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Suppetia ex machina: How can AI technologies aid financial decision-making of people with low socioeconomic status?

Christian T. Elbæk[1]*, Ifeatu Uzodinma[2], Zilia Ismagilova[3], Panagiotis Mitkidis[1]

Abstract
In this conceptual paper, we outline how individuals with low socioeconomic status are more vulnerable to making choices that undermine their welfare in economic decision environments that require an acceptable comprehension of risk. We propose that novel technologies, specifically Artificial Intelligence, can aid in improving financial decision-making for individuals with low risk awareness, and we suggest avenues where policy can leverage emerging Artificial Intelligence technologies to design specific choice architecture that may support more risk-aware decision-making of vulnerable socioeconomic groups. Lastly, we discuss the ethics of utilizing nudges in vulnerable populations, the limitations of our approach, and how our paper can pave way for future research to improve decision-making for socioeconomically vulnerable individuals.

JEL Classification: D91; D81; I30; O33; P46

Keywords
decision-making — SES — AI — nudging — choice architecture

[1] *Department of Management, Aarhus University, Denmark*
[2] *UCL School of Slavonic and East European Studies, University College London, United Kingdom*
[3] *Department of Economics and Management, University of Trento, Italy*
***Corresponding author**: chel@mgmt.au.dk

Introduction

Relative resource scarcity, in the form of economic inequality, is rising around the world. Recent reports from the OECD have outlined the severity of the problem by showing that an increasing number of people living in developed economies such as the US and Europe are slipping into lower-income classes (OECD, 2019). Importantly, rising inequality and poverty are problems with enormous societal costs. In 2015, childhood poverty costed the US 5.4 percent of its GDP, amounting to $1.03 trillion (McLaughlin and Rank, 2018), and from 2016 to 2017, the UK spent £78 billion just on public poverty service costs (McCarthy, 2016) including, for example, loss of economic productivity and increased health and crime costs (McLaughlin and Rank, 2018). Issues of poverty and income inequality, therefore, keep defining political agendas around the world, as predicted in 2013 by former US president Barack Obama terming it “the defining issue of our time” (Sargent, 2013).

Motivated by this, we critically review the current literature on how individual experiences of relative resource scarcity (i.e., low socioeconomic status) affect human judgment and decision-making in financial domains. Based on these findings, we then discuss how behavioral policy initiatives aimed at helping resource deprived individuals conduct more optimal financial decision-making might be effectively assisted by recent developments in Artificial Intelligence (AI) and the associated ethical considerations. The current paper contributes with an increased understanding of the psychological mechanisms involved in decision-making under resource scarcity and how anomalies in such decision-making strategies might be better mitigated by the use of AI, in order to help resource deprived individuals achieve better life outcomes.

Literature review

Generally, individuals from lower socioeconomic classes (SES), defined as individuals with low household income, educational level and occupational security are overrepresented in a number of worrying statistics. People with low SES have higher obesity rates (Drewnowski and Specter, 2004), lower levels of education (West, 2007), higher rates of teenage pregnancy (Young et al., 2001), take on more debt (Hartfree and Collard, 2014), consume more alcohol (Khan et al., 2002), and gamble more than people in higher income brackets (Blalock et al., 2007). These findings have one thing in common: successful decision-making in these specific domains requires the individual to be able to focus attention, resist stimuli, and delay gratification. This is a central problem for people with low SES as empirical evidence has identified that individuals who do not have enough of a needed resource, discount the future and fail to focus on the outcome that would serve them best

(Mullainathan and Shafir, 2014; Shah et al., 2012).

A theoretical framework that may help recognize the possible mechanisms at play and target the aforementioned problem is Subjective Expected Utility. The theory has dominated economic theory on choice in decision environments characterized by imperfect information (Camerer and Weber, 1992) and delineates how economic agents respond to uncertainty about states of nature by subjectively assigning probabilities to alternate outcomes in the absence of complete information (Savage, 1972). Intuitively, this subjectivity suggests heterogeneous beliefs about the future across economic agents, with recent studies showing that people in the low SES demography consistently discount future payoffs more than high SES individuals (Oshri et al., 2019; Carvalho et al., 2016). It might so be that low SES individuals generally hold pessimistic beliefs about unknown future states of nature. For them, having experienced events associated with low SES such as frequent negative income shocks (Haushofer and Shapiro, 2013), present consumption is preferred to some unknown future (Amir et al., 2018). With the tendency for this demographic group to be comparatively more risk averse and less willing to invest in education (Haushofer and Fehr, 2014), they are likely to be more vulnerable to financial illiteracy and financial exclusion (Barboni et al., 2017). In an economic decision environment, the absence of requisite financial literacy could indicate low SES individuals' inadequacies in risk cognition. Without satisfactory awareness and comprehension of risk, low SES individuals will likely defer to their inherently high level of risk aversion and inordinately discount pay-offs in the future. This failure to identify better long-term outcomes can in turn lead to a series of consistently poor financial decisions that make it near impossible for these individuals to escape poverty (Carvalho et al., 2016; Haushofer and Fehr, 2014).

As financial decision-making becomes increasingly digitized with a growing number of interactions happening online (Accenture, 2019), financial institutions such as banks, pension funds, and mortgage lenders have rapidly adopted new digital technologies to offer services entirely online (Gomber et al., 2018). Generally, this means that data collection becomes highly personalized and humans might become overwhelmed with data. This can lead individuals to become victims of information isolation by their own initial digital choices, perpetuated through search history, location, and past click behavior known as *filter bubbles* (Pariser, 2011). Although the phenomenon is more often associated with search engines, the formation of civil opinion, and marketing promotions, it is not clear yet how these filter bubbles affect the behavior of economic agents, especially those making financial decisions with a high level of uncertainty. Overloaded information-rich environments, governed mostly by artificial engines, interfere with humans' ability to embrace the existing information and consequently make optimal decisions. While such a digitized environment gives the feeling of conscious and optimal choice, individuals might fall into self-deception and lose awareness in such environments, especially if they lack the ability to discount future outcomes and focus on the task at hand (Helbing, 2019; Lipina and Posner, 2012; Shah et al., 2012; Banerjee and Mullainathan, 2008). This might in turn lead to polarization among social groups, ultimately deteriorating the already decreased economic and societal position of individuals with low SES. To avoid such negative consequences, we suggest using novel AI technologies to improve individual choices in complicated decision-making environments without restricting options, generally known as "nudging" (Leonard, 2008). While the literature suggests various definitions of AI, in this article we define AI as a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation (Kaplan and Haenlein, 2019).

We argue that suggested implementations can aid in improving financial decision-making for individuals with low-risk comprehension because these AI technologies (like machine learning), thanks to their ability to tackle issues involving large datasets, can take into account current financial limitations of an agent's personal financial situation and hence make the optimal financial choices more salient to such agents, without restricting their number of choices. Consequently, we suggest that institutions should adopt specific policy initiatives aimed at developing selected AI technologies as "nudging tools" to help individuals experiencing relative resource scarcity make more optimal economic decisions that can improve individual welfare and reduce societal costs associated with poverty. The current paper outlines a novel interdisciplinary approach to understanding and combating the fundamental problem of how to better help resource deprived individuals through specialized behavioral policy initiatives, an issue of prime importance for researchers in economic policy and policy-makers alike.

The effects of low SES on cognitive development and decision-making

A large and rapidly expanding body of research in the neuro and cognitive sciences has produced evidence demonstrating that growing up and living with a low SES can have detrimental effects on the development of particular vital cognitive functions of the human brain (Duval et al., 2017; Hackman et al., 2010; Giedd et al., 1999). These cognitive functions include areas of the brain associated with inhibitory and interference control, cognitive flexibility, stimuli control, and focus regulation, generally known under the broad term *executive functions* (Diamond, 2013; Sarsour et al., 2011; Hackman et al., 2010). Low SES is also directly tied to structural differences in the brain of children, in areas of the brain that are linked to educational skills and achievements (Hair et al., 2015), and has been shown to be associated with adult earnings and the number of working hours in later life (Duncan et al., 2010). IQ variance in low SES families is even shown to be prominently explained by the shared environment, while such a relationship does not exist for affluent families, where

IQ variance is greatly explained by genetics (Turkheimer et al., 2003).

As a result of this suppressed development in cognitive functions, living with resource scarcity, characteristic of low SES, has been shown to reduce what is often conceptualized as "mental bandwidth" (Mani et al., 2013). This means that scarcity makes individuals experience shifts in their cognitive attention or focus regulation (Tomm and Zhao, 2016) that can lead to sub-optimal economic decisions because, in the economic choice environment, certain problems which are considered less important or distal are neglected while others considered more proximal receive more attention (Shah et al., 2012; Spears, 2011). For example, an attention shift may result in undesirable behavior in the form of impulsive decision-making, where short-term gains i.e consumption are valued higher than the long-term ones such as investing in education that should normally increase the economic agent's welfare (Zhao and Tomm, 2018). Simply inducing thoughts about finances has been shown to impede the cognitive function of poor participants. A similar effect was not found among the "rich" subjects in the study, indicative of a resource scarcity effect on cognitive ability (Mani et al., 2013). More empirical findings further support this as individuals from low-income US households have been shown to be more present-biased in intertemporal choices when decisions are made just before payday (Carvalho et al., 2016). Scholars argue that such findings might explain why specific economic problems, such as over-borrowing, are more prevalent in resource-scarce populations (Shah et al., 2012). Individuals from low SES backgrounds tend to act more impulsively, exhibit greater risk-taking behavior, and approach temptations faster (Griskevicius et al., 2013).

Overall, these findings indicate that resource scarcity makes people focus on the problems at hand while neglecting the more long-term outcomes of their behavior (Hall et al., 2014; Mullainathan and Shafir, 2014; Shah et al., 2012). Experiencing scarcity is hence associated with reduced behavioral control, which leads to poorer short-term economic decision-making, with detrimental consequences for the long-term well-being of resource deprived individuals (Spears, 2011). Because the deprived individuals' focus on regaining resources in the short-term overshadows the opportunity to achieve better prospective outcomes, such opportunities are simply favored less compared to the immediate relief of deprivation (Shah et al., 2018, 2012; Spears, 2011). Shah, Zhao, Mullainathan, and Shafir shah2018money experimentally induced emotions relating to distinct correlates of low SES environments to isolate empirical effects of poverty on cognitive functioning. The first study examined how often induced concerns about money made subjects think about cost-related items –compared across high and low SES participants. Findings revealed that low-income individuals were more likely to think about cost-related items. In the second experiment, participants were primed with a treatable life-threatening health-experience and asked to write down the three most salient words that came to mind. Written words were grouped into two groups: 'emotion-related' or 'money-related.' In the results, low SES individuals wrote down more money-related words than high SES individuals. The third experiment specifically investigated interference regulation. The instructions required participants to allow their minds to wander freely while actively suppressing any thoughts related to monetary costs. Findings revealed that low SES subjects had more intrusions by cost-related thoughts than high SES subjects –indicative of the former being less able to regulate intrusions and maintain focus than the latter. Haushofer and Fehr (2019) attempted to distinguish the effects of negative income shocks. In a lab experiment, subjects were randomly assigned different starting endowments to experimentally create 'rich' and 'poor' subject groups. Both groups were then given tasks to complete to earn cash, after which all participants were exposed to positive and negative income shocks. Their findings revealed increased discounting resulting from the negative income shocks, though this effect was determined to be consistent across participants in both groups with non-significance in the discrepancy between 'rich' and 'poor' groups. Importantly, this evidenced lack of behavioral control can lead to the agents becoming confined to so-called "poverty-traps" – where the consequences of decision-making aimed at restoring resources in the short-term generate a vicious circle of having to engage in additional risky economic decision-making to alleviate the consequences of previous economic choices; for instance, in the form of borrowing money at high-interest rates to pay off current debts (Gandy et al., 2016). The importance of this problem in regards to policy is highlighted by longitudinal research showing that individuals who grow up in families with low SES are much more likely to end up with low SES in adulthood as well (Lesner, 2018; Wagmiller and Adelman, 2009), indicating that poverty is transmitted intergenerationally (De Lannoy et al., 2015). Thus, the detrimental consequences of economic decision-making under scarcity are not only tied to the long-term well-being of the individual, but also to the individual's family and thus future generations. This underscores the importance of implementing targeted policy campaigns aimed at helping individuals with low SES exhibit more optimal economic decision-making, not only for the life outcomes of the current generation but also for the well-being of future generations (Gandy et al., 2016).

The effect of resource scarcity on decision-making under uncertainty

Neoclassical economic theory assumed the goal of human decision-making to be utility maximization (Jerčić et al., 2012; Camerer and Weber, 1992). Behavioral theory has since found ample evidence to contradict this, establishing subjectivity as the core of human decision-making which presents as heterogeneous agents subjectively assigning probabilities to likelihood of occurrence across alternative outcomes (Loewenstein et al., 1997; Camerer and Weber, 1992; Kahneman and Tversky, 1979). These subjective probability assignments and expectations are the result of an agent's subjective perceptions and are often derived from experience (Fisher et al., 1956). Specific experiences, especially among low SES individuals, have been linked to imprudent spending (Sheehy-Skeffington, 2020; Amir et al., 2018), and negative experience (e.g., change in economic circumstances) has been shown to induce negative affective states like stress (Haushofer and Shapiro, 2013), anxiety and unhappiness (Ozer et al., 2011); all having an adverse effect on time-discounting and revealed preferences (Haushofer and Fehr, 2014). The prior adverse economic experience thus makes an agent prone to mistakes in financial decision-making (Carvalho et al., 2016) so where the choice environment is identical to both low and high SES individuals, the decision responses of low SES individuals are biased by emotions from the recall of prior adverse events. Emotions, broadly defined by their valence (negative or positive) and their intensity (level of arousal) therefore play a significant role in human decision-making (Jerčić et al., 2012; Loewenstein, 2000). In a cold state (little or no arousal), an agent's emotion-informed response is more controlled or reflective as opposed to the reverse hot state (heightened state of arousal) where the individual exhibits automatic responses and less control over their behavior.

However, not all instances of arousal and decision-making driven by emotion necessarily lead to negative behavior and sub-optimal payoff. Seo and Barrett seo2007being show that in some instances, making decisions based on emotions can lead to a positive payoff. In theory, emotions are exposed to bilateral effects that may lead to biased choices that are detrimental to the wellbeing of the agent, or reflective responses that lead to optimal decision-making (Jerčić et al., 2012). It follows that the ability to regulate emotion responses can lead to improved decision-making especially in stochastic environments with imperfect information (Heilman et al., 2010). This is critical for low SES individuals who, by their demographic features, generally have less education and, therefore, less chance of understanding stochastic environments. Research has shown that even among highly trained and risk-savvy traders, emotions have a strong impact; trading loss is usually followed by high risk aversion and extreme caution (Fenton-O'Creevy et al., 2011). It is conceivable, therefore, that both low SES and high SES individuals make choices in similar decision environments, but with fundamentally dissimilar appraisals of the presented choice architecture. The level of risk does not vary between the two groups (Haushofer and Fehr, 2014), but exogenous conditions like frequent income shocks, limited access to credit, and low financial literacy vary the level of risk perception, and as a result, the poor will consistently exhibit higher present bias than the non-poor (Muraven and Baumeister, 2000).

How can AI aid financial decision-making for low SES individuals?

Following from the previous section, can adverse economic decision outcomes of low SES demographic groups be mitigated? The situation is exacerbated by the information-rich environment where agents are increasingly surrounded by information that fits their initial interests while ignoring other relevant data. Choice manipulations and filter bubbles are not necessarily harmful to rational agents, but as established by science, *homo economicus* is rarely observed in everyday life (Sunstein, 2018; Thaler, 2000). Commercial companies, therefore, often use filter bubbles and information traps to manipulate individual decision-making. By using AI, these companies use collected information, for example, to create personalized marketing campaigns and advertisements based on personal preferences, behavior, and beliefs (Hern, 2014). Promotions are centered on using an individual's past behavior in connection with subconscious decision-making biases (social influence, emotional motivations, scarcity, etc.), to manipulate consumer choices (Dowling et al., 2020; Parker and Lehmann, 2011; Cialdini and Cialdini, 2007; Taylor, 2000). This consequently means that individuals might not necessarily be aware of the reasons triggering their actions.

While this is a general problem, low SES individuals are more vulnerable to these manipulations due to their reduced attention span, which leads such individuals to underestimate risk, discount the future, and favor short-term outcomes to restore needed resources (Schmidt et al., 2019; Tomm and Zhao, 2016; Hall et al., 2014; Mullainathan and Shafir, 2014; Griskevicius et al., 2013, 2011; Sarsour et al., 2011; Hackman and Farah, 2009), something that could have severe consequences for the individuals and for the society more generally. Furthermore, Botta and Wiedemann botta2020discriminate note that companies can both bring potential benefits to certain customer segments and contribute to the redistribution of wealth between different categories of consumers. Bergemann, Brooks, and Morris bergemann2015limits showed that additional (personal) information can both increase and decrease consumer surplus. In this respect, "strategic" customers, concerned by the risks of price discrimination, can estimate the value of their personal data, and therefore, hide their identity during online activity (Acquisti and Varian, 2005). Instead, "myopic" consumers (i.e., digital illiterate) would be less cautious about exposing their private data on the Internet, and therefore, would be more vulnerable to potential price discriminations (Acquisti and Varian, 2005). However, Bellaflamme and Vergote belleflamme2016monopoly showed that less cautious customers might benefit from price discrimination even in a monopolistic scenario: the customers relying on anonymizing technologies would be subject to the uniform price, which might be higher than a personalized one (Belleflamme and Vergote, 2016).

While scientists warn about the potentially harmful effects of the development of full AI, where robotic intelligence supersedes that of humans (Cellan-Jones, 2014), we suggest a change of emphasis, to look at the existing (weak) AI with a modern perspective, in line with new trends in technology adoption and in particular with the new concepts of augmented intelligence and its function in society. While augmented intelligence is an umbrella term that takes on a certain sense depending on the context (Porter, 2017; Pasquinelli, 2015), in this paper we define it as the use of technology to expand human information processing capabilities (Sharma, 2019). As high technology is penetrating society, policy-makers can benefit from the opportunities of digital technologies by combining technological solutions with social norms and legal regulations.

Recently, information systems (IS) have become a major component in enhancing competitive advantage on an organizational level, supporting decision making, and facilitating day-to-day operations (Checkland and Holwell, 1998). AI is enlarging the scope of application of IS not only through task automation but also through integrating and mimicking human intelligence. AI can be used to augment human capability by providing data-driven insights on risky financial decisions at speed, making more optimal choices and reminding individuals of potential alternative ways for them to improve their welfare in the long term (Karlan et al., 2016). Examples of such an application are currently arising in the fintech industry where an increasing number of AI startups implement solutions aimed at helping individuals with their financial decision-making (Kaya et al., 2019; Kashyap, 2018; Lui and Lamb, 2018).

Specifically, we suggest using these novel advancements in AI technologies to improve financial decision-making for low SES individuals with low risk comprehension. While many governments have already implemented behaviorally informed policies using choice architecture (Mousavi et al., 2017) to make individuals more environmentally friendly (Slapø and Karevold, 2019; Nielsen et al., 2017; Sunstein, 2016) or to promote retirement savings (Thaler and Benartzi, 2004), we particularly focus on how AI can be used to nudge individuals in digital financial decision environments. In addition to existing policies aimed at helping the poor, we propose to include behaviorally informed technological policies for the personal banking sector. An increasing number of people have to use banking services from online agents and hence interact through automated online support systems (Accenture, 2017). Managing finances in an environment swamped with information, such as lengthy contracts and difficult-to-understand banking terms, can be challenging for any decision-maker but especially for individuals who lack focus regulation and capacity for assessment of financial risk, which are some of the cognitive characteristics associated with low SES (Mullainathan and Shafir, 2014; Mani et al., 2013). For instance, chatbots use AI to generate personalized financial real-time advice with budgeting, savings goals, and expense tracking. More advanced virtual financial assistants integrate with voice assistants (web and mobile) to provide individuals with more convenient banking services, ranging from basic knowledge and support requests to personal finance management and conventional banking. Based on accumulated data, AI can read and analyze contracts, notify of specific terms, cancel money-wasting subscriptions, and find better insurance options - that is, those activities in which people with low SES can be especially vulnerable due to low financial literacy. Including chat-bots and digital assistants might increase transparency and clarity by analyzing and interpreting massive datasets which are difficult to comprehend, in particular for less educated and financially illiterate individuals (Gnewuch et al., 2017). Increasing the level of anthropomorphism might result in an even higher level of users' compliance with a chatbot's request for service feedback (Adam et al., 2020) which, with a well-formulated government policy, leads to more optimal decision making. Therefore, integrated government initiatives including AI to interact and communicate with users to make public services more tailored to all groups of individuals must be a prime focus.

Often, low SES individuals are faced with the problem of limited access to loans, because banks simply cannot assess the risk of default. To avoid such discrimination, scholars (Óskarsdóttir et al., 2019) suggest using AI in assessing the credit-scoring of low SES individuals, using data collected from mobile phones, such as detailed call records, social media analysis, or information on customers' credit and debit accounts. This AI initiative is primarily aimed at the external environment of the individual and assists in facilitating access to credit and insurance for low SES individuals. Furthermore, we suggest that the internal component is likely associated with decision-making because these tools allow legitimate individuals to develop confidence in their creditworthiness and reduce the variance of risk perception, thereby increasing the confidence and positive attitude that they often lack.

Utilizing AI to help individuals with low SES make better financial decisions comes with great individual as well as societal benefits. While the future might seem bright, some of the major challenges that AI currently faces are the lack of trust (Davenport, 2019), the risk of biases (Frank et al., 2019; Awad et al., 2018) and, more importantly, major regulatory concerns (Buiten, 2019). Establishing new social norms and legal regulations for social intelligence would require sufficient levels of transparency and accountability. Autonomy and automation should therefore come with responsibility, hence requiring a legal framework for such technologies. To achieve the most beneficial outcome in interactions with technology, two conditions should hold. Firstly, data used for targeting and enforcing social protection programs should be exhaustive and include all ranges of social and economic layers of the population. Otherwise, in case of the absence of data for certain societal groups, this can lead to discrimination and a larger gap between demographic groups. Additionally, individuals might have a choice – to rely on a system or not - depending on the system characteristics and the particular circumstances. Individuals must be given the possibility to consciously decide for or against a decision or action otherwise individual autonomy and responsibility is undermined. Moreover, cognitive offloading can be beneficial in some cases but can result in disaster in others (Parasuraman and Riley, 1997). Cognitive offloading can harm performance or might not be advisable, for instance, in tasks concerning efficiency (Weis and Wiese, 2019). Therefore, the subject of the impact of AI on human cognitive offloading and its impact on behavior should be studied in depth before specific policy initiatives are implemented. We consequently advise comprehensive research in human-AI interaction and augmentation in the behavioral science field. Namely, we urge future research to further investigate and develop more specific practical implementations of AI for the use of aiding individuals with low SES in conducting more optimal prospective financial decision-making.

Potential risks of using AI in financial decision-making

The fundamental idea of choice architecture, nudging, is to improve individual choices in complicated decision-making environments without restricting any options (Hansen et al., 2019; Leonard, 2008). The dark side of a *nudge* is a *sludge*, which directs attention to choices that make the decision-maker worse off, e.g., by encouraging self-defeating behavior such as taking loans with unfavorable terms when better options exist (Thaler, 2018).

AI is a powerful technology and can, as outlined above, be used to simplify and improve financial decision-making under uncertainty for people with low SES. However, it can just as well be used as a *sludge* to guide attention towards choices that will make the decision-maker worse off, ultimately trapping low SES individuals in poverty. Therefore, to avoid (intentionally or unintentionally) undermining individual freedom of decision-making and ethical guiding principles, demanding certain quality standards and sufficient transparency is necessary when it comes to utilizing AI to aid financial decision-making of those less well off.

Conclusion

Growing up and living with low SES can have detrimental effects on successful decision-making in financial choice environments characterized by a high level of uncertainty. As outlined in the present paper, novel technologies, and specifically AI, can be utilized to simplify, organize, and optimize these financial environments for individuals who experience a lack of behavioral control and therefore discount the future and fail to focus on the outcome that would serve them best. However, this form of technological *nudging* comes with large responsibilities and ethical considerations. We, therefore, urge regulators and policy-makers to implement legal guidelines for the use of AI in financial decision-making so that the outcome can be beneficial for those most in need. While proposing specific legal frameworks and ethical guidelines concerning the use of AI in nudging better financial choices is beyond the scope of this paper, we acknowledge that this is one of the most important considerations concerning how such technologies should be successfully implemented.

Furthermore, as outlined above, human cognitive offloading and its impact on behavior should be studied in depth, before specific policy initiatives are implemented. Future research, across the behavioral sciences, should thus aim to comprehensibly investigate how specific problems related to financial decision-making under scarcity might be alleviated by the use of AI and particularly how such might be done without putting the individual at increased risk. That is, we urge future research to investigate and develop clear practical implementations of how AI could aid financial decision-making under economic scarcity. This form of research will then not only benefit the ones with the least available resources, but society as a whole.

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