CHALLENGING INDONESIA'S FINANCIAL LITERACY NARRATIVE: THE ROLE OF BEHAVIORAL BIAS IN ACQUIRING ONLINE LOAN AND BUY-NOW PAY-LATER (BNPL) SERVICES

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Abstract
The rapid growth of online loans and Buy-Now Pay-Later (BNPL) services in Indonesia requires a deeper understanding of the factors driving consumer borrowing decisions beyond traditional financial knowledge. This study investigates the influence of two key behavioral biases: overconfidence and anchoring bias, on individuals' decisions to engage with digital lending platforms. Focusing on a sample of 258 middle- to lower-income individuals in the Greater Jakarta area in Indonesia, the research employed Partial Least Squares Structural Equation Modeling (PLS-SEM) on cross-sectional, self-reported survey data to empirically test the relative association of these biases and financial literacy with the decision to use online loans/BNPL. The results demonstrate that all three factors are statistically significant predictors of the decision to use online loans/BNPL services. Anchoring bias was found to have the most substantial and significant effect, indicating that borrowers' decisions are strongly influenced by initial numeric cues, such as introductory rates or pre-filled loan amounts. Both overconfidence bias and financial literacy also show significant, though comparatively smaller, influence. These findings challenge the conventional narrative that financial knowledge alone is sufficient for responsible financial behavior, suggesting that within this sample, anchoring bias is more strongly associated with digital lending decisions than financial literacy. The study concludes by encouraging a paradigm shift in consumer protection and financial education, recommending targeted programs that prioritise psychological awareness and behavioral interventions to mitigate biases, and to promote a holistic approach to financial well-being.

Keywords
Anchoring bias, Buy-Now Pay-Later (BNPL), Digital lending, Financial literacy, Online loans, Overconfidence bias, SEM-PLS

JEL Classification
G40, I31, M40, R28

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Introduction

Indonesia's digital revolution has rapidly reshaped its financial landscape, with digital lending, especially online loans and Buy-Now Pay-Later (BNPL) services, emerging as solutions for unbanked and underbanked populations. The country's young, tech-savvy population, combined with increasing smartphone and internet penetration, has created fertile ground for fintech growth (Gerrans et al., 2022; Klapper et al., 2025; Novika & Septivani, 2022). Online loans are appealing due to fast access, minimal requirements, and convenience. Likewise, BNPL has surged in popularity through integration with e-commerce platforms like Shopee and Tokopedia, with fintech players such as Kredivo and Akulaku leading the market (Gerrans et al., 2022; Serenade et al., 2024; Susanto et al., 2024). However, this convenience has brought challenges, such as predatory lending, regulatory gaps, and debt traps (Hardayu et al., 2024; Hidayat & Sari, 2022; Novika & Septivani, 2022; Susanto et al., 2024). The problem of risky and excessive borrowing persists even among individuals with moderate to high financial literacy, which suggests that knowledge alone is insufficient to prevent consumers from becoming entangled in these digital debt cycles (Ainy et al., 2025; Rahman et al., 2021). This study looks at whether people decide to use online loans/BNPL, not at whether they borrow irresponsibly. How that credit is used afterwards is a separate question. Existing research on digital borrowing has largely centered on financial literacy and information gaps, while the roles of overconfidence and anchoring in the decision to use online loans and BNPL have been less examined in Indonesia. This study addresses that gap by comparing how strongly these two biases and financial literacy are associated with the decision to use these services among users in Greater Jakarta. This study highlights that financial literacy may not be the only factor that influences decision-making in online loans and BNPL services, but also considers the influence of non-traditional factors such as behavioral biases (Leković, 2020; Muñoz-Murillo et al., 2020; Pitthan & De Witte, 2025). Behavioral biases, particularly overconfidence and anchoring bias, may further complicate borrowing decisions (Aprilianti et al., 2023; Czerwonka, 2017). This study investigates how these behavioral biases influence decisions related to online loans/BNPL among middle- to lower-income individuals in Greater Jakarta. The research will contribute to policymaking and financial education strategies that address psychological as well as informational gaps.

1. Review of the Scientific Literature

- **Online Loans and Buy-Now Pay-Later (BNPL) in Indonesia**

Online loans are increasingly becoming an alternative solution for meeting people's needs. The Indonesian *Otoritas Jasa Keuangan* (OJK) or Financial Services Authority Fintech Lending Statistics showed that at the beginning of 2021, online loans distributed to the public were around IDR 159 trillion. However, by May 2021, the cumulative value had surged significantly to around IDR 207 trillion (OJK, 2024), which suggests that online loans are reaching a growing share of the public. The main advantage of online loans lies in the ease of access through technology and the straightforward requirements, unlike those of general banking, which is attractive for unbanked individuals (Hardayu et al., 2024).

Figure no. 1 shows the outstanding active personal online loans in terms of ownership based on gender, and it shows that in July 2023, there was a slight increase in the total active personal loans. From the latest data in March 2024, the outstanding active personal online loans consisted of 16,818,754 individuals, with 48% owned by men and 51% owned by women (OJK, 2024).

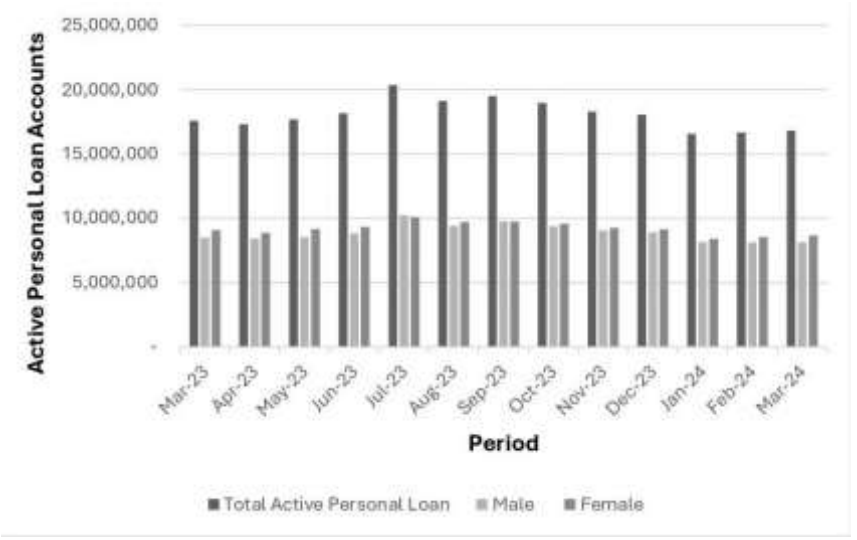


Figure no. 1: Outstanding Active Personal Online Loans Based on Gender (March 2023-March 2024)
Source: Otoritas Jasa Keuangan (2024)

Based on the age group of borrowers (Figure no. 2), online loans are most frequently accessed by the younger and productive age group. Fig. 2 shows that 55% of borrowers are in the age group of 19-34 years and 40% in the age group of 35-54 years (OJK, 2024c). Fig. 2 also indicates that these two age groups (19-34 years and 35-54 years), being in their productive years, frequently need financial flexibility to support their small businesses, lifestyle, or educational needs (Huda et al., 2024). By offering rapid processing and relaxed eligibility criteria, online loans have become a popular alternative to traditional banking (Hardayu et al., 2024; Hidayati et al., 2024). Yet, this accessibility is a double-edged sword: high interest rates and short repayment windows frequently trap borrowers in cycles of default. Most dangerously, illegal platforms often engage in data theft, using personal information to fuel coercive and aggressive debt collection tactics (Anggraini & Wiraguna, 2025; Putri & Rinaldi, 2023).

One of the key factors influencing the adoption of online lending in Indonesia is the issue of financial inclusion (Davis et al., 2017; Hidayat & Sari, 2022). The low levels of formal financial account ownership, saving, and borrowing from traditional institutions have created a significant gap that online lenders have sought to address (Hidayat & Sari,

2022). The lack of access to conventional financial services and the demand for alternative borrowing options have driven the growth of financial technology, especially online lending platforms (Davis et al., 2017; Uthaileang & Kiattisin, 2023). The rapid increase in online loans/BNPL has led to concerns about the need for strong regulations to safeguard consumers from excessive borrowing and to maintain financial stability (Novika & Septivani, 2022).

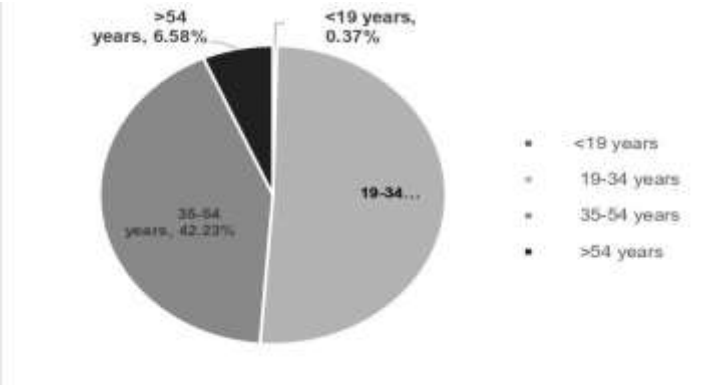


Figure no. 2: Outstanding Online Loans Based on Age Group (March 2023–March 2024)
Source: Otoritas Jasa Keuangan (2024)

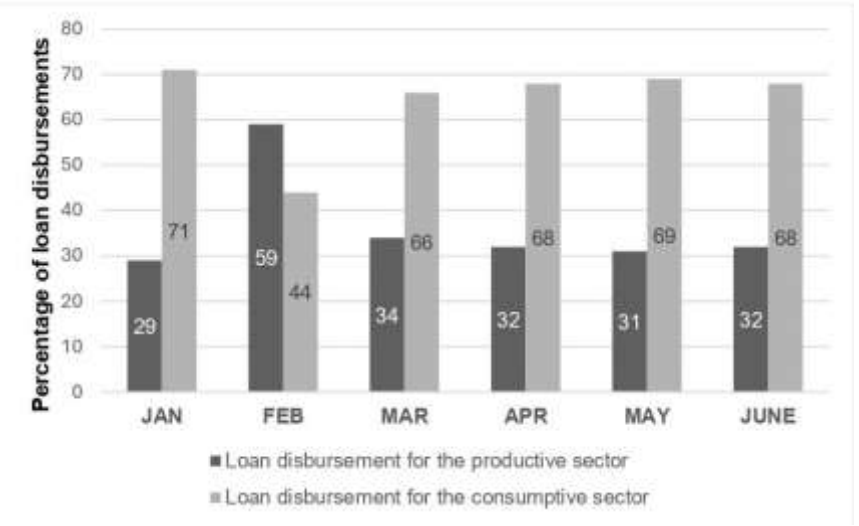


Figure no. 3: Trends in Online Loan Disbursement (January-June 2024)
Source: Otoritas Jasa Keuangan (2024)

Figure no. 3 shows a higher percentage for loan disbursement to consumptive sector compared to the productive sector during the first semester of 2024. This trend could be caused by a number of things, including the desire for lifestyle fulfillment, the rising cost of living as a result of inflation, or even the increasing popularity of online gambling (Juita et al., 2023; Serenade et al., 2024). Borrowers who use online loans/BNPL without adequate financial literacy can risk becoming stuck in a debt cycle that is hard to break (Rahman et al., 2021). Moreover, due to an increase in spending on lifestyle items, the younger generation is taking over consumer-focused financing (Juita et al., 2023). Many young people have turned to online loans/BNPL as a short-term fix because they want to be fashionable, own the newest technology, be able to gamble online, or look good (Ainy et al., 2025). However, they frequently do not take their long-term repayment capacity into consideration.

The consumer-driven spending on lifestyle, gambling, and the immediate availability of online loans and BNPL services exploits psychological vulnerability and, in the end, leads to debt cycles (Rahman et al., 2021). Individuals are led to believe that debt is temporary and easily manageable, a psychological error that makes them susceptible to financial decisions that do not result in optimal outcomes and exposes them to financial vulnerabilities (Juita et al., 2023; Susanto et al., 2024).

- **The Anchoring Trap**

Behavioral biases are systematic mistakes in thought that impact our ability to judge and make decisions. These psychological biases are natural to humans and can result in illogical and poor decision-making (Agrawal, 2012; Barrafrem et al., 2020). People often make financial decisions based on biases rather than facts due to limited time and mental capacity to process all available information (Afriani & Halmawati, 2019; Pompian, 2021). Various researchers have tried to classify these biases into various types. Comprehending behavioral biases is crucial, particularly in domains like finance where financial success is largely determined by decision-making (Wang, 2023). According to Wang (2023), evaluating possibilities, balancing risks and rewards, and making decisions based on facts at hand are all part of the process of making financial decisions. On the other hand, behavioral biases have the power to influence this process, producing erroneous conclusions and prejudiced assessments (Afriani & Halmawati, 2019; Agrawal, 2012; Hendricks, 2018; Kumar et al., 2022).

Anchoring bias is a process where people are influenced by specific information given before a judgment (Furnham & Boo, 2011). Anchoring bias, a documented behavioral bias, leads individuals to overemphasise the initial information (anchor) when making judgments, even if irrelevant (Kahneman et al., 1982; Wang, 2023). Anchoring bias is a significant behavioral bias that has been thoroughly researched in relation to financial decision-making (Jia, 2024; Wang, 2023). In the context of digital lending, the anchor often influences the perceived value, necessity, or affordability of the loan. When making financial decisions regarding digital lending, the first piece of information borrowers see can unfairly influence their decision-making due to anchoring bias. It could lead to pitfalls, such as fixating on introductory rates, ignoring repayment details, and making misguided comparisons (Kahneman et al., 1982; Pompian, 2021; Schulz, 2023). Online

lenders usually advertise low introductory rates, and someone with anchoring bias might get stuck on this initial number, ignoring other information, e.g., higher long-term interest rates. Anchoring bias would give the impression that borrowers receive a good deal based on the first number without considering the total loan cost (Owusu & Laryea, 2023). The advertised loan amount itself can also become an anchor (Czerwonka, 2017; Furnham & Boo, 2011). Borrowers might focus solely on getting the needed amount, overlooking the repayment schedule and how it might strain their budget (Czerwonka, 2017; Furnham & Boo, 2011). Anchoring bias can also come from past experiences or external comparisons. For example, comparing an online loan offer to a credit card interest rate would cause borrowers to miss key differences in fees and repayment structures.

- **The Overconfidence Effect**

Overconfidence bias is a behavioral bias where people overestimate their knowledge or abilities (Russo & Schoemaker, 1992). Overconfidence bias describes a situation where individuals hold an inflated view of their abilities and knowledge (Tunved & Byfält, 2024). Overconfidence bias manifests in several ways. Individuals might believe they are more skilled or knowledgeable than they truly are, leading them to underestimate the capabilities of others. Additionally, overconfidence can cause misjudgment of the difficulty or complexity of a task (Kudryavtsev & Cohen, 2011; Russo & Schoemaker, 1992; Tunved & Byfält, 2024). These misperceptions often have negative consequences. Overconfident individuals underestimate risks and overestimate their abilities, leading to poor decision-making and unrealistic goals (Czerwonka, 2017; Tunved & Byfält, 2024). Overconfidence bias can significantly influence online borrowing decisions, leading to potentially risky choices (Afriani & Halmawati, 2019; Rafinda et al., 2025). Individuals with overconfidence bias overestimate their financial capabilities, such as income stability or future earning potential (Rafinda et al., 2025). This results in borrowing more than they can comfortably afford, assuming repayment will be easy. Borrowers might believe they can repay quickly or overlook hidden fees due to a false sense of control (Rafinda et al., 2025). Overconfidence bias can obstruct critical thinking during the online loan application process, potentially leading to rushed decisions without a full understanding of the loan terms, potential risks, and their true capacity for repayment (Rafinda et al., 2025).

- **The Power of Financial Literacy**

Financial literacy has been shown to play a crucial role in shaping an individual's ability to make informed financial decisions (Lusardi & Mitchell, 2014). Financial literacy can greatly influence how people borrow money online by giving them the necessary understanding to make informed decisions (Uthaileang & Kiattisin, 2023). Having a good understanding of money can help people evaluate loan terms more carefully. Individuals with good financial knowledge should be better at assessing loan conditions, understanding how much they need to repay, and resisting the temptation to accept the first loan offer or overestimate their income (Lusardi & Mitchell, 2014; Sekita et al.,

2022). Financial literacy helps people make smarter choices when borrowing online (Sekita et al., 2022; Tunved & Byfält, 2024; Uthaileang & Kiattisin, 2023). Financially literate individuals can better understand the terminology and structures associated with online loans/BNPL and empower individuals with better decision-making skills (Rosyidah & Pratikto, 2022). Financial literacy can also help mitigate the influence of behavioral biases like overconfidence and anchoring bias (Widyakto et al., 2022). However, online loans/BNPL decisions are highly susceptible to behavioral biases such as overconfidence and anchoring bias, which can bypass rational thinking (Czerwonka, 2017; Muñoz-Murillo et al., 2020; Pitthan & De Witte, 2025). While individuals with good financial knowledge should be better at resisting these behavioral biases, existing literature and real-world outcomes demonstrate that these biases can weaken the protective role of financial literacy (Muñoz-Murillo et al., 2020; Novika & Septivani, 2022; Pitthan & De Witte, 2025; Putri & Rinaldi, 2023). By overestimating their future income or becoming fixated on initial low-rate anchors, consumers can make subjective loan decisions that challenge their objective understanding of the risks (Sekita et al., 2022; Tunved & Byfält, 2024). The evidence points to a two-sided relationship: financial and digital literacy can help people access and choose fintech products, but literacy or fintech adoption alone does not ensure safer borrowing or better financial outcomes (Dewi et al., 2026; Klapper et al., 2025; OECD, 2025; Yahya et al., 2025). In a survey of digital-loan borrowers, financial knowledge was linked to decisions about using digital financial products, which in turn related to planning and management behaviors (Dewi et al., 2026). Financial literacy is best understood as one part of responsible-use capacity and not a stand-alone safeguard (Yahya et al., 2025). A 2025 OECD policy brief similarly frames short-term online credit and BNPL as potentially useful for smoothing temporary income shortfalls, while warning of over-indebtedness and impulsive buying and identifying digital financial literacy as support for safer use (OECD, 2025). The available studies vary substantially in design and setting, and most do not establish that literacy training itself reduces borrowing harms. Therefore, this study compares how behavioral biases and financial literacy are associated with the decision to use online loans/BNPL, without examining risky borrowing behavior.

- **Research Gap and Research Objectives**

The literature outlines the growing adoption of online loans and BNPL as accessible financial tools in Indonesia. While online loans offer ease of access, they also bring risks, especially when used for consumptive rather than productive purposes. The research objectives for this study are: (1) to profile borrowers who use online loans and BNPL services and to assess how overconfidence bias and anchoring bias influence borrowing tendencies, and (2) to generate insights on financial literacy and borrowing behavior based on the presence of behavioral biases.

The novelty of the research lies in its direct challenge to standard financial education models by shifting the focus from simple information gaps to deep psychological traps. While traditional research and current narratives mistakenly assume that a lack of basic financial literacy is the sole reason people fall into digital debt, this study fills a major research gap by empirically examining the overlooked roles of anchoring and

overconfidence biases within digital lending contexts. By demonstrating how these two cognitive biases impact critical stages of the digital borrowing process, the study positions financial literacy alongside cognitive biases as correlates of the decision to use digital credit. Current narratives often overlook these psychological dimensions, focusing only on informational deficits. This study proposes to fill that gap by empirically examining how these biases shape borrower behavior in digital contexts.

2. Research methodology

This study used a quantitative approach using causal-explanatory research, aiming to understand cause-effect relationships between behavioral biases, financial literacy, and borrowing decision-making, particularly for online loans and BNPL services. Since the data collection involves human participants, the research has obtained clearance from the institution's Research and Community Development Unit through an ethical approval letter.

Data were collected from June 1 to August 31, 2025, using a structured questionnaire distributed online via Google Forms. The questionnaire consists of: (1) socio-demographic information, (2) behavioral bias scales (for overconfidence and anchoring), (3) financial literacy, (4) online loan/BNPL usage behavior.

Table no.1. Operational Definition

Variable	Operational Definition	Indicators	Scale	Source
Overconfidence bias (X1)	Respondents' self-rated certainty in their ability to manage borrowing and repayment; higher scores mean stronger overconfidence	OB1–OB4, OB6–OB8	5-point Likert scale	(Afriani & Halmawati, 2019; Costa et al., 2025; Jain et al., 2022; Kahneman et al., 1982; Pertiwi & Panuntun, 2023; Pompian, 2012; Russo & Schoemaker, 1992; Tunved & Byfält, 2024)
Anchoring bias (X2)	Extent to which respondents rely on the first loan amount, limit or monthly instalment offered; higher scores mean stronger anchoring	AB1–AB6	5-point Likert scale	(Barrafrem et al., 2020; Owusu & Laryea, 2023; Wang, 2023; Yahya et al., 2025)

Financial literacy (X3)	Self-rated understanding of / score on a knowledge test about interest, fees, instalments and repayment; higher scores mean higher literacy	FL1–FL5	5-point Likert scale	(Lusardi et al., 2017; Lusardi & Mitchell, 2014; Prado et al., 2022)
Online loan/BNPL decision-making (Y)	Respondents' propensity to use these services among active users; it does not measure risky or irresponsible borrowing	OLDM1–OLDM5	5-point Likert scale	(Pitthan & De Witte, 2025; Rosyidah & Pratikto, 2022; Wang, 2023)

Source: Author's conceptualization

The research uses Partial Least Squares Structural Equation Modeling (PLS-SEM) for data analysis. PLS-SEM was chosen because the study is prediction-oriented, comparing the relative strength of behavioral biases and financial literacy and assessing explanatory (R^2) and predictive (PLSpredict) power, and because theory in this context is still developing (Hair et al., 2019, 2022; Shmueli et al., 2019). It also does not require normally distributed data, and the sample of 258 exceeds the minimum of 77 needed for a medium effect with three predictors using G*Power (Faul et al., 2009). The sample was selected and defined based on the criteria as follows:

a. Target population: Middle- to lower-income individuals living within the Greater Jakarta area (Jakarta, Bogor, Depok, Tangerang, and Bekasi). Respondents were recruited through purposive and convenience sampling with a non-probability approach, since no sampling frame of online loans/BNPL users is publicly available.
b. Screening criteria: To qualify for the final sample, respondents had to be active users of online loans or Buy-Now Pay-Later (BNPL) services and fall within the productive age range of 19 to 54 years old. Participation was voluntary with informed consent, and screening questions were used to confirm that respondents met the criteria. The questionnaire link was distributed via WhatsApp groups, social media and community networks across Greater Jakarta between June 1 and August 31, 2025.
c. Final sample size: Out of 265 total responses collected via Google Forms, 6 did not meet the criteria. This resulted in a final valid sample of 258 respondents used for the PLS-SEM analysis.

To systematically examine the behavioral factors that influence digital borrowing through online loans/BNPL, this study establishes a conceptual framework that links behavioral

biases and financial literacy directly to consumer choice (Czerwonka, 2017; Muñoz-Murillo et al., 2020; Pitthan & De Witte, 2025). The conceptual framework isolates overconfidence bias (X_1) and anchoring bias (X_2) as two primary factors that influence objective decision-making in the context of digital borrowing. Simultaneously, financial literacy (X_3) is integrated alongside these behavioral biases to evaluate its association with the decision to use online loans/BNPL. The framework provides a visual pathway between the independent variables and the digital borrowing decision (Y), which is illustrated in Fig. 4 below.

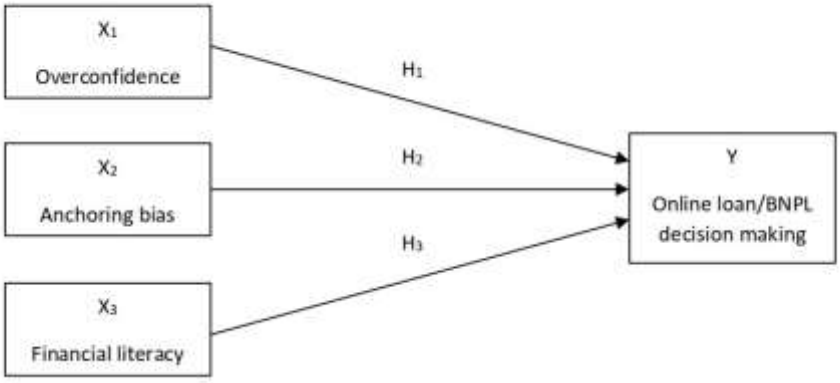


Figure no. 4: Conceptual framework
Source: Author's conceptualization

The conceptual framework in Figure no. 4 explains that overconfident borrowers often overestimate their future earning potential and income stability when it comes to digital lending. During the digital application process, this cognitive distortion impairs critical thinking, leading consumers to sign up for multiple online loans/BNPL services at once or accept greater loan amounts under the mistaken belief that payback will be simple. Consequently, the following first hypothesis is proposed:

H_1: Overconfidence bias (X_1) has a positive and significant effect on online loan/BNPL decision-making.

On the other hand, anchoring bias causes borrowers to become fixated on these initial figures, which gives them a false sense of affordability and causes them to overlook complex fee structures, overall long-term borrowing expenses, or their true ability to repay. As a result, people are influenced by superficial numerical cues to accept offers without careful evaluation.

Thus, the second hypothesis is proposed:

H_2: Anchoring bias (X_2) has a positive and significant effect on online loan/BNPL decision-making.

Theoretically, having a solid grasp of financial principles should enable people to make the best financial decisions and safely navigate online financing possibilities. The third hypothesis is proposed to investigate whether objective financial information and

borrowing decisions are directly related in this behavioral context: Financial literacy is hypothesized to have a positive effect on the decision to use online loans/BNPL for three reasons. First, knowledge makes digital credit easier to understand and use: people who understand loan terms, fees, and repayment schedules face less uncertainty when applying, and financial and digital financial literacy are associated with greater adoption of fintech services, including online loans (literature). Second, literacy builds confidence in one's own ability to manage credit, and perceptions of one's financial competence shape financial decisions and can encourage engagement with financial products (literature). Third, evidence on online loans/BNPL shows that individuals with higher literacy are more likely to use these services (literature). This hypothesis therefore concerns whether individuals use digital credit, not how prudently they use it. The protective role of financial literacy relates to the quality of use, such as prudent borrowing decisions (literature), which this model does not test.

Accordingly, the third hypothesis is proposed:

H_3: Financial literacy (X_3) has a positive and significant effect on online loan/BNPL decision-making.

3. Results and discussion

- **Socio-Demographic Profile of Respondents**

The demographic profile establishes the social and economic context of the study by analyzing the characteristics of the 258 valid respondents who met the strict inclusion criteria, presented in Table no. 2. Table 2 indicates a sample that is predominantly female (62%) and heavily dominated by young adults, with 46% of participants aged between 26 and 30 years and another 22% aged 21 to 25 years. Thus it indicates that the sample is dominated by young adults, a demographic typically associated with active economic participation and increased technology usage, potentially relevant to their engagement with financial services like BNPL or online lending.

Academically, the vast majority have completed senior high school (59.69%), followed by a substantial portion holding a bachelor's degree (28.68%). Geographically, the sample is entirely concentrated within the Greater Jakarta metropolitan area (Jabodetabek), with the single largest group residing in Jakarta itself (45.35%). Financially, the respondents primary fall into the lower-middle to middle-income bracket, with 42.64% earning between Rp 2,000,001 and Rp 5,000,000 per month and a corresponding 22.48% allocating Rp 2,000,001 to Rp 3,000,000 toward monthly expenses. These figures suggest that while income and expenditures are generally balanced, there is limited financial flexibility for a substantial portion of the sample. Overall, the demographic profile indicates that the participants are predominantly young, female, moderately educated, urban-based individuals with modest incomes and expenditures, providing valuable context for interpreting the findings of the study.

Table no. 2. Socio-Demographic Profile of Respondents

Attribute	Characteristic	Frequency	Percentage
Gender	Male	98	38
	Female	160	62

Age	Below 21 years old	6	2
	21-25 years old	56	22
	26-30 years old	119	46
	31-35 years old	58	22
	Above 35 years old	19	7
Education	Junior high school	5	1.94
	Senior high school	154	59.69
	Diploma (D1/D2/D3/D4)	23	8.91
	Bachelor (S1)	74	28.68
	Graduate (S2/S3)	2	0.78
Domicile	Jakarta	117	45.35
	Bekasi	50	19.38
	Tangerang	41	15.89
	Bogor	28	10.85
	Depok	22	8.53
Income	Below Rp500.000	11	4.26
	Rp 500.000 - Rp 2.000.000	48	18.60
	Rp 2.000.001 - Rp 5.000.000	110	42.64
	Rp 5.000.001 - Rp 10.000.000	81	31.40
	Above Rp 10.000.000	8	3.10
Monthly expenses	Below Rp500.000	12	4.65
	Rp 500.000 - Rp 1.000.000	27	10.47
	Rp 1.000.001 - Rp 2.000.000	49	18.99
	Rp 2.000.001 - Rp 3.000.000	58	22.48
	Rp 3.000.001 - Rp 4.000.000	37	14.34
	Rp 4.000.001 - Rp 5.000.000	54	20.93
	Above Rp 5.000.000	21	8.14

Source: Smart PLS v. 4, 2025.

- **Measurement Model of the Study**

The data analysis was conducted using SmartPLS version 4 with a total sample size of 258 respondents. This analysis employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach to evaluate the relationships between the constructs: overconfidence bias, anchoring bias, financial literacy, and online loan/BNPL decision-making. In the measurement model assessment, all indicator items were tested for reliability through outer loadings. Based on Hair et al. (2019, 2022), indicators with loadings below 0.40 were removed, while indicators between 0.40 and 0.70 were retained unless their removal improved composite reliability or AVE above the recommended thresholds or the item was conceptually inconsistent with its construct.

During the evaluation process, most indicators met the criteria. One item from the Overconfidence Bias construct, labeled OB5, was removed due to a factor loading of 0.397.. This item stated: "Confident in having borrowed more than originally planned,

but later struggled to repay." It refers to repayment difficulty after borrowing, an outcome rather than confidence at the time of the decision, and combines two ideas in one statement. Its exclusion therefore does not weaken the construct's conecptual coverage.. Overall, the remaining indicators for each construct: overconfidence bias, anchoring bias, financial literacy, and online loan/BNPL decision making, demonstrated acceptable factor loadings, indicating that the measurement model possesses adequate reliability for further structural analysis.

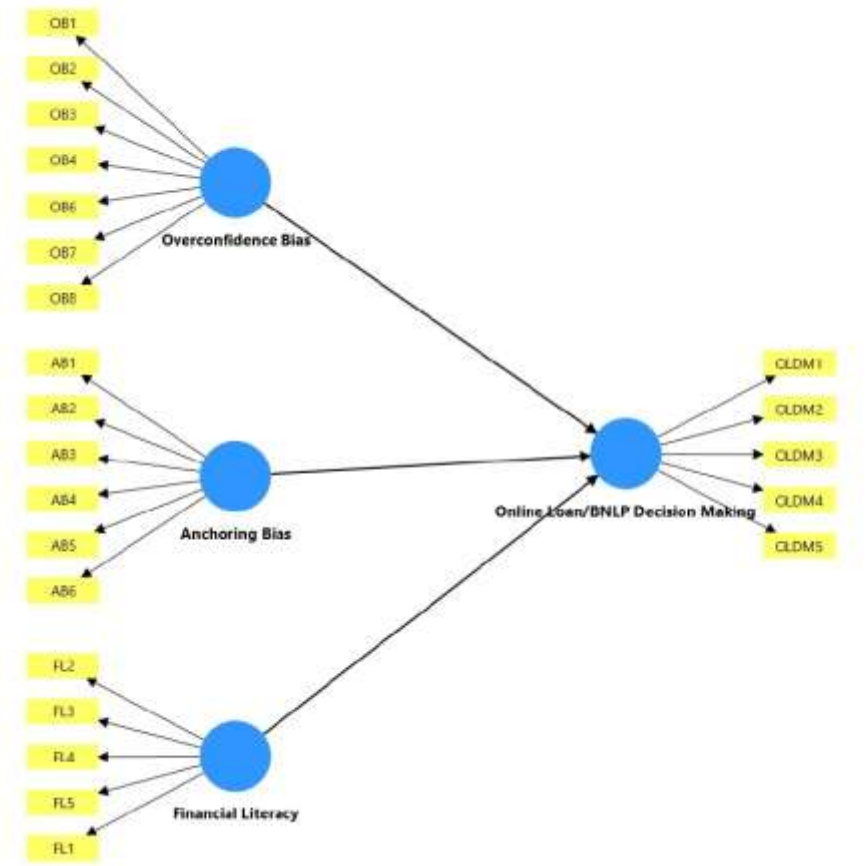


Figure no. 5: Research Model and Factor Loading Results
Source: Smart PLS v. 4, 2025.

Table 3 establishes the structural reliability and convergent validity of the measurement model across its four core constructs: Overconfidence Bias, Anchoring Bias, Financial

Literacy, and Online Loan Decision Making. After removing OB5, the remaining indicators for overconfidence bias, anchoring bias, financial literacy, and online loan/BNPL decision-making showed acceptable outer loadings (Table 3). Most exceed 0.70, while three indicators fall between 0.40 and 0.70 (OB6 = 0.628, OB8 = 0.698, and AB5 = 0.599). These were retained because their removal did not improve composite reliability or AVE, indicating the measurement model has adequate reliability for the structural analysis (Hair et al., 2019, 2022). Furthermore, internal consistency is strongly supported as the Cronbach's Alpha values (0.807 to 0.885) and Composite Reliability (CR) metrics (0.865 to 0.916) comfortably exceed the standard 0.70 benchmark (Hair et al., 2019; Malhotra et al., 2020). Finally, convergent validity is confirmed for all constructs since each Average Variance Extracted (AVE) value is greater than the required 0.50 threshold, ranging from 0.544 for anchoring bias up to 0.685 for financial literacy. These results confirm that the measurement model demonstrates satisfactory reliability and convergent validity across all constructs.

Table no. 3. Factor Loading and Construct Reliability and Validity

Construct	Items	Factor Loading	Cronbach's Alpha	Composite Reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Overconfidence Bias	OB1	0.758	0.867	0.868	0.897	0.557
	OB2	0.787				
	OB3	0.739				
	OB4	0.772				
	OB6	0.628				
	OB7	0.825				
	OB8	0.698				
Anchoring Bias	AB1	0.705	0.83	0.845	0.876	0.544
	AB2	0.741				
	AB3	0.794				
	AB4	0.831				
	AB5	0.599				
	AB6	0.732				
Financial Literacy	FL1	0.818	0.885	0.901	0.916	0.685
	FL2	0.845				
	FL3	0.884				
	FL4	0.847				
	FL5	0.737				
Online Loan/BNPL Decision Making	OLDM 1	0.757	0.807	0.809	0.865	0.563
	OLDM 2	0.736				
	OLDM 3	0.748				
	OLDM 4	0.752				

	OLDM 5	0.757				

Source: Smart PLS v. 4, 2025.

Table no. 4 reports the cross-loading values for all observed indicators, used to assess discriminant validity. According to Hair et al. (2019), each indicator should load higher on its assigned construct than on any other constructs. The results in Table 3 present the cross-loading values used to confirm discriminant validity at the item level. It proves that each survey question measures its intended concept because every single indicator loads higher on its assigned construct than it does on any of the other constructs. These findings affirm that discriminant validity is well established at the item level in the model.

Table no. 4. Discriminant Validity - Cross Loading

Items	Anchoring Bias	Financial Literacy	Online Loan/BNLP Decision Making	Overconfidence Bias
AB1	**0.705**	0.367	0.369	0.339
AB2	**0.741**	0.309	0.331	0.326
AB3	**0.794**	0.284	0.398	0.338
AB4	**0.831**	0.194	0.43	0.261
AB5	**0.599**	-0.119	0.249	-0.003
AB6	**0.732**	0.167	0.385	0.159
FL1	0.274	**0.818**	0.276	0.455
FL2	0.282	**0.845**	0.309	0.444
FL3	0.253	**0.884**	0.352	0.503
FL4	0.235	**0.847**	0.275	0.441
FL5	0.143	**0.737**	0.224	0.436
OB1	0.203	0.474	**0.201**	0.758
OB2	0.222	0.499	**0.278**	0.787
OB3	0.166	0.44	**0.296**	0.739
OB4	0.183	0.524	**0.182**	0.772
OB6	0.357	0.225	**0.272**	0.628
OB7	0.181	0.456	**0.256**	0.825
OB8	0.388	0.3	**0.291**	0.698
OLDM1	0.469	0.175	0.757	**0.245**
OLDM2	0.527	0.095	0.736	**0.118**
OLDM3	0.314	0.414	0.748	**0.359**
OLDM4	0.257	0.343	0.752	**0.307**
OLDM5	0.238	0.326	0.757	**0.31**

Source: Smart PLS v. 4, 2025.

Table no. 5 confirms discriminant validity using the Fornell-Larcker criterion. Every construct meets the requirement because the square root of its AVE (the diagonal value) is higher than its correlations with all other constructs (Fornell & Larcker, 1981; Hair et al., 2017; Kline, 2016), proving that each variable in the model is empirically distinct.

Table no. 5 Discriminant Validity - Fornell-Larcker

	Anchoring Bias	Financial Literacy	Online Loan/BNPL Decision Making	Overconfidence Bias
Anchoring Bias	0.737			
Financial Literacy	0.291	0.828		
Online Loan/BNPL Decision Making	0.496	0.352	0.75	
Overconfidence Bias	0.336	0.551	0.352	0.746

Source: Smart PLS v. 4, 2025.

Finally, the analysis provided guidelines on how to handle discriminant validity issues in variance-based structural equation modeling (Hair et al., 2019; Henseler et al., 2015). Table no. 6 presents the results of HTMT values in this study, which are below the conservative threshold of 0.85, ranging from 0.378 (anchoring bias–financial literacy) to 0.639 (overconfidence bias–financial literacy). These results provide strong evidence of discriminant validity, indicating that each construct is empirically distinct and conceptually sound within the model.

Table no. 6. Discriminant Validity - Heterotrait-Monotrait (HTMT)

	Anchoring Bias	Financial Literacy	Online Loan/BNPL Decision Making	Overconfidence Bias
Anchoring Bias				
Financial Literacy	0.378			
Online Loan/BNPL Decision Making	0.581	0.420		
Overconfidence Bias	0.426	0.639	0.423	

Source: Smart PLS v. 4, 2025.

In table no. 7, the coefficient of determination (R^2) for Online Loan/BNLP Decision was 0.304, with an adjusted R^2 of 0.296, indicating that the predictor variables explain approximately 30.4% of the variance in the dependent construct. As noted by Hair et al. (2019), this value is regarded as a moderate level of explanatory power in PLS-SEM analysis.

Table no. 7. R square (R^2) Results

Construct	R-square	Adjusted R-square	Category
Online Loan/BNPL decision-making	0.304	0.296	Moderate

Source: Smart PLS v. 4, 2025.

Based on the Path Analysis results in Table 8, the relationships between the constructs: anchoring bias, financial literacy, overconfidence bias, and online loan/BNPL decision making were analyzed. Table 8 interprets the path coefficients, statistical significance, and effect sizes from the structural model.

Table no. 8. Path Analysis

Hypothesis		Beta	SE	t-value	p-value	LL-CI	UL-CI	VIF	F-square	Results
H_1	Overconfidence Bias -> Online Loan/BNLP Decision Making	0.124	0.056	2.223	0.026	0.011	0.229	1.508	0.015	Supported
H_2	Anchoring Bias -> Online Loan/BNLP Decision Making	0.406	0.088	4.617	0.000	0.193	0.552	1.148	0.207	Supported
H_3	Financial Literacy -> Online Loan/BNLP Decision Making	0.165	0.076	2.164	0.031	0.02	0.321	1.462	0.027	Supported

Source: Smart PLS v. 4, 2025.

Table 9 shows that this study utilised the PLS prediction methodology, implementing a holdout sample technique to produce case-level predictions at the construct level. The PLS predict was applied with a 10-fold procedure to evaluate predictive relevance. Strong predictive relevance is attained when all item differences (PLS-LM) fall below the predictive relevance threshold, while moderate predictive power is indicated when most item differences are below this threshold. The findings of the study demonstrate that the model shows robust predictive ability. The value of Q2 must also be positive. The analysis revealed that most items showed a negative value across all variables, suggesting a moderate predictive ability of the model (Shmueli et al., 2019).

Table no. 9. PLS Predict

Items	PLS RMSE	LM RMSE	PLS LM	Q^2	Decision
OLDM1	1.134	1.134	0	0.185	Strong predictive
OLDM2	1.095	1.033	0.062	0.174	

OLDM3	0.851	0.873	-0.022	0.169	
OLDM4	0.813	0.838	-0.025	0.107	
OLDM5	0.867	0.918	-0.051	0.089	

Source: Smart PLS v. 4, 2025.

Analysis

H_1: Overconfidence Bias → Online Loan/BNPL Decision Making

The analysis confirms that overconfidence bias significantly increases risky digital borrowing, showing a path coefficient of 0.124 (t = 2.223, p = 0.026). Although its effect size is small (f^2= 0.015), this bias causes individuals to inflate their financial capabilities, underestimate debt risks, and take out larger or multiple loans under the false assumption that future income will cover repayments (Afriani & Halmawati, 2019; Kudryavtsev & Cohen, 2011; Russo & Schoemaker, 1992; Tunved & Byfält, 2024). While its modest impact suggests it likely acts alongside situational factors like social pressure, overconfidence remains a persistent barrier to prudent borrowing, meaning fintech platforms should integrate reflective tools and feedback to help users better calibrate their financial expectations (Hendricks, 2018; Kumar et al., 2022). These findings imply that interventions to reduce overconfidence, such as reflective decision tools or peer comparison feedback, could be integrated into fintech platforms to help users calibrate their financial expectations.

H_2: Anchoring Bias → Online Loan/BNPL Decision Making

The analysis confirms that anchoring bias significantly drives digital borrowing decisions, showing a strong path coefficient of 0.406 (t = 4.617, p < 0.001) and a medium effect size (f^2 = 0.207). This supports the hypothesis that borrowers rely heavily on initial reference points, e.g. pre-filled amounts or low advertised rates (Furnham & Boo, 2011; Kahneman et al., 1982), which distorts rational evaluation and leads to impulsive choices while overlooking hidden fees and total costs. Because app-based promotional tactics easily trigger these heuristics (Jia, 2024; Owusu & Laryea, 2023; Schulz, 2023; Wang, 2023), consumer protection and education must shift from basic transparency to changing how loan information is presented and helping users recognize psychological biases.

This finding resonates with past research indicating that digital borrowing decisions are increasingly shaped by heuristics rather than rational calculation (Agrawal, 2012; Pompian, 2021). Therefore, efforts to improve consumer protection in digital lending should not only focus on transparency but also address how information is presented, as the anchoring effect may skew otherwise rational decisions. Educating users about these biases could empower them to question initial offers and seek more holistic loan evaluations (Jia, 2024).

H_3: Financial Literacy → Online Loan/BNPL Decision Making

The analysis shows that financial literacy has a statistically significant, positive relationship with online loan and BNPL decisions, with a path coefficient of 0.165 (t = 2.164, p = 0.031). While higher financial knowledge helps borrowers better evaluate long-term costs, resist digital marketing, and understand compound interest (Ainy et al., 2025; Lusardi & Mitchell, 2014; Sekita et al., 2022), its small effect size (f^2= 0.027) proves that knowledge alone cannot guarantee responsible borrowing. Ultimately, because

psychological and emotional factors heavily influence financial decisions, education programs must expand beyond basic math to include bias recognition and psychological awareness (Barrafrem et al., 2020; Czerwonka, 2017; Huda et al., 2024; Muñoz-Murillo et al., 2020; Pitthan & De Witte, 2025; Tunved & Byfält, 2024; Uthaileang & Kiattisin, 2023).

Conclusions

This study examines how anchoring bias, overconfidence bias, and financial literacy influence online loan and BNPL choices in Indonesia. The findings challenge the traditional narrative by proving that objective financial literacy alone is not enough to guarantee responsible borrowing, as psychological shortcuts often override rational knowledge in fast-paced digital environments (Barrafrem et al., 2020; Gerrans et al., 2022; Lusardi & Mitchell, 2014).

The empirical results show that anchoring bias has the strongest impact on borrowing behavior, causing individuals to fixate on initial cues like low promotional rates while ignoring long-term debt risks (Furnham & Boo, 2011; Jia, 2024; Kahneman et al., 1982; Owusu & Laryea, 2023; Wang, 2023). Financial literacy and overconfidence bias also play significant roles, though with smaller effects; overconfident borrowers frequently inflate their financial control and take on excessive debt (Afriani & Halmawati, 2019; Davis et al., 2017; Huda et al., 2024; Kudryavtsev & Cohen, 2011; Russo & Schoemaker, 1992; Tunved & Byfält, 2024), while literate users are slightly better equipped to spot risks but can still fall victim to cognitive traps (Lusardi & Mitchell, 2014; Pompian, 2021; Sekita et al., 2022; Uthaileang & Kiattisin, 2023).

However, this study has several limitations. First, the data are cross-sectional, so the findings indicate associations within this sample, not cause and effect. Second, every construct came from the same self-reported questionnaire, and common method bias was not formally tested. Future studies could test for it, for example, with Harman's single-factor test or a full collinearity assessment. Third, respondents were reached through an online questionnaire using a non-probability (convenience) approach and all live in Greater Jakarta, so the results may not apply to other groups or regions. Fourth, the outcome is the decision to use online loans/BNPL, not risky or irresponsible borrowing, so the study cannot show how people handled that credit after taking it. Future research could use longitudinal or experimental designs, probability-based or multi-region samples, and behavioral or administrative borrowing data. It could also add outcome measures that separate use from repayment difficulty or over-indebtedness.

In conclusion, the study suggests that Indonesia's financial education needs to change completely. Although there is little proof of long-term consequences, financial education has been shown to increase financial literacy, and this might be the result of cognitive biases like myopia, which have also been connected to making wrong choices (Pitthan & De Witte, 2025). Educational programs should include "behavioral literacy" to assist people with comprehension and how to fix their cognitive biases, instead of teaching only basic financial knowledge (Muñoz-Murillo et al., 2020; Pitthan & De Witte, 2025). As Muñoz-Murillo et al. (2020) stated, individuals with higher cognitive abilities are more financially literate. While financial knowledge remains important, understanding and managing psychological biases such as overconfidence and anchoring is equally essential

in promoting safe financial behavior (Agrawal, 2012; Ainy et al., 2025; Hendricks, 2018). The study also suggests that regulators should monitor the digital lending apps to ensure that these platforms do not unfairly exploit anchoring bias to encourage excessive indebtedness among vulnerable populations.

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