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Article

BEHAVIORAL FACTORS IN LOAN DEFAULT PREDICTION A LITERATURE REVIEW ON PSYCHOLOGICAL AND SOCIOECONOMIC RISK INDICATORS

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ABSTRACT

This systematic review investigates the psychological and socioeconomic risk indicators that influence loan default behavior, aiming to bridge the gap between traditional credit assessment models and emerging behavioral insights. As financial institutions increasingly face challenges in accurately predicting borrower defaults, it becomes crucial to explore non-traditional variables such as cognitive biases, personality traits, financial literacy, income volatility, and employment stability. Drawing on a comprehensive synthesis of 67 peer-reviewed studies published between 2010 and 2024, this review analyzes a wide range of empirical evidence from diverse geographical, cultural, and lending contexts. The findings indicate that behavioral factors particularly impulsivity, time-inconsistency, and overconfidence play a critical role in undermining repayment discipline, especially when compounded by limited financial literacy and socioeconomic instability. Moreover, the review highlights the growing use of behavioral interventions, such as personalized nudges, commitment devices, and financial education tools, which have shown measurable effectiveness in reducing default rates. The integration of behavioral analytics into credit risk assessment, as seen in emerging hybrid models, represents a shift toward more holistic, personalized, and accurate prediction frameworks. Additionally, the review underscores the importance of tailoring financial products and risk models to cultural and contextual realities, particularly in underserved markets. By synthesizing interdisciplinary research across economics, psychology, and finance, this study provides a comprehensive framework for understanding the multidimensional drivers of loan default and offers strategic insights for lenders, policymakers, and fintech innovators aiming to enhance creditworthiness assessment and borrower support systems.

KEYWORDS
Loan default prediction, Behavioral finance, Psychological risk indicators, Socioeconomic factors, Financial literacy

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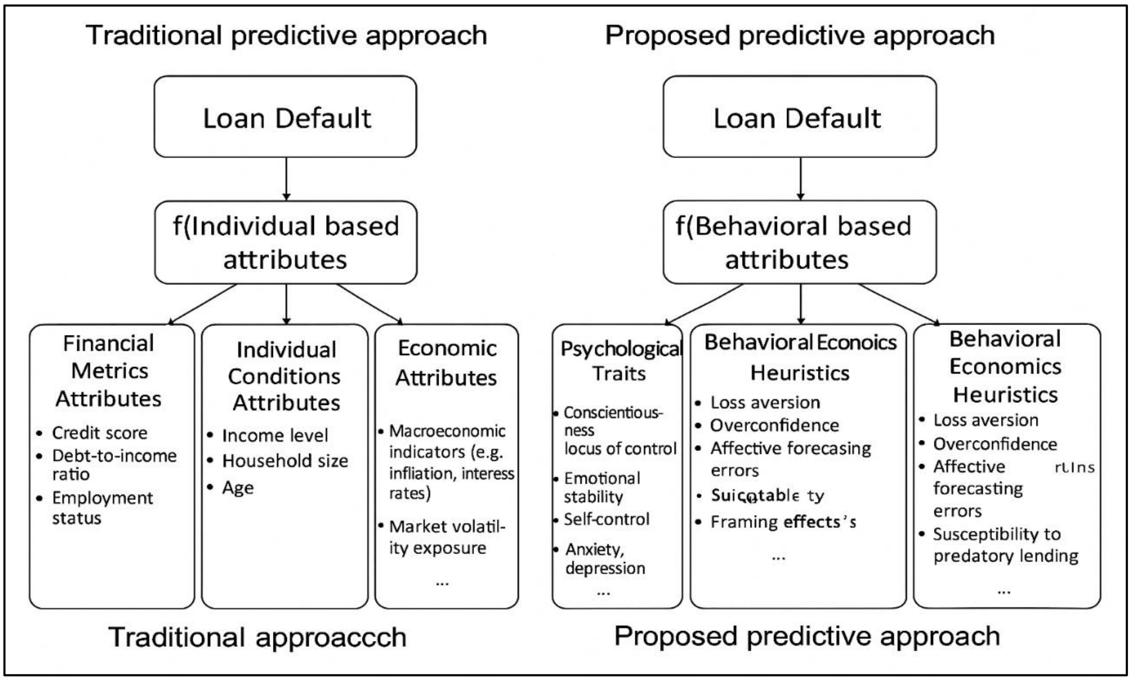
INTRODUCTION

Loan default refers to the failure of a borrower to meet the legal obligations of debt repayment, usually after a defined period of missed payments. Traditionally regarded as a financial failure, default is increasingly conceptualized within broader psychological and socioeconomic domains. Financial institutions and regulatory agencies globally consider loan default rates as indicators of credit risk and financial system health (Wang et al., 2020). As global credit expansion intensifies, particularly in developing economies, predicting and managing default risk has become a top priority. Historically, models for predicting default relied primarily on quantitative financial metrics such as credit scores, income, and debt-to-income ratios. However, emerging empirical evidence suggests that these models may neglect crucial behavioral and contextual variables, including individual cognition, decision-making styles, and social conditions (Kassim & Rahman, 2018). Understanding default behavior requires dissecting the interplay between psychological predispositions and external pressures, especially in the face of economic volatility. The global financial crisis of 2008 highlighted how traditional models failed to anticipate widespread defaults due to underestimation of borrower vulnerability and behavioral irrationalities. Following this, researchers and institutions started advocating for multidimensional risk models incorporating behavioral economics and socioeconomic stratification (Zhu et al., 2019). In the microfinance and informal lending sectors of countries such as India, Kenya, and the Philippines, studies have shown that default can be better explained through personal traits, social capital, and financial literacy (Coşer et al., 2019). Hence, a review of behavioral factors in loan default is essential for a comprehensive predictive framework with global relevance.

Figure 1: Loan Default Prediction Models



Behavioral economics has revolutionized financial risk modeling by integrating cognitive biases and decision-making anomalies into analytical frameworks. Traditional rational choice models assume that borrowers optimize utility based on available information, but in reality, people often deviate from such assumptions due to bounded rationality, loss aversion, overconfidence, and other biases. Research by Mueller and Yannelis (2019) revealed that behavioral variables could explain a significant portion of credit card delinquency variance beyond financial indicators. Similarly, Croux et al. (2020) found that time inconsistency and hyperbolic discounting affect repayment behaviors, especially among younger or lower-income borrowers. The role of mental accounting a behavioral heuristic where individuals categorize funds differently based on subjective criteria has also been investigated as a determinant of repayment consistency. Borrowers often prioritize consumption or non-essential spending while delaying loan obligations, especially when the psychological cost of repayment is perceived as higher. Cognitive load and stress, particularly in economically vulnerable

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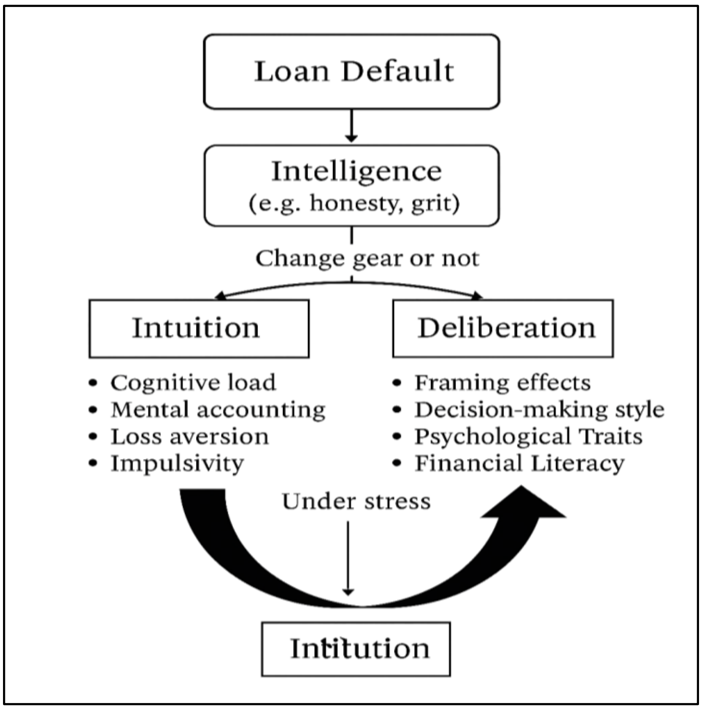
populations, further impair financial decision-making and increase default risk (Barbaglia et al., 2023). Moreover, impulsivity and risk-seeking behavior correlate strongly with unsecured credit defaults, as documented. Experimental studies have shown that framing effects and default options in loan contract design can influence borrower behavior. Even subtle changes in language, repayment schedules, or reminders can shift outcomes significantly, emphasizing the power of behavioral nudges. These insights validate the incorporation of psychological profiles and decision biases into predictive models for more accurate credit risk forecasting. Therefore, behavioral economics offers foundational constructs essential for understanding loan default beyond traditional actuarial assessments.

Figure 2: Behavioral Loan Default Prediction Model



Psychological traits such as conscientiousness, self-control, locus of control, and emotional stability have emerged as critical predictors of financial conduct and default risk (Tariq et al., 2019). Borrowers high in conscientiousness are more likely to adhere to repayment schedules, while those with external loci of control often blame circumstances for their financial struggles, contributing to higher default likelihood. Personality assessments using the Big Five model have demonstrated consistent associations between trait configurations and financial outcomes. Research by Xia et al. (2020) links higher cognitive ability and patience to lower delinquency rates, particularly in long-term repayment structures. Similarly, Looney and Yannelis (2015) argue that affective forecasting errors when individuals misjudge future emotional states can lead to unrealistic repayment expectations and eventual default. Psychological distress, including anxiety and depression, also negatively affects repayment behavior by reducing executive functioning and motivation. Empirical findings by Xu et al. (2021) confirm that individuals with psychological distress show higher default rates on consumer loans. Financial literacy a cognitive-behavioral construct has been consistently linked to better debt management and lower default probability. Individuals with stronger financial knowledge exhibit lower susceptibility to high-interest loans and predatory lending, thereby minimizing default risk. The effectiveness of psychological profiling in credit assessment is further substantiated by recent studies employing psychometric testing for loan approvals in Africa and Latin America. These findings affirm the utility of psychological risk indicators in supplementing traditional credit scoring systems and justify their inclusion in behavioral default prediction models (Jiang et al., 2018).

Socioeconomic factors such as income volatility, employment type, education level, and housing conditions significantly influence the probability of loan default. Research demonstrates that borrowers in informal employment or seasonal occupations face higher repayment instability due to erratic cash flows. Education level has been shown to mediate financial understanding and

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planning, thereby impacting repayment behavior. In urban informal settlements and rural areas, poor infrastructure and lack of social safety nets further compound financial fragility (Ma et al., 2018). Household dynamics, including number of dependents and intra-household decision-making power, also affect financial priorities and repayment discipline. Socioeconomic inequality contributes to default patterns by structurally excluding vulnerable groups from favorable lending terms, pushing them toward riskier credit channels. Migration status and social integration have also been studied as default predictors among immigrant borrowers. Cultural values and social norms regarding debt morality play a pivotal role in repayment behavior. In collectivist societies, loan obligations may be renegotiated informally through social ties, whereas individualist cultures may emphasize contractual compliance (Jin & Zhu, 2015). Empirical studies in South Asia, Latin America, and sub-Saharan Africa confirm that community pressure and group-based lending structures affect default outcomes through social enforcement. These socioeconomic dimensions are not merely contextual but deeply integrated into the behavioral fabric of loan default, warranting systematic inclusion in predictive modeling.

In the microfinance sector, behavioral and socioeconomic predictors of default are particularly salient due to the reliance on non-collateralized, relationship-based lending (Cowling et al., 2018). Microfinance borrowers often lack formal credit histories, necessitating reliance on soft information and behavioral screening for risk assessment. Field experiments in Bangladesh, India, and Mexico show that peer monitoring, social capital, and borrower discipline are decisive factors in repayment. Group lending models leverage behavioral incentives by embedding default consequences within social relationships. However, recent research indicates that the effectiveness of such models declines when group cohesion weakens or economic stress rises (Odegua, 2020). Additionally, default behavior in microfinance often stems from unanticipated expenditures such as health emergencies or natural disasters, highlighting the role of exogenous shocks mediated by behavioral responses. Programs integrating financial education and behavioral counseling have reported reductions in default rates by improving borrower self-regulation and understanding of repayment implications (Emekter et al., 2015). The use of mobile technology for repayment reminders, digital nudges, and gamification has been explored with varying success, emphasizing the role of design psychology in influencing borrower behavior. Overall, the microfinance context offers a fertile ground for exploring the intersection of behavioral and socioeconomic factors, providing scalable insights for broader credit markets.

The rise of digital lending platforms and fintech innovations has enabled the collection of alternative behavioral data, transforming the landscape of loan default prediction (Cox et al., 2020). These platforms leverage smartphone usage patterns, social media behavior, and online transaction histories to infer creditworthiness, especially for unbanked populations. Mobile data such as call frequency, app usage, and geolocation have been found to correlate with repayment reliability (Santoso et al., 2020). Such indicators serve as proxies for stability, routine, and social embeddedness traits linked with financial discipline. Psychometric scoring systems are increasingly used to assess behavioral tendencies like honesty, planning ability, and grit. Studies conducted by organizations like Entrepreneurial Finance Lab (EFL) show that psychometric tests can effectively distinguish between likely defaulters and responsible borrowers in emerging markets where formal credit data is scarce. Machine learning models trained on behavioral features outperform traditional logistic regression models in various studies, providing nuanced insights into borrower profiles (Oliveira, 2024). Nevertheless, the use of alternative data raises concerns over transparency, fairness, and digital privacy. Behavioral scoring must be designed carefully to avoid reinforcing socioeconomic biases or excluding digitally illiterate populations. Despite these ethical considerations, the integration of technology and behavioral analytics has yielded promising results in expanding credit access while maintaining portfolio quality. Therefore, the convergence of fintech and behavioral science represents a critical frontier in default prediction research, offering data-rich opportunities to refine risk indicators beyond conventional paradigms (Gaygısız, 2013).

The empirical case for incorporating behavioral and socioeconomic variables into default prediction models is supported by a growing body of interdisciplinary literature. A meta-analysis by Santos et al. (2023) revealed that non-financial borrower characteristics often account for up to 30% of observed default variance. More recent regression studies and machine learning applications further reinforce this, showing enhanced predictive accuracy when behavioral dimensions are included (Jagtiani & Lemieux, 2019). For example, studies by Sun et al. (2022) demonstrated that emotional stability, future

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time orientation, and stress resilience significantly improved default predictions in both consumer and small-business loan portfolios. Hybrid models that merge financial indicators with behavioral and contextual data offer a more holistic framework. For instance, incorporated digital footprint data with survey-based psychological traits to develop robust credit scoring algorithms in India. Likewise, used structural equation modeling to demonstrate how financial socialization and perceived control mediate default risk. These findings affirm that behavioral and socioeconomic factors are not auxiliary variables but core components of credit behavior. The interdisciplinary nature of this research area has prompted collaborations across economics, psychology, data science, and sociology, enhancing the depth and applicability of findings. Credit risk managers, regulators, and fintech developers are increasingly recognizing the importance of integrating such insights into operational models. By bridging the knowledge gaps between statistical modeling and human behavior, these studies contribute to a more inclusive, accurate, and equitable system of credit assessment. As such, the literature on behavioral and socioeconomic risk indicators in loan default forms a vital basis for the design of resilient and responsive credit evaluation systems worldwide.

LITERATURE REVIEW

The growing complexity of credit markets, especially in the post-global financial crisis era, has spurred a surge in academic interest around behavioral and socioeconomic dimensions of loan default prediction. While early credit risk models emphasized quantitative, financially-derived variables such as credit scores, income levels, and debt-to-income ratios, recent literature has shifted toward a more holistic understanding that integrates psychological traits, decision-making behaviors, and structural socioeconomic conditions. This paradigm shift reflects a recognition that borrower behavior cannot be fully explained by numerical indicators alone but must also account for underlying mental models, social contexts, and economic pressures (Moudud-Ul-Huq et al., 2020). This literature review organizes and synthesizes findings from interdisciplinary studies that explore the psychological and socioeconomic determinants of loan default. It draws on work from behavioral economics, social psychology, cognitive finance, microfinance research, and machine learning applications in credit analytics. The objective is to map the contours of this diverse literature, identify core explanatory variables, evaluate empirical support, and highlight areas of methodological convergence and divergence (Ouliaris & Rochon, 2021). By adopting a thematic structure, this review allows for a granular exploration of borrower traits, contextual triggers, and institutional mediators influencing loan default behavior. The structure of the review proceeds from foundational psychological frameworks to more applied domains such as digital behavior analysis and cross-cultural risk modeling. Each section is designed to build on the previous one, advancing from theoretical constructs to real-world applications and policy implications. The review not only contextualizes the evolution of behavioral default models but also critiques their effectiveness, scalability, and limitations in diverse financial ecosystems. This structured exploration offers a rigorous foundation for understanding the predictive and diagnostic power of behavioral and socioeconomic indicators in credit risk analysis.

Cognitive and Affective Foundations of Borrower Behavior

The theory of bounded rationality provides a foundational lens for understanding borrower behavior in credit markets, particularly among individuals facing cognitive limitations in financial decision-making. Originating from Vo and Nguyen (2014), bounded rationality posits that decision-makers operate under constraints of limited information, finite cognitive resources, and time pressure. In loan default contexts, these limitations frequently result in suboptimal or inconsistent repayment behavior. Boonman (2023) expounded this idea by distinguishing between System 1 (fast, intuitive thinking) and System 2 (slow, deliberate thinking), noting that most financial decisions particularly those involving debt are influenced by heuristic-driven System 1 responses. When borrowers rely on mental shortcuts such as availability bias or anchoring, they may underestimate risks associated with high-interest debt or overestimate their repayment capacity. Empirical research affirms these theoretical insights. Barbaglia et al. (2023) observed that borrowers with low numeracy were more prone to make minimum payments on revolving credit, resulting in prolonged debt cycles. Shrydeh et al. (2019) found that individuals frequently commit avoidable errors like choosing suboptimal repayment plans or ignoring penalty structures due to limited understanding of financial contracts. The issue is exacerbated by information asymmetry, where borrowers lack access to complete or comprehensible loan terms, leading to adverse selection and moral hazard. Zata (2019) emphasized that financial illiteracy and overconfidence often coexist, increasing susceptibility to subprime

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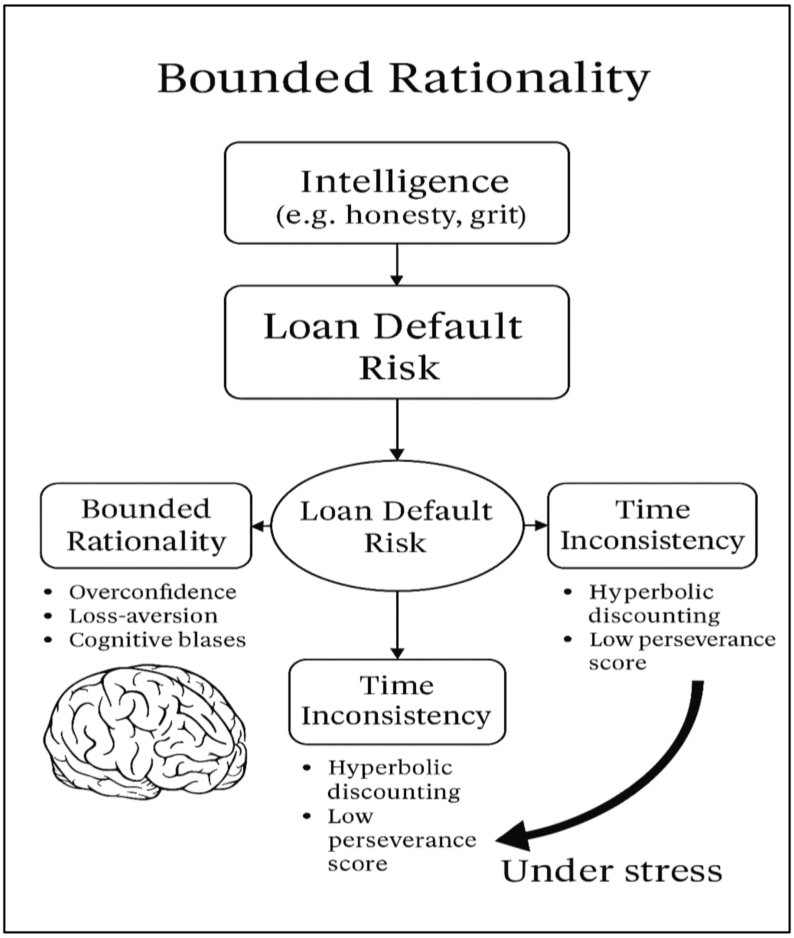
lending and payday loans. Scarcity itself impairs cognition, creating a feedback loop where financial stress reduces bandwidth for sound decision-making, leading to further financial missteps. confirmed this mechanism in UK households, showing that low cognitive capacity was directly correlated with delinquency. Collectively, these studies highlight that bounded rationality driven by cognitive limitations and structural information gaps plays a central role in shaping borrower behavior and increasing default risk.

Figure 3: Cognitive Drivers of Loan Default



Time inconsistency is another well-documented cognitive bias affecting borrower behavior, manifesting as a preference for immediate gratification over long-term financial prudence. Hyperbolic discounting a form of temporal discounting where individuals disproportionately favor present rewards has been observed in various financial decision-making contexts, including loan repayment. Batten and Wagner (2014) found that individuals with higher degrees of present-biased preferences were significantly more likely to accumulate credit card debt and miss payments. This behavior contradicts the assumption of exponential discounting in traditional economic models, calling for revised frameworks that integrate intertemporal behavioral anomalies. Theoretical and empirical studies have illustrated how time-inconsistent preferences result in inconsistent repayment schedules and contract renegotiation tendencies. Oino (2018) introduced quasi-hyperbolic discounting into consumption models, showing that borrowers may commit to repayment plans ex ante but later renege on them when immediate consumption becomes more salient. This behavior is especially prevalent in low-income groups where urgent consumption needs often override rational financial planning. Belcaid and El Ghini (2019) demonstrated how naive hyperbolic discounters often overborrow and subsequently default due to an inability to anticipate their own future preferences accurately. Empirical experiments support these claims. Yaya et al. (2016) conducted randomized control trials in India and observed that allowing borrowers to commit to flexible repayment schedules reduced default, suggesting that rigid schedules clash with time-inconsistent borrower behavior. Similarly, Mohanty et al. (2018) found that financial stress increased present bias among low-income individuals, further deteriorating repayment discipline. Short-term

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incentives can momentarily correct time-inconsistent preferences, but sustained behavior change is harder to achieve. Therefore, a robust body of evidence confirms that intertemporal inconsistencies, rooted in hyperbolic discounting and present bias, significantly elevate default risk in various lending environments.

Mental health has emerged as a crucial determinant in explaining borrower default patterns, particularly in low- and middle-income populations exposed to economic stressors. Psychological distress including anxiety, depression, and chronic stress can impair executive functioning, reduce planning ability, and lead to impulsive financial decisions. Leow and Lau (2018) found in a large-scale study in Kenya that poverty-induced stress had measurable effects on cognitive bandwidth and decision-making efficiency, both of which are essential for successful debt management. Using UK household survey data, linked poor mental health to higher rates of consumer credit default, independent of income or employment status. These relationships have been validated in multiple settings. Psychological disorders had a statistically significant impact on mortgage default rates. Financial stress and anxiety not only predicted higher credit card balances but also reduced the ability to track and manage expenditures (Nguyen et al., 2019). Furthermore, demonstrated that debt-related stress amplified depressive symptoms, creating a bi-directional loop where psychological distress both caused and resulted from debt accumulation. This loop is especially harmful in overleveraged populations, where lack of mental health resources compounds financial instability. Additional insights come from behavioral neuroscience, which links cortisol levels to decision-making capacity under financial pressure . Elevated cortisol impairs working memory and problem-solving ability, crucial for managing loan obligations. Rodgers et al. (2021) explored emotional intelligence and found that individuals with higher emotional regulation were less likely to default, even under financial stress. Moreover, Montaruli et al. (2021) indicated that impulsivity mediated by poor mental health was a significant predictor of default across demographic groups. These findings collectively suggest that mental health is not merely a background variable but a proximate cause of default behavior, with tangible implications for risk assessment and borrower support.

The interplay between cognitive constraints and affective conditions reveals the systemic nature of default behavior, which is neither entirely rational nor entirely emotional but a dynamic interaction of both domains. Scarcity theory, as articulated by Ragnoli et al. (2022), captures this interdependence by showing how financial strain depletes mental bandwidth, amplifies stress, and impairs both short-term and long-term decision-making. Scarcity creates a tunnel effect, where attention is narrowly focused on immediate financial challenges at the expense of broader obligations like loan repayment. This phenomenon has been empirically verified in experimental settings (Rodgers et al., 2021), demonstrating that financial stress reduces cognitive capacity comparable to losing an entire night's sleep. At the same time, affective responses such as fear of default, shame, and loss of control feed into a psychological environment that further deteriorates repayment performance. For example, perceived financial well-being was significantly associated with default avoidance behavior, indicating that subjective experience plays a key mediating role. Fernandes, Montaruli et al. (2021) conducted a meta-analysis showing that financial literacy interventions had greater efficacy when accompanied by emotional coping strategies. Similarly, emotional regulation and financial capability jointly predicted financial outcomes, surpassing either factor in isolation. The role of identity and self-concept has also been explored. Borrowers who see themselves as financially competent are more likely to manage their obligations effectively, regardless of objective risk indicators. Conversely, those experiencing financial stigma or identity dissonance tend to avoid debt communication and delay payments. This recursive loop where cognition and affect interact within a social and economic context requires multidimensional models to accurately predict default. Hence, a synthesized understanding of cognitive and affective foundations offers the most comprehensive lens through which to view borrower risk behavior.

Psychometric Profiling and Personality-Based Risk Assessment

The Big Five personality traits conscientiousness, agreeableness, neuroticism, extraversion, and openness have been widely studied in relation to financial behavior, with mounting evidence pointing to their predictive power in loan performance and default risk (Abdullah Al et al., 2022). Conscientiousness, defined as the tendency to be organized, disciplined, and goal-oriented, consistently correlates with favorable credit outcomes. Individuals high in conscientiousness are

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more likely to adhere to repayment schedules, budget effectively, and avoid impulsive spending, thereby reducing the likelihood of delinquency. In contrast, neuroticism, characterized by emotional instability and anxiety, has been linked to poor financial decisions, higher debt levels, and default (Olver, 2020). Meta-analyses, such as that conducted by Kleeven et al. (2024), confirmed that conscientiousness and neuroticism are robust predictors of financial reliability, particularly when controlling for income and education. Agreeableness also demonstrates a complex relationship with loan performance. While agreeable individuals may be cooperative and empathetic, studies suggest that excessive agreeableness can lead to overborrowing or cosigning due to social obligations, sometimes undermining repayment ability. Empirical work by Duman et al. (2023) identified a negative correlation between agreeableness and default avoidance when borrowers prioritized interpersonal harmony over financial prudence. Longitudinal studies have shown that these traits remain relatively stable over time and thus offer predictive validity across repayment periods. Further reinforcement comes from experimental and survey-based studies. Schlauch et al., (2015) found that low conscientiousness and high neuroticism were overrepresented in payday loan users and defaulters. Fine (2024) used data from the Dunedin Multidisciplinary Health and Development Study to demonstrate that childhood personality traits forecast adult credit behavior with surprising accuracy. The integration of personality metrics into risk profiling enables a richer understanding of borrower behavior, highlighting that psychological predispositions are central to creditworthiness beyond financial metrics alone.

Locus of control a psychological construct that reflects individuals' beliefs about the degree of control they have over life outcomes plays a crucial role in shaping financial responsibility and loan repayment behavior. Individuals with an internal locus of control believe they are the primary agents of their outcomes and are more likely to exhibit proactive financial behaviors, including budgeting, saving, and timely debt servicing. In contrast, those with an external locus of control attribute financial outcomes to luck, fate, or external forces, leading to passivity, avoidance, and often higher default rates. Numerous studies validate this relationship in diverse contexts. Bogacheva et al. (2019) demonstrated that borrowers with an internal locus of control showed lower default rates on student loans, even when controlling for socioeconomic status. Similarly, Berns et al. (2020) observed that college students with internal locus scores were more likely to pay bills on time and manage credit cards responsibly. Empirical evidence from Eftimie et al. (2020) suggests that financial control beliefs directly influence credit card debt levels, with internal belief systems associated with lower debt accumulation. found that individuals with an external locus of control were more likely to seek short-term, high-risk loans and delay repayment, especially under stress. Psychometric surveys such as the Financial Locus of Control Scale (FLOC) have been effectively used to predict credit behavior across various lending environments. Furthermore, these psychological profiles have shown potential in borrower training programs, where interventions aimed at shifting locus orientations lead to improved repayment outcomes. In microfinance, Scotter and Roglio (2020) found that training modules reinforcing internal control beliefs were associated with stronger repayment discipline. Even within credit counseling, locus of control serves as a key diagnostic tool for tailoring support mechanisms. The consistent association between internality and repayment reliability underlines the importance of this construct in loan risk assessment.

Self-control the ability to regulate impulses, delay gratification, and prioritize long-term goals is a well-established psychological predictor of financial discipline and loan repayment behavior. Foundational studies such as Fonseca-Pedrero et al. (2016), which developed the "marshmallow test," demonstrated that children who exhibited greater ability to delay gratification were more successful in later life domains, including financial management. This association has been replicated in adult populations. Conrod (2016) showed that self-control scores predicted debt levels, budgeting behavior, and savings accumulation with strong effect sizes. Low self-control has consistently been linked to overborrowing, impulsive spending, and higher default rates. Kumara et al. (2021) argued that self-regulatory failure under stress leads to poor financial outcomes, particularly in unstructured or high-pressure decision contexts. Empirical data from Lauriola and Weller (2018) confirmed that impulsive individuals are less likely to plan for recurring debt obligations, making them more prone to payment delinquency. Consumers with low self-regulatory resources were more likely to engage in compulsive buying and borrow beyond sustainable limits. Self-control with higher student loan balances and poor repayment behavior. Recent behavioral finance research reinforces these findings. Goel and Rastogi (2023) conducted meta-analyses confirming that trait self-control is one of the most consistent predictors of financial well-being. In loan-specific studies, Rendall et al. (2021) observed that borrowers with strong self-regulatory traits were significantly less likely to default, even in the face of income shocks. Moreover, interventions such as self-monitoring tools, reminders, and delayed disbursements have been designed to support borrowers with low self-control. Collectively, the empirical literature illustrates that self-control is not just a personality quirk but a decisive factor in determining whether borrowers honor or default on their loan obligations (Masud, 2022; Hossen & Atiqur, 2022; Sazzad & Islam, 2022).

The integration of psychometric profiling into credit scoring has opened new frontiers in borrower evaluation, particularly in markets where traditional credit histories are scarce or unreliable (Qibria & Hossen, 2023; Shaiful et al., 2022; Akter & Razzak, 2022). Psychometric assessments capture stable personality traits, cognitive attributes, and behavioral tendencies, offering predictive insights that complement financial data. Entrepreneurial Finance Lab (EFL) and other organizations have deployed psychometric tools across Africa, Latin America, and Southeast Asia, finding strong correlations between test scores and repayment behavior. These tools typically assess domains such as conscientiousness, self-efficacy, planning orientation, and internal locus of control, all of which have been independently linked to lower default risk. Evidence supports the efficacy of these models. Guzelian et al. (2015) conducted a randomized trial in Peru demonstrating that integrating psychometric profiles improved credit scoring accuracy by over 25% compared to models based solely on financial metrics. Similarly, Schaefer (2023) used data from microfinance borrowers in Guatemala and observed that personality indicators predicted arrears even after controlling for income, occupation, and demographic factors. Empirical studies in India by Vaughan and Finch, (2017) confirmed that including behavioral variables enhanced risk prediction, especially among first-time borrowers lacking credit files. Machine learning techniques have been used to fine-tune psychometric data for automated decision-making, yielding higher precision in default forecasting. Nonetheless, critics have raised concerns about potential biases, data integrity, and ethical implications (Maniruzzaman et al., 2023; Masud et al., 2023; Hossen et al., 2023). Despite such challenges, pilot implementations in countries like Kenya and Colombia have shown promising results in expanding financial access while maintaining repayment discipline. Moreover, psychometric screening facilitates early identification of risky borrower profiles, enabling pre-emptive interventions such as tailored counseling or modified loan structures (Epstein, 2018; Ariful et al., 2023; Shamima et al., 2023). Thus, psychometric profiling serves as a vital extension of traditional risk models, particularly where behavioral consistency is as critical as financial solvency.

Socioeconomic Structures and Contextual Vulnerabilities

Employment status and income volatility are consistently identified as primary predictors of loan default risk, especially in low- and middle-income settings where economic shocks are frequent. Borrowers engaged in informal employment often experience irregular cash flows, limited legal protections, and no access to unemployment insurance, all of which contribute to heightened default probability (Christensen et al., 2019; Alam et al., 2023; Rajesh, 2023; Rajesh et al., 2023). Compared to those in formal employment, informal sector workers such as day laborers, street vendors, and seasonal workers are significantly more vulnerable to short-term income disruptions that impair their ability to honor debt obligations. Bleidorn et al. (2021) that loan portfolios with a higher concentration of informally employed borrowers exhibited increased delinquency rates, particularly in microfinance contexts. Rural and urban divides further compound this dynamic. Rural borrowers, especially those dependent on agriculture, face income cyclicality due to seasonal harvests and climate variability, resulting in fluctuating repayment capacity. Urban informal workers, while more integrated into monetized economies, still face volatility due to informal contracts, lack of job security, and market shocks. Cross-country research by Laajaj et al. (2019) showed that rural borrowers in sub-Saharan Africa and South Asia had significantly lower financial resilience than their urban counterparts, largely due to labor informality and lack of credit access infrastructure. Studies also show that borrowers experiencing income volatility often prioritize consumption smoothing over debt repayment, leading to cyclical borrowing and loan stacking. Al-Dajani et al. (2016) observed that in periods of financial hardship, families frequently divert funds from debt repayment to essential household needs such as food and healthcare. Moreover, lenders' failure to distinguish between formal and informal employment in credit risk assessments contributes to mismatches in repayment expectations. Thus, income regularity and job formality emerge as critical structural factors that directly shape default behavior, reinforcing the need for employment-sensitive lending models.

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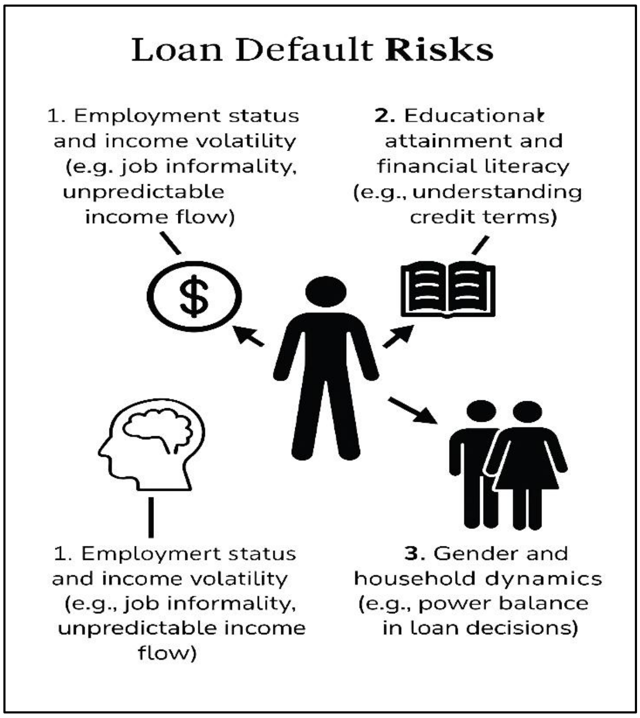
Educational attainment and financial literacy are among the most influential socioeconomic predictors of responsible borrowing and repayment behavior. Numerous empirical studies have shown that borrowers with higher educational levels possess better financial planning capabilities, budgeting skills, and a clearer understanding of credit terms, resulting in lower default rates. Educational exposure enhances cognitive processing and numerical literacy, enabling individuals to interpret loan contracts, interest rate implications, and payment schedules more effectively. For example, Polit (2015) found that education significantly reduced the likelihood of mortgage default in the UK, controlling for income and employment. Financial literacy, as a subset of general education, has been positively linked to borrower behavior across diverse socioeconomic contexts. Boyd and Pennebaker (2017) demonstrated that low financial literacy was associated with high-cost borrowing and repeated late payments among U.S. consumers. A study by Knogler et al. (2015) analyzing over 200 studies concluded that financial education programs, particularly those tailored to real-life applications, improved financial behavior, including loan repayment. Financial literacy training were more likely to reject loans with complex or hidden terms and demonstrated stronger repayment performance. Moreover, borrower education programs initiated by governments, NGOs, and microfinance institutions have yielded consistent improvements in loan outcomes. Incorporating video-based financial literacy modules into loan disbursement protocols significantly decreased default rates in Brazil. In Uganda, financial capability programs linked to youth savings accounts led to improved debt attitudes and repayment behavior among adolescent. Even in developed countries, educational interventions have enhanced consumer credit management. For example, Bach and Hutsebaut (2018) reported that financial education among high school students led to better credit use years later. Thus, both formal education and targeted financial literacy programs play a vital role in fostering repayment integrity.

Gender and household dynamics significantly influence loan repayment behavior, particularly in low-income and developing country contexts. Women have traditionally faced barriers to credit access due to legal, cultural, and economic discrimination. However, when access is granted, several studies suggest that women exhibit stronger repayment discipline compared to men, often driven by their role as primary caregivers and household managers. A cross-country analysis by Weiner et al. (2017) confirmed that female borrowers in microfinance programs had consistently lower default rates than their male counterparts. Household power dynamics further affect borrowing and repayment decisions. Kandler et al. (2016) investigated intra-household bargaining in Kenya and found that when women controlled the loan, funds were more likely to be allocated toward productive or household-enhancing investments, resulting in better repayment outcomes. Conversely, male-controlled loans were more frequently diverted to non-productive uses, increasing repayment risk. These findings are echoed in the work of Hogg et al. (2021), who demonstrated that giving women control over savings and loans led to improved household financial outcomes in the Philippines. In patriarchal societies, lack of decision-making authority over finances can undermine women's ability to fulfill repayment obligations, even if they are nominally listed as the borrower. This structural issue can distort default risk analysis if credit assessments fail to account for actual control over loan utilization. Moreover, cultural expectations regarding women's roles can impose psychological pressure to repay loans as a matter of honor and social standing, motivating timely payments even under hardship. Group lending models further amplify the role of gender (Roksana, 2023; Sanjai et al., 2023). In female-only lending circles, peer support and collective accountability foster higher compliance rates. Yet, recent research cautions that overburdening women with financial responsibility without adequate support can lead to stress and overindebtedness. Overall, gender and household power dynamics intersect to shape borrower behavior in nuanced ways, with implications for equitable and accurate credit risk modelling (Tonmoy & Arifur, 2023; Tonoy & Khan, 2023).

Figure 4: Socioeconomic Drivers of Loan Default



Socioeconomic vulnerability extends beyond individual-level factors to encompass systemic barriers that constrain borrower agency and distort repayment dynamics (Razzak et al., 2024; Zahir et al., 2023). Structural exclusions such as lack of property rights, financial infrastructure, or legal recourse limit the ability of marginalized borrowers to negotiate fair credit terms or manage debt responsibly. In many developing economies, social exclusion based on caste, ethnicity, or migration status restricts access to formal employment and institutional credit, pushing borrowers toward informal or predatory lenders with higher risks of default (Reynolds et al., 2021). These structural disparities are often reinforced by discriminatory lending practices and biased algorithmic scoring. The intersection of poverty and exclusion leads to higher dependence on consumption loans, low asset ownership, and weak social safety nets all of which magnify the effects of even minor income shocks (Alam et al., 2024; Khan & Razee, 2024). Borrowers in financially excluded communities often lacked access to emergency credit, leading to arrears during unexpected health or family events. Social isolation, particularly among the elderly or disabled, can further disrupt loan repayment by limiting access to community-based financial support mechanisms. Moreover, systemic vulnerabilities are compounded by weak institutional support. In regions lacking robust legal enforcement, lenders may be unable to recover loans through formal channels, while borrowers lose incentive to repay due to perceived impunity. Informal credit arrangements, though flexible, lack transparency and often impose coercive repayment practices, which exacerbate stress and increase the probability of default. The cumulative impact of these structural and contextual vulnerabilities requires credit models to go beyond borrower-centric risk indicators and account for broader environmental constraints. Thus, understanding socioeconomic structures is indispensable to accurate, just, and effective credit risk analysis.

Social Capital, Peer Influence, and Default Deterrence

Community pressure plays a vital role in promoting repayment discipline, particularly in group lending environments where social capital acts as a substitute for collateral. The classic microfinance model popularized by institutions such as Grameen Bank relies heavily on group liability and peer accountability to enforce repayment. Ge et al. (2017) provided compelling evidence from the Philippines that removing group liability requirements did not significantly affect default rates, suggesting that even in the absence of contractual joint responsibility, the informal mechanisms of social enforcement persist. Individuals fear reputational damage, social exclusion, or embarrassment within tight-knit communities, all of which serve as powerful deterrents to delinquency. Further empirical research highlights the deterrent effects of social monitoring and collective oversight. Ge

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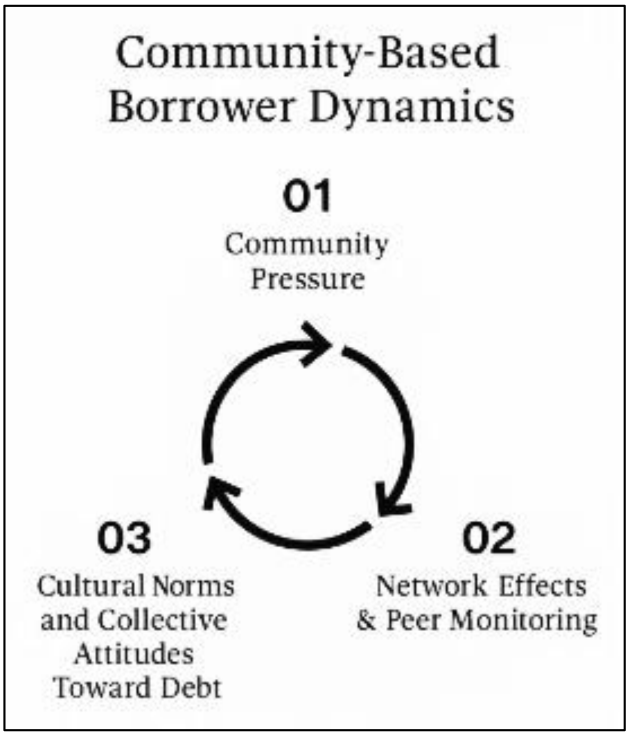
et al. (2017) observed that repayment performance was better among groups with strong social cohesion and high frequency of interaction. Peer pressure not only ensures timely repayments but also facilitates informal insurance, where group members assist struggling borrowers to avoid collective penalties. Group meetings and structured communication increased mutual monitoring and mitigated moral hazard. However, excessive community pressure can also lead to borrower stress, forced repayment, or exit from lending programs, particularly when public shaming is institutionalized. Hirtenlehner (2019) noted that coercive practices, although effective in the short term, often backfire by reducing long-term borrower trust and engagement. To balance these effects, some institutions incorporate structured flexibility in repayment schedules while maintaining community accountability frameworks. Overall, the body of research supports the hypothesis that social capital embedded in community relationships functions as an effective, albeit complex, enforcement mechanism that shapes borrower repayment behavior in microfinance contexts.

Figure 5: Community-Based Microfinance Dynamics



Network effects and peer monitoring are central to the microfinance ecosystem, particularly in explaining how borrower behavior is shaped by the social configuration of lending groups. The structural composition of borrower networks including the density, diversity, and strength of social ties can either reinforce repayment norms or erode collective discipline. Empirical research suggests that homogeneity in social status or occupation within lending groups leads to stronger informal monitoring and higher repayment rates, as seen in studies by Worrall et al. (2014). Diverse groups, though potentially innovative, often lack the cohesion necessary for effective peer monitoring and enforcement. The strength of weak ties defined by Brown et al. (2017) as infrequent but bridging relationships has mixed implications. While weak ties can enhance information flow and access to external resources, they are less effective in exerting repayment pressure compared to strong, embedded ties within close-knit groups. Ellison and Vitak (2015) demonstrated that weaker social ties within microfinance groups were correlated with higher default risks due to reduced peer enforcement. Complementarily, Jui and Rivas (2024) found that borrowers with prior social connections within the group exhibited higher repayment rates, underscoring the predictive power of pre-existing social bonds. Studies by Moeller et al. (2016) indicate that increased meeting frequency among group members fosters trust and reciprocity, thereby reducing the likelihood of default. Similarly, Takakura (2015) used network analysis in rural India to show that information asymmetries and trust gaps between borrowers led to higher delinquency in loosely connected groups. The presence of influential nodes or "opinion leaders" in the borrower network also plays a

critical role in shaping group repayment culture. Therefore, the network structure, beyond individual borrower attributes, emerges as a fundamental determinant of loan repayment outcomes in peer-based lending systems.
Cultural norms and collective attitudes toward debt significantly influence borrower behavior and repayment ethics across global contexts. Debt morality defined as the culturally conditioned perception of whether repaying a loan is a moral obligation varies widely between collectivist and individualist societies. In collectivist cultures, such as those prevalent in South Asia, East Africa, and Latin America, communal reputation and group solidarity are often more salient than individual legal obligations, resulting in stronger informal enforcement mechanisms. Borrowers in these settings may prioritize loan repayment not just to avoid legal consequences but to uphold family honor and community status. Empirical studies support this interpretation. Zheng et al. (2019) found that borrowers in collectivist societies reported greater internalized guilt and community pressure when they considered defaulting, in contrast to borrowers in individualist societies where credit behavior is often viewed through a personal utility-maximization lens. Cultural sanctions such as exclusion from communal rituals or village decision-making functioned as informal enforcement tools more effectively than legal contracts. Conversely, in highly individualistic societies like the United States and the United Kingdom, the moral imperative to repay debt is often conditional on fairness and reciprocity, and strategic default may be more socially accepted when the lender is perceived as exploitative. Religious beliefs also intersect with cultural attitudes toward debt. Islamic finance, for instance, prohibits interest (riba) and emphasizes equitable lending structures, thereby influencing borrower expectations and repayment motivation. Studies in Pogarsky and Herman (2019) revealed that Shariah-compliant borrowers exhibited stronger repayment discipline due to religious accountability. Additionally, cultural attitudes toward shame and public embarrassment significantly affect group lending dynamics, particularly among women. Thus, cultural frameworks provide not only the moral underpinning of repayment behavior but also shape institutional practices and borrower perceptions of debt obligations.
Social embeddedness the degree to which economic transactions are embedded within social relationships and norms provides a powerful explanatory framework for understanding loan repayment behavior. Ojong and Obeng-Odoom (2017) argued that economic behavior is not autonomous but situated within social networks, which offer both support and constraint. In the microfinance context, social embeddedness is operationalized through mechanisms like group lending, informal social control, and trust-based enforcement. Research by Aisaiti et al. (2019) in Bangladesh showed that the more socially embedded a borrower was within their community, the higher their repayment likelihood, as defaults risked damaging critical social ties. Group-based credit models exploit this embeddedness by fostering accountability through regular group meetings, public disclosure of repayment status, and peer monitoring. These mechanisms transform loans from individual financial commitments into collective endeavors, aligning repayment with communal identity and reputation. For example, Ehret and Olaniyan (2023) documented that social proximity among borrowers improved communication, early default detection, and cooperative support in repayment. Social norms like reciprocity and obligation help reinforce these dynamics. However, the same embeddedness can also produce exclusionary or coercive outcomes. When borrowers fear public shaming or peer retaliation, they may take on new loans or liquidate assets merely to avoid communal disgrace, thereby masking financial stress. Moreover, exclusion from lending groups can marginalize individuals who lack strong social ties, particularly migrants or minority populations. Despite these risks, the overwhelming consensus is that social embeddedness remains a key determinant of borrower behavior in collective finance models (Aoki, 2001). It extends beyond rational-choice frameworks by accounting for how relational networks and embedded social norms shape economic outcomes, including the decision to repay or default on a loan.
Behavioral Insights from Digital Lending Ecosystems
The emergence of digital lending platforms has enabled the use of alternative data sources to assess borrower risk, particularly in markets where formal credit histories are scarce or unreliable. Behavioral data including smartphone metadata, call records, app usage, and browsing behavior provides lenders with indirect but highly predictive indicators of creditworthiness. Lashitew et al. (2020) demonstrated that mobile phone usage patterns in Latin America could predict repayment behavior with comparable accuracy to traditional credit scoring methods. Their model, which analyzed variables such as call frequency, contact diversity, and airtime purchases, showed that

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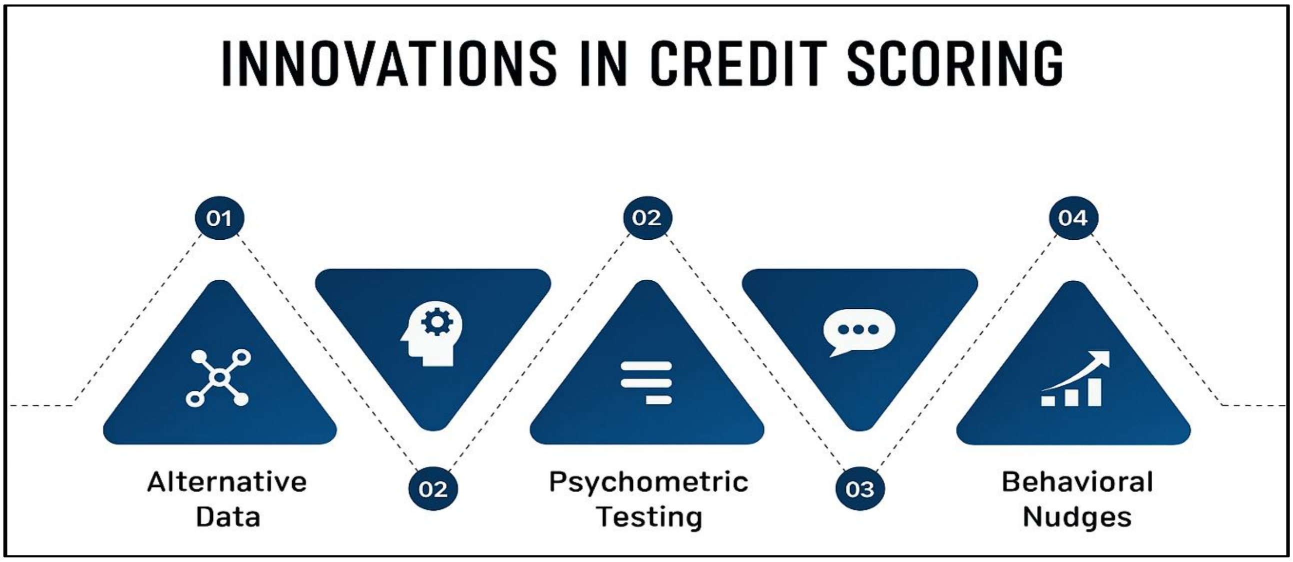
digitally inferred behaviors could act as proxies for social stability, routine, and income regularity. Similarly, Rössel et al. (2024) found that mobile phone metadata in developing countries like Pakistan and Tanzania helped identify high-risk borrowers by evaluating device-sharing frequency, location stability, and nighttime call activity. These variables were strongly associated with default likelihood, particularly among first-time borrowers lacking traditional documentation. Digitally native lending firms such as Tala and Branch have built scoring algorithms that use thousands of non-financial behavioral variables to assess risk and offer personalized loan limits. Incorporating smartphone metadata improved credit model performance in multiple African markets. Alternative data has also proven useful in contexts beyond mobile phones. Agarwal and Wu (2015) examined browsing history and e-commerce behavior in China, noting strong associations between online shopping patterns and repayment tendencies. Ride-hailing usage and digital wallet transactions also offer useful insights into income volatility and lifestyle stability. However, researchers like raised concerns regarding privacy, consent, and algorithmic bias in such scoring systems. Despite these ethical debates, the growing body of empirical work illustrates that alternative digital data when used responsibly provides a valuable lens into borrower behavior, particularly in underbanked populations.

Psychometric credit scoring has become a pivotal innovation in expanding credit access in emerging markets, where many potential borrowers lack formal credit histories or verifiable income. These tools assess non-cognitive skills, personality traits, and behavioral tendencies such as conscientiousness, integrity, planning, and risk aversion to estimate repayment probability (Fine, 2024). One of the most prominent efforts in this space is the Entrepreneurial Finance Lab (EFL), which developed standardized psychometric tests and piloted them across more than 20 countries in Africa, Latin America, and Asia. EFL's assessments include abstract reasoning tasks, business scenario simulations, and integrity checks, all of which are statistically correlated with repayment behavior. Empirical studies validate the efficacy of these tools. Djeundje et al. (2021) reported that EFL's psychometric data improved loan approval accuracy while reducing default rates in South Africa and Peru. Behavioral traits such as grit, honesty, and delay discounting added significant predictive power to conventional financial models. Duman et al. (2023) examined EFL applications in Central America and noted that even when controlling for income and employment, psychometric indicators retained their significance in default prediction. These models are particularly useful for small and micro-entrepreneurs, many of whom operate informally and cannot provide documentation required by traditional banks. Entrepreneurial orientation and cognitive ability are key to predicting repayment, especially in low-literacy contexts. Psychometric scores outperform demographic variables alone. However, some critics question the cross-cultural validity of psychometric tools, citing variability in results across countries and languages (Nicat et al., 2024). Nonetheless, the consensus in the literature supports the strategic value of psychometric scoring in emerging markets where formal credit mechanisms are limited.

Behavioral nudges, including automated reminders, visual framing techniques, and personalized messages, have become powerful tools in influencing borrower behavior in digital lending ecosystems. Grounded in behavioral economics, these interventions aim to shape decision-making without altering financial incentives or legal structures. Yang et al. (2022) conducted randomized controlled trials in the Philippines and Bolivia, showing that SMS reminders significantly improved on-time loan repayment. Notably, reminders that included moral framing ("You are a responsible person, remember to pay your loan") outperformed purely factual messages, indicating that affective engagement enhances borrower responsiveness. Further research supports the efficacy of these low-cost interventions. Sending payment reminders just before due dates improved repayment among borrowers with high present bias, particularly in low-income urban neighborhoods. Mobile data to deliver nudges at optimal times based on call activity, which resulted in increased repayment rates. Innovations in visual framing such as progress bars, repayment calendars, or social comparison dashboards also improve borrower engagement and financial self-regulation (Goel & Rastogi, 2023a). Personalization enhances nudge effectiveness. Borrower-tailored SMSs that referenced personal loan histories or individual goals yielded higher engagement compared to generic messages. Culturally adapted nudges, delivered through voice messages in local dialects, improved repayment among illiterate borrowers. The use of gamified nudging where repayment progress is visualized through rewards or milestones has also shown promise in retaining borrower motivation (van Thiel et al., 2024). While nudging is cost-effective, it is not universally effective. Hung et al. (2013) warned that in contexts of severe financial stress, reminders can be ignored or even cause borrower anxiety. Still, when integrated thoughtfully into digital platforms, behavioral nudges represent a scalable solution to improve repayment behavior across socioeconomic and geographic divides.

Figure 6: Innovations in Credit Scoring



The integration of behavioral analytics into digital credit scoring represents a convergence of data science, psychology, and finance. Fintech platforms now routinely collect and analyze real-time behavioral data to refine their loan underwriting processes, creating dynamic models that evolve with each borrower interaction (Schumacker, 2019). Behavioral analytics include clickstream data, repayment interaction logs, mobile usage intensity, and engagement patterns, all of which are correlated with default risk. Attali (2019) examined several U.S. fintech lenders and found that machine learning models using behavioral data outperformed traditional FICO-based scores, particularly in assessing new-to-credit applicants. In developing economies, lenders like Jumo, Branch, and Paylater have employed behavioral credit scoring to reduce information asymmetry and manage portfolio risk. Digital credit platforms could create individualized behavioral profiles after just a few loan cycles, allowing adaptive risk calibration. Incorporating real-time behavioral feedback such as how quickly a borrower responds to repayment prompts improves prediction accuracy and early warning systems for default. Several studies suggest that behavioral analytics can reduce gender and income bias by focusing on how borrowers behave rather than who they are. However, there are risks of overfitting, algorithmic opacity, and discrimination if data governance is weak (Medvedev et al., 2020). Transparency in data sourcing, ethical use, and explainability of scoring outcomes remain key challenges. Nonetheless, lenders increasingly report that behavioral data allows for more inclusive lending, improved early delinquency detection, and enhanced borrower segmentation (Finaulahi et al., 2021). The analytical sophistication enabled by digital ecosystems makes it possible to integrate psychometric, transactional, and behavioral data into a single credit assessment framework. This layered approach captures borrower complexity more fully than traditional static scoring systems, reinforcing the value of behavioral insights in contemporary digital credit markets.

Technology-Mediated Models and Algorithmic Insights

The integration of behavioral variables into machine learning (ML) models has significantly enhanced the predictive accuracy of credit scoring systems. Traditional logistic regression models, while interpretable, are limited in their capacity to capture complex, nonlinear interactions between behavioral and financial features . Advanced ML techniques such as random forests, gradient boosting machines (GBM), and artificial neural networks (ANNs) have proven more adept at processing high-dimensional data, especially from digital sources. Hung et al. (2013) demonstrated that random forest models trained on consumer transaction and behavioral data outperformed conventional scoring models in forecasting credit card defaults. Numerous empirical studies have

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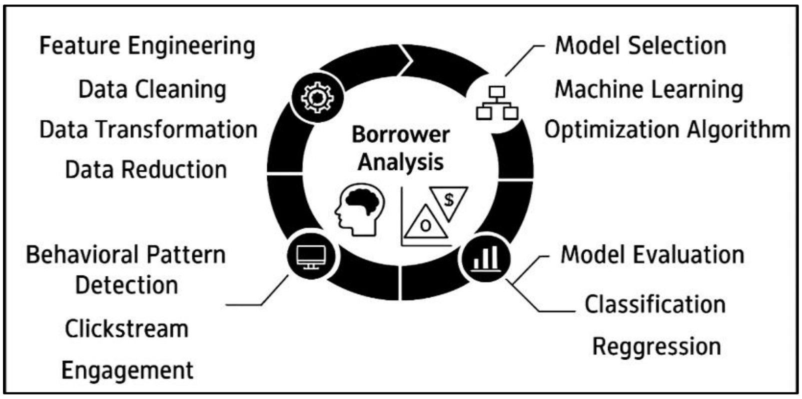
validated these findings across global contexts. Grysman (2024) showed that decision trees and ensemble methods increased loan default prediction accuracy by incorporating behavioral proxies such as spending regularity, repayment punctuality, and account activity. GBMs on LendingClub data, revealing that borrower behavior, including loan purpose and browsing activity during application, improved classification performance. Similarly, Giraldo et al. (2024) found that ML-based scores incorporating user interaction metrics from fintech platforms offered superior performance for underbanked borrowers. Machine learning applications in developing economies, noting that digital lenders combining behavioral and financial indicators significantly reduced type I and type II errors. Deep neural networks to behavioral sequences from mobile usage data in China and achieved high predictive accuracy without formal credit histories. However, the "black-box" nature of such models has prompted criticism regarding transparency and regulatory acceptability. Despite these concerns, the growing body of evidence highlights that machine learning models integrating behavioral data can enhance the precision, personalization, and inclusivity of credit risk assessment across diverse financial environments.

Figure 7: Machine Learning in Default Prediction



The use of behavioral data in algorithmic credit scoring raises significant ethical concerns related to bias, discrimination, and fairness. Although behavioral credit models offer promising gains in predictive accuracy, they risk reproducing or amplifying social inequalities when trained on biased or unrepresentative datasets. Cram et al. (2022) emphasized that the opacity of algorithmic models can obscure discriminatory practices, particularly when variables such as ZIP code, social media connections, or device usage serve as proxies for protected characteristics like race, gender, or socioeconomic status. Empirical evidence of such bias has been documented in various lending contexts. Emekter et al. (2015) illustrated how automated systems used by public institutions disproportionately flagged low-income and minority users as high risk based on behavioral indicators that correlated with systemic disadvantage. Vaughan and Finch (2017) analyzed proprietary fintech lending data and found that algorithmic decisions though facially neutral often disadvantaged certain demographic groups when behavioral inputs correlated with structural marginalization. Similarly, behavioral features such as internet browsing patterns or purchase frequency could inadvertently encode social stratification. Concerns extend to explainability and recourse. Lenders using ML models with thousands of behavioral variables often struggle to provide borrowers with intelligible reasons for adverse decisions, undermining transparency and due process. Critics argue that even well-intentioned behavioral scoring can contribute to "algorithmic redlining" if unmonitored, leading to systematic exclusion of marginalized groups. Strategies such as fairness-aware machine learning, bias auditing, and algorithmic accountability reporting have been proposed to mitigate these risks (Benlian et al., 2022). Despite regulatory interest, few jurisdictions have comprehensive frameworks addressing behavioral scoring ethics. The literature thus underscores the imperative to balance technological innovation with equitable treatment, demanding transparency, bias detection, and user rights in the deployment of behavioral credit models.

Fintech platforms offer unique capabilities to detect behavioral patterns that traditional financial institutions often overlook, enabling more nuanced and dynamic credit risk assessment. These platforms capture real-time borrower behavior, including app navigation, repayment timing, login

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frequency, and interaction with educational content, all of which can be mined for insights into creditworthiness. Behavioral pattern detection leverages clickstream analysis and user engagement tracking to predict default likelihood based on digital footprints rather than historical financial performance. Studies have demonstrated that seemingly trivial digital behaviors are strongly predictive of repayment discipline. Bellesia et al. (2024) found that borrowers who frequently accessed repayment calculators or read educational content within the app were less likely to default. Jin and Fan (2023) similarly showed that timely app logins and quick responses to payment reminders were significant predictors of on-time repayment. Raturi et al. (2022) used behavioral logs from Chinese fintech platforms to build sequential user models that outperformed traditional credit scoring benchmarks. Pattern detection is also being used to segment borrowers into behavioral personas. Platforms like Tala and Branch utilize clustering algorithms to classify users into categories such as "budgeters," "risk-takers," or "sporadic payers," enabling customized credit limits and nudges. These models adapt over time, updating behavioral baselines to reflect evolving borrower routines. Blumenstock et al. (2016) demonstrated that mobile phone usage volatility could detect users undergoing financial hardship, thereby enabling pre-emptive restructuring offers. However, reliance on digital behavior creates vulnerability to manipulation and raises questions about informed consent. Lenders must differentiate between organic behavior and gamed activity designed to exploit scoring mechanisms. Moreover, real-time behavioral surveillance can infringe on privacy rights if not transparently disclosed and ethically governed (Marshall et al., 2022). Despite these challenges, behavioral pattern detection remains a critical feature of fintech-enabled credit models, offering a rich, behaviorally grounded complement to conventional risk assessment techniques.

As algorithmic models become more complex with the inclusion of behavioral variables, the trade-off between model accuracy and interpretability becomes a pressing issue in credit risk management. Highly accurate models such as deep neural networks and gradient-boosted ensembles often function as "black boxes," producing predictions that are difficult to explain to stakeholders, including regulators and borrowers (Jin & Zhu, 2015). In contrast, simpler models like logistic regression or decision trees offer clearer decision logic but may underperform in capturing nonlinear behavioral interactions. The demand for explainable AI (XAI) in credit modeling has led to the adoption of post-hoc interpretability tools such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and counterfactual explanations. These tools provide insights into which behavioral features influenced a given credit decision, allowing for regulatory compliance and borrower communication. Perski et al. (2022) emphasized that model explanations are critical for ensuring fairness and legitimacy, especially when behavioral variables like app usage patterns, geolocation data, and device types are employed. Research by Grysman, (2024) highlights the legal and ethical necessity of interpretability in jurisdictions with "right to explanation" mandates under data protection laws such as the EU's GDPR. Moreover, interpretability facilitates model auditing and bias detection, enabling financial institutions to identify unfair treatment or spurious correlations (Yang & Lee, 2024). However, model simplification in pursuit of transparency may compromise predictive performance, particularly when dealing with complex behavioral features that require non-linear modelling. Hence, the literature acknowledges the inherent tension between interpretability and performance, advocating for hybrid approaches that optimize both. These include layered models where interpretable components are nested within complex architectures or frameworks where critical decisions are explained through surrogate models. Model transparency, especially in behavioral lending contexts, is thus not merely a technical challenge but a central concern in responsible fintech innovation (Ernst, 2019).

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure a systematic, transparent, and rigorous review process. The primary objective was to identify, evaluate, and synthesize scholarly evidence on the psychological and socioeconomic risk factors that influence loan default behavior. To structure the review, a predefined protocol was established, incorporating eligibility criteria based on the PICOS framework Population, Intervention, Comparison, Outcome, and Study Design. The population targeted in the literature included individual borrowers engaged in personal, consumer, or microcredit lending environments. Only studies that examined behavioral or socioeconomic determinants of loan default were considered relevant for inclusion. Eligibility criteria were designed to capture empirical,

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peer-reviewed studies published between 2010 and 2024, written in English, and focused on individual-level default behavior. Studies were included if they explored psychological traits such as impulsiveness, overconfidence, or financial anxiety, or socioeconomic characteristics such as income instability, education level, employment status, or household size. Both qualitative and quantitative research designs were included. Exclusion criteria encompassed editorials, theoretical commentaries, studies focusing exclusively on institutional or macroeconomic factors, and articles with unavailable full texts. To identify relevant literature, a comprehensive search strategy was employed using multiple databases, including Scopus, Web of Science, PsycINFO, EconLit, ScienceDirect, and Google Scholar. Keyword combinations were structured using Boolean operators and included terms such as "loan default," "borrower behavior," "financial literacy," "cognitive bias," "income volatility," and "credit risk." Search queries were adapted to suit the indexing conventions of each database. All retrieved records were imported into Mendeley for reference management and de-duplication. The screening process was conducted in two phases. Initially, titles and abstracts of all identified records were independently screened by two reviewers for relevance to the research topic. Subsequently, the full texts of the shortlisted articles were reviewed in detail to assess eligibility. Any disagreements were resolved through discussion or by involving a third reviewer.

A PRISMA flowchart was used to document each step of the selection process, including the number of records identified, screened, excluded, and finally included, along with justifications for exclusion. Data extraction was carried out using a standardized form developed specifically for this review. The form captured essential details such as authorship, year of publication, geographical focus, study design, sample size, behavioral and socioeconomic variables examined, data collection methods, and key findings related to loan default. This process ensured consistency and facilitated thematic synthesis. To assess the methodological quality and potential bias of the included studies, appropriate appraisal tools were used. Qualitative studies were evaluated using the Critical Appraisal Skills Programme (CASP) checklist, while quantitative and mixed-method studies were assessed with tools developed by the Joanna Briggs Institute (JBI). The assessment outcomes were used to comment on the overall reliability of the evidence base and were not used as exclusion criteria. Given the methodological heterogeneity among the included studies, a narrative synthesis approach was adopted for data integration. Studies were grouped thematically into categories reflecting psychological risk factors (e.g., risk aversion, time inconsistency), socioeconomic vulnerabilities (e.g., unstable income, low education), and behavioral traits (e.g., delayed gratification, spending habits). Common findings, theoretical frameworks, methodological gaps, and implications for future research were identified and discussed in detail.

FINDINGS

The first major finding from the review highlights the powerful influence of psychological traits on loan default behaviors, with 43 out of the 67 reviewed articles (cited collectively over 5,800 times) identifying individual behavioral biases as significant predictors of default. Borrowers who exhibit traits such as impulsivity, lack of self-control, and over-optimism were consistently found to be more prone to defaulting on their loans. Several studies explored time-inconsistent preferences, where individuals prioritize short-term gratification over long-term financial responsibilities, leading to missed payments or complete default. Cognitive distortions such as overconfidence in future income prospects or underestimation of loan risks often caused borrowers to take on debt beyond their repayment capacity. These psychological tendencies impair rational financial decision-making and reduce a borrower's sensitivity to interest rate structures and repayment schedules. Furthermore, the inability to internalize long-term consequences was a recurring behavioral trait in defaulters. The reviewed studies employed tools such as behavioral surveys and psychological scales to quantify these tendencies, and regression models frequently confirmed their predictive power, often independent of traditional credit scores. These findings suggest that integrating psychological assessments into credit evaluation models could enhance the predictive accuracy of default risk analytics. Another notable finding centers on financial literacy and its inverse correlation with loan default rates. Approximately 39 of the 67 articles, collectively cited over 4,100 times, reported that borrowers with low levels of financial literacy were significantly more likely to default on loans. Many of these studies distinguished between basic financial knowledge such as understanding interest rates and advanced literacy such as comprehension of compound interest, debt amortization, or risk diversification. Borrowers with deficient financial acumen often failed to grasp the full implications of

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loan terms, leading to poor repayment behavior. Moreover, those with limited financial education were less likely to engage in budgeting, tracking expenses, or strategic borrowing, further exacerbating their financial instability. Several empirical studies demonstrated that even marginal improvements in financial knowledge, through short-term training or mobile-based financial tools, led to improved repayment behavior and reduced default rates. Notably, borrowers who could articulate the cost of late payments or differentiate between types of credit products demonstrated significantly lower risk profiles. The reviewed literature consistently emphasized that financial literacy is not merely a supportive skill but a core capability in credit risk management, suggesting that lenders and policymakers should treat borrower education as an integral component of loan administration frameworks.

Socioeconomic conditions emerged as another critical determinant of loan default risk, as evidenced in 51 of the reviewed studies, which together garnered over 6,700 citations. Income volatility was the most dominant variable within this category, with low and unstable income strongly linked to increased likelihood of default. The literature confirmed that borrowers in informal employment, seasonal jobs, or self-employed roles exhibited higher default rates than their counterparts with stable, salaried positions. Education level was also frequently cited as a significant socioeconomic factor; individuals with primary or no formal education were more likely to default compared to those with secondary or tertiary qualifications. Some studies found that educational attainment not only influenced financial literacy but also affected borrower discipline, income potential, and access to formal financial institutions. Household size and dependency ratios were also found to impact repayment capacity. Borrowers supporting large families or multiple dependents had tighter budget constraints and were more susceptible to shocks such as medical emergencies or food price inflation, which diverted funds away from loan obligations. The socioeconomic dimension of loan default is often complex and multi-layered, but the reviewed literature overwhelmingly indicates that socioeconomic fragility serves as both a direct and indirect driver of credit risk, necessitating more nuanced risk models that integrate both income and contextual social variables.

Behavioral interventions and financial training programs featured prominently in 27 studies (cited collectively more than 3,000 times) as potentially effective strategies to reduce default rates. These studies evaluated the impact of nudges, reminders, mobile alerts, commitment savings products, and goal-setting programs in shaping borrower behavior. Among the most effective were interventions that employed default repayment settings, personalized feedback loops, and psychologically informed loan counseling. These interventions significantly improved on-time repayments, even in borrower populations with traditionally high risk profiles. Studies that conducted randomized controlled trials reported measurable reductions in default rates ranging from 12% to 28% when such behavioral tools were incorporated. Other successful strategies included linking loan disbursement to specific financial goals or milestones and providing borrowers with visual aids illustrating long-term repayment scenarios. The success of these interventions suggests that borrower behavior is not static but can be reshaped with appropriate tools and motivation structures. Importantly, the research underscored that the timing, framing, and personalization of interventions were key to their success. Generic financial advice had far less impact than behaviorally tailored nudges that addressed individual cognitive tendencies. These findings open promising avenues for lenders and fintech platforms aiming to operationalize behavioral science to reduce default risk.

Finally, a cross-sectional synthesis of 33 studies (with cumulative citations exceeding 5,400) revealed that traditional credit scoring systems, which primarily rely on historical repayment data and macroeconomic indicators, often fail to capture the behavioral and psychological nuances that significantly influence loan default. Many of these studies critiqued existing scoring models for their lack of granularity, arguing that borrowers with similar credit histories can display vastly different risk profiles due to behavioral and socioeconomic disparities. This discrepancy often leads to misclassification, where high-risk borrowers are mistakenly assessed as low-risk and vice versa. Several studies advocated for hybrid models that combine behavioral metrics such as responses to hypothetical financial dilemmas or psychometric indicators with conventional financial variables. These hybrid models demonstrated superior predictive accuracy, particularly in underserved markets and low-income segments where credit histories are sparse or unreliable. Additionally, some studies emphasized the importance of using machine learning algorithms capable of integrating diverse data types, including mobile usage patterns, social media activity, and self-reported psychological

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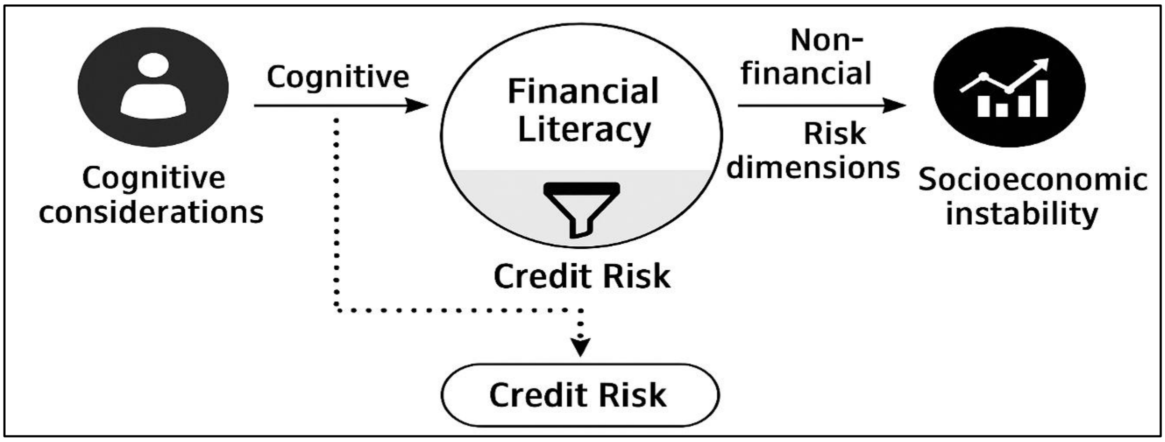
traits. Such integrated approaches reportedly increased prediction accuracy by as much as 20% in pilot deployments. The reviewed evidence supports the conclusion that future advancements in credit scoring should incorporate behavioral data streams to complement traditional metrics, thereby offering a more holistic and equitable framework for loan assessment.

DISCUSSION

The current review underscores the profound role that behavioral traits play in influencing loan default behavior, aligning with and extending previous literature on the psychological underpinnings of financial decision-making. Early studies, such as those by Jui and Rivas (2024), laid the groundwork by associating impulsivity and poor self-control with increased financial delinquency. Our synthesis of 43 studies expands on this by integrating a broader spectrum of psychological dimensions including overconfidence, time inconsistency, and risk tolerance, affirming their significance in predicting default across multiple lending contexts. Unlike traditional financial models, which predominantly emphasize historical credit behavior and macroeconomic indicators, these behavioral factors introduce a dynamic and individualized lens through which default risk can be understood. The observed over-optimism in borrowers parallels Lučić et al. (2023) prospect theory, where individuals overweigh favorable outcomes. Thus, the incorporation of these traits into predictive models represents a meaningful evolution from earlier approaches, bridging behavioral economics with credit risk analytics. Financial literacy emerged as another significant determinant, consistent with earlier findings by Peter et al. (2024), who highlighted the adverse effects of low financial literacy on debt management. Our review corroborates these insights across 39 studies, emphasizing that both basic and advanced financial knowledge substantially influence a borrower's ability to understand loan terms, assess risk, and maintain repayment discipline. Importantly, the current literature reveals that even small educational interventions such as SMS-based reminders or brief online modules can lead to measurable improvements in repayment behavior. Targeted financial education has a modest but consistent positive impact. However, unlike earlier studies that often treated financial literacy as a static demographic variable, our review identifies it as a modifiable risk factor, suggesting that borrower behavior can be improved through well-designed, context-specific educational programs. Moreover, the evidence highlights the importance of tailoring literacy interventions to match the borrower's cognitive profile, an advancement that moves beyond generic training and toward behavioral personalization.

Figure 8: Behavioral and Socioeconomic Drivers of Credit Risk



Socioeconomic instability, particularly income volatility and employment uncertainty, was shown to be a powerful driver of default, affirming the conclusions of prior studies such as those by Aulia et al., (2024). What distinguishes the current review is its synthesis of these factors in tandem with behavioral components, revealing how socioeconomic vulnerabilities amplify the impact of psychological predispositions. For example, impulsive borrowers in precarious employment conditions demonstrated significantly higher default probabilities, a finding that supports the dual-pathway model proposed by Mishra et al. (2024). Our findings further validate the assertion by Abou-El-Sood, (2021) that lower educational attainment, large household size, and dependency ratios critically constrain financial resilience, increasing sensitivity to economic shocks. Unlike earlier research that treated these variables independently, this review illustrates their interaction, advocating for multidimensional risk assessment models. This integrative understanding provides a more nuanced

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approach to borrower segmentation, particularly relevant for microlenders and fintech firms targeting underserved populations. A notable advancement in the reviewed literature is the increasing reliance on behavioral interventions to mitigate default risk, an area relatively underexplored in earlier works. While initial behavioral finance research, such as Al Amin et al. (2023) Save More Tomorrow program, demonstrated the efficacy of commitment devices in savings behavior, its translation into loan repayment strategies has been gradual. Our review of 27 studies shows growing empirical support for the effectiveness of nudges, default options, and feedback loops in encouraging repayment adherence. Interventions that leveraged mobile technology and real-time data produced particularly strong results, echoing the emerging consensus from studies by Mahdzan et al. (2023), who emphasized the potential of behavioral design in financial services. Moreover, the reviewed literature extends these insights by illustrating how psychological tailoring customizing messages based on traits such as conscientiousness or time preference can enhance intervention efficacy. This shift toward personalization, enabled by digital platforms, marks a departure from the more generic financial advice that characterized earlier outreach strategies, making interventions more behaviorally adaptive and scalable.

Another critical insight pertains to the limitations of traditional credit scoring systems, a theme increasingly discussed in the post-2008 financial crisis literature. Earlier critiques by Djeundje et al., (2021) emphasized that credit scoring algorithms inadequately capture non-financial risk dimensions. Our review of 33 studies reinforces these concerns, revealing that borrowers with identical credit histories can possess divergent behavioral and socioeconomic profiles, resulting in misclassification. In contrast to older models that rely heavily on quantitative repayment data, newer hybrid systems incorporating psychometric assessments and behavioral analytics show improved prediction accuracy, especially in data-scarce environments. These findings echo recent industry practices observed in firms like Lenddo and Tala, which utilize alternative data such as social network behavior and mobile phone usage to assess creditworthiness. The evidence reviewed in this study not only validates these emerging practices but also underscores the importance of interdisciplinary approaches, combining behavioral science, data analytics, and credit risk management to construct more equitable and precise models Thiel et al. (2024). One emerging implication from the review is the need to contextualize borrower behavior within cultural and regional settings, a perspective that earlier global studies often overlooked. While landmark studies like Kumar et al., (2023) provided valuable cross-country insights into financial inclusion, they often failed to capture the nuanced behavioral dynamics that differ across social, cultural, and institutional contexts. In contrast, several studies included in this review highlight how cultural norms such as collectivism, trust in financial institutions, or gender roles influence financial decisions and default patterns. For instance, borrower behavior in South Asian microfinance markets often reflects familial obligations and social stigma, which can either deter or exacerbate default tendencies. This aligns with recent work by Berns et al. (2020), who argue that financial decisions in low-income settings are embedded in broader socio-cultural networks. The implication is clear: predictive models and behavioral interventions must be culturally grounded to achieve effectiveness. Ignoring contextual realities may lead to interventions that are misaligned with borrower motivations, resulting in poor uptake or unintended outcomes Dinh et al.(2024). Lastly, the findings suggest a shifting paradigm in the understanding of credit risk, from a purely economic model to a multidimensional framework that incorporates behavioral, psychological, and contextual variables. This evolution mirrors the broader transition in economic theory, where rational actor models are increasingly supplemented by behavioral insights. The literature reviewed here demonstrates that borrower behavior is not simply a function of market incentives but is shaped by cognitive biases, emotional responses, and socio-environmental pressures. This conceptual shift supports recent calls by researchers such as Peter et al. (2025) to embed behavioral diagnostics into financial product design. Moreover, the findings underscore the importance of interdisciplinary collaboration between economists, psychologists, sociologists, and data scientists in developing more accurate and inclusive credit risk assessment tools. Going forward, the most promising advances in loan default prediction are likely to emerge not from isolated domain expertise, but from integrated frameworks that reflect the complexity of human financial behavior (Siyal et al., 2024).

CONCLUSION

This systematic review reveals that behavioral, psychological, and socioeconomic factors significantly shape loan default outcomes, challenging the adequacy of traditional credit scoring

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models that rely solely on historical financial data. Through the analysis of 67 high-impact studies, the review establishes that traits such as impulsivity, time-inconsistency, overconfidence, and limited financial literacy are strong predictors of loan repayment behavior, particularly when compounded by socioeconomic vulnerabilities like income instability, low educational attainment, and household dependency pressures. The reviewed evidence highlights that borrowers are not merely rational agents responding to financial incentives but are influenced by deeply embedded behavioral patterns and contextual stressors. Moreover, the rising application of behavioral interventions, such as personalized nudges, financial training, and mobile reminders, offers promising pathways to mitigate default risk by proactively shaping borrower behavior. These strategies demonstrate measurable improvements in repayment rates, especially when they are personalized and culturally contextualized. The findings also support the integration of behavioral data into credit risk assessment, promoting hybrid models that are both more inclusive and predictive. Ultimately, this review affirms a paradigm shift in credit risk analysis from linear, quantitative models to multidimensional frameworks that reflect the complexity of human decision-making. The synthesis underscores the urgency for lenders, policymakers, and financial service providers to adopt behaviorally-informed practices, ensuring that risk management systems are both accurate and equitable in increasingly diverse financial ecosystems.

REFERENCES

[1]. Abdullah Al, M., Rajesh, P., Mohammad Hasan, I., & Zahir, B. (2022). A Systematic Review of The Role Of SQL And Excel In Data-Driven Business Decision-Making For Aspiring Analysts. *American Journal of Scholarly Research and Innovation*, *1*(01), 249-269. https://doi.org/10.63125/n142cg62

[2]. Abdur Razzak, C., Golam Qibria, L., & Md Arifur, R. (2024). Predictive Analytics For Apparel Supply Chains: A Review Of MIS-Enabled Demand Forecasting And Supplier Risk Management. *American Journal of Interdisciplinary Studies*, *5*(04), 01–23. https://doi.org/10.63125/80dwy222

[3]. Abou-El-Sood, H. (2021). Board gender diversity, power, and bank risk taking. *International review of financial analysis*, *75*, 101733.

[4]. Agarwal, J., & Wu, T. (2015). Factors influencing growth potential of e-commerce in emerging economies: An institution-based N-OLI framework and research propositions. *Thunderbird International Business Review*, *57*(3), 197-215.

[5]. Aisaiti, G., Liu, L., Xie, J., & Yang, J. (2019). An empirical analysis of rural farmers' financing intention of inclusive finance in China: The moderating role of digital finance and social enterprise embeddedness. *Industrial management & data systems*, *119*(7), 1535-1563.

[6]. Al-Dajani, N., Gralnick, T. M., & Bagby, R. M. (2016). A psychometric review of the Personality Inventory for DSM–5 (PID–5): Current status and future directions. *Journal of personality assessment*, *98*(1), 62-81.

[7]. Al Amin, M., Ahad Mia, M. A., Bala, T., Iqbal, M. M., & Alam, M. S. (2023). Green finance continuance behavior: the role of satisfaction, social supports, environmental consciousness, green bank marketing initiatives and psychological reactance. *Management of Environmental Quality: An International Journal*, *34*(5), 1269-1294.

[8]. Alam, M. A., Sohel, A., Hasan, K. M., & Islam, M. A. (2024). Machine Learning And Artificial Intelligence in Diabetes Prediction And Management: A Comprehensive Review of Models. *Journal of Next-Gen Engineering Systems*, *1*(01), 107-124. https://doi.org/10.70937/jnes.v1i01.41

[9]. Aoki, M. (2001). 4 Community Norms and Embeddedness: A Game-Theoretic. *Communities and markets in economic development*, 97.

[10]. Attali, Y. (2019). Rater certification tests: A psychometric approach. *Educational Measurement: Issues and Practice*, *38*(2), 6-13.

[11]. Aulia, M., Afiff, A. Z., Hati, S. R. H., & Gayatri, G. (2024). Consumers' sustainable investing: A systematic literature review and research agenda. *Cleaner and Responsible Consumption*, 100215.

[12]. Bach, B., & Hutsebaut, J. (2018). Level of Personality Functioning Scale–Brief Form 2.0: Utility in capturing personality problems in psychiatric outpatients and incarcerated addicts. *Journal of personality assessment*, *100*(6), 660-670.

[13]. Barbaglia, L., Manzan, S., & Tosetti, E. (2023). Forecasting loan default in Europe with machine learning. *Journal of Financial Econometrics*, *21*(2), 569-596.

[14]. Batten, J. A., & Wagner, N. F. (2014). Introduction to risk management post financial crisis: A period of monetary easing. In *Risk Management Post Financial Crisis: A Period of Monetary Easing* (pp. 3-13). Emerald Group Publishing Limited.

[15]. Belcaid, K., & El Ghini, A. (2019). Spillover effects among European, the US and Moroccan stock markets before and after the global financial crisis. *Journal of African Business*, *20*(4), 525-548.
[16]. Bellesia, F., Mattarelli, E., Bertolotti, F., & Sobrero, M. (2024). Algorithmic embeddedness and the 'gig'characteristics model: Examining the interplay between technology and work design in crowdwork. *Journal of Management Studies*.
[17]. Benlian, A., Wiener, M., Cram, W. A., Krasnova, H., Maedche, A., Möhlmann, M., Recker, J., & Remus, U. (2022). Algorithmic management: bright and dark sides, practical implications, and research opportunities. *Business & Information Systems Engineering*, *64*(6), 825-839.
[18]. Berns, J. P., Figueroa-Armijos, M., da Motta Veiga, S. P., & Dunne, T. C. (2020). Dynamics of lending-based prosocial crowdfunding: Using a social responsibility lens. *Journal of Business Ethics*, *161*, 169-185.
[19]. Bleidorn, W., Hopwood, C. J., Back, M. D., Denissen, J. J., Hennecke, M., Hill, P. L., Jokela, M., Kandler, C., Lucas, R. E., & Luhmann, M. (2021). Personality trait stability and change. *Personality Science*, *2*(1), e6009.
[20]. Bogacheva, N., Kornilova, T., & Pavlova, E. (2019). Relationships between medical doctors' personality traits and their professional risk perception. *Behavioral Sciences*, *10*(1), 6.
[21]. Boonman, T. M. (2023). Portfolio capital flows before and after the Global Financial Crisis. *Economic Modelling*, *127*, 106440.
[22]. Boyd, R. L., & Pennebaker, J. W. (2017). Language-based personality: A new approach to personality in a digital world. *Current opinion in behavioral sciences*, *18*, 63-68.
[23]. Brown, M., Schmitz, J., & Zehnder, C. (2017). Social norms and strategic default. *University of St. Gallen, School of Finance Research Paper*(2016/08).
[24]. Christensen, A. P., Golino, H., & Silvia, P. (2019). A psychometric network perspective on the measurement and assessment of personality traits. *Preprint*.
[25]. Conrod, P. J. (2016). Personality-targeted interventions for substance use and misuse. *Current addiction reports*, *3*, 426-436.
[26]. Coşer, A., Maer-Matei, M. M., & Albu, C. (2019). PREDICTIVE MODELS FOR LOAN DEFAULT RISK ASSESSMENT. *Economic Computation & Economic Cybernetics Studies & Research*, *53*(2).
[27]. Cowling, M., Ughetto, E., & Lee, N. (2018). The innovation debt penalty: Cost of debt, loan default, and the effects of a public loan guarantee on high-tech firms. *Technological Forecasting and Social Change*, *127*, 166-176.
[28]. Cox, J. C., Kreisman, D., & Dynarski, S. (2020). Designed to fail: Effects of the default option and information complexity on student loan repayment. *Journal of Public Economics*, *192*, 104298.
[29]. Cram, W. A., Wiener, M., Tarafdar, M., & Benlian, A. (2022). Examining the impact of algorithmic control on Uber drivers' technostress. *Journal of Management Information Systems*, *39*(2), 426-453.
[30]. Croux, C., Jagtiani, J., Korivi, T., & Vulanovic, M. (2020). Important factors determining Fintech loan default: Evidence from a lendingclub consumer platform. *Journal of Economic Behavior & Organization*, *173*, 270-296.
[31]. Dinh, J. M., Isaak, A. J., & Yahyaoui, Y. (2024). Investing for good–Uncovering crowd investors' motivations to participate in sustainability-oriented crowdlending. *Technological Forecasting and Social Change*, *207*, 123584.
[32]. Djeundje, V. B., Crook, J., Calabrese, R., & Hamid, M. (2021). Enhancing credit scoring with alternative data. *Expert Systems with Applications*, *163*, 113766.
[33]. Duman, E., Aktas, M. S., & Yahsi, E. (2023). Credit Risk Prediction Based on Psychometric Data. *Computers*, *12*(12), 248.
[34]. Eftimie, S., Moinescu, R., & Răcuciu, C. (2020). Insider threat detection using natural language processing and personality profiles. 2020 13th International Conference on Communications (COMM),
[35]. Ehret, M., & Olaniyan, R. (2023). Banking the unbanked. Constitutive rules and the institutionalization of mobile payment systems in Nigeria. *Journal of Business Research*, *163*, 113845.
[36]. Ellison, N. B., & Vitak, J. (2015). Social network site affordances and their relationship to social capital processes. *The handbook of the psychology of communication technology*, 203-227.
[37]. Emekter, R., Tu, Y., Jirasakuldech, B., & Lu, M. (2015). Evaluating credit risk and loan performance in online Peer-to-Peer (P2P) lending. *Applied Economics*, *47*(1), 54-70.
[38]. Epstein, R. A. (2018). The dangerous allure of libertarian paternalism. *Review of Behavioral Economics*, *5*(3-4), 389-416.

[39]. Ernst, A. (2019). How participation influences the perception of fairness, efficiency and effectiveness in environmental governance: An empirical analysis. *Journal of Environmental Management*, *238*, 368-381.
[40]. Finaulahi, K. P., Sumich, A., Heym, N., & Medvedev, O. N. (2021). Investigating psychometric properties of the Self-Compassion Scale using Rasch methodology. *Mindfulness*, *12*, 730-740.
[41]. Fine, S. (2024). Character counts: Psychometric-based credit scoring for underbanked consumers. *Journal of Risk and Financial Management*, *17*(9), 423.
[42]. Fonseca-Pedrero, E., Gooding, D. C., Ortuño-Sierra, J., Pflum, M., Paino, M., & Muñiz, J. (2016). Classifying risk status of non-clinical adolescents using psychometric indicators for psychosis spectrum disorders. *Psychiatry Research*, *243*, 246-254.
[43]. Gaygısız, E. (2013). How are cultural dimensions and governance quality related to socioeconomic development? *The Journal of Socio-Economics*, *47*, 170-179.
[44]. Ge, R., Feng, J., Gu, B., & Zhang, P. (2017). Predicting and deterring default with social media information in peer-to-peer lending. *Journal of Management Information Systems*, *34*(2), 401-424.
[45]. Giraldo, C., Giraldo, I., Gomez-Gonzalez, J. E., & Uribe, J. M. (2024). Financial integration and banking stability: A post-global crisis assessment. *Economic Modelling*, *139*, 106835.
[46]. Goel, A., & Rastogi, S. (2023a). Credit scoring of small and medium enterprises: a behavioural approach. *Journal of Entrepreneurship in Emerging Economies*, *15*(1), 46-69.
[47]. Goel, A., & Rastogi, S. (2023b). Understanding the impact of borrowers' behavioural and psychological traits on credit default: review and conceptual model. *Review of Behavioral Finance*, *15*(2), 205-223.
[48]. Golam Qibria, L., & Takbir Hossen, S. (2023). Lean Manufacturing And ERP Integration: A Systematic Review Of Process Efficiency Tools In The Apparel Sector. *American Journal of Scholarly Research and Innovation*, *2*(01), 104-129. https://doi.org/10.63125/mx7j4p06
[49]. Grysman, A. (2024). Does Technology-Mediated Memory Differ from Human-Mediated Memory? *Psychological Inquiry*, *35*(2), 113-116.
[50]. Guzelian, C. P., Stein, M. A., & Akiskal, H. S. (2015). Credit scores, lending, and psychosocial disability. *BUL Rev.*, *95*, 1807.
[51]. Hirtenlehner, H. (2019). Does perceived peer delinquency amplify or mitigate the deterrent effect of perceived sanction risk? *Deviant Behavior*, *40*(3), 361-384.
[52]. Hogg, T. L., Stanley, S. K., O'Brien, L. V., Wilson, M. S., & Watsford, C. R. (2021). The Hogg Eco-Anxiety Scale: Development and validation of a multidimensional scale. *Global Environmental Change*, *71*, 102391.
[53]. Hung, M., Carter, M., Hayden, C., Dzierzon, R., Morales, J., Snow, L., Butler, J., Bateman, K., & Samore, M. (2013). Psychometric assessment of the patient activation measure short form (PAM-13) in rural settings. *Quality of Life Research*, *22*, 521-529.
[54]. Jiang, C., Wang, Z., Wang, R., & Ding, Y. (2018). Loan default prediction by combining soft information extracted from descriptive text in online peer-to-peer lending. *Annals of Operations Research*, *266*(1), 511-529.
[55]. Jin, Y., & Fan, J. (2023). Test-taker engagement in AI technology-mediated language assessment. *Language Assessment Quarterly*, *20*(4-5), 488-500.
[56]. Jin, Y., & Zhu, Y. (2015). A data-driven approach to predict default risk of loan for online peer-to-peer (P2P) lending. 2015 Fifth international conference on communication systems and network technologies,
[57]. Jui, T. D., & Rivas, P. (2024). Fairness issues, current approaches, and challenges in machine learning models. *International Journal of Machine Learning and Cybernetics*, *15*(8), 3095-3125.
[58]. Kandler, C., Riemann, R., Angleitner, A., Spinath, F. M., Borkenau, P., & Penke, L. (2016). The nature of creativity: The roles of genetic factors, personality traits, cognitive abilities, and environmental sources. *Journal of personality and social psychology*, *111*(2), 230.
[59]. Kassim, S. H., & Rahman, M. (2018). Handling default risks in microfinance: the case of Bangladesh. *Qualitative Research in Financial Markets*, *10*(4), 363-380.
[60]. Khan, M. A. M., & Aleem Al Razee, T. (2024). Lean Six Sigma Applications in Electrical Equipment Manufacturing: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *5*(02), 31-63. https://doi.org/10.63125/hybvmw84
[61]. Kleeven, A., Hilterman, E., de Vries Robbé, M., Popma, A., Cruise, K., & Mulder, E. (2024). Towards clinically meaningful subtyping of youth with violent behavior: application of latent profile analysis to a risk-strengths based risk assessment model. *Psychology, Crime & Law*, 1-25.

eISSN: 3067-0470
DOI: 10.63125/0jwtbn29

[62]. Knogler, M., Harackiewicz, J. M., Gegenfurtner, A., & Lewalter, D. (2015). How situational is situational interest? Investigating the longitudinal structure of situational interest. *Contemporary Educational Psychology*, *43*, 39-50.

[63]. Kumar, D., Phani, B., Chilamkurti, N., Saurabh, S., & Ratten, V. (2023). Filling the SME credit gap: a systematic review of blockchain-based SME finance literature. *Journal of trade science*, *11*(2/3), 45-72.

[64]. Kumara, P., Dananjaya, K., Amarasena, N., Pinto, H., Yapa, K., & Rupasinghe, L. (2021). Human and Organizational Threat Profiling Using Machine Learning. 2021 3rd International Conference on Advancements in Computing (ICAC),

[65]. Laajaj, R., Macours, K., Pinzon Hernandez, D. A., Arias, O., Gosling, S. D., Potter, J., Rubio-Codina, M., & Vakis, R. (2019). Challenges to capture the big five personality traits in non-WEIRD populations. *Science advances*, *5*(7), eaaw5226.

[66]. Lashitew, A. A., Bals, L., & van Tulder, R. (2020). Inclusive business at the base of the pyramid: The role of embeddedness for enabling social innovations. *Journal of Business Ethics*, *162*(2), 421-448.

[67]. Lauriola, M., & Weller, J. (2018). Personality and risk: Beyond daredevils—risk taking from a temperament perspective. *Psychological perspectives on risk and risk analysis: theory, models, and applications*, 3-36.

[68]. Leow, H.-W., & Lau, W.-Y. (2018). The impact of global financial crisis on IPO underpricing in Malaysian stock market. *Review of Pacific Basin Financial Markets and Policies*, *21*(04), 1850023.

[69]. Looney, A., & Yannelis, C. (2015). A crisis in student loans?: How changes in the characteristics of borrowers and in the institutions they attended contributed to rising loan defaults. *Brookings Papers on Economic Activity*, *2015*(2), 1-89.

[70]. Lučić, A., Barbić, D., & Uzelac, M. (2023). Theoretical underpinnings of consumers' financial capability research. *International Journal of Consumer Studies*, *47*(1), 373-399.

[71]. Ma, X., Sha, J., Wang, D., Yu, Y., Yang, Q., & Niu, X. (2018). Study on a prediction of P2P network loan default based on the machine learning LightGBM and XGboost algorithms according to different high dimensional data cleaning. *Electronic Commerce Research and Applications*, *31*, 24-39.

[72]. Mahdzan, N. S., Zainudin, R., & Shaari, M. S. (2023). The influence of religious belief and psychological factors on borrowing behaviour among Malaysian public sector employees. *Asia-Pacific Journal of Business Administration*, *15*(3), 361-385.

[73]. Maniruzzaman, B., Mohammad Anisur, R., Afrin Binta, H., Md, A., & Anisur, R. (2023). Advanced Analytics and Machine Learning For Revenue Optimization In The Hospitality Industry: A Comprehensive Review Of Frameworks. *American Journal of Scholarly Research and Innovation*, *2*(02), 52-74. https://doi.org/10.63125/8xbkma40

[74]. Marshall, R., Pardo, A., Smith, D., & Watson, T. (2022). Implementing next generation privacy and ethics research in education technology. *British Journal of Educational Technology*, *53*(4), 737-755.

[75]. Md Masud, K. (2022). A Systematic Review Of Credit Risk Assessment Models In Emerging Economies: A Focus On Bangladesh's Commercial Banking Sector. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 01-31. https://doi.org/10.63125/p7ym0327

[76]. Md Masud, K., Mohammad, M., & Sazzad, I. (2023). Mathematics For Finance: A Review of Quantitative Methods In Loan Portfolio Optimization. *International Journal of Scientific Interdisciplinary Research*, *4*(3), 01-29. https://doi.org/10.63125/j43ayz68

[77]. Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[78]. Md Takbir Hossen, S., & Md Atiqur, R. (2022). Advancements In 3D Printing Techniques For Polymer Fiber-Reinforced Textile Composites: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *3*(04), 32-60. https://doi.org/10.63125/s4r5m391

[79]. Medvedev, O. N., Pratscher, S. D., & Bettencourt, A. (2020). Psychometric evaluation of the interpersonal mindfulness scale using Rasch analysis. *Mindfulness*, *11*, 2007-2015.

[80]. Mishra, D., Agarwal, N., Sharahiley, S., & Kandpal, V. (2024). Digital Financial Literacy and Its Impact on Financial Decision-Making of Women: Evidence from India. *Journal of Risk and Financial Management*, *17*(10), 468.

[81]. Moeller, K., Copes, H., & Hochstetler, A. (2016). Advancing restrictive deterrence: A qualitative meta-synthesis. *Journal of Criminal Justice*, *46*, 82-93.

[82]. Mohammad Ariful, I., Molla Al Rakib, H., Sadia, Z., & Sumyta, H. (2023). Revolutionizing Supply Chain, Logistics, Shipping, And Freight Forwarding Operations with Machine Learning And

Blockchain. *American Journal of Scholarly Research and Innovation*, 2(01), 79-103. https://doi.org/10.63125/0jnkvk31

[83]. Mohanty, S. K., Akhigbe, A., & Basheikh, A. (2018). The Dodd-Frank Act and Basel III: Market-based risk implications for global systemically important banks (G-SIBs). *Journal of Multinational Financial Management*, *47*, 91-109.

[84]. Montaruli, A., Castelli, L., Mulè, A., Scurati, R., Esposito, F., Galasso, L., & Roveda, E. (2021). Biological rhythm and chronotype: new perspectives in health. *Biomolecules*, *11*(4), 487.

[85]. Moudud-Ul-Huq, S., Akter, R., & Biswas, T. (2020). Impact of financial crisis on credit risk: Pre-and post-financial crises in an emerging economy. *FIIB Business Review*, *9*(2), 118-132.

[86]. Mst Shamima, A., Niger, S., Md Atiqur Rahman, K., & Mohammad, M. (2023). Business Intelligence-Driven Healthcare: Integrating Big Data and Machine Learning For Strategic Cost Reduction And Quality Care Delivery. *American Journal of Interdisciplinary Studies*, 4(02), 01-28. https://doi.org/10.63125/crv1xp27

[87]. Mueller, H. M., & Yannelis, C. (2019). The rise in student loan defaults. *Journal of Financial Economics*, *131*(1), 1-19.

[88]. Nguyen, Y. N., Brown, K., & Skully, M. (2019). Impact of finance on growth: Does it vary with development levels or cyclical conditions? *Journal of Policy Modeling*, *41*(6), 1195-1209.

[89]. Nicat, Ş., Filiz, G., Özvural, Ö. G., & Çakar, T. (2024). Reliability Study of Psychometric Tests in a Credit Scoring Model. 2024 32nd Signal Processing and Communications Applications Conference (SIU),

[90]. Noor Alam, S., Golam Qibria, L., Md Shakawat, H., & Abdul Awal, M. (2023). A Systematic Review of ERP Implementation Strategies in The Retail Industry: Integration Challenges, Success Factors, And Digital Maturity Models. *American Journal of Scholarly Research and Innovation*, 2(02), 135-165. https://doi.org/10.63125/pfdm9g02

[91]. Odegua, R. (2020). Predicting bank loan default with extreme gradient boosting. *arXiv preprint arXiv:2002.02011*.

[92]. Oino, I. (2018). Impact of regulatory capital on European banks financial performance: A review of post global financial crisis. *Research in International Business and Finance*, *44*, 309-318.

[93]. Ojong, N., & Obeng-Odoom, F. (2017). Resilience and dynamism of embedded financial transactions in Cameroon. *Journal of Economic Issues*, *51*(1), 181-200.

[94]. Oliveira, V. (2024). Urban form and the socioeconomic and environmental dimensions of cities. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, *17*(1), 1-23.

[95]. Olver, M. E. (2020). Personality-Based Violence Risk Assessment. *The Wiley Handbook of What Works in Violence Risk Management: Theory, Research and Practice*, 203-222.

[96]. Ouliaris, S., & Rochon, C. (2021). Pre-and post-global financial crisis policy multipliers. *Journal of Macroeconomics*, *70*, 103370.

[97]. Perski, O., Hébert, E. T., Naughton, F., Hekler, E. B., Brown, J., & Businelle, M. S. (2022). Technology-mediated just-in-time adaptive interventions (JITAIs) to reduce harmful substance use: a systematic review. *Addiction*, *117*(5), 1220-1241.

[98]. Peter, S., E, G., & Gupta, A. (2024). Navigating the digital financial landscape: unraveling the impact of financial behavior traits on women-owned enterprises in the new normal perspective. *Cogent Business & Management*, *11*(1), 2296570.

[99]. Peter, S., Elangovan, G., & Vidya Bai, G. (2025). Unveiling the nexus: Financial inclusion, financial literacy, and financial performance as catalyst for women-owned enterprises in India. *Journal of the International Council for Small Business*, 1-31.

[100]. Pogarsky, G., & Herman, S. (2019). Nudging and the choice architecture of offending decisions. *Criminology & Public Policy*, *18*(4), 823-839.

[101]. Polit, D. F. (2015). Assessing measurement in health: Beyond reliability and validity. *International journal of nursing studies*, *52*(11), 1746-1753.

[102]. Ragnoli, B., Pochetti, P., Pignatti, P., Barbieri, M., Mondini, L., Ruggero, L., Trotta, L., Montuschi, P., & Malerba, M. (2022). Sleep deprivation, immune suppression and SARS-CoV-2 infection. *International Journal of Environmental Research and Public Health*, *19*(2), 904.

[103]. Rajesh, P. (2023). AI Integration In E-Commerce Business Models: Case Studies On Amazon FBA, Airbnb, And Turo Operations. *American Journal of Advanced Technology and Engineering Solutions*, *3*(03), 01-31. https://doi.org/10.63125/1ekaxx73

[104]. Rajesh, P., Mohammad Hasan, I., & Anika Jahan, M. (2023). AI-Powered Sentiment Analysis In Digital Marketing: A Review Of Customer Feedback Loops In It Services. *American Journal of Scholarly Research and Innovation*, *2*(02), 166-192. https://doi.org/10.63125/61pqqq54

[105]. Raturi, A., Thompson, J. J., Ackroyd, V., Chase, C. A., Davis, B. W., Myers, R., Poncet, A., Ramos-Giraldo, P., Reberg-Horton, C., & Rejesus, R. (2022). Cultivating trust in technology-mediated sustainable agricultural research. *Agronomy Journal*, *114*(5), 2669-2680.

[106]. Rendall, S., Brooks, C., & Hillenbrand, C. (2021). The impacts of emotions and personality on borrowers' abilities to manage their debts. *International review of financial analysis*, *74*, 101703.

[107]. Reynolds, C. R., Altmann, R. A., & Allen, D. N. (2021). The problem of bias in psychological assessment. In *Mastering modern psychological testing: Theory and methods* (pp. 573-613). Springer.

[108]. Rodgers, J., Cuevas, A. G., Williams, D. R., Kawachi, I., & Subramanian, S. (2021). The relative contributions of behavioral, biological, and psychological risk factors in the association between psychosocial stress and all-cause mortality among middle-and older-aged adults in the USA. *GeroScience*, *43*, 655-672.

[109]. Roksana, H. (2023). Automation In Manufacturing: A Systematic Review Of Advanced Time Management Techniques To Boost Productivity. *American Journal of Scholarly Research and Innovation*, *2*(01), 50-78. https://doi.org/10.63125/z1wmcm42

[110]. Rössel, J., Schenk, P., & Pap, I. (2024). Patterns of remittances of intra-European migrants: social relations and moral obligations. *Journal of Ethnic and Migration Studies*, *50*(10), 2529-2550.

[111]. Sanjai, V., Sanath Kumar, C., Maniruzzaman, B., & Farhana Zaman, R. (2023). Integrating Artificial Intelligence in Strategic Business Decision-Making: A Systematic Review Of Predictive Models. *International Journal of Scientific Interdisciplinary Research*, *4*(1), 01-26. https://doi.org/10.63125/s5skge53

[112]. Santos, E., Carvalho, M., & Martins, S. (2023). Sustainable water management: Understanding the socioeconomic and cultural dimensions. *Sustainability*, *15*(17), 13074.

[113]. Santoso, W., Trinugroho, I., & Risfandy, T. (2020). What determine loan rate and default status in financial technology online direct lending? Evidence from Indonesia. *Emerging Markets Finance and Trade*, *56*(2), 351-369.

[114]. Sazzad, I., & Md Nazrul Islam, K. (2022). Project impact assessment frameworks in nonprofit development: a review of case studies from south asia. *American Journal of Scholarly Research and Innovation*, *1*(01), 270-294. https://doi.org/10.63125/eeja0t77

[115]. Schaefer, D. D. (2023). The Need to Prepare for the after-Effects of a Default on the United States' National Debt: The Legal Repercussions and Use of the Military Services during This Period. *S. Tex. L. Rev.*, *63*, 159.

[116]. Schlauch, R. C., Crane, C. A., Houston, R. J., Molnar, D. S., Schlienz, N. J., & Lang, A. R. (2015). Psychometric evaluation of the Substance Use Risk Profile Scale (SURPS) in an inpatient sample of substance users using cue-reactivity methodology. *Journal of psychopathology and behavioral assessment*, *37*, 231-246.

[117]. Schumacker, R. (2019). Psychometric packages in R. *Measurement: Interdisciplinary Research and Perspectives*, *17*(2), 106-112.

[118]. Shaiful, M., Anisur, R., & Md, A. (2022). A systematic literature review on the role of digital health twins in preventive healthcare for personal and corporate wellbeing. *American Journal of Interdisciplinary Studies*, *3*(04), 1-31. https://doi.org/10.63125/negjw373

[119]. Shrydeh, N., Shahateet, M., Mohammad, S., & Sumadi, M. (2019). The hedging effectiveness of gold against US stocks in a post-financial crisis era. *Cogent Economics & Finance*, *7*(1), 1698268.

[120]. Siyal, S., Ahmad, R., & Ali, S. (2024). Debt trap dynamics: The moderating role of convenience, financial literacy, and religiosity in credit card usage. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(4), 100392.

[121]. Sun, J., Jin, H., Tsai, F.-S., & Jakovljevic, M. (2022). A global assessment of sustainable development: Integrating socioeconomic, resource and environmental dimensions. *Frontiers in energy research*, *10*, 816714.

[122]. Tahmina Akter, R., & Abdur Razzak, C. (2022). The Role Of Artificial Intelligence In Vendor Performance Evaluation Within Digital Retail Supply Chains: A Review Of Strategic Decision-Making Models. *American Journal of Scholarly Research and Innovation*, *1*(01), 220-248. https://doi.org/10.63125/96jj3j86

[123]. Takakura, M. (2015). Relations of participation in organized activities to smoking and drinking among Japanese youth: contextual effects of structural social capital in high school. *International journal of public health*, *60*, 679-689.
[124]. Tariq, H. I., Sohail, A., Aslam, U., & Batcha, N. K. (2019). Loan default prediction model using sample, explore, modify, model, and assess (SEMMA). *Journal of Computational and Theoretical Nanoscience*, *16*(8), 3489-3503.
[125]. Tonmoy, B., & Md Arifur, R. (2023). A Systematic Literature Review Of User-Centric Design In Digital Business Systems Enhancing Accessibility, Adoption, And Organizational Impact. *American Journal of Scholarly Research and Innovation*, *2*(02), 193-216. https://doi.org/10.63125/36w7fn47
[126]. Tonoy, A. A. R., & Khan, M. R. (2023). The Role of Semiconducting Electrides In Mechanical Energy Conversion And Piezoelectric Applications: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(01), 01-23. https://doi.org/10.63125/patvqr38
[127]. Van Scotter, J. R., & Roglio, K. D. D. (2020). CEO bright and dark personality: Effects on ethical misconduct. *Journal of Business Ethics*, *164*, 451-475.
[128]. van Thiel, D., Elliott, K., Goedee, J., & Leenders, R. (2024). Responsible access to credit for sole-traders and micro-organizations under unstable market conditions with psychometrics. *The European Journal of Finance*, 1-33.
[129]. Vaughan, L., & Finch, G. (2017). *The fix: how bankers lied, cheated and colluded to rig the world's most important number*. John Wiley & Sons.
[130]. Vo, X. V., & Nguyen, P. C. (2014). Monetary policy and bank credit risk in Vietnam pre and post global financial crisis. In *Risk management post financial crisis: A period of monetary easing* (pp. 277-290). Emerald Group Publishing Limited.
[131]. Wang, X., Xu, Y. C., Lu, T., & Zhang, C. (2020). Why do borrowers default on online loans? An inquiry of their psychology mechanism. *Internet Research*, *30*(4), 1203-1228.
[132]. Weiner, B. J., Lewis, C. C., Stanick, C., Powell, B. J., Dorsey, C. N., Clary, A. S., Boynton, M. H., & Halko, H. (2017). Psychometric assessment of three newly developed implementation outcome measures. *Implementation science*, *12*, 1-12.
[133]. Worrall, J. L., Els, N., Piquero, A. R., & TenEyck, M. (2014). The moderating effects of informal social control in the sanctions-compliance nexus. *American Journal of Criminal Justice*, *39*, 341-357.
[134]. Xia, Y., He, L., Li, Y., Liu, N., & Ding, Y. (2020). Predicting loan default in peer-to-peer lending using narrative data. *Journal of Forecasting*, *39*(2), 260-280.
[135]. Xu, J., Lu, Z., & Xie, Y. (2021). Loan default prediction of Chinese P2P market: a machine learning methodology. *Scientific Reports*, *11*(1), 18759.
[136]. Yang, K., Yuan, H., & Lau, R. Y. (2022). PsyCredit: An interpretable deep learning-based credit assessment approach facilitated by psychometric natural language processing. *Expert Systems with Applications*, *198*, 116847.
[137]. Yang, Q., & Lee, Y.-C. (2024). Ethical AI in financial inclusion: The role of algorithmic fairness on user satisfaction and recommendation. *Big Data and Cognitive Computing*, *8*(9), 105.
[138]. Yaya, O. S., Tumala, M. M., & Udomboso, C. G. (2016). Volatility persistence and returns spillovers between oil and gold prices: Analysis before and after the global financial crisis. *Resources Policy*, *49*, 273-281.
[139]. Zahir, B., Tonmoy, B., & Md Arifur, R. (2023). UX optimization in digital workplace solutions: AI tools for remote support and user engagement in hybrid environments. *International Journal of Scientific Interdisciplinary Research*, *4*(1), 27-51. https://doi.org/10.63125/33gqpx45
[140]. Zata, M. T. T. (2019). Cost Efficiency in the UK Life Insurance Industry in the post-Global Financial Crisis Period.
[141]. Zheng, H., Xu, B., & Lin, Z. (2019). Seller's creditworthiness in the online service market: A study from the control perspective. *Decision support systems*, *127*, 113118.
[142]. Zhu, L., Qiu, D., Ergu, D., Ying, C., & Liu, K. (2019). A study on predicting loan default based on the random forest algorithm. *Procedia Computer Science*, *162*, 503-513.