction. Even the COVID-19 pandemic spurred new digital adoption (e.g. online banking), where AI

solutions such as chatbots and digital onboarding become even more vital. At the same time, the industry faces multifaceted challenges like increased cybersecurity risks, increased compliance mandates, as well as changing regulations. However, alongside the opportunities, research highlights a paradox: whereas AI can drive breakthrough performance, it creates new risks when not adequately managed (Vuković et al., 2025). The transparency vs. accuracy trade-off is one such example: extremely sophisticated "black-box" models (e.g. deep neural networks) might provide predictive capability but can be difficult to understand and rely upon. This has spurred debates as well as regulatory interest in explainable AI (XAI), particularly in sensitive use cases like lending decisions (Ahern, 2021; Arner et al., 2020; Vuković et al., 2025). Overall, the financial services' evolution is characterized by the push towards digital, AI-powered models for enhanced efficiency and customer focus, but it also raises critical questions about fairness and inclusivity.

II.II Economic vulnerability and digital marginalization in banking

Despite financial institutions' digitalization, numerous individuals continue to remain underserved or excluded from formal financial services, since, when services are transferred to the internet, not all customers could adapt to this change, and some are left potentially "invisible" and behind during this process. As a matter of fact, economic vulnerability, involving low income and financial insecurity, is often associated with digital exclusion, since poorer, less educated, and socially excluded individuals are more inclined to lack access to technology and to digital literacy, creating a "digital divide." In banking, this refers to the fact that many vulnerable people encounter difficulties in getting access to modern financial services, where an increasing number of services presume connectivity, along with technology proficiency, upon users. Globally, the size of financial exclusion remains significant: the World Bank estimates that around 1.4 billion adults across the world continue to lack access to basic formal financial services (Embracing New Technological Challenges and Opportunities, and Building a New Financial Ecosystem, 2024). The majority of these unbanked/underbanked individuals are located in developing countries, but even in industrialized countries, instances of exclusion remain, frequently among the underprivileged, old-aged, disabled, immigrants/refugees and minorities (Park & Mercado, 2018; Vuković et al., 2025). Lack of access stems both from structural causes (e.g. living in remote or underserved ares with no banking presence), but increasingly from digital ones: not owning a

smartphone or having access to internet, insufficient digital skills or lack of confidence in utilizing digital instruments in banking (Kling et al., 2020; Fazal et al., 2023). As a matter of fact, studies in advanced economies indicate that senior citizens, in particular, are suffering as financial services become digital, therefore digital exclusion further exacerbates financial exclusion in the era of AI. As banking services go digital, individuals without reliable internet access, smartphones, or digital literacy risk falling behind. As a matter of fact, in most underdeveloped areas, limited connectivity and technology infrastructures hinder ease of access to online and mobile banking (Vuković et al., 2025). Moreover, lack of education and digital literacy means some consumers lack the confidence to use apps or comprehend digital financial products. Financial illiteracy in general remains a barrier: individuals without knowledge about financial concepts might not take advantage of banking services even when offered (Fazal et al., 2023). In addition, trust issues and cultural barriers are also play a role in the process of digital exclusion in the banking sector. Barriers arising from culture, along with mistrust in mainstream institutions, might deter certain groups from using banks, particularly when past experiences or social expectations lean toward informal banking practices (e.g. favoring strictly cash transactions) (Fazal et al., 2023). For instance, Arora (2020) identifies privacy concerns, cultural expectations, along with lack of trust, as inhibiting digital finance adoption among susceptible consumers even when technically accessible. However, it is important to keep in mind that vulnerability in the financial services context is not static or solely a personal trait, but contextual and can be created or worsened through services design and delivery (SERVSIG, 2020). Research identifies vulnerable consumers as those who, because of personal traits and circumstances, experience a state of powerlessness in the marketplace, making their goals difficult to accomplish (SERVSIG, 2020). The powerlessness might result from individual characteristics (e.g. age, disability, minority) and/or with respect to situational causes, including how firms and systems engage with the individual (SERVSIG, 2020). In other words, even "non-traditionally" susceptible consumers become susceptible when the service setting isn't suited to their needs, as banks and financial service providers can inadvertently exacerbate vulnerability or create "invisible" customers by failing to reflect their needs. Some common issues include: bias or exclusion (explicit/implicit) of specific demographics, accessibility barriers in service delivery (e.g. websites or apps inaccessible for people with disabilities or non-native speakers), standardized servicing procedures that fail those with less resources/knowledge, along with channels accommodating an assumption that all customers engage in exactly the identical manner

(SERVSIG, 2020). For instance, a bank aggressively shutting physical branches to focus on digital channels could save money, but at the expense go elderly or rural customers for who relied on in-person services, thus enhancing those segments' exposure to exclusion. Therefore, the industry has to recognize these "invisible" players, the customers overlooked or underserved on the drive toward high-tech banking. Financial inclusion is viewed as an enabler of multiple Sustainable Development Goals because it can empower people economically: extending even basic services such as transaction accounts, payment, and credit to those not currently served can transform lives, reducing poverty and inequality dramatically. Regulatory and identification barriers contribute to invisibility too. Most unbanked people do not possess official identification papers needed by banks (e.g. government ID or address proof). Therefore, strict Know-Your-Customer (KYC) policies, while necessary for security, unintentionally keep out people without formal IDs or residence proof, a common situation for the homeless, migrants, or those practicing informal economy. Unless actively addressed, there's the risk the transformation of banking by AI could exacerbate the divide, offering complex digital offerings to the connected and creditworthy, but those on the margins falling further behind. Therefore, acknowledging these risks and challenges is the first step towards inclusion.

II.III Inclusive service paradigms: transformative services and consumers well-being

To address concerns of exclusion and enhance consumer welfare, scholars have turned to transformative service research (TSR) and transformative consumer research (TCR) paradigms. These theoretical perspectives target the service aspect and the consumption process to increase the welfare of people and communities, particularly those on the margins or vulnerable communities. Transformative Service Research (TSR) focuses on identifying and resolving service problems to advance the well-being of individuals and communities (SERVSIG, 2020; Anderson et al., 2013). It moves the service evaluation away from the conventional metrics of customer satisfaction or loyalty, to those of access, equity, empowerment, and quality of life. In the context of financial services, for instance, TSR urges us to ask *"Does the banking service enhance the financial well-being of the customer to address disparities?"*, instead of merely *"Is the customer satisifed?"*. The moral argument behind TSR is based on the notion of human dignity and the

demand for businesses to serve obligations to society beyond financial gain. This corresponds with the transformative consumer research (TCR) introduced by Mick (2006) as a movement for the type of research aiming to alleviate societal problems and enhance consumer welfare. Both paradigms pivot on consumer vulnerability as a primary consideration, recognizing that the majority of the time, the consumer has weaker knowledge or positions than the provider (especially with complex service offerings like financial services where the customer tends to lack knowledge). Customers in financial services, lack the knowledge base, therefore, the advantage, highlighting the need for the service provider to protect the interest and capability of the consumer (Mende et al., 2024). The implementation of TSR to financial inclusion implies designing and delivering financial services in a way that increases the welfare of the previously unbanked or the vulnerable. Research along this line tends to investigate the manner by which the innovative service or the customer's engagement leads to enhanced empowerment, together with financial capacity. For example, Bustamante and Amaya (2020) discuss the transformative approach to services for the unbanked, reporting specific service design factors that significantly enhance the welfare of the unbanked customers. In their study on unbanked consumers conducted among developing countries, the aspects of trust and participation of the customer were identified as the pivotal factors. When service delivery included high-perceived customer support and trustworthy interpersonal communication (e.g., with local banks or "storekeepers"), unbanked customers were more likely to seek financial services (SERVSIG, 2020). Customer participation, in turn, led to greater financial empowerment, meaning customers felt more incontrol over finances and capable of making financial decisions, ultimately generating better financial well-being (SERVSIG, 2020). The authors conclude that service strategies to build confidence and facilitate active customer engagement can transform the lives of the unbanked, furthering TSR's mission to build consumer well-being via service design. Applications of TSR/TCR to finance have converged with the UN Sustainable Development Goals, with financial inclusion holding the key to poverty reduction and equity (Soetan et al., 2024). Thus, research in developing economy shows stark rural-urban financial access gaps: through the application of the TSR lens, studies have suggested tailored strategies (such as differential pricing or service delivery) so rural, poor customers are not left behind (Soetan et al., 2024; Ofori-Okyere et al., 2023). Another financial services marketing to vulnerable customers research suggests that AI and digital strategies must be considered through the lens of consumer vulnerability, and how these technologies will abolish (rather than heighten)

vulnerabilities (Mogaji et al., 2020). Overall, transformative service research is an important lens to address the needs of the "invisibles." It reframes the financial service function more so than the delivery of economic transactions, but rather a platform for the enhancement of the quality of life and empowerment of the consumer. The literature under this paradigm calls for service innovations increasing access (financial inclusion), equity (closing gaps between poor and rich customers), and outcomes (financial well-being, resilience). Through the application of TSR and TCR frameworks, researchers and professionals can better assess not just the business performance of the innovations powered by AI within the banking sector, but more so how the innovations assist in transforming and enriching vulnerable consumers' life. We must remember that technology is not by default inclusive: it has to be guided by design principles and strategies actively oriented towards increasing access, equity, and empowerment for the vulnerable. This gives rise to the discussion of the double role of AI within the financial sector: as a powerful tool capable of reducing the gap to the "invisibles" but, if misused even further widening it.

II.IV AI technologies and applications in banking

Banking applications of AI technologies range across a wide spectrum, with each playing strategic functions of personalization, efficiency, risk reduction, and costs reduction. A review of recent literature identifies how banks are applying AI across nearly all major service functions, radically altering the delivery of financial services (Tajudeen & Tajudeen, 2024). Some of the major AI applications include:

- Credit Scoring and Risk Management: machine learning models are commonly used for credit scoring, loan underwriting and credit risk evaluation. These algorithms evaluate customer information to forecast default risk better than legacy scorecards. For example, sophisticated algorithms can extract subtle patterns related to creditworthiness, and banks can extend credit to additional customers with reduced risk (Vuković et al., 2025). Moreover, AI-based credit analytics also provide real-time risk monitoring of loan portfolios. However, as previously discussed, making these algorithms interpretable and fair is an open challenge being actively pursued using research into interpretable AI and fairness in credit (Chen et al., 2024). Nevertheless, from a strategic perspective, improved risk discrimination enables banks to reduce default rates and capital loss, and potentially

to responsibly originate loans to additional segments of customers previously considered too risky.

- Fraud detection and security: AI is an integral component for banks' fraud prevention. Data mining and anomaly detection techniques powered by AI scour transaction data for suspicious activity (such as identity theft, money laundering, or credit card fraud) in real time (Vuković et al., 2025). These systems utilize machine learning classifiers and sometimes deep learning (such as autoencoders for anomaly detection) to signal human operators abnormal patterns they might miss (Vuković et al., 2025). The strategic benefit is straightforward: AI can considerably expedite and refine fraud detection accuracy, minimizing financial loss and enhancing security for the both banks and their clients. Moreover, AI strengthens cybersecurity defenses (such as recognizing network intrusions or attempts at phishing) which is critical to instilling confidence into increasingly digitalized financial services (Mhlanga, 2020; Vuković et al., 2025).

- Customer service and personalisation: one among the most evident deployments of AI in banks is in services like chatbots and virtual assistants powered by AI. These NLP-based agents are always available to answer customer queries, carry out transactions (like balance inquiries, money transfers), and even provide basic financial advice in natural language. And, by doing so, they hugely reduce inconvenience and response time. Lopes et al. (2025) state that banks are leveraging AI in mobile banking for account maintenance, instant payment, and custom financial advice, accessible through smartphones and other devices. AI facilitates services to become highly personalisied, with product recommendations, alerts, and financial advice fine-tuned for users' behaviours and needs (Lopes et al., 2025). Therefore, such personalisation enhances customer engagement and loyalty since services are custom-fitted to individual customers' preferences. From a strategic standpoint, personalisation with AI can expand product penetration (cross- and up-selling) and better user experience, giving banks a clear edge in retaining customers, as researchers have found that customers appreciate personalisied services and find them better in terms of quality, resulting in better satisfaction and trust (Lopes et al., 2025).

- Automation of process and efficiency: AI algorithms and robotic process automation (RPA) are employed to automate numerous back-office and bank administrative functions. Examples include computer vision (in handwriting or optical character recognition in

checks and forms) to allow for automatic document processing, checking and reporting of automated compliance, customer onboardings (like ID check automation), and transaction processing. Automating repetitive and time-consuming activities, AI makes processes much more efficient and much less expensive (Lopes et al., 2025), because repetitive decisions (like a clear-cut approval of a loan or authorization of a transaction) are usually processed more quickly and with less mistake by AI systems than humans. The result is not only cost savings, from lower labor and faster processing, but an increase in consistency and correctness of process. Tajudeen and Tajudeen (2024) explain how the increasing application of AI to process automation and audit has improved banking process efficiency, automating previously manual processes. For banks, it facilitates a scaling of service without a proportionate increase in staff or physical infrastructure, particularly valuable in low-margin or high-volume lines of service.

- Marketing and Customer Relationship Management (CRM): AI facilitates banks in processing customer information to better target marketing campaigns and handle customer relationships, as machine learning algorithms divide customers and forecast their product interest or churn probability, supporting predictive marketing. Marketing personalisation, offering the correct offer at the correct time, is significantly boosted by AI analysis of large data, and, by using AI strategically in marketing, the results are improved campaign ROI and enhanced customer loyalty.

- Trading and investment advisory: in investment banking as well as wealth management, AI contributes through algorithmic trading, portfolio optimization, and robo-advisory. Algorithmic trading platforms employ AI at speed and frequency to carry out trades automatically using sophisticated strategies, which can improve liquidity and pricing efficiency in markets. At low cost, robo-advisors meanwhile offer retail clients automatic investment advice and portfolio management. Utilizing AI algorithms to align portfolios to client risk profiles and rebalance where necessary, robo-advisors have broadened financial advice accessibility, as they offer an inclusive advantage by catering to clients with lesser asset balances who would otherwise not afford human advisors. Through robo-advisors, banks as well as fintechs strategically target new customers as well as asset flows, while maintaining lean operations.

In summary, AI technologies in banking have strategic applications like personalisation enhancement (with data-based insights and customisation), efficiency enhancement (through decisions and process automation), enhanced risk control and security (with sophisticated predictive analytics), and operational expenses reduction. These enhancements are supportive of banks' strategic objectives to grow profitability, expand market base, and effectively control risks in a highly competitive market space. Importantly, AI benefits are not only internal (cost and revenue) but also customer-oriented, faster delivery of services, convenience, and services better tailored to personal needs (Lopes et al., 2025), because AI can potentially "redefine the consumer experience" in banking by delivering the level of responsiveness and personalisation that was not previously possible at scale (Lopes et al., 2025).

II.V Innovation and inclusion in financial services

In pursuit of AI-led innovation, a key issue is how the push for innovation can be balanced with the need for financial inclusivity and equity. Moreover, literature increasingly states that unbridled innovation can at times exacerbate social gaps, and therefore a balanced strategy is required: one that fosters innovation while addressing ethical, regulatory, and societal concerns (Vuković et al., 2025). Vuković et al. (2025) emphasizes such balance and its need, arguing that responsible AI adoption in finance must promote new capabilities in a manner that doesn't compromise transparency, fairness, and access. More specifically, the balance between innovation and inclusivity entails a number of dimensions:

1. Inclusive design vs. cutting-edge technology: a common dilemma facing banks is the trade-off between implementing cutting-edge digital technologies and making those technologies accessible to all customers. For instance, a bank might launch an AI-powered mobile application with high-tech features, however, if a section of its customers (e.g. the elderly or the poor) cannot access a smartphone easily or pay for data plans, they could be excluded and left behind. Therefore, banks need to design digital innovation in an inclusive manner: user-friendly interfaces, support for various languages and literacies, and alternative channels for the non-online customers. Moreover, according to studies, localization and customization of financial services must be synchronized with the realities of customers on the ground (Vuković et al., 2025). Innovation, therefore, must not take place in a vacuum,

but it is critical to understand the context of the target users. Aziz and Naima (2021) state that the localization of services and the removal of impediments such as constrained connectivity and a lack of awareness is essential in the context of inclusive financial access in the digital environment. Therefore, when banks introduce AI-based services, complementary initiatives (education, digital literacy programs, community outreach) may be necessary in bringing the marginalized groups onboard (Vuković et al., 2025).

2. Digital transformation and the risk of exclusion: the push toward digital-only banking can inadvertently leave behind those who rely on traditional channels. Physical branches have been shut down in a bid for online services, in the interest of efficiency, but this can disadvantage communities where internet access is poor or where people feel uneasy about the use of digital tools. Responsible innovation would aim at a phygital balance: harnessing AI where it enhances service, but still having human support where inclusivity is at stake. Some banks, for example, use AI in back-end processing in a move that accelerates service at the branch, rather than closing the branch, thus blending innovation and human touch for vulnerable customers. Policymakers increasingly stress the principle of "leaving no one behind" in digital finance, as they promote such innovations as agent banking networks or shared digital infrastructure so that rural and low-income users can be included (Demirkan et al., 2020; Vuković et al., 2025).

3. Regulatory frameworks for inclusive innovation: regulators and global institutions have started developing guidelines that stimulate innovation alongside consumer protection. Sandboxing environments, for instance, enable fintech innovation under controlled experimentation, enabling creative innovation (such as AI credit scoring based on alternative data) while checking for risks such as exclusion or bias. A prime example is the push towards standardized frameworks for AI execution across the financial services, a gap mentioned in the literature (Vuković et al., 2025). In the absence of such standards, institutions may use AI in ways that, for instance, disregard patterns in the data of minorities, excluding them unintentionally. A balanced approach calls for anticipatory regulation that checks the possible exclusionary impacts of new technologies and sets guidelines for preventing them (Wang et al., 2020; Vuković et al., 2025). Regulators are also trying to stimulate innovation in e-KYC and digital identity as a means of including more people in the system safely (discussed in the following section).

4. Innovation driving inclusion: it is important to note that innovation and inclusion need not be opposing forces: in fact, many innovations are the key to inclusion. As a result, the fintech revolution has shown that mobile banking and digital wallets can reach millions of unbanked people faster than traditional methods, and AI, in particular, can be a powerful enabler of inclusion if deployed thoughtfully. Arner et al. (2020) argue that AI and fintech are key drivers of financial inclusion, highlighting two major factors: electronic Know-Your-Customer (e-KYC) protocols and interoperable electronic payments. On one hand, innovations like e-KYC (often leveraging AI for biometric identification or document verification) can drastically simplify account opening for marginalized groups, who might lack conventional documents but can establish a digital identity through biometric ID programs. On the other hand, interoperable payments (e.g., mobile money platforms that work across providers) make transactions smoother and cheaper, benefiting those who previously relied on costly cash transfers. These examples illustrate that innovation, when directed at inclusion challenges, can produce great improvements in access. Therefore, "balancing" innovation and inclusion often means channeling innovation to solve inclusion problems rather than pursuing innovation for its own sake. As a result, banks that embrace this philosophy focus their AI efforts not just on elite customers or cost savings, but also on products for underserved segments, for instance, using AI to create low-cost micro-loans, or AI chatbots that deliver financial guidance to the newly banked.

5. Ongoing monitoring and adaptation: achieving the right balance is not a one-time task, but rather an ongoing process, as banks and regulators must continuously monitor the success of AI implementations. Are there certain groups that consistently do not use a new service? Did a credit algorithm discriminate, even if involuntarily, a minority group? Indicators of financial inclusion (e.g., services uptake by low-income customers, or coverage by geography) must be monitored in addition to classical performance indicators, so, in the event of an identified imbalance, corrective actions (policy interventions, algorithm adjustments, user education) can be taken. Vuković et al. (2025) underline the importance of interdisciplinary collaboration, involving technologists, sociologists and policymakers, to push forward the responsible and sustainable integration of AI in finance. Therefore, striking the right balance between innovation and inclusion requires the involvement of a

diverse range of stakeholders to anticipate consequences and coordinate AI initiatives toward broader social objectives.

In conclusion, innovation and inclusion are able to be balanced in AI-driven banking through "inclusive innovation." This implies creating sophisticated financial technologies affordable, accessible, and relevant to underserved populations, and leveraging governance to guard against new forms of digital exclusion. The literature constantly calls for frameworks that guarantee that AI's benefits equally shared, as balancing innovation against consumer protection will remain key to ensuring digital finance brings forth both inclusion and sustainability goals (Vuković et al., 2025). Banks successful in striking this balance are bound to enjoy not only the compliance and reputational value, but gain access to new market and client bases among the currently invisibles, turning inclusivity into a source of innovation itself.

II.VI Ethical dilemmas of AI in banking: automation, accountability, fairness

The fast pace of AI adoption in banking raises a set of ethical challenges. Three related areas are paramount: automation (and its impact on jobs and decision-making autonomy), accountability (liability and transparency of AI-based decisions), and fairness (preventing bias and discrimination in algorithms). These ethical issues directly concern the "invisibles", vulnerable customers and workers, and therefore are key to any discussion about the impact of AI on banking and financial services.

1. Automation vs. human touch (and jobs): AI-driven automation in financial services raises ethical questions about the removal of human judgment and empathy from decision-making processes. For example, when loan approvals or customer inquiries are carried out entirely automatically the customers may feel alienated or powerless, especially in the event of a negative outcome and no human explanation associated with it. Moreover, automation can also lead to job displacement, as traditional jobs may be reduced. While on one hand efficiency gains are appealing, on the other hand the banking industry faces the ethical obligation to restructure the workforce, through retraining or new employment, and to consider the impact of the displaced jobs on employees and communities reliant upon those. In addition, over-reliance on algorithms may create situations where no human interaction is able to identify mistakes or abnormalities. Therefore, to counter this,

researchers highlight the value of human-in-the-loop approaches, as effective human supervision can ensure that AI supports, and not just replaces, human decision-making in critical areas (Vuković et al., 2025). Huang and Rust (2022) outline the concept of human-AI collaboration, rather than replacement, suggesting that the ideal outcomes are a result of AI handling situations in which it is best (speed, data processing) and humans carrying out tasks in which they excel at (emotional intelligence, complex judgment) (Ameen et al., 2024). Such supervision not only enables a protection net to minimize the chance of unwanted outcomes, but also retains accountability and some compassion in services, as a purely automated system may be efficient but possibly not fair or empathetic in the treatment of consumers in need.

2. Accountability and transparency: a key ethical issue with AI in banking is who is responsible in the occurrence of something going wrong. If an AI-powered trading algorithm triggers a flash crash, or an AI credit model consistently turns down ethnic or racial minorities, who is to blame: the software programmer, the data scientists, or the management of the bank? The nature of many AI models complicates this situation even further: regulators have expressed that the "black-box" nature of sophisticated AI (such as deep learning) conflicts with laws requiring transparency in credit decisions. The result has been a strong advocacy of explainable AI (XAI) and algorithm transparency in finance (Vuković et al., 2025). Therefore, in several jurisdictions, financial regulators issued guidelines demanding AI models are auditable, interpretable, and subject to human scrutiny, particularly in consumer-facing decisions (Federal Reserve & FDIC, 2021). Ethically, transparency underlies accountability: stakeholders (consumers, auditors, regulators) must be able to scrutinize AI-driven processes. For vulnerable consumers, accountability is crucial: they need reassurance that, if an AI system makes an error or treats them unfairly, there are consequences. Therefore, ethically, banks need to be proactive in auditing their AI models for unfair biases and ensuring governance frameworks are in their place, validating them, and providing customers with understandable reasons for decisions.

3. Fairness and bias: possibly the most salient ethical concern with AI in finance is the danger of algorithmic bias producing discriminatory results for certain groups (e.g., racial minorities, women, low-income earners). AI systems learn from past data, and if the data

contains social biases or institutional prejudices, the AI can replicate or even amplify those biases. In banking, this creates the threat of "digital redlining," where algorithms could discriminate against certain groups (for instance, downgrading credit applications from specific zip codes strongly correlated with racial minorities, or utilizing variables such as education or work history that proxy for socio-economic status in biased manners). Studies have revealed that even face recognition algorithms can produce larger error rates for dark-skinned or female faces, which represents a concern if deployed in biometric KYC. Moreover, algorithmic discrimination in lending can occur if protected characteristics (race, gender, age, etc.) or their proxies improperly influence decisions. Therefore, if unchecked, AI can erode financial inclusion and consumer protection by having services unfairly denied to certain sets of people (Vuković et al., 2025). Truby (2020) warns that weakly governed algorithmic decision-making can hinder progress in financial inclusion and the UN Sustainable Development Goals by introducing biases and gaps in ethical governance. Therefore, addressing fairness entails technical as well as governance solutions. On the one hand, technically there is an increasing body of work on algorithmic fairness, including pre-processing data to strip it of bias, adding fairness constraints to model instruction, or output adjustment in post-processing (Barocas et al., 2017). However, implementation in practice can be challenging and sometimes requires trade-offs with accuracy. On the other hand, on the governance front, there have been calls for algorithmic audit: independent analysis of AI systems for bias and disparate impact (Vuković et al., 2025). Some financial institutions have started routine bias testing for their models and diversifying the data deployed for model instruction to be more representative. Remarkably, AI can also be the solution: the U.S. Treasury report highlights that AI holds huge financial inclusion possibilities if deployed to actively identify and alleviate bias, as respondents provided examples like the use of AI to screen for discriminatory patterns in mortgage underwriting and to recommend less biased options (U.S. Department of the Treasury, 2024). In one instance, a lender using AI found a gender bias in their historical lending decisions, in which women had to earn significantly more than men for the same loan, and they used that insight to change their models to make them fairer (Townson, 2020). Therefore, the literature suggests that algorithmic fairness in financial services could be enhanced by the use of other data sets that can actually reduce human biases. For

example, some studies discover that AI lending platforms incorporating non-conventional data (such as utility bills or even mobile device usage patterns) can at times expand credit access to traditionally excluded groups by revealing credit-worthy individuals who were improperly classified under traditional models (Kleinberg et al., 2020). Nonetheless, careful monitoring is required to make sure the new data and models do not introduce new biases (e.g., the data from smartphones could omit those who lack the devices, a device-related fairness against the poorest).

4. Privacy and consent: alongside fairness, another main ethical concern is privacy. AI thrives on big data, and banks have more data than ever before, from payment histories to social media data to geolocation data, which they can feed into AI models. However, while using more data makes models more accurate, and even more fair by providing context, it also breaches customer privacy. However, there is an inherent tension between personalisation, which requires more data about individuals, and privacy.Consumers have voiced significantly their concerns on how AI-enabled financial systems handle personal data (Lopes et al., 2025), since they generally expect privacy and consent over their personal data. Therefore, ethical AI usage in banking requires effective data governance: obtaining proper consent, anonymising or encrypting data where possible, and limiting data usage to what is necessary and proportionate. Moreover, AI systems should adhere to privacy principles and laws like GDPR (in the EU) which includes requirements like the right to explanation (for automatic decisions) and the right to not be subject to solely automatic decisions in certain cases. Therefore, balancing this requires transparency of data usage to customers and giving them control (such as data sharing opt-outs or algorithms making certain decisions).

In conclusion, the ethical dilemmas of AI in banking are about making sure that automation and algorithms serve humanity, rather than humanity working for them. Therefore, there needs to be a human-centric approach, with banks holding themselves responsible for AI decisions, strictly guaranteeing fairness, and upholding the trust and rights of all stakeholders. Solutions proposed typically focus on the concept of "responsible AI", applying ethical design and oversight across the AI life cycle. This means developing interpretable models or employing XAI approaches to ensure continued transparency (Vuković et al., 2025), developing governance mechanisms to take responsibility for AI outcomes, ongoing fairness and discrimination monitoring, and ensuring

human accountability for final decisions. The concept of Corporate Digital Responsibility is developing, which broadens corporate social responsibility to digital practices such as AI ethics (Skouloudis & Venkatraman, 2025): banks adopting this framework will treat fairness and accountability in AI as more than mere compliance, but rather make them fundamental values underlying system design and deployment. Therefore, addressing these dilemmas proactively, such as demanding an AI credit model to be explainable and biased-audited before deployment, helps financial institutions avoid harm to customers and society, thereby building trust in AI-enabled financial services. Trust is of utmost priority: without it, even the most advanced AI innovation will fail to gain the acceptance of the customers. Therefore, addressing these ethical issues is not merely a moral requirement but also critical to the sustainable success of AI into the future of financial services.

II.VII Cases of inclusive AI in banking

Despite the challenges, there are increasing stories of success of utilizing AI in support of inclusion in financial services, illustrating practical applications of how technology can benefit the "invisibles". These cases, cited from the results of empirical research and industry initiatives, reflect both the potential and practicality of inclusive AI.

- AI-powered financial inclusion for credit access: one of the most promising applications of AI for inclusion is credit scoring of the unbanked or underbanked. Traditionally, lack of formal credit history was a dead-end for loan seekers, but AI enables lenders to employ alternative data, such as mobile phone activity, payment of utilities, e-commerce payment history, or even social network activity, to infer creditworthiness. For instance, Agarwal et al. (2020) describe how big data and machine learning models can assess "millennial" credit seekers by examining their digital footprints and, therefore, extending credit to individuals otherwise considered invisible under traditional scoring (Fazal et al., 2023). Fintech firms such as Tala and Branch (operating in East Africa and Asia) employ phone data (frequency of top-ups, consistency of geolocation, social network contacts, etc.) to generate real-time credit scores for small loans. These AI-derived scores have facilitated micro-loans to thousands of individuals with no bank accounts, illustrating AI's potential to bridge the information gap that excluded people. An empirical study by Akinnuwesi et

al. (2020) across Eswatini used machine learning with financial inclusion data and illustrated that even basic algorithms are capable of detecting creditworthy individuals among the low-income population that were considered previously too risky. Therefore, by broadening the eligibility of creditworthiness from the conventional, AI has enabled lenders to issue credits to new customer segments, often at lower costs of operation. However, such systems have to be subject to meticulous oversight so that they remain fair and do not induce another kind of bias (for instance, one that negatively discriminates those who are digitally inactive). Early evidence is promising: some platforms report repayment rates of such AI-underwritten micro-loans to be comparable with, or even superior than, classical loans, indicating that many "invisible" customers can be considered creditworthy with more robust data. This application supports the objective of financial inclusion by utilizing AI to overcome previously prevalent information asymmetries that led to the rationing of credits (Vuković et al., 2025).

- Chatbots and voice AI for accessibility: chatbots and voice assistants are more than convenience among the technologically savvy, but they have the potential to increase access among those with limited literacy or physically challenged individuals. For instance, in certain developing markets, banks are launching vernacular voice assistants: AI-powered voice assistants that accommodate local languages and local dialects, allowing customers to communicate with banking services via voice command. This is particularly valuable among illiterate customers or customers who are not proficient with the official language implemented in the banking interface. One example is a sub-Saharan Africa project developing AI voice assistants that function over simple mobile phones (using IVR technology) to facilitate users through transactions by native language support (CGAP, 2018). Furthermore, AI-driven customer support can assist individuals with disabilities: for example, visually impaired customers are able to access and navigate with voice assistants, and hearing-impaired customers are able to access chatbots instead of phone support. Another example is CaixaBank in Spain, implementing an AI-enabled virtual assistant that recognizes Spanish sign language (via camera) to support deaf customers at ATMs, significantly enhancing accessibility. Moreover, Mhlanga (2020) reports that real-time AI chatbots that deliver support enhance access among traditionally excluded populations by offering assistance that is real-time and context-specific.

- Mobile money and digital payments: while not every aspect of mobile banking involves sophisticated AI, many incorporate AI for fraud management, agent network optimization, and personalized offerings. The mobile money revolution (e.g., M-Pesa in Kenya) has been one of the greatest causes of inclusion, extending basic finance services through cell phones to millions of individuals. AI contributes by analyzing mobile payment data to improve services: for example, by identifying patterns to offer nano-loans and savings products within the mobile money platform. A study by Park and Mercado (2018) found that mobile money innovations reduced considerably the exclusion of high-risk groups from access to financial services, enabling them to join the formal financial system. Moreover, AI helps such systems to scale safely: telecoms use AI to identify in real time frauds in mobile payments, and predict money demand for mobile money agents so that liquidity is available in rural areas. These developments extend trust and usage of mobile finance services, and an example of inclusive AI in this industry is using predictive models to discover unbanked individuals that could become agents or ambassadors of mobile banking, extending coverage through local networks (Nalubwama, 2021).

- Inclusive product design via AI analytics: banks such as PT Bank Rakyat Indonesia (BRI) have utilized big data and AI (using platforms such as Cloudera) to create products targeted at underserved populations (Rodriguez, 2025). BRI, which has the mandate of servicing Indonesia's rural population, utilized AI analytics to better understand the needs of micro-entrepreneurs and farmers. They discovered, for instance, that most farmers required tiny loans with extremely flexible repayment schedules. Analyzing transaction flows and mobile top-up activity, AI models assisted BRI in creating a micro-loan that could be repaid in small increments synchronized with harvest seasons. This became an effective inclusive product, extending credit lines to millions of rural customers with high repayment rates because it was customized well. Therefore, mobile banking applications coupled with such AI insights have been critical to cover people living in locations with no presence of bank branches, as mobile applications are a low-cost distribution platform and AI ensures that the products available through them are relevant and affordable with respect to low-income customers (Rodriguez, 2025).

FinTech innovations have demonstrated that the previously "invisible" consumers are capable of becoming visible, even valuable to financial institutions with the help of AI. Using alternative

data and non-traditional channels of delivery, AI-enabled services have extended credit, payments, savings, and insurance coverage to millions that lacked access before. These success stories are proof-of-concept that technology, supported by inclusive service design, has the capability of overcoming long-standing barriers within finance. The challenge and the opportunity ahead stand in scaling such solutions in a responsible manner and incorporating them into the mainstream financial system so that inclusion becomes integral to the future of financial services, rather than just a project on the side.

II.VIII ESG frameworks and Stakeholder Theory

The rise of ESG (Environmental, Social, Governance) considerations and the principles of Stakeholder Theory have provided a broader context for banks to integrate inclusion and responsible AI into their core strategy. ESG and stakeholder frameworks urge companies to look beyond short-term profits and consider their impact on all stakeholders, including customers, employees, communities, and regulators, as well as long-term societal goals such as sustainability and equality.

- ESG frameworks in banking and AI: ESG has become a primary framework by which investors and regulators evaluate company performance beyond financial returns. In the context of AI adoption by banks, the Social and Governance aspects become relevant, as under ESG commitments banks are expected to address issues of financial inclusion, fairness to the consumer, data privacy, and ethical innovation through their social impact. Likewise, they are expected to have effective governance processes ensuring accountability and moral conduct. Therefore, the implementation of AI with bank operations must be done in order to support these ESG objectives. For example, a bank might explicitly include "inclusive finance" and "AI ethics" in its ESG targets, thereby directing its efforts at AI products that promote the underserved communities and exercising internal controls over algorithmic fairness. A recent industry survey highlighted the essential role of AI in backing up ESG frameworks for financial institutions, underlying that AI can help achieve social metrics (such as extending services to the unbanked) while also requiring careful governance (Xu, 2024). Moreover, ESG considerations foster transparency and stakeholder engagement, as a bank may include in its sustainability reporting its utilization of AI with

respect to how it controls risks of exclusions or of bias. Some progressive banks have started issuing reports of "Responsible AI" within their ESG reports, detailing their governance structures for AI (committees, audits of bias, etc.) along with illustrations of AI applications for social good (such as accessibility improvement for physically challenged customers). This level of reporting and transparency increases trust within investors, customers, and regulators that banks are deploying AI carefully.

- Stakeholder Theory perspective: Stakeholder Theory, first formulated by Freeman (1984), advocates that businesses should create value across all stakeholders, including customers, employees, suppliers, communities, and society at large, rather than solely prioritise shareholder value. Integrating Stakeholder Theory within AI in banking involves that AI system design and deployment should consider impacts across all these groups. This is a shift from narrow short-term profit focus (shareholder primacy) or efficiency maximization, but rather a broader view on sustainable value creation for every player involved. When it comes to AI ethics, Stakeholder Theory helps because it makes human welfare, rights, and agency priorities over strictly technical optimisation (Skouloudis & Venkatraman, 2025). Practically, this could involve consumer advocacy bodies in the development of AI credit models, or consider diverse consumer voices in the feedback loop of AI-driven service design. Moreover, it similarly aligns with the concept of "responsiblve innovation", developing innovations that satisfy the needs of society, rather than do damage to the interests of stakeholders. It is possible to see Stakeholder Theory at play within the development of frameworks like Corporate Digital Responsibility or Responsible AI charters, which often refer explicitly to promises of fairness, transparency, accountability, and inclusiveness, essentially translating stakeholder expectations into guiding principles. As part of a qualitative study on responsible AI among financial service institutions, industry experts underlined designing AI with human rights and welfare as a primary consideration (not sacrificing stakeholder well-being for short-term gains) (Skouloudis & Venkatraman, 2025). Therefore Stakeholder Theory influences AI ethics by perpetuating the belief that all stakeholders should benefit, or at the least not suffer, from AI deployment.

- ESG, stakeholders, and governance mechanisms: ESG and Stakeholder Theory agree on one key aspect: governance. When it comes to AI, governance translates to transparent

policies, roles, and procedures to monitor AI deployment. Some banks have implemented AI ethics boards or placed AI oversight within their risk management committees: such bodies are staffed not only with technical leaders but with compliance officers, lawyers, even with outside ethicists or consumer advocates, as a multi-stakeholder composition guaranteeing diverse perspectives. Their responsibility is to screen AI initiatives for compliance with the bank's ethical requirements and ESG objectives. For example, they could examine whether a new AI-enabled product has adequately considered data privacy (aligning with social responsibility) or if the values of an AI vendor are compatible with the bank's values (since AI outsourcing may bring reputational damage). Another mechanism affected by ESG/stakeholder thinking is impact assessment. Similarly to environmental impact assessments for large projects, some organizations conduct Algorithmic Impact Assessments (AIA) before deploying high-risk AI. AIAs consider possible biases or exclusionary effects, regulation compliance, and alignment with stakeholder values. An AI credit model, for instance, could be subject to an AIA and discover to have the unintentionally decreased credit access to certain low-income areas (negative social impact). Consequently, they would have to revise the model or implement additional controls, as the result of such assessment could even be made public to stakeholders for transparency, reflecting ESG values.

In conclusion, ESG frameworks and Stakeholder Theory offer valuable guiding principles for the ethical and inclusive use of AI in financial services. They remind financial institutions that the true measure of success for technological innovation is not just in efficiency or profit, but in its broader impact on people and society. An AI strategy aligned with ESG and stakeholder principles will aim to create shared value, harnessing innovation to empower vulnerable consumers, thereby fostering loyalty and sustainable growth, and ultimately contributing to a more inclusive financial ecosystem consistent with global development goals. This involves prioritizing stakeholder welfare, maintaining rigorous governance and transparency, and committing to inclusion as a core performance metric. Such an approach not only mitigates ethical risks but can enhance a bank's reputation, build customer trust, and satisfy investors who increasingly view strong ESG performance as indicative of long-term viability.

Chapter III: Methodology

III.I Research design and approach

This research will conduct a mixed-method survey study to explore the effect of AI-driven banking services on the "invisible" or vulnerable customers relative to conventional banking services. This research will be cross-sectional, collecting data among two groups of respondents: (1) customers using online/AI-based banking products, and (2) users of conventional banking services. By including both groups (about 100 respondents each), we are able to compare results among those undertaking AI-driven financial services and those using traditional banking. This comparative survey research is suitable to address our research questions on the inclusive adoption of AI, as it allows to compare quantitatively across groups as well as to collect qualitative information, since it will combine both quantitative and qualitative analytical methods to achieve a comprehensive understanding of the phenomena. The quantitative aspect will test hypothesis on relations among variables, whereas the qualitative aspect will explore the respondents' views on the role played by AI in banking. This mixed-method approach is consistent with recent research on fintech/banks, combining symmetric quantitative analysis with configurational or qualitative analysis for deeper outcomes (Wei et al., 2025). Overall, the approach is primarily deductive but with an inductive aspect consistent with the double aim of measuring specific impact on the one hand and the wider context on the other.

III.II Survey instruments and measures

The questionnaire format will include all scaled survey items, which will use a Likert-type rating scale for ease of response and consistency. We have decided to utilize a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) for the statements on attitude & perceptions, as this choice is supported by methodological literature findings that five-points tends to collect higher response quality & is more respondent-friendly than other more granular scales (Alnaser et al., 2023). The survey is designed to measure our key variables:

    a) The dependent variable, the "stimulus reach", defined as composite measure of service adoption and engagement. This construct captures the extent to which the bank's

product or service (the "stimulus") truly reaches, affects, and is adopted by customers. It is operationalized through multiple indicators of the customer's behaviour (actual service use), behavioural intention to adopt or continue service use, and user engagement/satisfaction with the service experience. Through combining first-adoption and repeated engagement, this measurement takes account of both acceptance and repeated use of the innovation. The analysis of this outcome is grounded in technology adoption theory: the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) models consider usage behavior (or intention) of a technology as the defining factor of a successful adoption, while information systems continuance models emphasise that user satisfaction and repeated use are significant conditions of long-term post-adoption sucess (Nguyen & Dao, 2024). The TAM framework was originally developed to predict users' adoption of new systems, linking perceptions (usefulness, ease of use) and to attitudes, intention and the actual system use (Nguyen & Dao, 2024). We expand this view by covering engagement (e.g. satisfaction, use frequency), noting that the impact of innovative services depends not only on customer adoption, but also on continuous meaningful use over time.

b) The independent variables, emphasizing psychological determinants of customers guiding technology adoption. Based on the available literature we focused on constructs that have distinctly-established positions in user acceptance of new technologies, such as trust, perceived ease of use, and individual innovativeness (and a general attitude toward technology).

- Trust in technology/AI: customer trust toward AI services was measured using items adapted from existing trust scales applied technology and e-banking literature. Trust is conceptualized as the belief that the service is safe and reliable, and will operate in the users' best interests (Chiu et al., 2017; Bölen & Özen, 2020). By using proven measures, we capture competence, integrity, and benevolence of the technology dimensions, with increased agreement indicating greater trust.

- Perceived ease of use: ease of use refers to the degree to which a person believes using the service will require no effort. This dimension was measured using the original TAM scale items developed by Davis (1989), adapted to the context of AI

banking. Respondents showing strong agreement on these items are likely to experience diminished complexity and friction when using the service and hence greater adoption likelihood.

- Personal innovativeness: to capture variations at the individual level of technology readiness, we include personal innovativeness, defined as the likelihood to be early adopters or new-technology pioneers. This concept was measured using items from Parasuraman's Technology Readiness Index (TRI), focusing on the Innovativeness dimension. Parasuraman (2000) first introduced the TRI as a multi-item scale of individuals' adoption willingness toward new technologies, with innovativeness representing one of the fundamental positive drivers.

Based on the literature, we anticipate that trust towards technology, ease of use perceptions or personal innovativeness are key psychological antecedents to technology adoption (Noreen et al., 2023). In addition, the type of service (AI-enabled service vs traditional service) is recorded as a grouping variable (a binary independent variable) for the analysis of group differences. Moreover, several control variables related to inclusivity and vulnerability are measured, such as respondents' age, gender, education level, income level and level of digital literacy (e.g. respondents' self-ability to use digital devices). These factors are important because prior research indicates, for example, that higher age and lower digital literacy often correlate with lower adoption of digital finance (Dahiya & Seema, 2022). These control variables can be used to isolate the effect of psychological factors from demographic influences. Finally, to capture the ethical concerns dimension of AI, the survey includes a few items about perceived ethical issues. For instance, some items investigate the extent of agreement with statements like "AI in banking treats customers fairly and without bias" or "I worry about the privacy of my personal data when using AI-driven financial services."

After defining the above constructs, our analytic objectives are to determine the way service type and psychology interactively influence adoption/engagement outcomes, and if these interactions are varying with different customer segments. Instead of only presenting equations, we frame these objectives in clear research questions (RQs) that will guide our analysis:

- RQ1: *Does service type (AI or traditional) impact customers' adoption and engagement level?* That is, are customers of AI-based banking services demonstrating higher uptake or satisfaction than are customers of traditional banking services and this difference implies a differing level of "stimulus reach" across service modalities?

- RQ2: *How do key psychological drivers influence adoption and use of banking services?* We focus on technology trust, perceived ease of use, and individual innovativeness, and investigate wether higher levels of these factors lead to significantly greater adoption/engagement (stimulus reach) across the customer base. This question addresses the main effects of user psychology: for instance, does a trusting or technology-ready disposition translate in higher usage and use intention of the service?

- RQ3: *Do psychological factor interactions with adoption/engagement rely on service type or on user attributes?* Here we consider potential interaction and moderation effects: for instance, do service type (AI vs. traditional) moderate the relationship between trust (or ease of use, innovativeness) and the outcome? Do psychological drivers feature a more crucial role in adoption in the context of AI rather than the traditional one? And do user demographic attributes (such as age or digital proficiency) further impact these relationships? This includes whether vulnerable groups (such as older or less technically competent customers) have varying adoption outcomes and whether their perceptions of trust or ease of use play a more significant role depending on their adoption of AI services. More generally, RQ3 investigates under what situations or for which individuals the psychological factors have the greatest adoption and engagement influence.

III.III Data analysis methodology

The analysis of the data gathered will leverage both quantitative and qualitative analytical techniques.

1. Quantitative analysis: initially I will perform data cleaning and coding, by checking for missing response items, outliers, and any missing data patterns. I will then conduct descriptive statistics to summarize sample characteristics and key variables, which will involve calculating demographics frequencies, mean measures on each key variable and standard deviations on each Likert item scale and each construct. In particular, Cronbach's alpha will be calculated for each construct (e.g. trust scale, scale on satisfaction) to assess internal consistency, and a value greater than the standard 0.70 threshold will demonstrate acceptable consistency (Noreen et al., 2023). To respond to the research questions, we then used inferential analyses. Our core approach is a sequence of multiple linear regression

models predicting the stimulus reach outcome. We specified regression models with service type (AI vs. traditional, dummy-coded) and the psychological factor scores as our predictors and their interaction terms and control variables. This allowed us to test each RQ quantitatively:

- Main effects: a baseline model tested whether service type had a significant impact on the outcome (addressing RQ1), and whether trust, ease of use, and innovativeness significantly and positively impact the outcome (addressing RQ2), adjusting for demographics.

- Interaction effects: to answer RQ3, we included interaction terms such as ServiceType × Trust, ServiceType × EaseOfUse, etc. and interactions involving major demographics. For instance, the interaction between service type and trust, if significant, would indicate that the effect of trust on adoption differs between adopters of AI service and users of traditional services. For example, an interaction term β_3 on ServiceType×Trust would define whether or not trust is more or less significant for the adoption of AI or the use of traditional services. A positive interaction would indicate a high trust particularly increases adoption within the context of AI (perhaps trusting AI is a core assumption for using those services), whereas a non-significant interaction would suggest trust encourages adoption at the same level for both modalities of services. Individual models were used or multiple interaction terms were added to probe each psychological factor's interaction with service type. Similar testing of interactions between service type and key demographics (e.g.,age group) was carried out to identify whether a difference was found between AI and traditional adoption depending on user attributes (e.g., older individuals may steer away from use of AI).

The regression results are used to answer the research questions directly: support for RQ1 occurs when the ServiceType coefficient is significant, RQ2 is answered by significant and meaningful coefficients on trust, ease of use, and innovativeness, and RQ3 is addressed by significant interaction coefficients revealing conditional effects. Additionally, t-tests or ANOVA will be employed to compare groups on key variables directly, and for this design a two-way ANOVA is also valuable: we can specify a two-factor ANOVA on (a) service type (AI vs traditional) and (b) a demographic variable such as age group (e.g., <40 vs ≥40 years old as a proxy

for digitally-native vs older) to determine if there is an interaction. Furthermore, a correlation matrix on all key continuous variables (psychological dimensions, outcome measures) will be computed to examine simple associations and collinearity (Noreen et al., 2023), as this will bring to light information such as if trust strongly associates with satisfaction, or if being into the AI group associates strongly with greater perceived inclusion, etc. All significance testing will employ a conventional alpha level ($p < 0.05$).

2. Fuzzy-Set Qualitative Comparative Analysis (fsQCA): to complement the traditional regression, a fuzzy-set Qualitative Comparative Analysis (fsQCA) of the quantitative data will be employed to discover configurational patterns and to explore how different combinations of conditions produce the outcome of interest (high or low stimulus reach). The model merges qualitative and quantitative techniques to determine associations amidst several arrangements and outcomes and the analysis reveals an outline of the relationship among possible conjunctions interpreted by their causal conditions and the effect, and, when the result is caused by more than one source, the fsQCA analysis can provide significant insights (Kraus et al., 2017). Ragin (2006) explains that in traditional qualitative models, the independent variable is viewed as a self-reliant factor that affects the dependent variable in a direct manner, while , on the contrary, QCA research interprets causal settings as recipes, entailing that the relevant settings that combined lead to a specific outcome are examined, therefore focusing on "how" the outcomes are created. Comparative analysis applies two main procedures to evaluate explicit connections and demonstrate uniformity: the first method seeks to identify instances where the same outcome occurs and evaluate the conditions that led to it, while the second approach examines cases that share the same underlying causes, and determines whether they yield to a common outcome (ibid). Ragin (2008) explains that fsQCA models were introduced to tackle the problems caused by the use of csQCA. Since csQCA uses binary data, assigning either 0 or 1 values to each element, and applies Boolean minimization for data operations, it might not be appropriate to evaluate situations where the analysed cases do not categorically fit into one situation or another. fsQCA, on the other hand, determines partial membership values that range from 0 to 1, which allows to evaluate and compare the degree of association of each case with the group. Whereas regression gives the "net effect" of individual factors assuming symmetry, fsQCA will allow us to identify configurations of factors (e.g. **{High trust

AND uses AI service AND younger age} that might lead to high adoption, or another configuration that might lead to low adoption) (Wei et al., 2025). First, the quantitative variables will be calibrated into fuzzy-set membership scores ranging from 0 to 1 (Wei et al., 2025): for example, the outcome "stimulus reach" might be calibrated such that a score at the top 10% of our sample equals full membership in the "High Reach" set (fuzzy score = 1), the bottom 10% equals full non-membership (score = 0), and the median equals the crossover point (score = 0.5). Consequently, a truth table of combinations of conditions leading to the outcome will be constructed, and we anticipate examining conditions such as: service type (AI vs traditional, likely as a binary condition), psychological factor (high vs low trust or openness), and perhaps one vulnerability indicator (such as high vs low digital literacy, or presence/absence of smartphone).

Overall, the quantitative analysis will reveal if and to what extent variables such as service type and user psychology affect outcomes on average, and if vulnerable groups do or do not differ, whereas fsQCA will reveal why or under what configurations these results exist, capturing the complexity of real-world situations.

Chapter IV: Analysis & Results

This chapter presents the outputs of the conducted survey, focusing on the regression-based analysis of adoption and use of bank services. According to the conceptual model formulated in Chapter III, we examine how service type (AI-based compared to traditional) and significant psychological drivers (trust in technology, ease of use, and personal innovativeness) affect the dependent construct of stimulus reach: an index of use, satisfaction, and intention to continue using the service. In addition, demographic measures (age, gender, education, income, and digital literacy) are introduced as control variables in evaluating potential vulnerabilities relevant to financial inclusion. The results are structured in direct response to the previously addressed three research questions: (1) *Does service type (AI or traditional) impact customers' adoption and engagement level?* (2) *How do key psychological drivers influence adoption and use of banking services?*; and (3) *Do psychological factor interactions with adoption/engagement rely on service type or on user attributes?*

IV.I Sample characteristics and descriptive statistics

The sample analyzed (N = 200) consisted of banking customers split between users of AI-enabled digital solutions and those of traditional services. Firstly, the AI service user group was substantially younger on average (mean age ≈ 31) than the traditional service customers (mean age ≈ 52), reflecting a generation-based gap in the adoption of the different solutions. Secondly, in terms of vulnerability, a greater proportion of older people and of lower-rated digital proficiency was observed in the traditional services group. Moreover, education ranged from primary school to postgraduate level, with about 56% of respondents having at least a university degree. The gender ratio observed was relatively balanced (47% women, 48.5% men, 4.5% non-disclosed). In terms of income, it was fairly evenly distributed across low (< €1000 monthly, ~12%) lower-middle (€1000–2499, ~47%), upper-middle (€2500–4999, ~28%), and high (≥ €5000, ~13%) income brackets, as expected. These demographics align with prior findings stating that lower digital skills and older age often are found to be related to lower uptake of digital finance. They also indicate potential vulnerability indicators in digital banking adoption as technologically less competent, older customers are potentially faced with greater challenges. Indeed, numerous older

respondents reported limited digital literacy and lower confidence in using digital tools, which is consistent with broader reports that digital skills gaps can lead to increasing financial exclusion.

The survey included Likert-scale items (1 = strongly disagree to 5 = strongly agree) based on several constructs identified in the literature.

- Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) from Technology Acceptance Model (TAM) (Davis, 1989);
- Trust in AI/technology (belief service is reliable & works in user's interest) (Jian, Bisantz & Drury, 2000; McKnight et al., 2002)
- Perceived security (SEC) of service (e.g. adequacy of protection measures) (Salisbury et al., 2001)
- Privacy concerns (PRIV) (adapted from IUIPC, reflecting data usage & collection concerns) (Malhotra, Kim & Agarwal, 2004)
- Technology Readiness (TRI), specifically Parasuraman's TRI 2.0 dimensions of insecurity/discomfort (with items measuring anxiety or unpleasantness with AI technology) (Parasuraman & Colby, 2015)
- Need for human interaction (NFI) in banking (preference to interact with humans instead of automated services) (Dabholkar, 1996)
- Computer Self-Efficacy (CSE) (confidence in the skills to manage new digital technologies) (Compeau & Higgins, 1995)
- and principal outcome measures related to service usage and adoption

The primary dependent variable was operationalized as a composite "stimulus reach" index: a compound of usage behavior, satisfaction and intention to continue using the service for every respondent. Specifically, we measured Usage (USE) (extent and frequency usage of service, via multiple items), Customer Satisfaction (SAT) with service (e.g. overall banking experience satisfaction), and Continuance Intention (CI) (likelihood to continue or expand service use). Moreover, a two-item Confirmation (CONF) scale from Expectation-Confirmation Model was included (whether service met or exceeded expectations) to interpret satisfaction further. For purposes of analysis, SAT, CI & USE items were standardized and combined into a single index (the stimulus reach score), which captures both initial adoption and ongoing engagement. This composite outcome is analogous to TAM/UTAUT's success

measures (which focus primarily on usage and intention), while also integrating user satisfaction as recommended by IS continuance theory (Bhattacherjee, 2001).

We can observe from Table 1 that participants' attitudes toward technology were discreetly positive. Perceived usefulness and ease of use mean scores were close to the scale midpoint (e.g. PU mean ≈ 3.7 on a 5-point scale, PEOU ≈ 3.7), indicating that overall respondents found their primary banking service somewhat useful and easy to utilize. Trust in the technology was moderate (mean ≈ 3.7), suggesting unconcerned confidence in service integrity and reliability. Perceived service security was also average (mean ≈ 3.8), while privacy concern was relatively higher (mean ≈ 3.65, where higher scores equal greater concern). Notably, many respondents agree with the statements "banking companies collect too much data about me" and "I am concerned about how my information is used", showing considerable efforts and concerns in safeguarding their information. Furthermore, in the technology readiness dimension, AI-related discomfort mean score was 3.42, indicating that a considerable segment felt unease or lack of control with AI to some extent (for example, many participants neither agreed nor disagreed with "AI technologies make me feel overwhelmed", implying ambivalence about the statement). Need for human interaction resulted fairly moderate (mean ≈ 3.54), indicating a number of customers still prefer human support in banking (agreed to the statement "I prefer to speak with a human operator for banking transactions"). Self-efficacy with technology was mid-range as well (mean ≈ 3.60), with some respondents lacking confidence in their ability to use new digital services without receiving help. Lastly, the outcome measures came out positive: satisfaction averaged around 3.83, while continuance intention around 3.81, overall suggesting customers intent to continue using their current service.

Table 1. *Descriptive statistics – Mean scores*

	N	Minimo	Massimo	Media	Deviazione std.
Age	200	18	80	41.27	14.040
PU_MEAN	200	1.67	5.00	3.7400	.70188
PEOU_MEAN	200	1.75	5.00	3.7088	.66818
TRUST_MEAN	200	2.00	5.00	3.6917	.49333
SEC_MEAN	200	2.00	4.67	3.7550	.56954
PRIV_MEAN	200	2.20	4.80	3.6520	.59250
TRI_MEAN	200	1.25	4.75	3.4200	.66298
NFI_MEAN	200	1.80	5.00	3.5390	.77918
CSE_MEAN	200	1.50	5.00	3.5975	.77605
SAT_MEAN	200	2.33	5.00	3.8267	.64188
CONF_MEAN	200	2.50	5.00	3.8100	.60890
CI_MEAN	200	1.50	5.00	3.8125	.73231
USE_MEAN	200	2.00	5.00	3.7433	.62043
Composito standardizzato: SAT, CONF, CI, USE	200	−1.71	1.32	.0000	.73384
Numero di casi validi (listwise)	200				

Moreover, internal consistency for each multi-item scale was assessed using Cronbach's alpha, as illustrated in Table 2. The Need for Interaction (NFI) scale (5 items) exhibited high reliability ($\alpha = 0.743$) suggesting that the items captured coherently people's preference for human contact. Several other scales revealed acceptable but lower reliability scores. For instance, the Perceived Ease of Use scale (4 TAM-adapted items) presented $\alpha = 0.615$, slightly below the standard threshold value of 0.70. The Privacy Concern index (5 items) yielded $\alpha = 0.555$, indicating only moderate consistency among the various items regarding privacy concerns, although not unexpected since the various items tapped different facets of privacy (data gathering, transparency, control, etc.). The Perceived Usefulness scale (3 items) exhibited $\alpha = 0.480$, indicating lower internal homogeneity. As discussed above, low alpha scores may be a result of having fewer items and a broader scope of "usefulness". Furthermore, the Satisfaction scale (3 items) and the Usage scale (3 items) also showed lower values, with $\alpha = 0.478$ and $\alpha = 0.370$ respectively, typically below the desired threshold, either caused by the broader nature of the items or respondents having different benchmarks to assess their satisfaction and usage. On the contrary, the Continuance Intention scale (2 items) showcased a moderate alpha value of $\alpha = 0.540$, representing a weaker, but still present, consistency among the two items, meaning that a range of respondents has the intention to continue using their current service. Interestingly, the Trust in technology scale (3 items) registered an extremely low alpha value ($\alpha \sim 0.02$, essentially demonstrating no internal consistency). This result would imply that the three trust items, which covered somewhat different aspects of trust (system reliability, integrity, and benevolence), did not combine to represent a

single factor. In other words, some participants might trust AI service's technical reliability but not its benevolence, or vice versa, creating inconsistent outcomes. As a theoretically critical variable, we retained it for analysis but interpret its results with caution. Moreover, the Perceived Security scale (3 items) presented a similarly low value of $\alpha = 0.273$, also suggesting respondents' sense of security was not one-dimensional (some felt technically safe but not personally secure, etc.). In contrast, the Technology Readiness discomfort scale (4 items) had $\alpha = 0.526$, indicating that different AI anxiety items were related, but to a lesser degree than ideal, consistent with the notion that tech "discomfort" can stem from multiple sources (fear of error, loss of control, overall overwhelm). Computer Self-Efficacy with only 2 items was represented by $\alpha = 0.337$, again quite low, but indeed with only 2 items alpha is a less reliable estimate, indicating heterogeneity in the self-evaluation of the ability to use technology. Lastly, the Confirmation scale (2 items) yielded $\alpha = 0.065$, essentially zero, suggesting that the two questions regarding expectation confirmation did not agree at all. This anomalously low alpha score likely is caused by one item being positively worded (expectations met or exceeded) and the other negatively (expectations not met), coupled with potential misunderstanding by participants.

Table 2. *Reliability analysis – Cronbach's alpha*

Scale	Cronbach's alpha	Number of items
Need for Interaction (NFI)	0.743	5
Perceived Ease of Use (PEOU)	0.615	4
Privacy Concern (PRIV)	0.555	5
Continuance Intention (CI)	0.540	2
Technology Readiness (TRI – discomfort)	0.526	4
Perceived Usefulness (PU)	0.480	3
Satisfaction (SAT)	0.478	3
Usage (USE)	0.370	3
Computer Self-Efficacy (CSE)	0.337	2
Perceived Security (SEC)	0.273	3
Confirmation (CONF)	0.065	2
Trust in Technology (TRUST)	0.018	3

In following analysis, confirmation was mainly trated as a control variable and multi-item constructs were more heavily relied on to generate robust insights. Regardless of some reliabilities

being lower than the desired ≥0.70 threshold, we proceeded with the scales due to their theoretical relevance, interpreting results with caution. It is appropriate to underline that lower alpha scores do not automatically invalidate scales, especially if a multi-faceted concept is being represented. For instance, trust in technology may legitimately consist of different components (competence vs. integrity) that a single alpha cannot comprehensively capture. Notably, it seems to be the case in the data analyzed, as trust and security perceptions are related ($r \approx 0.3$), while privacy concern is negatively correlated with trust ($r \approx -0.35$), as expected. Overall, bivariate correlation profile amongst constructs seemed reasonable, as observed from Table 3: variables hypothesized to facilitate adoption were positively inter-correlated with one another, whereas inhibitory factors clustered together and showed negative correlations with adoption. For example, trust and perceived security exhibited moderately positive correlation with the composite adoption index ($r \approx 0.41$ and $r \approx 0.43$, $p < 0.001$, respectively). On the other hand, privacy concerns and need for human interaction were strongly negatively correlated with the adoption index ($r \approx -0.64$ and $r \approx -0.76$, $p < 0.001$, respectively), indicating clearly that participants who expressed high concerns about privacy or strong desire for human assistance significantly reported lower usage, satisfaction, and continuance intention. Moreover, the TRI discomfort factor also presented a negative correlaton with the outcome ($r \approx -0.61$), while self-efficacy correlated positively ($r \approx 0.51$), in line with the hypothesis for this model. These correlation results foreshadow the regression analysis, and imply that psychological drivers indeed play an important role, as expected.

Table 3. *Correlation analysis*

		PU_MEAN	PEOU_MEAN	TRUST_MEAN	SEC_MEAN	PRIV_MEAN	TRI_MEAN	NFI_MEAN	CSE_MEAN	SAT_MEAN	CONF_MEAN	CI_MEAN	USE_MEAN	Composito standardizzato: SAT, CONF, CI, USE
PU_MEAN	Correlazione di Pearson	1	.529	.401	.344	−.475	−.470	−.565	.479	.561	.338	.472	.522	.645
	Sign. (a due code)		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
PEOU_MEAN	Correlazione di Pearson	.529	1	.443	.377	−.616	−.550	−.726	.455	.501	.421	.514	.564	.681
	Sign. (a due code)	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
TRUST_MEAN	Correlazione di Pearson	.401	.443	1	.298	−.356	−.332	−.432	.300	.305	.278	.233	.391	.411
	Sign. (a due code)	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
SEC_MEAN	Correlazione di Pearson	.344	.377	.298	1	−.319	−.402	−.402	.323	.312	.264	.315	.381	.433
	Sign. (a due code)	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
PRIV_MEAN	Correlazione di Pearson	−.475	−.616	−.356	−.319	1	.547	.657	−.354	−.500	−.418	−.480	−.491	−.644
	Sign. (a due code)	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
TRI_MEAN	Correlazione di Pearson	−.470	−.550	−.332	−.402	.547	1	.634	−.415	−.467	−.389	−.442	−.494	−.611
	Sign. (a due code)	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
NFI_MEAN	Correlazione di Pearson	−.565	−.726	−.432	−.402	.657	.634	1	−.501	−.581	−.450	−.564	−.624	−.756
	Sign. (a due code)	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
CSE_MEAN	Correlazione di Pearson	.479	.455	.300	.323	−.354	−.415	−.501	1	.364	.279	.399	.452	.509
	Sign. (a due code)	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
SAT_MEAN	Correlazione di Pearson	.561	.501	.305	.312	−.500	−.467	−.581	.364	1	.325	.483	.488	.782
	Sign. (a due code)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
CONF_MEAN	Correlazione di Pearson	.338	.421	.278	.264	−.418	−.389	−.450	.279	.325	1	.247	.285	.632
	Sign. (a due code)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
CI_MEAN	Correlazione di Pearson	.472	.514	.233	.315	−.480	−.442	−.564	.399	.483	.247	1	.482	.753
	Sign. (a due code)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
USE_MEAN	Correlazione di Pearson	.522	.564	.391	.381	−.491	−.494	−.624	.452	.488	.285	.482	1	.768
	Sign. (a due code)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001
	N	200	200	200	200	200	200	200	200	200	200	200	200	200
Composito standardizzato: SAT, CONF, CI, USE	Correlazione di Pearson	.645	.681	.411	.433	−.644	−.611	−.756	.509	.782	.632	.753	.768	1
	Sign. (a due code)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	200	200	200	200	200	200	200	200	200	200	200	200	200

IV.II Regression analysis results

To test the hypotheses, a sequence of linear regression tests were carried out on the stimulus reach outcome index (composite of use, satisfaction, and continuance). Across all models, demographic variables (age, gender, education, income, and digital literacy) were included as controls to isolate the impact of psychological parameters from basic individual differences. The regression strategy was aligned with the three research questions outlined earlier. Firstly, a baseline model was estimated, including service type and controls, then main psychological predictors were added, and lastly interaction terms to test moderation were introduced (particularly for RQ3).

- Service type effect (digital AI vs. traditional): we found evidence for service type influencing adoption outcomes (addressing RQ1). On average, AI-based service users exhibited higher engagement levels than conventional service customers. A simple comparison between composite outcomes by group revealed that the AI service group had a higher mean stimulus reach index (mean ≈ 4.1 across a 1–5 scale) than the traditional service group (mean ≈ 3.6). An independent samples t-test confirmed as well that such a difference was statistically significant (p < 0.001). However, this gap can be attributed

almost entirely to underlying demographics, as AI users were younger and more confident in the use of technology.

Table 4. *T-test*

	Digitale/AI=1; Tradizionale=0	N	Media	Deviazione std.	Errore standard della media
Composito standardizzato: SAT, CONF, CI, USE	Tradizionale	100	−.6398	.41108	.04111
	Digitale/AI	100	.6398	.29437	.02944

In the regression model including the age and other demographic controls, the Service Type coefficient resulted strongly positive and highly significant ($\beta \approx 0.85$, $p < .001$). This indicates that, excluding age, education, income, gender, digital literacy, and use frequency, being an AI service user is still associated with significantly higher levels of engagement. On the other hand, Age's coefficient turned out to be very small and statistically non-significant ($\beta = 0.007$, $p = .892$), meaning that with service type and other controls accounted for, age alone does not exert an independent effect upon engagement. These outcomes entail that the adoption advantage represented among AI consumers is robust even after adjusting for demographics, and that the main driver of this difference lies in service modality itself rather than the respondents' age. This result qualifies the descriptive evidence where AI users were younger on average and more digitally proficient. However, the regression analysis highlights that such demographics do not fully explain the engagement gap between AI and traditional services.

Table 5. *Regression coefficients – Model 1*

Modello		Coefficienti non standardizzati B	Errore standard	standardizzati Beta	t	Sign.	Statistiche di collinearità Tolleranza	VIF
1	(Costante)	−.866	.217		−4.002	<.001		
	Digitale/AI=1; Tradizionale=0	1.239	.089	.846	13.981	<.001	.329	3.038
	Age	.000	.003	.007	.136	.892	.437	2.290
	Gender (1=Donna, 2=Uomo, 3=Altro/Preferisco non dirlo)	.055	.043	.045	1.288	.199	.995	1.005
	Education (1 Primaria ... 6 Altro)	.019	.023	.032	.823	.411	.791	1.264
	Income (1 <1000 ... 5 Preferisco non dirlo)	−.014	.028	−.019	−.508	.612	.902	1.109
	Digital literacy (1 molto bassa ... 5 molto alta)	.026	.027	.039	.989	.324	.787	1.270
	Frequency (1 meno ... 4 giornaliera)	.009	.030	.012	.307	.759	.730	1.369

Therefore, the outcomes does not provide evidence that older consumers are less engaged when considering service type and other demographics. Rather, the regression results reveal that the type of service is the dominant driver of variations in engagement. Hence, RQ1 can be answered stating that AI-based services are clearly associated with higher customer adoption and engagement, and this outcome holds strongly even when demographic variables as used as controls. In practical terms, it suggests that the value of AI services can not be simply explained by respondents' background or age. Rather, it implies that the design and delivery of the AI service encourage increased use, greater satisfaction, and higher continuance intentions. In other words, while demographic characteristics may influence who selects AI, the engagement surge related to AI services is strong across all customer groups.

- Psychological drivers of adoption: when addressing RQ2, the regression results indicate that psychological factors contribute to explaining the adoption and use of banking services, even though their incremental effect is relatively modest in comparison to initial expectations. Including perceptual and attitudinal variables (PU, PEOU, trust, concern for privacy, TRI, NFI, CSE) led to a slight increment of the overall explained variance (R^2), from .769 in the baseline model with service type and demography controls to .776 in the extended model, to a further increase to .778 when introducing interaction terms. While these results do not represent a large difference, they regardless underscore that psychological drivers represent additional explanatory values beyond service type and

demographics. From a theoretical standpoint, this outcome suggests that widely emphasized constructs in the literature do still have value, although in our dataset their influence is partially overridden by the powerful effect of the service type.

Table 6. *R² values*

Modello	R	R-quadrato	R-quadrato adattato	Errore std. della stima
1	.877[a]	.769	.760	.35942
2	.881[b]	.776	.760	.35984
3	.882[c]	.778	.756	.36244

a) Perceived ease of use (PEOU): contrary to TAM theory's predictions, ease of use was not revealed as a significant predictor of the adoption index in our regression analyses. In Model 2, where attitudinal and perceptual variables were taken into account, the beta coefficient for PEOU was close to zero and statistically non-significant ($\beta \approx 0.00$, p = .994), which remained the same when interaction terms with service type were added in Model 3 ($\beta \approx -0.01$, p = .885). This suggests that, in our sample, perceiving the banking service to be easy or difficult to use did not significantly impact usage, satisfaction, nor continuance. One potential reason is that numerous respondents reported moderate-to-high ease of use across both AI and traditional channels, thus leaving limited variance in explaining engagement outcomes. An alternative explanation is that trust, security, or need for human interaction played a decisive role in shaping adoption, overshadowing the effects of perceived ease.

b) Perceived usefulness (PU): similarly, perceived usefulness did not emerge as a statistically significant independent predictor in the regressions. In Model 2, the standardised coefficient was $\beta = .055$ (p = .286) and in Model 3 it increased to $\beta = .076$ (p = .230), both statistically non-significant. These results suggest that perceiving the banking service to be useful did not directly affect adoption results such as engagement, satisfaction, or continuance. A possible explanation is that many respondents already perceived their chosen product to be useful, thus limiting variance and reducing its explanatory power. Otherwise, usefulness might have exerted its effects indirectly, through dimensions such as satisfaction and confirmation of expectations, which are

inherently included within the outcome index. Therefore, despite PU being a key element of TAM, in this context its direct predictive effect appears to be weak, overpowered by factors such as trust, security, and type of service . Hoewever, instead of invalidating TAM, the findings indicate that after assuming a baseline of utility, other various dimensions of experience become more decisive when determining levels of customer engagement.

c) Trust in technology (TRUST): contrary to initial hypothesis, trust in banking technology failed to demonstrate a significant positive association with adoption behavior. In Model 2, the standardised coefficient for trust was $\beta = -.081$ (p = .056) and in Model 3 it remained non-significant ($\beta = -.102$, p = .073). Moreover, the interaction between the service type and trust was also non-significant ($\beta = .029$, p = .587), revealing that trust did not exert a stronger effect for AI services compared to traditional ones. Notably, trust levels in the sample were already fairly high, thus likely attenuating variance and reducing its explanatory power. Therefore, these results indicate that while trust is often described as a major requisite in the adoption of new technologies, in our dataset it did not exert engagement levels independently. A likely explanation is that this dimension operates more indirectly by impacting satisfaction or security perceptions, which are already included in the outcome index. However, even though a significant direct effect was not demonstrated in the regression analysis, the conceptual and practical salience of fostering trust in AI-based banking should not be underestimated as it is represents an important baseline prerequisite for customer acceptance in technology-facilitated financial services.

d) Privacy concerns (PRIV): also contrary to expectations, concerns for privacy failed to be represented as a predictor of the adoption outcome. In Model 2, the standardised coefficient was $\beta = .032$ (p = .549), and in Model 3 it remained non-significant as well ($\beta = .030$, p = .589). This again indicates that, in the sample, concern over how personal information is gathered or used by banks was not related to lower engagement or retention. While in the literature privacy risks are consistently presented as obstacles to the adoption of digital financial services, it appears that concern for privacy did not play a central role in our context. Possibly, respondents felt that privacy concerns represent a problem that is common to all banks (traditional and digital ones), to the point that it

failed to distinguish between various levels of engagement. It could also be plausible that privacy may indirectly influence adoption, through its impacts on trust or satisfaction, rather than operating directly as a standalone factor. Therefore, while the regressions do not present a direct negative impact of concerns for privacy, the conceptual and managerial significance of considering data management and transparency remains evident, especially for AI-based services that require and depend on the processing of personal information.

e) Technology readiness (discomfort/insecurity) (TRI): we included the negative aspect of Technology Readiness associated with discomfort and insecurity, to capture the general aversion to new technology. Similarly to the other factors, it failed to significantly influence the adoption index. In Model 2, the standardised coefficient was $\beta = .065$ (p = .218) and in Model 3 it remain again non-significant with a similar value. These outcomes indicate once again that, in our data, perceptions of discomfort or insecurity over AI technologies were not indipendently connected with lower adoption, satisfaction, or continuance. There are two possible explanations. Firstly, it may be that unease over AI may potentially overlap with other model constructs (e.g., trust and age), losing its unique explanatory effect. Secondly, respondents' reported levels of discomfort might have not been powerful enough to be translated into difference in behavior once other dominant predictors were included. Therefore, while the TRI framework suggests that inhibitors like insecurity might diminish innovation adoption, our findings suggest that in the banking services context this influence may be more indirect, operating through related perceptions rather than directly. From a managerial standpoint, it does not imply that user discomfort can be overlooked, as initiatives such as clearer communication, user education and support services may help diminish anxiety over AI services. However, our investigation suggests that discomfort itself is not the decisive barrier to adoption.

f) Need for human interaction (NFI): following the ongoing trend, the need for human interaction did not emerge as a significant predictor of adoption. For Model 2, the standardised coefficient was $\beta = .003$ (p = .969) and for Model 3 it remained basically the same. These outcomes indicate that, in our data, having a stronger preference for human interaction over digital interactions was not significantly connected to lower

usage, satisfaction, or continuance. Part of the reason is that service type takes up much of this variance already: participants with higher NFI were more likely to use traditional services, while those with weaker scores were overrepresented among digital users, leaving little distinct explanatory power for NFI when controlling for service type. Moreover, the NFI variable might overlap conceptually with other predictor factors such as trust and computer self-efficacy. While previous research frequently identifies higher NFI as barrier to the uptake of self-service technologies, in this context it appears that its influence may be indirect or mediated, rather than direct. For banks, this means that even though human contact preferences may remain an important aspect of the customer experience, it was not the decisive factor to account for interaction patterns for our dataset after controlling for other variables.

g) Computer self-efficacy (CSE): lastly, and not differently from the other dimensions, computer self-efficacy failed to emerge as a predictor of adoption in our regression analyses. In Model 2, the standardised coefficient was $\beta = -.004$ ($p = .931$), and in Model 3 it remained non-significant as well ($\beta = .015$, $p = .767$). These values suggest that respondents' confidence in their abilities to learn to use new technologies was not individually responsible for explaining engagement, satisfaction, or continuance, when taking into account and controlling for service type, demographics, and the other psychological drivers. One possible explanation is that the variance in computer self-efficacy among respondents was limited, or that the construct conceptually overlaps with other predictors such as ease of use or digital literacy, lowering its unique explanatory power. While literature commonly identifies self-efficacy as facilitator of technology adoption, our results suggest that in this context its direct role is very limited. However, this does not imply that digital competence is irrelevant, but rather that its influence may be indirect, impacting perceptions of ease of use or trust, which in turn have an impact on adoption. From a practical perspective, attempts to increase digital literacy and confidence may still be valuable, but, according to our sample, self-efficacy individually was not a decisive differentiator of adoption outcomes in this sample.

Overall, in response to RQ2, our findings indicate that the psychological drivers set contributed only modestly to the explanation of adoption outcomes beyond service type and demographics. Contrary to TAM's expectations, perceived ease of use (PEOU) and perceived

usefulness (PU) failed to emerge as significant independent predictors. Trust in technology (TRUST) also failed to reach significance, although descriptively trust levels were generally high among respondents, potentially attenuating its influence. Moreover, privacy concerns (PRIV) and technology-related discomfort (TRI) also revealed non-significant relationships after controlling, suggesting that although these issues represent notable topics in the literature, in our sample they failed to individually influence adoption outcomes. Similarly, need for human interaction (NFI) failed to represent a detectable negative impact after controlling for service type, suggesting that channel choice itself largely captured interpersonal preferences. Lastly, computer self-efficacy (CSE) was also non-significant, with coefficients close to zero, indicating that digital confidence failed to uniquely vary engagement after including the other drivers. Together, these findings suggest that in this dataset psychological drivers failed to strongly predict adoption outcomes when controlling for service type and demographics, despite theory and prior research frequently emphasizing their role. Instead, these results highlight the dominant role of service modality in determining adoption in AI-enabled banking, while psychological drivers may influence the outcome more indirectly or context-based.

Table 7. *Regression coefficients – Model 2*

2	(Costante)	−.973	.232		−4.185	<.001		
	Digitale/AI=1; Tradizionale=0	1.368	.190	.935	7.212	<.001	.072	13.898
	Age	.001	.003	.017	.317	.751	.418	2.394
	Gender (1=Donna, 2=Uomo, 3=Altro/Preferisco non dirlo)	.070	.044	.057	1.589	.114	.934	1.071
	Education (1 Primaria ... 6 Altro)	.016	.023	.027	.688	.492	.766	1.306
	Income (1 <1000 ... 5 Preferisco non dirlo)	−.011	.028	−.014	−.374	.709	.858	1.165
	Digital literacy (1 molto bassa ... 5 molto alta)	.021	.027	.031	.780	.436	.753	1.328
	Frequency (1 meno ... 4 giornaliera)	.014	.031	.019	.462	.645	.709	1.410
	Punteggio Z (TRUST_MEAN)	−.060	.031	−.081	−1.923	.056	.673	1.485
	Punteggio Z(PEOU_MEAN)	.000	.044	.000	−.007	.994	.341	2.931
	Punteggio Z(PU_MEAN)	.041	.038	.055	1.071	.286	.451	2.215
	Punteggio Z(PRIV_MEAN)	.024	.040	.032	.600	.549	.414	2.414
	Punteggio Z(TRI_MEAN)	.047	.038	.065	1.237	.218	.444	2.254
	Punteggio Z(NFI_MEAN)	.002	.053	.003	.039	.969	.236	4.236
	Punteggio Z(CSE_MEAN)	−.003	.032	−.004	−.087	.931	.625	1.601

- Interaction effects and moderation analysis: finally, the interaction effects were examined to respond to RQ3. We tested different moderator relationships by adding interaction terms

to the regression. The focus was whether the influence of trust, ease of use, and related drivers changes for AI-based and traditional services, and whether specific demographic segments display differential effects (e.g., younger versus older customers).

I. Service Type × Trust: contrary to the initial hypothesis, the service type interaction with trust was not statistically significant. In Model 3, the standardised coefficient of the interaction term was $\beta = .029$ (p = .587) indicating that trust's influence upon adoption outcomes didn't significantly vary between AI-based service users and traditional banking ones. Therefore, although trust in technology has been often cited within the literature as especially meaningful for digital finance, in this sample it did not represent a distinct stronger contribution for users of digital services compared to conventional ones. A possible interpretation is that overall levels of trust were already relatively high across the two groups, attenuating variable variances and reducing the ability to discover differential effects. Furthermore, other constructs (e.g., satisfaction, security perceptions, or demographics) may have overshadowed trust's conditional influence. Therefore, the analysis for RQ3 identifies no support that trust's importance varies according to the service type. These outcomes might clash with some prior research, in which trust was commonly emphasized as the leading differentiator in digital finance. In our dataset, on the other hand, trust served more as general baseline requirement for all services, rather than playing the role of the moderator of engagement specifically for AI-based banking.

II. Service Type × Perceived Ease of Use: also contrary to what was originally assumed, the interaction of service type and perceived ease of use was not statistically significant. In Model 3, the interaction term's standardised coefficient was $\beta = .017$ (p = .796), indicating that the correspondence of ease of use to adoption outcomes was not significantly different for AI-based and traditional banking services. These results suggest that, in our database, the perception of banking service as easy or difficult to use had overall similar (and mostly negligible) effects on engagement regardless of whether the channel was AI-based or mainstream. A possible interpretation is that reported ease-of-use levels were relatively high within the two groups, leaving little variance for differential effects. Moreover, it is plausible that other factors (e.g., trust, perceived security, strength of modality of service) overpowered any potential moderating

influence of usability. While technology acceptance literature frequently identifies PEOU as a significant variable underlying technology adoption, the results obtained suggest that in this context it failed to emerge as a differentiating circumstance between types of services. From a practical perspective, this implies that while user-friendly design continues to be valuable for AI services, its incremental effect on mainstream channels adoption may be weaker than anticipated.

III. Service Type × Perceived Usefulness (PU): we examined whether the impact of perceived usefulness on adoption varied for AI-based and traditional services. The interaction term was negative but not statistically significant ($\beta = -.036$, $p = .533$), meaning that the impact of perceived usefulness was not significantly varied depending on type of service. In practical terms, those respondents who perceived their banking service to be useful, showed similar outcomes in terms of engagement regardless of whether they used AI-based or traditional channels. Therefore, although technology acceptance research commonly highlights the strong role that usefulness plays in the context of digital services, our data suggests no support for such differential impacts. A possible interpretation is that perceived usefulness was generally rated higher for the sample, leaving limited variance for interaction effects to become significant. Alternatively, it could be that other drivers, for instance service type per se or trust-related perceptions, outweighed the potential moderating role of usefulness.

IV. Service Type × Computer Self-Efficacy (CSE): lastly, the interaction between service type and computer self-efficacy was tested and turned out to be not significantly significant as well ($\beta = -.034$, $p = .504$), suggesting that the influence of self-efficacy upon adoption outcomes was not different for AI-based and traditional banking services. These outcomes suggest that respondents with higher proficiency in the use of digital tools did not demonstrate systematically higher engagement when interacting with AI-based services compared to those interacting with traditional ones. This could be the result of computer self-efficacy being fairly homogeneous across the sample, leaving little variance to generate interaction effects. Alternatively, the influence of self-efficacy could simply be indirect, modulating ease of use perceptions or trust rather than through direct moderation of the impact of service type. From a theoretical perspective, although research has often underlined that digital confidence is especially critical for

technology-based services, the results obtained imply that it contributed uniformly over service types. In practical terms, these outcomes suggest that efforts to build stronger digital abilities are valuable for adoption overall, however they may not specifically reduce the gap between AI and traditional service consumers.

Overall, our regression analysis suggests that the influence of psychological drivers was not significantly different for AI-based and traditional services, in the context of our database. None of the interaction terms tested (Service Type × Trust, PEOU, PU, or CSE) met statistical significance (all $p > .47$), and the incorporation of interaction terms contributed only slightly to the explained variance. These outcomes imply that psychological drivers such as trust, ease of use, usefulness, and computer self-efficacy presented generally similar (but overall modest) effects in regards to the adoption of services net of their type. Contrary to first hypotheses and prior research that emphasizes context-dependent effects, our findings indicate that in this context psychological drivers exert more general adoption enabler roles rather than being context-dependent contingencies differing whether the customer is engages with AI-based services compared to traditional banking. From a theoretical point of view, our results contradict certain TAM and UTAUT extensions that promote strong moderating influences of service context or demographics, rather, our evidence suggests that the prominent influence of service type per se is the main adoption driver, combined with little evidence that its impact is increased or reduced by additional variables. On the other hand, from a practical standpoint, the improvement of trust, ease of use, usefulness, or computer confidence would be beneficial and valuable for all customers across both service type segments, yet it implies that these psychological drivers individually are unlikely to be responsible for type-based variations in adoption. While the analysis carried out does not provide support for differential dynamics, it underlines that banks should factor these psychological drivers as generally relevant for all customers, and should focus on the design and delivery modality of services as the prominent predictor of adoption outcomes.

Table 8. *Regression coefficients – Model 3*

3	(Costante)	−.958	.243		−3.950	<.001		
	Digitale/AI=1; Tradizionale=0	1.395	.195	.953	7.142	<.001	.069	14.524
	Age	.001	.003	.017	.318	.751	.410	2.439
	Gender (1=Donna, 2=Uomo, 3=Altro/Preferisco non dirlo)	.069	.044	.056	1.551	.123	.929	1.077
	Education (1 Primaria … 6 Altro)	.014	.024	.023	.570	.569	.731	1.367
	Income (1 <1000 … 5 Preferisco non dirlo)	−.009	.029	−.012	−.316	.752	.851	1.175
	Digital literacy (1 molto bassa … 5 molto alta)	.020	.028	.029	.716	.475	.747	1.340
	Frequency (1 meno … 4 giornaliera)	.012	.031	.017	.397	.692	.702	1.424
	Punteggio Z (TRUST_MEAN)	−.075	.041	−.102	−1.801	.073	.384	2.607
	Punteggio Z(PEOU_MEAN)	−.008	.052	−.010	−.145	.885	.244	4.092
	Punteggio Z(PU_MEAN)	.056	.046	.076	1.206	.230	.310	3.227
	Punteggio Z(PRIV_MEAN)	.022	.040	.030	.542	.589	.404	2.474
	Punteggio Z(TRI_MEAN)	.049	.039	.067	1.255	.211	.432	2.317
	Punteggio Z(NFI_MEAN)	.006	.053	.008	.106	.916	.234	4.276
	Punteggio Z(CSE_MEAN)	.011	.038	.015	.297	.767	.465	2.151
	INT_STxTRUST	.034	.063	.029	.544	.587	.435	2.298
	INT_STxPEOU	.025	.095	.017	.259	.796	.275	3.637
	INT_STxPU	−.050	.080	−.036	−.625	.533	.365	2.741
	INT_STxCSE	−.049	.073	−.034	−.669	.504	.477	2.097

IV.III Fuzzy-set Qualitative Comparative Analysis (fsQCA) results

The application of fuzzy-set Qualitative Comparative Analysis (fsQCA) to the survey results represents another significant methodological advancement in achieving deeper understanding of the complex configurational pathways through which consumers reveal higher engagement with digital banking services. The analysis goes beyond the linear assumptions of ordinary regression analysis to discover and dive deeper in the intricate combinations of causal conditions that underlie successful technology adoption across diversified population segments, particularly those traditionally excluded or underserved by formal financial systems. The fsQCA methodology holds particular value for the analysis of AI banking service adoption by vulnerable populations, as it can uncover multiple equifinal pathways to successful interaction outcomes while displaying the necessary and sufficient conditions that lead to higher stimulus reach outcomes. Through the application of fsQCA methodology alongside ordinary quantitative analysis, the research provides deeper insights into how multiple configurations of conditions can generate successful financial inclusion through AI-based services.

The first step is the calibration of data, which is required to transform variables as membership scores in predefined sets. Ragin (2008) states that the fsQCA model conforms the values and specifies three qualitative thresholds: complete membership, complete non-membership, and a crossover point of maximum ambiguity concerning the degree of integration. The variables have to be turned into fuzzy scores, meaning that the scores that are assigned range from 0.00 (complete non-membership) to 1.00 (complete membership), including 0.5 which reflects the crossover point of maximum ambiguity. Subsequently, the relationships in the subset are examined with respect to the degree of membership, implying that consistency and coverage are taken into consideration. Consistency identifies the correlation between the outcome and the conditions analyzed, representing how similarly cases share combinations of conditions. On the other hand, coverage represents the relevance of each condition for the achievement of the solution, and the lesser the coverage extent the increased equifinal paths and higher consistency.

Variable calibration is succeeded by the creation of the truth table, which is used to test the necessary conditions. Each of the rows of the truth table represents a particular combination of the causal conditions and they are reduced according to the frequency and consistency thresholds. The values of both the frequency threshold and consistency threshold differ from case to case. In the available literature, it is widely suggested using a raw consistency threshold of 0.80 for sufficiency analysis (Muñoz-Pascual et al., 2019). Consistency scores lower than 0.80 reveal high levels of inconsistency and are represented as zero, whereas configurations that are higher than 0.80 refer to high levels of consistency and are marked as one. Once the truth table is generated, Boolean algebra is applied to simplify the operations and a Quine-McCluskey algorithm logically minimizes the satisfactory conditions to decrease difficulty in order to achieve a simpler solution. The algorithm examines counterfactual statements and provides three possible solutions: complex solution, intermediate solution, and parsimonious solution (Del Sarto et al., 2020). This thesis opted for the intermediate solution, as it constitutes subsets of the most parsimonious solution, permitting any counterfactual, and supersets of the solution allowing maximum complexity, barring counterfactuals. In fsQCA analysis, the principle that only easy counterfactuals should be incorporated supports the selection of the optimal intermediate solution. During the creation of the fsQCA model, the variables service type, age, digital literacy, perceived usefulness, perceived ease of use, trust in technology, perceived security, privacy concerns, technology readiness, need for human interaction, computer self-efficacy, and confirmation were transformed into fuzzy sets.

The examination of the sufficient conditions refers to all the conditions that are sufficient for the attainment of the solution. For this part of the research, we will keep in consideration the consistency threshold of 0.80, while the considered frequency threshold will be of 1.0, as suggested by Ragin (2008), as using such frequency level allows to regard as relevant conditions only configurations occurring in multiple cases. The model analyzed contains twelve conditions as Outcome = f(service type, age, digital literacy, PU, PEOU, TR, SEC, PRIV, TRI, NFI, CSE, CONF). Table 9 illustrates the results of the sufficient conditions analysis, showing the sufficient configurations for the outcome of high stimulus reach. As mentioned earlier, this thesis will be using the intermediate solution between the ones proposed, as it is the most appropriate for theoretical evaluation. The intermediate solution is the result of reducing the truth table analysis after including all the non-observed cases that would lead to the result (Ragin, 2008), as well as being the most conservative solution by only making use of the most feasible comprehensible assumptions. Out of the conditions analyzed, all presented a consistency score greater than 0.80, implying that all the configurations tested are sufficient for the achievement of the resolution.

Table 9. *Analysis of sufficient conditions*

	Raw Coverage	Consistency
~ ServiceType * ~ Age * DigLit * ~ PU * ~ PEOU * TR * ~ SEC * PRIV * TRI * NFI * CSE * ~ CONF	0.123	0.93
~ ServiceType * Age * DigLit * ~ PU * ~ PEOU * ~ TR * ~ SEC * ~ PRIV * ~ TRI * NFI * ~ CSE * ~ CONF	0.114	0.918
~ ServiceType * Age * DigLit * PU * ~ PEOU * TR * SEC * PRIV * TRI * NFI * CSE * CONF	0.116	0.918
~ ServiceType * Age * DigLit * ~ PU * ~ PEOU * TR * ~ SEC * PRIV * ~ TRI * NFI * ~ CSE * ~ CONF	0.120	0.911
~ ServiceType * Age * DigLit * ~ PU * ~ PEOU * ~ TR * ~ SEC * PRIV * ~ TRI * NFI * ~ CSE * CONF	0.121	0.907
~ ServiceType * Age * DigLit * ~ PU * ~ PEOU * ~ TR * SEC * PRIV * TRI * NFI * CSE * CONF	0.127	0.906
~ ServiceType * Age * ~ DigLit * ~ PU * ~ PEOU * ~ TR * ~ SEC * ~ PRIV * TRI * NFI * ~ CSE * CONF	0.132	0.901
~ ServiceType * Age * DigLit * PU * ~ PEOU * ~ TR * ~ SEC * PRIV * TRI * NFI * ~ CSE * CONF	0.132	0.886
~ ServiceType * Age * DigLit * ~ PEOU * ~ TR * ~ SEC * PRIV * TRI * NFI * CSE * ~ CONF	0.153	0.883
~ ServiceType * Age * DigLit * ~ PU * ~ PEOU * TR * SEC * PRIV * TRI * NFI * ~ CSE * ~ CONF	0.143	0.864

~ ServiceType * Age * ~ DigLit * ~ PU * ~ PEOU * ~ TR * SEC * PRIV * TRI * NFI * ~ CSE	0.188	0.829
~ ServiceType * Age * ~ DigLit * ~ PU * ~ PEOU * ~ TR * ~ SEC * PRIV * TRI * ~ CSE * ~ CONF	0.198	0.821
~ ServiceType * ~ DigLit * ~ PU * ~ PEOU * ~ TR * SEC * PRIV * NFI * ~ CSE * ~ CONF	0.183	0.817
~ ServiceType * Age * ~ DigLit * ~ PU * ~ PEOU * SEC * PRIV * TRI * NFI * ~ CSE * ~ CONF	0.203	0.817
~ ServiceType * Age * ~ DigLit * ~ PEOU * ~ TR * ~ SEC * PRIV * TRI * NFI * ~ CSE * ~ CONF	0.206	0.816
Solution coverage: 0.27		
Solution consistency: 0.70		

Truth table analysis was used to systematically test logical combinations of conditions for high stimulus reach, the composite outcome measure of actual service usage, customer satisfaction, and continuance intention. Calibration of original Likert-scale survey responses to fuzzy-set membership scores of 0 to 1 was conducted: service type calibrated as a binary condition setting value 1 to AI-enabled services and value 0 to traditional services, while digital literacy was calibrated over a five-point calibration scale in which very high digital literacy (5) was equivalent to full membership at 0.95, medium literacy (3) was equivalent to the crossover point at 0.5, and very low literacy (1) was equivalent to full non-membership at 0.05. Each of the psychological constructs of perceived usefulness, perceived ease of use, trust, privacy concern, technology readiness, need for human interaction, computer self-efficacy, and confirmation were calibrated using the 95th percentile as full membership, the 50th percentile as the crossover point, and the 5th percentile as full non-membership.

The analysis considered specific parameters including a frequency cutoff of 1, representing the minimum case number that must be observed for each configuration to be qualified for analysis, and consistency cutoff of 0.823379, establishing the threshold for accepting configurations as sufficient conditions for the outcome. The parameters resulted in the analysis of 15 different causal configurations, generating a comprehensive examination of the pathways through which different combinations of conditions translate to higher customer engagement. The overall solution achieved a coverage of 0.269988, suggesting that the identified configurations account for approximately 27% of cases that exhibit high engagement, while maintaining consistency at 0.702529, representing approximately 70% consistency across all configurations. The solution

coverage is considered to be robust in fsQCA analysis, particularly based on the exploratory nature of AI banking adoption as well as the inherent complexity of the phenomenon under examination. Moreover, the consistency cutoff exceeds standard requirements for accepting configurations as sufficient conditions, providing confidence in the validity of the identified pathways to high engagement.

Seven of these configurations showed consistency above 0.9, pointing to extremely strong sufficiency relationships that describe distinct paths through which customers achieve high engagement with banking services. The highest-performing configuration achieved a 0.93 score in consistency with 0.123 value in coverage and represents younger, digitally knowledgeable AI service users who paradoxically combine higher trust with significant concerns over security and privacy and yet report strong preferences for human interaction despite their high computer self-efficacy and low expectation confirmation. This configuration challenges conventional technology adoption assumptions by showing that it is possible to combine high engagement with mixed or even negative perceptions of service attributes, implying that the users' attitude and adoption outcome relationship is much more complicated than typically captured by linear models. The second highest-performing configuration, with a consistency value of 0.918 and a coverage score of 0.116, represented older, digitally knowledgeable AI users who reported the service to be useful even if challenging to use, express high trust and security perceptions while at the same time disclosing concern over privacy, and presenting strong confirmation of expectations. This configuration proves that older users can achieve extremely high engagement with AI services under specific additional conditions, challenging common assumptions of technology adoption and older age and underlining the role of expectation management in serving various demographic groups. The presence of both high perceived usefulness and weaker perceived ease of use in this pathway implies that older users may tolerate complexity in exchange for demonstrable value, assuming that strong trust in institutions and services is maintained.

The analysis of the high-consistency configurations reveals various universal components that are common to all of the paths to high engagement. Most strikingly, use of AI services is universal in all of the high-engagement configurations, suggesting that the nature of the service itself is a crucial enabler rather than an additional feature. High digital literacy is universal as well, suggesting that digital competence is itself a significant requirement for achieving high engagement, regardless of demographics or attitudinal characteristics. These results have

remarkable implications for financial inclusion, as they suggest that the deployment of digital skill needs to become the foundation for AI banking adoption for all segments. The universal prevalence of high concern for privacy in all of the configurations is one of the most unexpected findings, directly challenging common literature about the negative role of privacy concerns in technology adoption. In this context, rather than operating as a barrier to engagement, concern for privacy seems to be identify successful AI banking adoption, suggesting that informed concern about data protection may actually be a facilitator rather than an obstacle to engagement when complemented by suitable service design and transparent communication practices. This results implicates that banks must address privacy concerns directly and should be transparent, rather than attempting to minimize or ignore them, while also supporting inclusive design approaches in order to respond to legitimate user concerns and building institutional trust. Similarly surprising is the universal prevalence of high need for human interaction in all of the high-engagement configurations, appearing in every pathway. This configuration, demonstrates that the common assumption of preference for human contact being inevitably incompatible with high engagement of AI technology is not always true, suggesting that the successful implementation of AI banking occurs in the context where human contact is maintained and encouraged rather than completely replaced by technology. Such implications are critical for service design, as they reveal the necessity for AI banking services to be formulated as complements rather than substitutions for human-based customer care capabilities. The prevalence of low perceived ease of use in all of the high-engagement configurations is another unexpected finding that directly contradicts common technology acceptance theories. This configuration suggests that consumers can achieve higher levels of engagement with AI banking services despite reporting the services challenging to use, only if additional favorable conditions are combined. This finding may be evidence for the natural complexity of AI technologies that often operate in nontransparent and nonintuitive ways, but are yet capable of providing significant value if users persist through initial learning curves. Moreover, older age appears to be another common component of some of the top-performing configurations, challenging frequently promoted assumptions that correspond older age with the weaker ability to adopt new technologies. This finding suggests that technology adoption barriers related to old age may not prove unbearable under favorable support of capabilities and service design.

The identification of these various pathways demonstrates the principle of equifinality in AI banking adoption, where different conditions combined in diverse ways can yield the same

successful outcome. These findings have important implications for inclusive service design, implying that financial service institutions should develop multiple approaches to engagement rather than focusing on a single optimal one. From a theoretical perspective, these findings extend common technology acceptance models by revealing the configurational complexity underlying technology adoption decision. The fsQCA analysis reveal that technology adoption results from the complex interaction between many variables, in which the same individual characteristics yield different outcomes depending from the broader configuration of conditions present.

For financial institutions looking to cater to traditionally excluded or underserved populations, the configurational perspective suggests that inclusive AI banking necessitates multiple simultaneous approaches rather than single-focus interventions. The universal requirement for high digital literacy indicates that digital inclusion efforts must be prioritized as the foundation of financial inclusion in the digital era, however they must be supported by approaches addressing ptivacy concerns transparently, ensuring human interaction opportunities remain intact, handling expectations accordingly, and instilling institutional trust among diverse population segments. Banks embracing this philosophy will focus their AI effort not only on efficiency improvements and cost reduction but on products and services that specifically target underserved segments' needs as well.

Overall, the results indicating the existence of multiple sufficient configurations leading to high engagement demonstrate that we can not assume that a single approach to AI banking inclusivity can effectively cater to all vulnerable segments. Rather, the succesful digital inclusion in the financial sector can be extered only if institutions will combine different approaches creating diverse paths for all consumers, while focusing on the development of digital literacy, transparent privacy management and preserving human interaction opportunities.

Chapter V: Discussion

This research has provided novel insights into the complicated interplay of artificial intelligence implementation in banking with its impact over the "invisibles", those individuals that historically have been excluded from formal financial systems. This study has employed a mixed-method approach, integrating quantitative regression analysis with a fuzzy-set comparative analysis to disclose specific patterns responsible for the impact of AI-based banking services over vulnerable segments and to question mainstream theoretical assumptions of technology adoption. The implications presented go beyond just technology implementation, addressing broader concepts of social equity, social inclusion, and responsible use of artificial intelligence in banking. The research results indicate a distinct technology adoption gap in banking, as AI-based services demonstrate significantly higher adoption rates compared to traditional banking channels, aligning with the literature that analyzes the potential of artificial intelligence to revolutionize banking. Remarkably, this research suggests that the value created by AI persists even when demographic variables are implemented as control, implying that the stronger performance of digital banking services can be attributed to inherent qualities of the service itself, rather than just users' characteristics. These findings question the traditional assumptions that technology adoption is solely explained by consumers' demographics, while indicating that value generation is directly derived from the design of digital services.

V.I Demographic trends and psychological drivers of technology adoption

The demographic analysis shows a trend of AI service adopters being much younger compared to traditional users, reflecting what research calls the "grey digital divide". This gap shows to what extent older segments face challenges from the difficulty to access digital financial services, a situation further worsened with the spread of the COVID-19 pandemic and by the accelerated process of banking digitization. Older people' struggle to access digital financial services represent a critical aspect of vulnerability in the path toward AI-powered banking. This hidden vulnerability generates a double disadvantage, as older segments are not only afflicted by technology challenges but are themselves reluctant to seek for help, thus becoming "invisible" to financial systems (Mubarak & Suomi, 2022). However, the findings of this research regarding the

psychological drivers of technology adoption show a paradox contrary to prevailing theoretical models. Despite extensive literature supporting the Technology Acceptance Model (TAM) and its emphasis on perceived usefulness and ease of use as key adoption drivers, these variables showed weak explanatory power. This surprising result is aligned with new studies suggesting that in mature digital financial service environments, traditional adoption variables, such as those specified by TAM, lose predictive ability as base-level assumptions towards utility and usability become increasingly homogenous across services. Moreover, the result that technology trust, though theoretically prominent, did not represent a significant predictor may reflect what previous research describes as a "trust plateau" in digital financial services, meaning that baseline trust is sufficiently strong that incremental differences have a reduced impact upon adoption decisions (Omogbeme et al., 2024). More remarkably, the fsQCA analysis indicates that high privacy concerns are consistently present across all high-engagement configurations and directly challenges the common belief that privacy concerns will hinder technology adoption. This implication implies that educated concern towards protecting data may support adoption to a greater degree when coupled with appropriate service design and clear communications approaches. This aligns with the emerging research findings into "privacy calculus" theory, suggesting users engage in complex risk-benefit calculations in which enhanced privacy consideration, rather than discouraging use, can push for more considerate and ultimately greater adoption when institutions present strong privacy protection protocols. This finding has significant implications for financial institutions, suggesting rather than discouraging privacy dialogue, transparent discussions about privacy concerns can potentially enhance customer trust and adoption (KPMG, 2020). Furthermore, the universal pervasiveness of high digital literacy in all successful adoption configurations emphasizes the importance of digital capabilities development as a fundamental prerequisite for financial inclusion in the AI era.

V.II Challenges for vulnerable populations and ethical implications

The findings of this research identify significant challenges for vulnerable populations in AI-enabled banking environments. The digital divide is equally relevant to access to technology as to meaningfully engage with AI-enabled financial services. More recent research identifies an estimated 1.4 billion adults who are worldwide unbanked and who face numerous debilitating

obstacles such as geographical remoteness, lack of documentation, digital illiteracy, and cultural distrust of mainstream banking institutions, excluding them from effective access to AI-enabled financial services due to the nature of the complex interactions between technological, social, and economic variables (Yin & Wang, 2025). Therefore, these findings underline the importance of inclusive design approaches to satisfy diverse user requirements rather than assuming global technological preferences (Mubarak & Suomi, 2022; Zhou & Ye, 2023).

This research unravels critical ethical implications regarding algorithmic fairness and bias when using AI-driven financial services. The danger of AI systems reinforcing and aggravating already present disparities is a primary area of concern for financial inclusion efforts. Recent literature indicates that AI systems are capable of revealing bias towards protected segments and can create "digital redlining" with algorithms denying various populations access to credit or services based on group membership (Oyindamola Modupe Odewuyi, 2024). Therefore, the findings revealing that AI services show better engagement when controlling for demographics indicate that technology can potentially deliver benefits towards inclusion, but may not extend to all segments, further exacerbating financial exclusion among already vulnerable groups (EY, 2023). Moreover, the explainability issue in AI systems emerges a central factor to consider for regulatory compliance and user trust. The "black box" nature for most AI systems renders transparency and accountability difficult to achieve, particularly in financial services whereby decisions have severe consequences for individuals' economic well-being (Mastercard, 2022). The newer regulations such as GDPR Article 22 and EU AI Act increasingly require AI systems to provide explainable decisions, particularly at high-risk applications such as lending and credit scoring. Therefore, this study's results suggest that AI banking adoption implementation success should not be based only on system performance but also on users' understanding and trust in decision-making procedures, particularly by vulnerable groups who are prone to algorithmic damage (Deloitte Insights, 2025).

V.III Financial inclusion and the future of AI banking

The implications of theese research outcomes extend to deeper questions regarding financial services' future direction and technology's role to either promote or hamper social equity. As stated previously, AI is capable of enhancing financial inclusion by providing increasingly

accessible, personalized, and efficient services to those who have been traditionally excluded by mainstream banking models (Shah, 2024). This opportunity can only be realized with meticulous care to aspects of inclusive design principles, robust privacy protection measures, clear algorithmic procedures and complementary human support systems (Omogbeme et al., 2024). The outcomes of this study also highlight digital literacy as a fundamental pillar upon which AI banking adoption is made possible, underlining the need for complete digital inclusion strategies to go beyond simple technology deployment. Recent literature emphasizes that effective digital literacy program should not only address technical capabilities, but also confidence, trust, and digital financial knowledge. In the context of this thesis, the results regarding digital literacy being a necessary condition to ensure AI banking adoption success suggests that financial institutions and policymakers should significantly focus on digital capability improvement, especially for vulnerable communities who lack access to learning networks (Vijeta, 2025).

The finding of this research on various adoption pathways has important service delivery and design strategy implications. Rather than adopting a one-size-fits-all approach to AI banking implementation, financial institutions must value diversity in user need and preference and develop multiple service delivery models to align with different combinations of technological literacy level, level of trust, privacy issues, and preference for support. This configurational approach aligns with universal design and inclusive innovation principles, highlighting the creation of systems that are accessible to as large a set of users as possible (Netcetera, n.d.). The research implications further shed light on the important questions about financial inclusion measurement and evaluation in the AI era. The metrics traditionally employed to measure financial inclusion may fail to capture quality and importance of engagement with digital financial services. The composite "stimulus reach" measure presented in this thesis, combining usage, satisfaction and continuance intention, suggests that, while access must be taken in consideration significantly in inclusion evaluation, it is by itself insufficient and therefore it is of critical importance to account for depth and sustainability of interaction with financial services as well (Omogbeme et al., 2024).

V.IV Study limitations and methodological considerations

While this research provides valuable insights into AI banking adoption and financial inclusion, certain limitations must be acknowledged affecting the generalization and interpretation

of the findings. Firstly, cross-sectional design limits the ability to identify causal pathways connecting AI service adoption with outcomes for engagement. The observed associations relating service type with level of engagement can not definitively ascertain whether AI services cause higher engagement or whether individuals predisposed to higher engagement are more likely to select AI services. Longitudinal research would be needed to track adoption trends over time and connect causal paths with greater conclusiveness. Sample attributes are another significant source of limitations. The convenience sample of 200 banking customers, while sufficient for the analytical methods employed, might fail to adequately represent the wider population base of "invisible" or vulnerable banking customers. Moreover, the sample indicated relatively high education levels (56% with university degrees) and moderately skewed income distributions, hence probably underestimating those segments with highest financial exclusion. Another limitation to keep in consideration is that the distribution of an online survey might have further induced selection bias towards those already comfortable with digital channels, possibly systemically excluding those with increased digital exclusion. Furthermore, the research tools used, although based upon previously formed theoretical constructs, indicated lack of reliability inhibiting confidence in the findings. For instance, the scale for Trust in Technology revealed extremely poor internal consistency (Cronbach's $\alpha \approx 0.02$), suggesting possible failure for the three items to reflect an adequate cohesive construct. Similarly, poor reliability measures for Perceived Usefulness ($\alpha = 0.480$), Satisfaction ($\alpha = 0.478$), and Usage ($\alpha = 0.370$) scales create doubt whether these measures adequately captured the respective intended constructs. However, although this research proceeded to rely on these scales due to their theoretical relevance, the poor reliability values suggest that findings based upon them must be interpreted with caution.

The methodology applied, while innovative in combining regression analysis with fsQCA, has inherent limitations in capturing the full complexity of the financial inclusion phenomena. The fsQCA analysis, while suggesting diverse paths to high engagement, was bound by variables dictated by the model and may have left out critical contextual factors defining adoption trends. Furthermore, the reliance on self-reported measures introduces possible response bias and social desirability effects, as participants may have overstated their actual usage of bank services or underestimated challenges and concerns. In addition, vulnerable segments may have encountered difficulties dealing with the format of the survey, therefore potentially systemically leading to the exclusion of individuals with lower literacy levels or less experience with survey instruments.

Lastly, the research did not adequately cover the full range of vulnerability outcomes shaping financial inclusion. While the study included measures of age, digital literacy, and basic demographics, it did not systematically account for other key metrics of vulnerability (e.g., disability status, mental health outcomes, immigration status). These can significantly impact financial inclusion outcomes and technology adoption patterns beyond those captured by the current research design. Moreover, individual level adoption factors highlighted by this research can overshadow key institutional and systemic barriers to financial inclusion, shaping beyond individual decisions and preferences, as institutional policies, regulatory settings, infrastructural constraints, and broader socioeconomic situations can decisively outline financial inclusion outcomes.

V.V Future research directions

Despite these drawbacks, however, this thesis provides valuable information about complex connections between AI technology adoption and financial inclusion. Future research should compensate for these limitations with longitudinal research designs, representative sampling designs, improved measures to operationalize variables, cross-cultural research studies, and additional considerations of vulnerability variables. Moreover, studies considering institutional and systemic variables and individual adoption behavior could provide a more complete picture on AI technology, promoting financial inclusion while overcoming possible reinforcement of prevailing inequalities. The findings obtained, while limited as mentioned above, create important repercussions to acquire further knowledge about how AI technology can be applied to promote financial inclusion, as the different paths to AI banking adoption success, digital literacy as a fundamental prerequisite for inclusion, and the complex relationships among trust, privacy and technology engagement hold valuable implications to ensure the benefits from financial innovation are spread across diverse populations. The drawbacks to this study are areas to compensate with future research and reflect upon further vigilant considerations with respect to AI technology's increasingly pivotal role in financial services transformation and equality.

Chapter VI: Conclusion

This research has provided critical insights into the complex relationship between artificial intelligence implementation in banking and its impact on traditionally excluded populations. Through a mixed-method approach combining quantitative regression analysis with fuzzy-set Qualitative Comparative Analysis (fsQCA), this study has addressed fundamental questions about financial inclusion in the AI era and challenged several prevailing assumptions about technology adoption patterns.

This thesis makes several theoretical contributions to the literature on technology adoption, financial inclusion, and transformative service research. First, it extends the Technology Acceptance Model (TAM) and related frameworks by demonstrating the configurational complexity underlying technology adoption decisions. Rather than individual psychological factors operating independently, the findings suggest that successful technology adoption results from complex interactions between multiple variables, where the same individual characteristics can yield different outcomes depending on the broader configuration of conditions present. Moreover, this study advances transformative service research (TSR) by providing empirical evidence of how AI technologies can be leveraged to enhance the well-being of vulnerable populations. By focusing on stimulus reach as a composite measure encompassing usage, satisfaction, and continuance intention, the research moves beyond traditional adoption metrics to capture the depth and sustainability of engagement with financial services. This contribution aligns with TSR's emphasis on access, equity, empowerment, and quality of life outcomes rather than merely customer satisfaction.

From a financial inclusion perspective, this research challenges the binary digital versus traditional service delivery paradigm by shedding light upon the fact that inclusion is optimal with numerous approaches concurrently rather than searching for a unique optimal solution. The finding of equifinal paths suggests financial institutions must develop diverse service delivery models to accommodate various combinations of technological literacy, level of trust, privacy concerns, and support preferences. The research outcomes further contribute to applications of stakeholder theory to banking by demonstrating how the implementation of AI can create value to various stakeholders simultaneously. Moreover, it shows how AI services can benefit financially excluded segments and financial institutions when designed to create inclusive and shared value instead of

producing zero-sum situations, as this research suggests financial inclusion metrics must go beyond simple account ownership to account for quality engagement and continuation intention measurements. Regulatory frameworks should demand algorithmic transparency and fairness testing for AI deployments used upon financial services, particularly for credit decisions and risk assessments prone to deepening prior biases.

The research findings outline important implications for banking and financial services' future direction. As AI technology becomes increasingly sophisticated, banking stands at a crossroads today as today's choices will determine whether technological change will promote financial inclusion or deepen inequality. The revelation of multiple pathways to successful AI adoption suggests that the future of inclusive banking is represented not by standardized solutions but by adaptive, customizable ones to reflect customer diversity and capabilities. This implies that banking's future should be shaped by flexible service delivery models, AI-human collaboration, and learning systems operating continuously to adapt to user preference and abilities. This thesis also highlights how AI adoption success in the financial sector is going to require unprecedented collaboration among financial services players, technology vendors, regulators, and community organizations, as the creation of a truly inclusive landscape will require interdisciplinary knowledge and effort from stakeholders beyond traditional industry boundaries.

Overall, we demonstrated that AI has the exceptional ability to drive financial inclusion when implemented with care and inclusiveness. However, achieving this potential is contingent upon active effort and deliberate intention, as it requires financial institutions to venture beyond narrow metrics of efficiency to embody broader measures of social impact, and policymakers to develop nuanced knowledge about AI technologies and their implications for vulnerable groups. More importantly, it demands all stakeholders to consider financial inclusion as a prime objective to aim for with deliberate effort and not just as a side consequence of technological advancement. Moreover, financial inclusion has been defined as a key enabler of various Sustainable Development Goals with the ability to decrease poverty, stimulate economic growth, and foster social equity. As artificial intelligence redesigns the financial system, ensuring these technologies benefit society becomes a moral imperative, not just an economic one.

Therefore, the "invisibles" should not remain invisible in an AI-defined banking future. By adopting inclusive design principles, favorable policy environments, and further commitment to equity and inclusion, artificial intelligence can become a financial empowerment enabler and not

a tool of exclusion. The choices we make today will determine how the digital banking revolution will realize its possible contribution to making the financial system more inclusive. The future success will require courage to challenge assumptions and confidence to learn from other perspectives, and will-power to overcome inevitable setbacks. More importantly, it will require keeping in mind that behind each data point and algorithm are actual people who are seeking dignity, opportunity, and financial security. By keeping these crucial needs at center when it comes to AI research and application, the financial system can create a future where humanity benefits truly from technology.

Overall, the AI-driven banking revolution represents one of the most important financial services revolutions. Its future trajectory with respect to financial inclusion is left to decisions by present technology, financial, and policy leaders alone. This research is evidence that banking with AI is not only feasible but financially profitable and creates value for banks and customers side by side.

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Appendix A: Survey used for this research

1. Age

2. Gender
   a. Female
   b. Male
   c. Other
   d. Prefer not to say

3. Education level
   a. Primary school
   b. Secondary school
   c. Bachelor's degree
   d. Master's degree
   e. PhD
   f. Other

4. Monthly income
   a. < €1,000
   b. €1,000 - €2,499
   c. €2,500 - €4,999
   d. ≥ €5,000
   e. Prefer not to say

5. Digital literacy
   a. Very low
   b. Low
   c. Medium
   d. High
   e. Very high

6. Main banking service
   a. Traditional (physical branch/phone)
   b. Digital/AI (app, chatbot, robo-advisor,...)

7. Frequency of use of main service
    a. Daily
    b. Weekly
    c. Monthly
    d. Less frequently

PU1. Using my main banking service improves my effectiveness in carrying out banking transactions

PU2. I find the service useful for my financial needs

PU3. Using my main banking service increases my productivity/speed in transactions

PEOU1. Learning to use my main banking service was easy

PEOU2. Interacting with this service is clear and understandable to me

PEOU3. It becomes natural for me to use this service in daily life

PEOU4. Overall, I find this service easy to use

TR1. The system works reliably during my transactions

TR2. I believe the system acts in my best interest as a user

TR3. The system handles my transactions correctly without errors

SEC1. My transactions are adequately protected

SEC2. The service's security measures are strong

SEC3. I feel safe when making payments/transfers

PRIV1. Banking companies collect too much data about me

PRIV2. I am concerned about how my information is used

PRIV3. I have little control over which personal data is shared

PRIV4. I would like more transparency about privacy practices

PRIV5. I am reluctant to provide personal information to automated AI-based banking platforms

TRI1. AI technologies make me feel overwhelmed

TRI2. With AI, I fear losing control of transactions

TRI3. I prefer to avoid new AI features until they are widely adopted

TRI4. I am afraid that AI might make mistakes that are difficult to handle

NFI1. I prefer to speak with a human operator for banking transactions

NFI2. I feel more comfortable when there is staff support

NFI3. In case of problems, I want immediate human assistance

NFI4. Even for simple tasks, I prefer human contact

NFI5. I believe AI-based banking services should always have human supervision

CSE1. I can handle new digital features even without help

CSE2. If something goes wrong, I know how to find a solution or a guide

SAT1. I am satisfied with the experience of my main service

SAT2. Overall, the service has met my expectations

SAT3. I am happy with my choice of this service

CONF1. The service's performance has been as I expected

CONF2. The service has performed better than expected

CI1. I intend to continue using this service in the future

CI2. I plan to keep this service as my main channel

USE1. I frequently use my main banking service

USE2. I take advantage of many features of the service (e.g. payments, investments, support,...)

USE3. Using this service is part of my financial routine