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From Behavioral Interventions to Algorithmic Architecture: Nudging and Ethics in AI-Driven Finance

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Abstract

Many digital finance areas now include AI technology; however, it is still unclear exactly how people will perceive information and make decisions regarding their money using AI. Current research has primarily focused on the technical aspect of how reliable an AI system is or meeting compliance requirements. However, there has been limited research focused on the behavioral effects of the automated support and nudging provided by these AI systems. This paper addresses this research gap by discussing how the use of automated technology in combination with behavioral design influences the environment in which people are making financial decisions within a digital context. A structured qualitative review was conducted to bring together the findings of studies conducted in the fields of finance, behavioral science, and AI. The review of the literature identifies how AI technology will be used across the various stages in the decision-making process, as well as how behavioral nudges will help reduce the cognitive load and uncertainty involved in making a decision. The identification of only ten studies shows that empirical research at the intersection of AI, nudging, and financial decisions is still in its infancy. While many of the current AI tools are built to assist individuals in making the best decisions, most of the current tools are only designed to support individuals in executing their decisions and do not support tracking goals or enabling later reflections on the decisions made. Based on transparency, clear communication, and user independence, nudges are likely an effective way to increase trust and support users in making higher quality financial choices. Thus, it seems clear that the principles of behavioral design provide an excellent foundation for building transparent and user-centered solutions for digital finance.

Keywords: Artificial intelligence, Behavioral economics, Digital transformation, Ethical finance, Nudging.

JEL Codes: G41, D83, O33, G40

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ACM Codes: H.4.2, I.2.6, K.4.1

1. INTRODUCTION

Over the past decade, Artificial Intelligence (AI) has shifted from a specialized application domain to a structural component of digital financial systems [1]. AI continues to grow through many incremental advances allowing AI to find its way into people's every day financial processes as well as their strategic decision-making processes [2]. As AI is integrated into these processes, many financial institutions are increasingly reliant on automated systems to conduct risk modeling, anomaly detection, portfolio strategy adjustments and personalized advisory engagements with users [3]. Furthermore, with recent advancements in data analytics, the efficiency of financial services and how end-users think about and use financial information has changed dramatically [4]. Thus, digital financial environments have now become much more dynamic and responsive, but they are also more complicated and less transparent to end-users [5]. In addition, many additional uses for finance AI have been created through Large Language Models (LLMs), including advisory chat interfaces, automated report analysis, and new forms of interactive decision support [6, 7]. The introduction of these technologies has increased both the potential of finance AI and the ethical complexities associated with using them. The behavioral-economic implications behind this change in technology point out that, while formal information does play a role in making financial choices, it is behavioral limitations and contextual conditions that will play a much larger part [8, 9]. We are now seeing algorithms starting to influence user perception by structuring the visual representation of information, the framing of options and the apparent ease with which the user can access a path. This influence extends beyond computational efficiency into the structure of judgment itself. This raises new issues regarding transparency, accountability, and the underlying values embedded in algorithmic systems [10, 11]. This study therefore aims to analyze the extent to which AI can alter people's behavioral approaches to decision-making and the ethical considerations associated with these behaviors in financial systems [12, 13]. When nudges are made available in a transparent manner, they are seen to provide users with the ability to use nudges to support them rather than steer users, thereby reducing mental friction associated with complex digital environments. Therefore, the central question of the research will be: How can nudges support ethically and practically effective decision-making processes in AI-supported financial systems? Earlier studies have looked into how AI is used in banking and insurance [14–17]. Research has also examined the ethics and quality of Algorithmic Decision Support Systems (ADSS) [13, 18, 19], the relationship of AI with Digital Transformation in finance [20], and how behavior influences the design of digital decision environments [13, 16, 21]. The purpose of this work is to create a systematic understanding of how AI supported decision environments could potentially promote transparency, trust and user autonomy in the three dimensions of AI, digital nudging, and ethical principles. This review brings together AI, digital nudging, and ethical issues in relation to a staging-based framework of financial decisions that includes four phases: Finding information, evaluating choices, acting on the results, and reflecting upon the decision [22, 23]. The analysis of the stages of the decision-making process allows for a greater understanding of the ways that algorithmic influences occur and how the decision-making behavior of customers using algorithm-enabled systems is different from traditional, static decision-making systems. The resulting clearer and better structure for analyzing the diverse findings of the prior studies represents a significant contribution to the knowledge of AI-supported decision environments.

2. METHODOLOGY

This study performs a qualitative systematic review that brings together insights from several academic fields to provide a coherent analytical perspective. The spectrum covers conceptual and normative work as well as empirical investigations. Since the research area combines technological, behavioral, and ethical perspectives, a qualitative synthesis was chosen, as a statistical meta-analysis would limit this conceptual diversity [24]. To ensure transparency, the review process was carried out in line with the PRISMA guidelines [25]. The literature search was conducted in the major academic databases Scopus, Web of Science, ScienceDirect, Emerald Insight, JSTOR, Google Scholar, and Semantic Scholar. The inclusion criteria covered documents in English language and a publication period from 2008 to early 2025. This period reflects the rise of modern Machine Learning (ML) applications in finance and the growing academic interest in digital behavioral interventions after the publication of nudge. All databases were searched with systematically combined English keywords, the used search string was: (”Artificial Intelligence” OR ”Machine Learning” OR ”Deep Learning” OR ”Large Language Model”) AND (Finance OR Banking OR Fintech) AND (Nudge) AND (Ethics OR ”Responsible AI” OR ”Explainable AI” OR Transparency OR Accountability OR Fairness OR Trust). To account for recent developments in generative AI, the search string also included ”Large Language Model” as an additional keyword. For databases with character restrictions, the string was segmented into logically grouped terms to avoid truncation, ensuring comprehensive coverage of all conceptual domains. The initial search produced 522 entries. After duplicate removal (n = 391), title and abstract screening of the remaining 131 records excluded 84 studies that did not sufficiently address at least two of the three core domains (AI systems, financial decision-making, behavioral mechanisms), were conceptual or theoretical only without an empirical component, or fell outside the financial domain. Full-text assessment of the remaining 47 articles resulted in the exclusion of 37 studies. Reasons for exclusion included: failure to simultaneously address AI systems, financial decision-making, and nudging mechanisms; an exclusive focus on AI ethics without behavioral intervention analysis; insufficient empirical evidence or methodological transparency; or a scope outside financial application. The final qualitative synthesis therefore included 10 studies. FIGURE 1 presents the PRISMA flow diagram illustrating the study identification, screening, eligibility, and inclusion process.

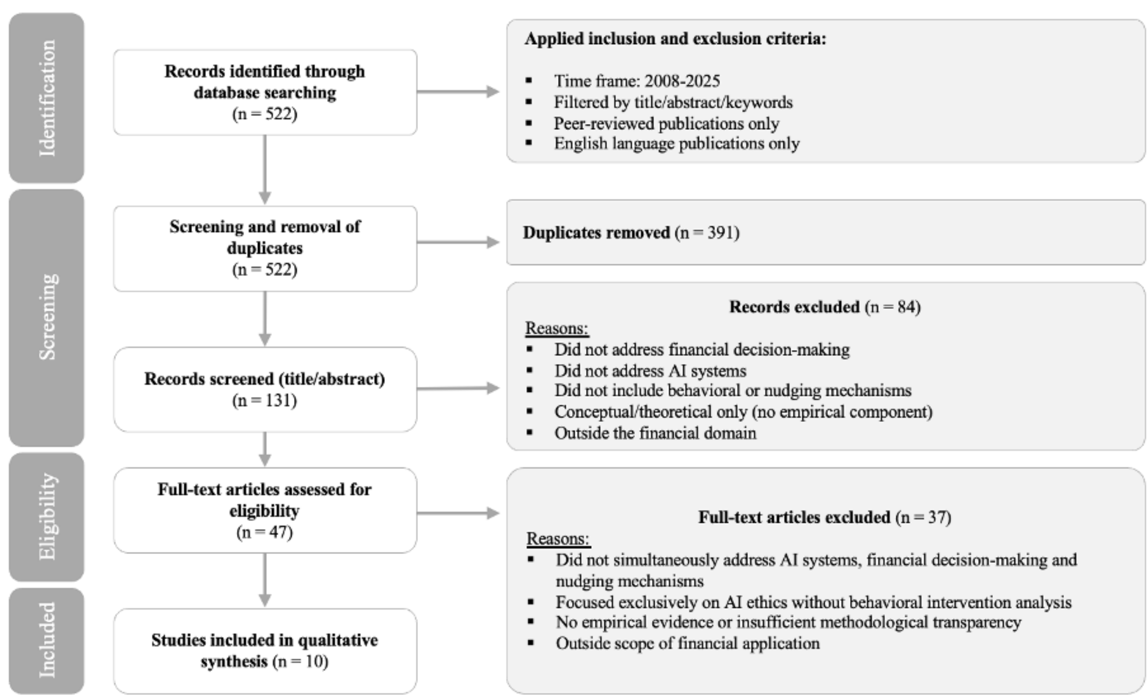

Figure 1: PRISMA Flow Diagram.

To ensure methodological rigor, each study was evaluated using established quality indicators for qualitative reviews in management and AI research. The assessment considered the relevance of core concepts, the clarity and suitability of the methodological approach, the depth and consistency of the analysis and the contribution to understanding the relationship between AI, financial decision-making and behavioral mechanisms. The strength of theoretical grounding was also examined. Only studies meeting these standards were included in the final synthesis. A final set of ten studies met all inclusion criteria. These studies lie at the intersection of algorithmic decision support, financial behavior and digitally mediated choice environments [16–18, 26]. They form the empirical basis for the thematic interpretations discussed in the later sections of this paper. FIGURE 2 summarizes how technological developments in AI-driven finance and behavioral–ethical insights jointly lead to an integrated algorithmic choice architecture. The framework represents how AI systems as well as Digital Transformation come together and interact within the same spaces as organizations who make financial business decisions based on behavioral decision-making processes, nudging, and ethical considerations; and that they bring together both of these factors into what we consider to be a new environment for algorithmic decision-making that impacts financial user-centric decision-making.

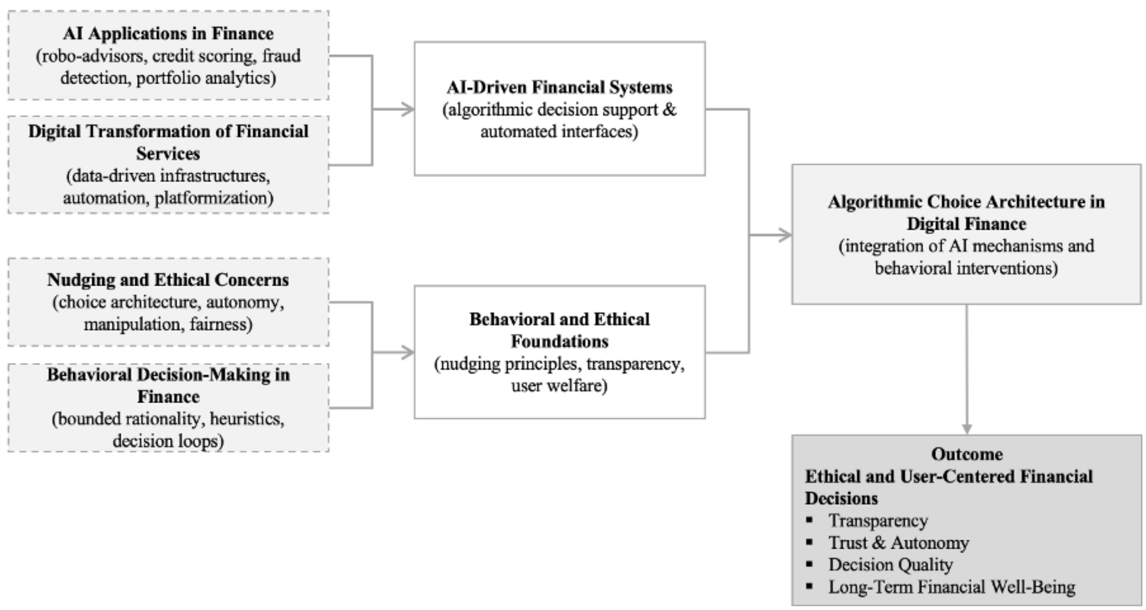

Figure 2: Conceptual Framework for Algorithmic Choice Architecture in Digital Finance.

3. THEORETICAL FOUNDATIONS

3.1 The Effect of Digital Transformation within the Finance Industry

The concept of Digital Transformation within the finance sector implies a ’complete change’ or restructure of how finance is conducted, wherein organizations are changing or developing their business models, their internal processes and the way that they engage with/serve customers through the implementation of data-driven technologies. As there is no single definition for Digital Transformation, the exact meaning will vary from organization to organization. However, in most literature, the description of Digital Transformation typically encompasses two elements, both technological advancement and organizational advancement. Digital Transformation contains data-driven technologies and related systems and organizations that are changing how they create value and how their organizational practices evolve as a result of that technology. Therefore, it is much more than just adding tools to an organization. It also involves the redesign of an organization’s business model, the reorganizing of its internal processes, and developing a new set of capabilities that allow the organization to conduct business in an environment supported by data [20]. The rapid rise of AI in Finance has created opportunities for more operationally enhanced financial services. AI has expanded operational options beyond traditional analytical support environments to automated advisor platforms. Simultaneously, however, AI has added significant challenges regarding ethical and regulatory issues as well as behavioral issues related to its use. Most current AI research in the finance sector continues to focus on the technical performance of AI-based products, such as predictive accuracy, operational efficiencies, assessments of risk, and compliance automation [14, 15]. Less focus has been directed at how AI impacts human judgment, affects trust in AI, changes the way we think about the financial decision-making process, and affects how financial services organizations ultimately implement their services using AI-based platforms. Because the behavioral and normative impacts of AI are so important in determining how financial services organizations will responsibly utilize AI-based platforms and the extent to which these platforms create environments conducive to informed decision-making [27], the existence of a gap between technological capability and human reasoning raises the question of how AI-based platforms will align with Behavioral Economics, Nudges and Ethical Governance.

3.2 The Typical Financial Decision-Making Process

Historical evidence supports that financial decision-making is usually neither a linear path nor entirely logical. A gradual development process that is repeatedly influenced by environmental factors such as cognitive capacity, emotions and context govern how individuals make these types of decisions over time. Previous scholars such as Simon (1955), Kahneman and Tversky (1979), as well as Thaler and Sunstein (2008) identified that when individuals are unsure, face pressure to act quickly, or are bombarded with too much new information, they tend to rely on both logical thought processes and hasty, impulsive decisions depending on their current circumstances. The context in which a decision is made will greatly affect its outcome, whether through default, pre-chosen, the type of interface used, or whether there is an incentive [21]. Once a decision has been made, individuals may find themselves reflecting on their satisfaction with the decision, whether they have modified their expectations since making the choice and what they learned for similar situations in the future [28]. As a result of reflecting on the circumstances surrounding the choice, this ongoing assessment of trust in that situation will either be enhanced or eroded based on how the choice turned out and how transparent the environment surrounding the choice was perceived to be. In order to facilitate the previously discussed reflection process, behavioral intervention options are available that provide individuals with a reduced level of mental effort required to process the choices made. This reduced mental effort will allow users to navigate complex options more easily [13], and build long-term alignment with their digital financial provider. As AI continues to play an increasingly prominent role in digital financial environments, it is critical to understand how human reasoning and AI-based systems interact with each other in creating the financial systems in compliance with ethical standards, while also respecting the autonomy of their users [18].

3.3 AI and Nudging: Definition and Differentiation

In order to create a common understanding of concepts used in this research, the following definitions define key concepts used in this paper. AI refers to computer systems capable of simulating human intelligence when performing tasks [29]. ML is a subcategory of AI that enables systems to learn patterns from large amounts of data without direct programming [30]. Recently, the emergence of LLMs provide an additional class of AI systems as generative interfaces that have been developed using transformer algorithm frameworks trained on vast amounts of text data [7]. In finance, ADSS refers generally to AI-enabled infrastructure that assists users with coding and analyzing financial information; robo-advisors refers to specific ADSS application using rule-based algorithms to manage and allocate investment portfolios. Many LLMs are currently being researched for uses such as automated financial report analysis, using sentiment-based analysis for monitoring financial markets, and providing users with an interface in the form of a conversational agent for providing financial advice [6]. Unlike traditional ML models that primarily provide structured outputs, LLMs provide users with opportunities to interactively engage and receive real-time expanded information regarding financial events and are therefore possibly reshaping the way financial information is prepared and interpreted. Conversational AI systems can work as dynamic nudging interfaces from a behavioral perspective by influencing the way that information is presented, highlighting specific options, and supporting people to reflect on their choices while they develop decisions. Unlike Algorithmic Personalization, which makes recommendations based on inferred characteristics of an individual user, nudging is about changing the way the options for making decisions are structured in the environment where those decisions are made but does not remove any options available to users [12, 31]. Thus, the convergence between AI-based personalization and behavioral decision architecture expands the boundary of Algorithmic Decision Environments beyond just providing static recommendations. However, the use of LLMs for the purposes of influencing financial decisions presents potential substantial risk. The presence of hallucinated output, lack of transparency in the underlying training data, embedded bias and lack of explainability raise issues related to transparency, accountability and user autonomy [19]. In high-stakes financial environments, the presence of persuasive, but factually unfounded, content may adversely affect the quality of decisions made by users as well as their influenced level of trust. As such, ethical governance frameworks for AI-based financial decisions must increasingly consider the characteristics of generative and conversational AI systems as separate from other technologies. The ability to process large sets of data, recognize behavioral patterns and generate near real-time recommendations has made AI one of the most important technologies in modern finance [6]. The conceptual roots of AI are based in early expert systems and later in the development of ML, which shifted from rule-based programming to algorithms that discover patterns autonomously [29, 30]. ML is structured into supervised, unsupervised and reinforcement learning, with each serving different analytical and predictive tasks [32, 33]. Algorithmic trading, robo-advisory services, fraud detection and credit scoring are application examples in the financial sector that already rely on AI as a core element. In spite of the benefit these applications provide with their ability to quickly and accurately make decisions, there is now some major concern over how transparent, fair, accountable, and governed the decisions are that are made through these applications [34, 35]. As the use of these applications continues to grow, so does the question of how people interpret the suggestions provided by AI and how much control people actually have over the decisions they make when an algorithmic system influences them. “Nudging” is a term used within the field of Behavioral Economics that describes the method of using small design changes to the environment in which a person makes a decision to help them make better decisions without removing their option to decide for themselves [12]. Default options, salience cues, simplified messages, and social norm signals are examples of these types of nudges in digital contexts, which can be referred to as digital nudges due to the deliberate manner in which they are designed to facilitate better informed and reflective choices by users [31]. The convergence between AI and nudging is an exciting new area that has seen considerable growth and continues to evolve at a rapid pace, while still developing and growing in size and scope. Some example technology can learn from the way that users behave within the algorithmic system and can adapt to those behaviors, based on environmental cues (signals), to provide the most personalized and context-based decision support [31]. At the same time, it raises ethical questions regarding autonomy, possible manipulation, and data security. Ethics guidelines for trustworthy AI stress the importance of transparency, human oversight and proportionality when behavioral interventions are embedded within algorithmic systems [11]. It is essential to ensure, that AI-based nudges respect these principles for responsible deployment in financial contexts.

4. RESULTS

The systematic search and screening process described in Section 2 [36], yielded a final sample of ten studies. Although numerically small, they collectively represent a wide range of methodological approaches to the issues of algorithmic decision-making. These studies also incorporate various methods of analysis and ethical considerations. As such, when taken together, they provide a comprehensive picture of contemporary discussions concerning algorithmic decision-making processes and form the basis for the subsequent thematic analysis. Notably, the search term ”Large Language Model” yielded additional records pertaining to AI ethics in finance, such as explainability, fairness and algorithmic accountability but did not produce any results that explicitly addressed behavioral nudging mechanisms. The review did not identify any previous research on the intersection of LLM-based systems and nudging within financial domains. In order to provide full transparency about the evidence base for this review, a comprehensive overview of the included studies and their methodologies, as well as thematic classification, are presented in TABLE 1 of the Appendix.

4.1 Current Uses of AI in the Financial Sector

AI is considered a technology and an increasing number of tools that are integrated into many different parts of the finance industry, not just a single technology. Much of the research on AI is focused on the use of robo-advisors and AI-based advisory systems that allow the average person using retail-level financial services to convert complicated financial information into a simpler form of information and recommendations. These types of applications rely on ML types of algorithms that utilize patterns of consumer behavior to compare various types of data and improve the quality of their recommendations based on the amount of data that is provided to them. [16, 26, 31]. In practice, these systems decrease cognitive demands and the perceived complexity of financial decisions. A repeated topic in the literature concerns explainability. The reviewed studies consistently show that providing users with even minimal insight into the logic behind algorithmic recommendations builds the trust in and willingness to engage with AI-driven advice. Individuals are more likely to continue using AI tools if transparent explanations are provided, even in situations where errors occur. Explainability therefore appears to function as a stabilizing mechanism that helps maintain trust in automated advice [37]. Recent advancements in LLMs indicate an expansion of financial decision support systems extending beyond traditional ML applications to include more interactive and dialogue-oriented forms. There were no empirical investigations on LLM-based nudging based on our review, but there are conceptual similarities: As conversational interfaces, LLMs can reframe financial data, provide real-time contextual explanations related to the options presented, and adapt how they present options to users based on user inquiries. The attributes of LLMs support core elements of digital nudges, including simplification, salience, and structure through defaults; however these attributes also create new challenges related to reliability of outputs and provide persuasive but ungrounded recommendations. The authors of this review also highlight several ethical and regulatory factors. Conceptual analysis suggests that current governance frameworks cannot fully address adaptive and complex algorithmic systems. The authors stress the importance of creating new oversight mechanisms, such as ethics-based audits, assigned accountability processes, and human-in-the-loop safeguards, to reduce the likelihood of ambiguous or biased results [35]. In addition, AI consumer behavior analytics influences how customers generally interact with companies on a daily basis, as AI systems help customers identify and track their uncertainties, forecast their potential behavioral tendencies, and generate customized reminders that remind them of their long-term financial objectives. As such, AI tools help customers reduce their cognitive fatigue in decision-making and prevent them from becoming stuck in their decision-making process [17]. Overall, the authors argue that AI is enhancing the personalization and efficiency of business interactions while introducing ethical issues regarding transparency, equality, and trust between the company and its customers.

4.2 The Role of Nudges in Ethical and Effective Financial Decision-Making

Researchers are increasingly intrigued by subtle design interventions used within digital finance. These interventions enable users to gain an understanding of their experiences when interacting with AI mediated environments. For instance, in the robo-advisory industry and through online banking systems, default letter templates; simplified displays; visual cues or icons such as arrows; or structured decision paths assist users in overcoming apprehensions so that their actions do align with their stated objectives [31]. The cognitive load placed on the user is lessened, while facilitating the user's ability to navigate through potentially complex/risky decisions without infringing upon the autonomy of choice by such methods. The literature has also suggested that using nudging for recommendations which are tailored specifically to the individual's preferences, desires, etc., creates additional complexities due to its delicate nature and enables greater levels of manipulation when compared against less tailored recommendation systems. This is particularly true since the algorithms used for forming these recommendations are often aligned more closely with institutional advantage than with individual user benefit or satisfaction [11, 38]. The studies mentioned reflect an important aspect of governance, as well as ethical requirements for the design of algorithms used in nudging. They indicate that a successful nudge should contain elements of transparency, value alignment, and user-centered design in order to maintain the autonomy of the individual and the ethical legitimacy of a nudge [17]. The finding from this body of research has also revealed that algorithm-generated nudges do not automatically produce positive results; instead, for algorithmic nudges to be successful they must help individuals understand the implications of their choices while considering their individual goals as well as avoiding the re-enforcement of pre-existing biases. Therefore, positive behavior change as a result of nudging occurs only when nudges promote aspects associated with long-term financial planning and do not trigger impulsive or short-term behavior [12, 13]. Several factors related to the design and evaluation of effective AI-based nudges in financial settings can be drawn from the body of research reviewed here. These factors include: (i) transparency of the method of nudging, i.e., whether users are aware that a behavior change intervention is being applied; (ii) preserving user control, ensuring the nudge does not limit users to fewer choices than before (autonomy); (iii) aligning with users' financial goals rather than the financial goals of financial institutions; and (iv) measuring the positive impact of the nudge on decision-making quality e.g., through reduced decision-making inertia, improved diversification of portfolios or increased savings [17, 18, 31]. These factors may serve as qualitative benchmarks for developing and evaluating AI-based nudges in real-world applications. The findings from the studies indicated that nudging has promise as a behavioral change tool; however, its effectiveness is highly dependent on the degree of transparency, ethical grounding, and intentionality with which nudges have been incorporated into an AI-enabled financial service delivery system. The majority of studies conducted have low external validity because they were conducted primarily in controlled laboratory settings, and as such, the generalization of the findings to situations of long-term financial decision-making through financial service delivery in the real world is uncertain.

4.3 Contribution to the Digital Transformation of Finance

AI is a significant factor in Digital Transformation [39], with many modern AI tools supporting the ability to analyze large volumes of data by means of behavioral monitoring based on situational cues and almost real-time re-organization of digital environments in which decisions are made. As a result, these tools provide the user with an easy way to develop and sustain healthy long-term financial behaviors i.e., through ongoing diversification, regular savings habits or risk minimization [17]. Accordingly, the cognitive burden of making complicated financial decisions is significantly alleviated by AI because AI can remove the mental burden of conducting mathematical calculations in order to make sound financial decisions. Nudging takes Digital Transformation in the finance sector one step further by providing decision-making architecture that is more user-friendly, has greater ethical alignment and reduced emotional distress on the user. The literature indicates consistently that Digital Transformation in the finance sector should not be equated solely with increased efficiency, it should also encompass the concepts of fairness, transparency and user protection, which become increasingly more important as decision-making moves toward AI-supported environments [35]. If used properly, nudges can help build trust and reduce unnecessary delays while ensuring that automated systems remain aligned with the needs of the user, rather than focus only on the needs of the institutions.

4.4 Contribution to the Financial Decision Process

At the point of action when users complete their decisions, the effect of using AI-support is apparent due to the use of structured steps, contextual prompts or personalized support. Better understanding on how the recommendations are formed can help increase financial literacy over time [18, 19]. However, current AI-managed nudges focus primarily on the execution phase of the decision-making cycle, with less emphasis on earlier stages such as problem recognition, goal setting, and evaluating alternatives. They also do not adequately support the reflective phase, in which users learn from past decisions and adjust their future behavior accordingly. Therefore, by creating a design that supports a wider range of user needs, financial autonomy, trustworthiness and informed consistent long-term decision-making will be enhanced. For example, 'nudges' to assist users with defining goals and comparing alternatives before making a decision [18, 31], as well as structured reflection prompts after making a decision, may assist with closing the gap between being algorithmically efficient and engaging users in a meaningful way. The complete set of studies included in this review is summarized in the appendix to ensure transparency regarding the empirical basis for these findings.

5. DISCUSSION

The studies examined in this article systematically indicate that AI is changing the conditions under which financial decisions are made. While these systems help individuals cope with information overload and complexity, they do not resolve the deeper questions surrounding autonomy, transparency and trust, as in many cases, tools developed to support decision-making introduce their own cognitive dynamics and are thereby influencing how users understand and interpret the options offered to them [40]. As shown in Section 4.1, AI systems adjust cues, timing, and information relevance in real time, often without users being aware of these dynamic changes. This raises the question of whether autonomy can be meaningfully exercised in environments where the structure of choices is continuously adjusted. According to Section 4.2, nudging can be a helpful tool for facilitating daily decision making, provided that the identified evaluation criteria are met to ensure that nudges support rather than undermine user choice. When AI is being used in supporting nudges, it can be difficult to decide if the user is being supported by the nudge or if they are being directed by the institution that is providing them with the nudge. After identifying the tension that can occur when using an AI-based solution to improve hyper-personalization in Section 4.2, it becomes even more difficult for users to separate well-designed support from systematic manipulation, particularly when algorithmic optimization prioritizes institutional metrics over the users' overall happiness. As a result, governance structure must address this inherent conflict of incentives between institutions and users. By incorporating LLMs into the realm of financial advisory, governance-related issues will inevitably take on an additional element of complexity. As outlined in Section 3.3 and Section 4.1, LLMs differ fundamentally from standard algorithm-based nudges by dynamically generating persuasive yet potentially unverified recommendations through conversational interaction [7, 19]. The implications are significant, as current governance systems were designed based on static or semi-dynamic systems and do not consider the fluid, generative nature of LLMs' output. Therefore, regulatory frameworks should create audit and oversight systems that specifically address LLMs and are separate from the requirements established for typical algorithmic support of decision-making. Nudging, when planned in a way that users know about it and can notice the effect of the nudge, can help users make independent decisions instead of hindering independent choice. The adaptive nudges discussed in Section 4.3 can only be effective, when organizations providing them are free from legal liability but accountable through a regulated system of rules designed to protect both users and organizations. Traditional nudging theory was developed for static choice environments [12]; by contrast, current AI powered financial systems create adaptive choice environments that adapt the choice architecture based on how users behave and how the system predicts the users' future behavior. This transition raises two significant issues: what will individuals do when they have to use a system that will change the way they make decisions?; how will individuals maintain legitimacy as independent agents in their use of an algorithm that is constantly adjusting their choice? These questions are outside the current boundaries of established theory and demonstrate the need for interdisciplinary research among the fields of behavioral economics, decision theory, and human-computer interaction. As mentioned in Section 4.4, this emphasis on implementation for nudge design means that other stages of the decision-making process remain underserved. Expanding nudge design to cover the entire decision-making process, from setting goals to evaluating and post-decision reflection, would improve not only the quality of each decision but also its long-run consistency with users' financial objectives [37]. The limited empirical basis identified in this review and discussed in Section 4 [41], reflects the early stage of research at this intersection. The expanded search, including the term "Large Language Model" confirmed that behavioral nudging in LLM-based financial systems remains entirely unexamined empirically. Another major limitation is the sample source. As noted in Section 4.2, most of the available evidence is based on laboratory or simulation experiments [14, 20], constraining external validity [15]. The link between explainability and lasting trust in a financial service provider beyond simulation environments is still a research gap [30, 33]. Future studies should include large, long-term, and actual financial or investment studies. The findings from this review can be used to derive some practical implications for practitioners, particularly in regard to facilitating the decision-making process for customers of financial services through the use of nudges. For example, by incorporating nudges at every stage of the decision-making process, such as prior to and after making a decision, financial services firms can encourage customers to form and sustain ongoing trust. Simplifying the decision-making process through easier to comprehend risk comparisons or other visual tools for presenting possible scenarios will reduce the cognitive burden placed on customers during the search for information prior to making an investment decision. Reminders to review a portfolio periodically will enable customers to track the progress of their investments over time, and therefore maintain alignment with their long-term goals. Similar to financial services providers; for regulators and designers of financial systems, it is critical to consider the transparency of nudges within the design of financial advisory systems, specifically in regard to the presence and rationale for their recommendation. This is particularly true for LLM-powered financial advisory systems because the conversational nature of the recommendations may obfuscate the actual architecture of the decision-making process. Finally, when evaluating nudges that use AI, practitioners should use the criteria of transparency in their recommendation, preservation of autonomy in decision making, alignment with the customer's goal, and measurable impact on determining a customer's decision-making quality as a starting point.

6. CONCLUSION

The findings of this research reveal how drastically the advent of AI and nudging has revolutionized the digital finance system. Nonetheless, there is a lack of empirical literature on the interactions of AI, nudging, and financial decisions. The fact that only ten studies met the criteria for inclusion in this research indicates that there are many ways for future research in this area, especially regarding long-term effects and practical applications of AI-enabled nudges and their ethical implications. The difference between static and adaptive nudge models, together with the preponderance of attention on the execution phase as revealed in this review, may result in threats to user autonomy and potentially to decisions that are not aligned with users' intended financial objectives. Additionally, the growing presence of LLMs as conversational agents with potentially persuasive forms of algorithmic decision support creates an additional reason to implement governance that is not currently captured in existing regulation. Practically speaking, these results show that there should be implementations of nudging across all aspects of the financial decision-making process, that transparency about algorithmic nudging should be a primary design consideration, and that evaluation of AI-based behavioral interventions should rely upon dedicated evaluation criteria, as described in Section 4.2. Future research should consider additional settings beyond controlled environments, specifically, long-term evaluation of the effectiveness and ethical acceptance of AI-driven nudging requires conducting field trials and longitudinal studies within actual financial contexts.

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Appendix

Table 1: Summary of Key Studies on Nudge AI in Banking.

Study	Key Findings (short)	Practical Contribution (short)
Mali & Devmane (2025)	AI-powered financial services personalize advisory processes and reshape user interactions	Define the concept of personalized AI-based financial advice (whether it be through natural language generation, chatbot systems, etc.) while providing explicit descriptions of the ethical guidelines associated with these types of systems
Jung, Erdfelder & Glaser (2018)	Digital nudges in robo-advisory can reduce decision inertia and support more deliberate investment choices	Principles from choice architecture can reduce the effects of cognitive bias in automated financial advice and improve the likelihood of making good financial decisions for individuals
Brüggen et al. (2025)	Ethical reflection is essential for AI-based financial advice; nudges must respect autonomy and avoid manipulation.	The ethical orientations model can help create a framework for using user-focused AI advice to assist with a responsibly understood design process
Ben David, Resheff & Tron (2021)	Explainable AI significantly reduces adoption drop after model failures and increases trust in algorithmic advisors.	Tools and guidance that support the user-friendly and accessible design of regulatory structures must also include mechanisms for providing explanations of how AI-enabled financial tools will work
Buckley, Zetzsche, Arner & Tang (2021)	Human-in-the-loop governance and explainability are key to regulation of AI in finance	A framework for accountability, oversight, and a transparent approach to the design of AI systems must also provide the framework for creating trustworthy financial guidance and recommendations
Kurshan et al. (2021)	Identifies risks of opaque behavioral steering and fairness issues in AI–nudge interactions	The governance requirements surrounding the use of responsible behavioral interventions (nudges) are required to ensure that the nudges in question do not lead to unintentional or excessive influence by the nudges
Mökander & Floridi (2021)	Ethical auditing increases transparency and trustworthiness in AI decision-making	The audit tools needed to develop responsible and non-manipulative AI nudges must also focus on transparency and the integrity of how the AI systems behave
Dietzmann, Jaeggi & Alt (2023)	AI-driven CRM supports personalization, reduces cognitive load and enhances user engagement	Insights gained through the design of nudges can help create a more tailored and effective process for delivering advisory services to financial customers based on their preferences and financial goals
Jung (2019)	Behavioral inertia strongly affects financial decision-making; digital nudges can counteract suboptimal behavior	The empirical basis for implementing nudges in robo-advisory environments will provide evidence of improvements in the quality of financial decisions made by users
Olanrewaju & Oba (2024)	AI personalization improves fairness, trust and alignment with user needs but requires ethical safeguards	Guidelines should exist to advise on how to balance personalization and transparency with respect to AI-enabled advisory services, in order to promote accountable, transparent and user-oriented designs of such systems