

Breaking New Ground: LLMs as Catalysts in Consumer Financial Decision-Making Research

Abstract

This paper introduces a novel framework for leveraging Large Language Models (LLMs) to transform consumer financial decision-making research. By bridging AI and financial decision-making literature, it maps Generative Artificial Intelligence (GenAI) capabilities to key research challenges, revealing promising new avenues for future investigations. The framework positions GenAI as a powerful tool for overcoming persistent obstacles in studying dispersed populations, capturing long-term behaviors, and navigating ethical concerns. While acknowledging current GenAI limitations, this work argues that the strategic integration of AI could unlock unprecedented insights, potentially reshaping our approach to financial behavior research.

Keywords: Generative AI, Large Language Models, Consumer Financial Decision-Making, Research Methodology

Introduction

Financial decision-making is a fundamental aspect of consumer behavior. It is defined as “the accumulation and use of resources across time, as reflected by consumers’ behavior and choices” (Sussman et al., 2023, p. 365). This domain encompasses a wide range of choices, from daily spending to long-term planning. Consumers must navigate decisions about budgeting, borrowing when resources are scarce, repaying debts, investing savings, and ensuring financial stability for retirement and unexpected hardships. These financial choices significantly impact consumers’ lives, influencing their stress levels related to money management, their anticipated financial security, and ultimately, their overall well-being and life satisfaction (Diener, 1984; Netemeyer et al., 2017).

Despite receiving increased scholarly attention for over a decade (Lynch, 2011), many aspects of consumers’ financial decision-making remain unexplored. In a 2023 special issue of the *Journal of the Association for Consumer Research*, Sussman et al. (2023) highlighted various open questions, including understudied areas, such as one-time or infrequent transformative decisions or temporal dynamics in consumers’ financial decisions. These topics often receive little attention due to their complexity and difficulty to study (Sussman et al., 2023). At the same time, emerging research on Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs) suggests a potential transformation in consumer research methodologies (Brand et al., 2023; Sarstedt et al., 2024). This raises a couple of questions: Could these technologies advance financial decision-making research, and what opportunities and caveats might they present? This paper offers a conceptual perspective by mapping GenAI’s capabilities as a research tool to address salient challenges in consumer financial decision-making research.

In what follows, I provide a brief review of existing literature on AI in consumer financial

decision-making, the emerging use of generative AI as a research tool, and salient challenges in consumer financial decision-making. Next, I map GenAI's research capabilities to address these salient challenges, describing how LLMs could potentially advance knowledge by helping to overcome them. The article concludes with a critical examination of the current limitations of LLMs for research purposes and outlines promising avenues for future research.

Theoretical Background

This section introduces the evolving landscape of AI in consumer financial decision-making, setting the stage for examining how generative AI can address persistent challenges in the field.

AI in Consumer Financial Decision-Making

Artificial Intelligence (AI) can be defined as “the use of computational machinery to emulate capabilities inherent in humans” (Huang & Rust, 2021, p. 31). A subset of AI, Generative Artificial Intelligence (GenAI), focuses on creating new content based on the data it has been trained to process. This content can range from text and images to audio and video (Hermann & Puntoni, 2024). Within GenAI, Large Language Models (LLMs) are specialized tools designed for understanding and generating text. Prominent examples of LLMs include GPT-4, which powers OpenAI's ChatGPT and Microsoft's Copilot, as well as Google's Gemini and Anthropic's Claude. As these AI technologies have evolved, researchers have begun to explore their applications in various domains, including consumer financial decision-making.

A growing body of research explores the intersection of AI and consumer financial decision-making. For example, Hildebrand and Bergner (2021) found that conversational robo-advisors, compared to non-conversational ones, foster higher affective trust among users, which

leads to more favorable company evaluations and changes in investor behavior, including greater acceptance of recommendations and higher asset allocation. Yalcin et al. (2022) examined consumer reactions to algorithmic versus human decision-making in the context of loan applications. They found that consumers react less positively when a loan application is accepted by an algorithmic rather than a human decision-maker because humans facilitate the internalization of favorable decisions. However, this difference is mitigated for unfavorable decisions, as these are easily externalized regardless of the decision-maker. In a recent piece, De La Rosa and Bechler (2024) provided a broader conceptualization introducing the AI-IMPACT model, which describes how AI influences financial decisions through marketplace changes in access, personalization, flexibility, and automation.

While substantial research has investigated the influence of AI and GenAI on consumer financial experiences, a gap remains in exploring how GenAI can be leveraged as a methodological tool to enhance the study of financial decision-making itself.

GenAI as a Research Tool

Computer scientists, psychologists, and marketing researchers have begun exploring how GenAI could impact various stages of the social science research process. At the idea generation stage, GenAI was suggested to aid in hypothesis generation (Stremersch, 2024). At the stage of developing a research design, GenAI might help with generating items, scenarios, and stimuli (Sarstedt et al., 2024). In the data collection and analysis stage, GenAI can replace human participants and generate insights from text, image, and video data provided by participants (Krugmann & Hartmann, 2024; Zong et al., 2024). Finally, at the stage of data visualization and reporting, GenAI can aid with creating data visualizations and dashboards (Ye et al., 2024).

Among these various applications, the use of synthetic personas has garnered particular

attention. Synthetic personas refer to AI-generated research participants mimicking human respondents to describe, explain, and predict human behavior (Sarstedt et al., 2024). Responses to market research questions generated with such artificial research participants were shown to correlate surprisingly well with responses to the same research questions when answered by human respondents. For example, it has been shown that LLMs rate scenarios equally in terms of morality as humans would (Dillion et al., 2023). In a more marketing related context, they were shown to produce human-like brand similarity ratings which were used to create perceptual maps in the context of brand positioning (Li et al., 2024). Moreover, LLMs were shown to value product attributes such as toothpaste packaging and ingredients similarly to humans in conjoint analyses, making them suitable for estimating willingness-to-pay (Brand et al., 2023). How can these capabilities now aid in overcoming challenges in consumer financial decision-making research?

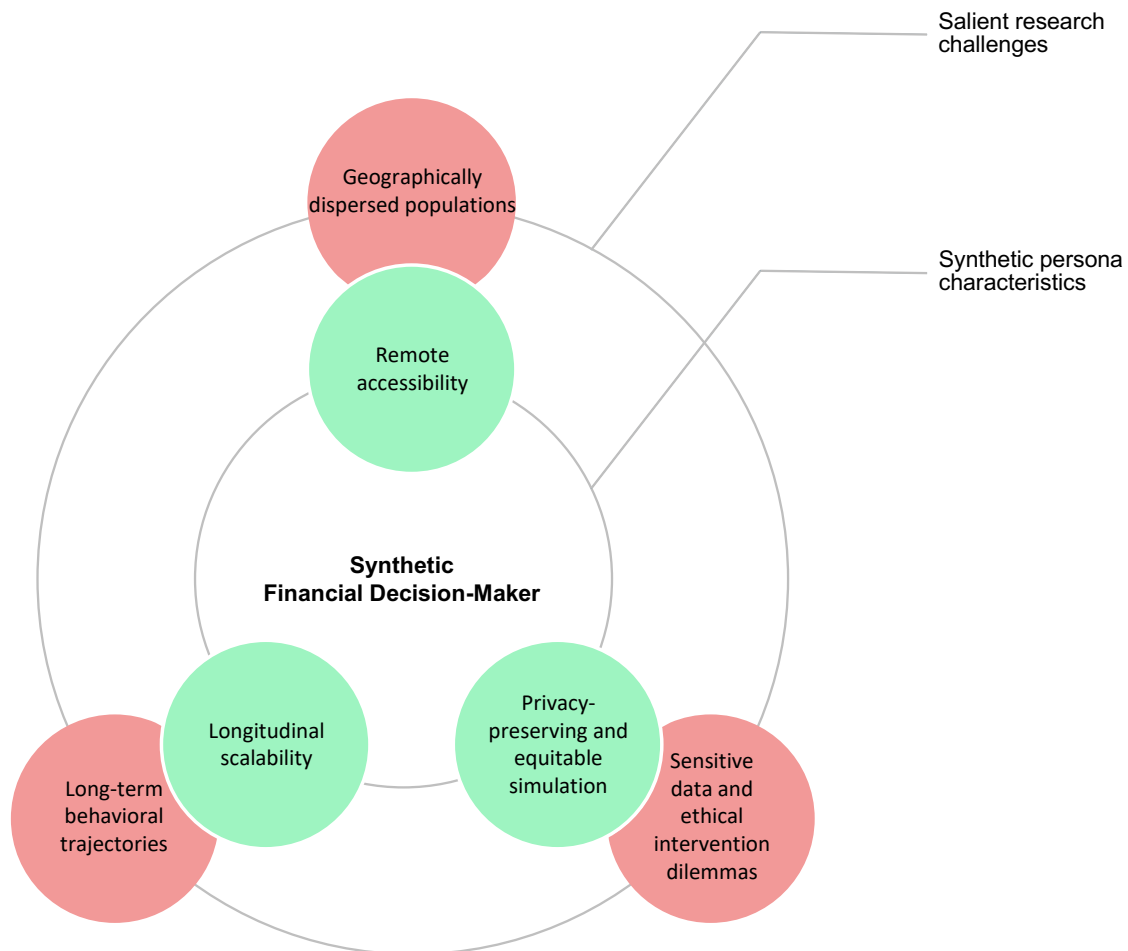
Salient Challenges in Consumer Financial Decision-Making Research

Recent work highlighted various open questions related to the way that consumers acquire and decide upon financial resources. For instance, it has been suggested that there is a need to better understand heterogeneous consumer groups, joint decision-making, decisions around accumulating resources, and temporal dynamics of income and event flows, or transformative financial decisions, such as getting married or buying a house (Sussman et al., 2023). I propose that some of these open questions could particularly benefit from investigation using GenAI methodologies, as they involve key challenges that are especially salient in financial decision-making research. These challenges can be categorized into three primary areas: 1) geographically dispersed populations (Berry et al., 2018; Carpena et al., 2019; Mende et al., 2020), 2) long-term behavioral trajectories (Samanez-Larkin et al., 2014; Sussman et al., 2023), and 3) concerns of sensitive data handling and ethical intervention dilemmas (American Psychological Association,

2023; Pickard et al., 2018).

Mapping Financial Decision-Making Research Challenges to GenAI Capabilities

The field of consumer financial decision-making research faces several salient challenges that can potentially be addressed through the application of GenAI technologies, particularly through the use of synthetic personas. Figure 1 illustrates the mapping between these research challenges and the corresponding characteristics of synthetic personas that might help mitigate them.



**Figure 1: Conceptual mapping of salient research challenges
and synthetic persona characteristics**

Geographically Dispersed Populations

Research Challenge. Many research questions in consumer financial decision-making involve the study of geographically dispersed populations. For instance, they may involve hard-to-reach groups, such as consumers in remote or underserved regions where traditional banking services are scarce or financial literacy low (Berry et al., 2018; Carpena et al., 2019; Mende et al., 2020). Accessing these populations is logistically challenging and costly using conventional methods. For example, Mende et al. (2020) highlighted the difficulties of studying consumers in areas lacking traditional banking infrastructure. Similarly, Carpena et al.'s (2019) research in India demonstrated the challenges of obtaining reliable financial data from rural populations that may be disconnected from formal banking systems and are less likely to participate in research studies. These populations are not only underserved financially but also geographically dispersed, compounding the difficulties of data collection.

GenAI Potential. Synthetic personas generated by LLMs might facilitate access to these underrepresented populations or, more accurately, their simulations. Consumer researchers might craft synthetic personas that represent the demographic and socioeconomic characteristics of consumers in “banking deserts” or other remote areas, allowing them to simulate their financial behaviors without the need for physical presence or direct data collection. For instance, LLMs could model the potential impact of introducing mobile banking in a banking desert, predicting adoption rates and identifying possible barriers.

Long-Term Behavioral Trajectories

Research Challenge. Consumer decision-making research frequently involves temporal complexities. Researchers aim to understand financial behaviors across various life stages

(Barcellos et al., 2016), during rare events such as retirement, marriage, or economic downturns (Sussman et al., 2023), and their interconnections throughout the consumer lifespan, particularly in areas such as retirement planning (Benartzi & Thaler, 2007; Thaler & Benartzi, 2004). However, studying these temporal aspects presents significant challenges. Identifying representative consumer groups at specific life stages, including very young and elderly individuals, can prove difficult (Marpsat & Razafindratsima, 2010). Moreover, conducting longitudinal studies to capture these temporal dynamics is fraught with obstacles. Such studies are not only costly and time-consuming but also prone to high dropout rates, compromising the collection of comprehensive long-term data (White & Arzi, 2005).

GenAI Potential. LLMs might function as a time machine, simulating consumers of different age groups at various points in life in both cross-sectional and longitudinal settings. For example, to study lifecycle financial behavior, researchers could create synthetic personas representing individuals at different life stages, from young adults to retirees. These personas can be “aged” over time, simulating how financial decision-making evolves throughout a person’s lifecycle. Additionally, to study the impact of major life events, synthetic personas could be programmed to experience significant life changes (e.g., marriage, having children, job loss) and make related decisions “in vitro” (Drinkall et al., 2024).

Sensitive Data and Ethical Intervention Dilemmas

Research Challenge. Financial decision-making is often perceived as a highly sensitive topic, with many individuals reluctant to share detailed personal data. A recent study conducted by the American Psychological Association found that only 52% of adults reported feeling comfortable talking with others about money (American Psychological Association, 2023). This hesitancy can create significant barriers to collecting accurate, comprehensive information on

financial behaviors and decision-making processes from consumers (Pickard et al., 2018). Additionally, research on financial decisions may present ethical challenges that are particularly salient compared to other consumer behavior domains. For example, administering a potentially beneficial financial literacy intervention to only a subset of consumers while withholding it from a control group could raise ethical concerns (Gaurav et al., 2011). The potential impact on participants' financial well-being might be more substantial than in studies investigating the effect of different advertisements, for instance.

GenAI Potential. Synthetic personas, as they do not correspond to real individuals, can mitigate some privacy concerns associated with handling sensitive financial data. This approach reduces the challenge of privacy breaches related to individual participants. Additionally, synthetic personas allow researchers to explore various interventions or treatments across different simulated populations without the ethical dilemma of withholding potentially beneficial treatments from real individuals. Also, researchers might simulate the effects of potentially controversial financial advice or products on consumer behavior before applying these findings in practice.

Limitations of GenAI as a Research Tool

GenAI offers potential for advancing research into financial decisions. However, it is at least as important to point out the limitations and possible adverse effects (De La Rosa & Bechler, 2024; Valenzuela et al., 2024). The next section provides some of the most critical considerations.

Synthetic samples generated by AI models often overrepresent Western, Educated, Industrialized, Rich, and Democratic (WEIRD) consumers (Henrich et al., 2010). This bias stems from the data these models are trained on, which predominantly reflect WEIRD populations (Sarstedt et al., 2024). Consequently, to realize the potential of studying geographically dispersed and remote populations, researchers must actively diversify their training data and validate their

synthetic personas against real-world data from underrepresented groups. According to Mailer (2023), this may involve collaborating with local experts or institutions in target regions to ensure accurate representation.

AI models struggle to capture the full range of situational factors that influence real-world financial decisions (Li et al., 2024). To address long-term behavioral trajectories effectively, researchers need to incorporate dynamic contextual elements into their models (Gui & Toubia, 2023). This could involve regularly updating AI models with current economic data, cultural trends, and policy changes. Additionally, researchers might complement AI-generated insights with qualitative research methods to capture nuanced, context-specific factors that influence financial decisions over time (Peñaloza & Barnhart, 2011).

While synthetic personas can mitigate some privacy concerns, they introduce new ethical challenges. For instance, GenAI models used to create synthetic personas are often trained on vast datasets that may include personal financial information. This raises questions about the original data sources, consent, and whether individuals whose data contributed to the model's training are inadvertently participating in research without their knowledge or permission. Further, the use of synthetic personas could potentially reduce opportunities for human participants to earn money from research studies. This may disproportionately affect vulnerable populations who rely on such income, raising concerns about equitable distribution of research benefits. To address this, researchers could prioritize the use of open-source LLMs or those with publicly available documentation of their training process, adopt hybrid approaches that combine synthetic personas with real participant involvement and establish clear guidelines for when and how synthetic data can be used in place of real participants.

Conclusion and Directions for Future Research

This paper presented a framework for leveraging Generative AI (GenAI), particularly Large Language Models (LLMs), to address longstanding challenges in consumer financial decision-making research. By mapping GenAI capabilities to salient research challenges, the current work illustrates its potential to transform how researchers approach spatial, temporal, and ethical obstacles in the field.

The study contributes to the literature in several ways. First, it provides a timely and comprehensive mapping of GenAI's potential in consumer financial decision-making research, offering insights into a rapidly evolving technological landscape. Second, the framework bridges AI technology and consumer financial behavior, fostering interdisciplinary collaborations and methodological innovations. Third, the proposed application of GenAI for synthetic data generation and simulations represents a methodological advancement in consumer finance research, establishing a foundation for future work.

Building on the proposed framework, future research could empirically test and refine the proposed applications of GenAI in consumer financial decision-making research. Comparative studies might evaluate how effectively the framework's suggested GenAI approaches address geographically dispersed and underrepresented populations compared to traditional methods. Researchers could empirically assess the framework's propositions for using GenAI to model long-term financial behaviors, particularly in capturing complex life-changing decisions and evolving economic contexts. Lastly, the article advocates for increased interdisciplinary collaboration in developing and refining LLM-based methodologies for consumer finance. This collaboration should extend beyond scholars from marketing, psychology, finance, and economics to include scholars from computer science and ethicists.

In conclusion, while GenAI and LLMs present promising opportunities for advancing

consumer finance research, their integration necessitates careful consideration of both their potential and limitations. As the field progresses towards the incorporation of these new tools, maintaining scientific rigor and ethical integrity will be crucial in ensuring these technological advancements genuinely enhance our understanding of consumer financial decision-making.

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