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Pinjol is a Bad Way to Provide Short-Term Funding for Women Entrepreneurs

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ABSTRACT

This study examines whether *Pinjaman Online (Pinjol)* helps or harms women micro-entrepreneurs in Medan, Indonesia. Using survey data from 302 borrowers, the study employs a two-stage design: Propensity Score Matching (PSM) to estimate the average treatment effect of *Pinjol* use on business outcomes, and Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the behavioral and structural drivers of credit decisions. The findings show that *Pinjol* users experience short-term gains in sales compared to matched non-users; however, high borrowing costs and tight repayment cycles compress margins and weaken overall performance. Financial literacy and risk perception significantly reduce the likelihood of adopting *Pinjol*, while larger loan needs increase it; age and education condition these effects. The results indicate that demand-side factors and liquidity pressures have a more substantial influence on digital credit uptake than price awareness. Theoretically, the study integrates credit rationing and behavioral finance by demonstrating a shift from collateral-based exclusion in formal banking to literacy and risk-awareness constraints in fintech borrowing. Policy implications include transparent cost disclosure, repayment schedules aligned with micro-enterprise cash flows, gender-sensitive financial literacy programs, and pathways from high-cost digital credit to safer, lower-cost financing options.

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1. Introduction

The rapid growth of digital financial services has transformed credit access in emerging markets (Balachandra, 2020; Ongena & Popov, 2016; Servon et al., 2010). Among these innovations, peer-to-peer (P2P) lending has expanded rapidly by offering short-term, collateral-free loans through digital platforms. In Indonesia, this practice is popularly referred to as *Pinjaman Online* (*Pinjol*). *Pinjol* has attracted millions of micro-entrepreneurs, particularly women, who often face significant barriers to accessing traditional credit (Fu, 2017). *Pinjol's* speed and convenience make it appealing (Geiger, 2020), particularly for women in the informal economy (Fu, 2017; Moss & Stine, 1993). Yet this accessibility raises concerns about over-borrowing, financial stress, and long-term vulnerability (Ikram et al., 2016). This paradox raises the question of whether *Pinjol* empowers or exposes women entrepreneurs.

Studies have shown that P2P lending can promote financial inclusion by providing immediate liquidity and bridging gaps left by conventional banking (Lenz, 2016; Turiel & Aste, 2020; Wen et al., 2017). Most studies also highlight the emergence of assessing creditworthiness by reducing human biases and improving access to funding (Sun, 2020; Turiel & Aste, 2020). However, most existing research has concentrated on adoption patterns, default risks, or regulatory challenges, with relatively few focusing on gendered outcomes or the behavioral dimensions of credit use in emerging economies (Fu, 2017; Geiger, 2020). This leaves a gap in understanding how women entrepreneurs, who face persistent barriers to formal credit and financial literacy, experience both the opportunities and risks associated with P2P lending.

In Indonesia, *Pinjol* has become one of the fastest-growing fintech segments, attracting millions of borrowers, including women micro- and small businesses (Indra et al., 2021; Natsir & Ishlah, 2022). Its simplified application process, and the absence of collateral requirements make it appealing to micro-entrepreneurs (Demirguc-Kunt et al., 2017), including those who are often excluded from government credit schemes such as *Kredit Usaha Rakyat* (KUR). Yet this accessibility also comes with significant drawbacks: high cost and limited credit evaluation mechanisms. These features produce a paradox where *Pinjol* simultaneously expands financial access and exacerbates women's vulnerability to financial stress and over-indebtedness (Bucher-Koenen et al., 2017; OJK, 2023a).

P2P lending has advanced financial inclusion globally, but localized adaptations in emerging markets remain underexplored (Darmawan & Prianto, 2021). In Kenya, mobile-based credit services, such as Fuliza and M-Shwari, have disbursed over \$350 million, with default rates of less than 2.2% (Kivuva, 2022). Conversely, India's case illustrates regulatory struggles to protect borrowers, and in Kenya, the impressive adoption has raised criticism due to loan stacking and high defaults (Aracil et al., 2022). In Indonesia, the rapid adoption of *Pinjol* is evidenced by its contribution to 38.39% of the total MSME loans disbursed in 2023, amounting to IDR 19.76 trillion (OJK, 2023a). However, anecdotal evidence from Indonesia shows that women micro-entrepreneurs often struggle with *Pinjol's* short repayment cycles and high daily interest rates (≈0.3%) (OJK, 2023b), leading to financial stress. These comparisons highlight the need for risk mitigation (Bollen & Posavac, 2018; Fehr-Duda et al., 2006), and gender-sensitive approaches in fintech adoption (Bollen & Posavac, 2018; Fehr-Duda et al., 2006).

Despite the rapid growth of *Pinjol*, a growing body of research is also specific to the implications compared to other financing options available to women entrepreneurs, such as microfinance institutions or government-backed schemes. Prior studies emphasize the efficiency and cost-effectiveness of P2P platforms (Sun, 2020; Wen et al., 2017). Past research has rarely examined the effect of such loans on women's financial performance, operational stability, and risk perception. Moreover, the behavioral dynamics of borrowing, which are shaped by financial literacy, cognitive biases, and demographic factors, remain largely overlooked in this context (Amaroh & Istianah, 2020; Kaur & Sahni, 2023). Risk aversion and decision-making dynamics also remain underexplored in *Pinjol* adoption, despite their critical role in shaping borrowing outcomes (Haider Syed et al., 2020; Servon et al., 2010).

While prior studies have extensively documented fintech lending's role in promoting financial inclusion (Aracil et al., 2022; Demirguc-Kunt et al., 2017; Sarma, 2008), a critical gap remains in understanding the behavioral dynamics and financial literacy challenges faced by women entrepreneurs in emerging markets. Existing research has not sufficiently examined how gendered borrowing behaviors, cognitive biases (e.g., overconfidence, present bias), and financial literacy disparities interact with high-cost, short-term fintech products, such as *Pinjol*, which may lead to harmful financial outcomes. This paper examines that gap through the case of women micro-entrepreneurs in Medan city, North Sumatra. While Medan city cannot represent Indonesia as a whole, its urban scale, cultural diversity, and entrepreneurial activity (BPS-Statistics Indonesia, 2023; OJK, 2023a) provide a critical context for analyzing how women adopt P2P loans, and how these platforms both empower and expose them to new financial risks.

Despite the rapid expansion of digital lending in Indonesia, especially among women micro-entrepreneurs, limited empirical work has assessed not only whether *Pinjol* promotes business performance but also how underlying behavioral and structural factors drive its adoption and outcomes. This study addresses these gaps by empirically examining the paradox of *Pinjol*, whether it benefits or harms women micro-entrepreneurs, through three core questions: how *Pinjol* use affects post-loan business outcomes, which behavioral and structural factors shape the decision to adopt it, and whether demographic characteristics influence these relationships.

The originality of the study lies in its quasi-experimental PSM-PLS design, which provides a clearer understanding of the liquidity–vulnerability paradox in women's fintech borrowing. PSM is used to approximate causal inference and estimate the treatment effect of Pinjol adoption on business performance. At the same time, PLS-SEM examines how financial literacy, risk perception, credit cost, and demographics influence borrowing decisions and outcomes, including moderating effects. Medan city offers a relevant urban context for observing these dynamics. Guided by these questions and analytical choices, this study develops a set of hypotheses that form the conceptual model and anchor the empirical analyses, linking behavioral drivers, demographic moderators, and credit decisions to post-loan performance.

2. Literature Review

2-1. Conceptual Background

2-1-1. Credit Rationing Theory

Credit rationing theory (Stiglitz & Weiss, 1981) provides a foundation for understanding why women entrepreneurs are often excluded from formal credit markets. Exclusion occurs not only because financial institutions have limited funds to lend but also because of information asymmetry and concerns about default risk. Borrowers with insufficient collateral or incomplete documentation are more likely to be rejected or offered less favorable loan terms. In Indonesia, these conditions disproportionately affect women micro-entrepreneurs, who frequently operate in the informal sector with limited assets and weaker credit histories (Demirguc-Kunt et al., 2017; Fu, 2017). As a result, many women are pushed toward alternative digital financing sources (Lusardi & Mitchell, 2014), including *Pinjol*. Within this framework, *Pinjol* can be seen as both a response to credit rationing, by lowering entry barriers, and as a new form of exclusion, since higher borrowing costs and shorter repayment cycles offset the absence of collateral requirements. This tension between access and affordability positions credit rationing theory as a central lens for evaluating *Pinjol's* role in women's entrepreneurship.

2-1-2. Behavioral Finance Theory

Behavioral finance theory (Barber & Odean, 1998; Xiao & Porto, 2019) explains how women entrepreneurs make borrowing decisions under conditions of uncertainty. It emphasizes that financial decision behaviors are not purely rational but are shaped by cognitive biases, limited information, and risk perceptions (Kahneman & Tversky, 1979). For women entrepreneurs, low levels of financial literacy may exacerbate present bias (favoring immediate liquidity) and overconfidence in their ability to repay high-cost loans (Bucher-Koenen et al., 2017). In fintech contexts, these biases are amplified by simplified digital interfaces and urgency-driven decision-making environments (Plekhanov et al., 2023).

Financial literacy and risk perception are recognized as crucial factors in entrepreneurial decision-making (Hermansson & Jonsson, 2021; Klapper & Lusardi, 2020), yet there is a limited understanding of how these factors influence the preference for funding sources, particularly among women. Studies often examine the immediate effect of credit on business performance (Atnafu & Balda, 2018; Sardana, 2008). However, little attention has been paid to the broader dilemmas that women entrepreneurs face, such as balancing accessibility with high costs or addressing the psychological toll of debt. Most research on women entrepreneurship and financing is conducted in developed economies or within formal credit systems (Abebe & Kegne, 2023; Bucher-Koenen et al., 2017; Constantinidis et al., 2006; Singh & Dash, 2021). This raises the need to understand the informal lending landscape, including loan sharks (informal loans), and its contextual challenges, especially in emerging markets.

Risk perception is defined as some women may underestimate repayment risks due to optimism about sales, while others may overestimate risks of formal credit due to past rejection or bureaucratic barriers (Hermansson & Jonsson, 2021; Klapper & Lusardi, 2020). These behavioral factors help explain why *Pinjol*, despite high interest rates and short repayment cycles, remains an attractive option for women's microenterprises. Thus, behavioral finance offers a complementary lens to credit rationing, illustrating how decision-making processes and psychological constraints influence the adoption of high-cost fintech credit.

Together, those theories provide a complementary foundation for understanding women’s borrowing behavior in fintech contexts. Credit rationing highlights how institutional and informational constraints prompt women micro-entrepreneurs to seek alternative digital lending options, such as *Pinjol*, while behavioral finance reveals how cognitive biases, limited literacy, and emotional pressures influence borrowing decisions under uncertainty. Integrating these perspectives allows this study to capture both structural exclusion and behavioral vulnerability, offering a comprehensive basis for the hypotheses that follow. This integration also aligns with recent International Journal of Management Studies (IJMS) work that emphasizes the role of financial innovation and women’s entrepreneurial practices in shaping performance (Anggraini et al., 2024), the constraints imposed by loan procedures on women’s empowerment (Noor et al., 2021), and the influence of behavioral biases on credit decision-making (Azouzi & Bacha, 2023).

2-2. Hypothesis Development

The conceptual framework (Figure 1) outlines the theoretical basis for understanding the borrowing behavior of women micro-entrepreneurs. Behavioral finance theory suggests that overconfidence and present bias can influence borrowing decisions, leading women to prioritize immediate liquidity over long-term repayment considerations, which increases the risk of financial stress. However, beyond psychological biases, financial access remains structurally limited. Credit rationing theory argues that fintech does not eliminate access barriers but instead shifts them: from collateral-based exclusions to literacy-based constraints. Building on these theoretical foundations, the model translates the main concepts into measurable constructs:

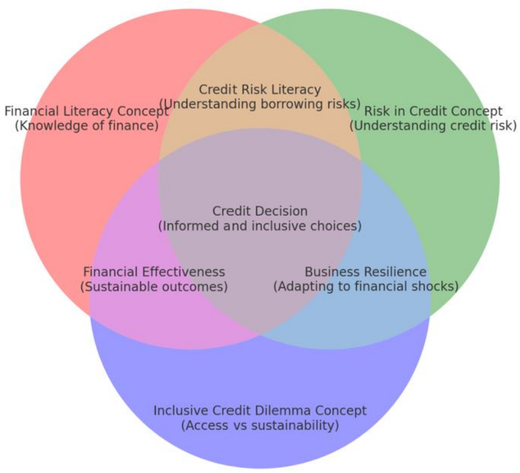

Fig. 1. Conceptual Framework

a) Financial literacy (FL) refers to the ability to understand and evaluate financial information. Low literacy is linked to poor credit choices and over-indebtedness (Bucher-Koenen et al., 2017; Lusardi & Mitchell, 2014). The framework frames FL as a causal factor in whether women perceive *Pinjol* as an opportunity or a risk. Higher FL is expected to reduce the likelihood of adopting *Pinjol*.

b) Risk perception (RP) captures subjective judgments of potential adverse outcomes, such as repayment difficulties (Weber et al., 2002). RP influences the choice between high-cost but accessible loans (*Pinjol*) versus lower-cost but restrictive alternatives, such as bank loans. Higher RP is expected to deter *Pinjol* adoption.

c) Credit cost (CC) includes perceived and actual borrowing costs—interest rates, fees, and repayment cycles (Geiger, 2020; Sun, 2020). Yet *Pinjol* remains attractive because speed and convenience may outweigh cost concerns. Higher perceived cost is generally expected to discourage adoption.

d) Loan amount (LA) represents the total external funds borrowed by the entrepreneur, reflecting the scale of liquidity needs (Indra et al., 2021). Higher loan needs are expected to increase reliance on *Pinjol* due to its speed and efficiency.

e) Demographics (age, education, experience) shape financial decision-making and digital capability (Kaur & Sahni, 2023; Servon et al., 2010). These factors are expected to moderate the effects of FL, RP, CC, and LA on credit decisions.

f) Credit decision (CD) refers to the choice between *Pinjol* and other financing options, such as microfinance institutions, government-backed loans, or informal credit (Darmawan & Prianto, 2021; Poon & Chan, 2008).

g) Business performance (BP) refers to the financial and operational outcomes of entrepreneurial activities, often assessed through sales growth or profitability (Rauch et al., 2009), as well as resilience under financial pressure.

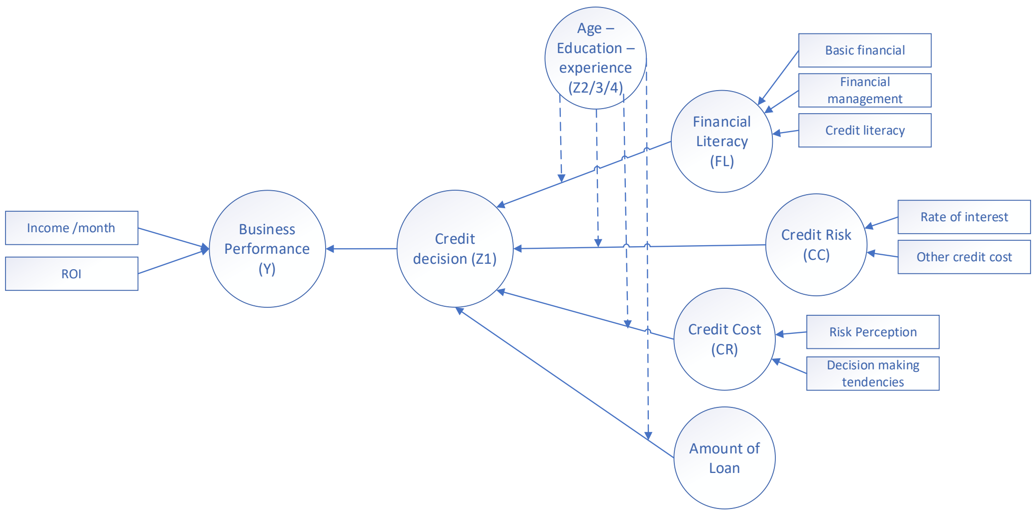

Fig. 2. Model Development

Access to short-term capital is a critical factor in micro-enterprise performance (Mattare et al., 2016; Moss & Stine, 1993). However, the cost and structure of this capital, particularly in the context of fintech platforms like *Pinjol*, can create unique challenges for women entrepreneurs. Grounded in Figure 2, this study proposes the following hypotheses:

H1. *Pinjol* on Business Performance

Credit rationing theory suggests that women micro-entrepreneurs frequently encounter structural barriers in accessing formal credit, making fintech loans a viable alternative for securing short-term liquidity (Demirguc-Kunt et al., 2017; Stiglitz & Weiss, 1981). Liquidity injections from digital credit can support immediate operational needs and improve short-term sales or ROI (Darmawan & Prianto, 2021; Sun, 2020). However, behavioral finance theory suggests that present bias and over-optimism may lead borrowers to underestimate the burden of high interest rates and short repayment cycles, creating financial pressure that offsets short-term gains (Bucher-Koenen et al., 2017; Kahneman & Tversky, 1979). IJMS research has also highlighted how women entrepreneurs' financial decisions influence performance through their interactions with financial innovation and constraints (Anggraini et al., 2024; Noor et al., 2021).

H1: The use of *Pinjol* significantly affects post-loan business performance.

H2. Behavioral and Structural Determinants of Credit Decision

Behavioral finance theory emphasizes that borrowing decisions are shaped by limited financial literacy, subjective risk assessments, and decision biases rather than pure rational evaluation (Barber & Odean, 1998; Klapper & Lusardi, 2020). Women micro-entrepreneurs with lower literacy are more likely to rely on heuristics, focus on immediate cash needs, or underestimate repayment burdens (Hermansson & Jonsson, 2021). Structural factors, such as credit costs and loan size, also play a significant role in determining the outcome. High interest rates and short cycles can either deter borrowing or, paradoxically, increase reliance among liquidity-constrained entrepreneurs (Demirguc-Kunt et al., 2017; Fu, 2017). Empirical studies indicate that both behavioral and structural factors jointly shape digital borrowing decisions in emerging markets (Azouzi & Bacha, 2023).

H2: Financial literacy, risk perception, credit cost, and loan amount significantly influence the credit decisions of women entrepreneurs.

H3. Demographic Moderators in Borrowing Decisions

The influence of financial literacy and risk perception on borrowing decisions varies across entrepreneurs. Behavioral research shows that age, education, and business experience shape how individuals interpret financial information and assess risk (Alsos & Ljunggren, 2017; Fehr-Duda et al., 2006). Younger or more educated borrowers may better understand digital loan terms, evaluate interest rates more effectively, or mitigate decision biases. In comparison, older or less-educated borrowers may rely more heavily on heuristics or emotional cues. IJMS studies similarly emphasize how demographic and empowerment factors condition women's financial decision-making (Noor et al., 2021).

H3: Age, education, and experience moderate the relationships between financial literacy, risk perception, credit cost, loan amount, and credit decision.

H4. Credit Decision and Business Performance

Credit Rationing Theory suggests that entrepreneurs' choice of credit source determines the suitability and sustainability of financing for their business context (Stiglitz & Weiss, 1981). When women choose high-cost financing such as Pinjol, the infusion of capital may improve short-term business metrics, but repayment obligations can erode margins and increase vulnerability (Ikram et al., 2016; OJK, 2023). Behavioral Finance Theory adds that decisions made under bias or urgency may lead to suboptimal credit choices, influencing how effectively borrowed funds enhance ROI or sales (Klapper & Lusardi, 2020). Evidence from IJMS indicates that financial decision-making patterns among women entrepreneurs significantly influence performance outcomes (Anggraini et al., 2024).

H4: Credit decision significantly influences post-loan business performance.

3. Research Methods

This study is grounded in a post-positivist paradigm, which assumes an external reality that can be approximated with empirical indicators while acknowledging measurement error and contextual complexity (Creswell & Creswell, 2022; Phillips & Burbules, 2000). This stance aligns with the study's methodological design, which employs quantitative approaches and reflects a commitment to causal explanation and empirical rigor. The study deploys abductive reasoning (Mingers & Brocklesby, 1997), combining field research with experimental and survey methods to understand real-world financial behavior. It allows the study to move iteratively between theory and data, consistent with the post-positivist emphasis on approximation and refinement.

3-1. Research Design

This study employed a novel methodological approach, a quasi-experimental design that integrated propensity score matching (PSM) to approximate causal inference by reducing selection bias between borrowers who use *Pinjol* and those who rely on alternative credit sources (e.g., microfinance institutions, government-backed lenders, or informal lenders), and provides a framework to approximate experimental conditions by balancing observed covariates across groups (Austin, 2009). Then, it was combined with partial least squares structural equation modeling (PLS-SEM) to analyze the structural relationships of *Pinjol* on business outcomes among women micro-entrepreneurs. After matching, the study applied PLS-SEM to test the relationships.

This two-stage design, which combines the causal identification strengths of PSM with the predictive and structural modeling strengths of PLS-SEM, represents a robust approach for simultaneously addressing causal and behavioral dimensions. PSM helps control for observable selection bias, approximating the conditions of an experimental design when randomization is not feasible (Austin, 2009; Rosenbaum & Rubin, 1983). Meanwhile, PLS-SEM captures the structural relationships among latent constructs, enabling simultaneous estimation of measurement validity and path strength (Shmueli et al., 2019). Together, these techniques enhance both internal and external validity, allowing the study to identify whether observed behavioral factors translate into measurable performance outcomes.

3-2. Sampling and Data Collection

The empirical setting was Medan city (North Sumatra, Indonesia). Diverse cultures and religions, as well as rapid fintech adoption, characterized Medan city (BPS-Statistics Indonesia, 2023; OJK, 2023a). While not representative of Indonesia as a whole, Medan city offers a critical case for exploring women's experiences with high-cost, short-term fintech loans. The chosen sample reflects both the social and economic diversity of Indonesia's urban informal sector. This focus ensures the findings remain contextually grounded within a rapidly digitizing, yet financially constrained, setting. By selecting data that faces both credit exclusion and fintech exposure, the study directly addresses the paradox of financial inclusion versus vulnerability, a phenomenon highlighted in previous regional studies (Darmawan & Prianto, 2021; Fu, 2017). This context-sensitive sampling strengthens the interpretive relevance of the results.

A purposive sampling strategy was employed to target women micro-entrepreneurs who had accessed external financing within the past two years, complemented by cluster sampling to ensure representation across various areas in Medan city. The minimum sample size was determined using the Lemeshow formula with a 90% confidence level and 10% margin of error (Tinungki, 2010). In total, 302 valid responses were collected: 151 Pinjol users (treatment group) and 151 non-Pinjol users (control group).

Data collection was conducted using closed-format questionnaires and structured interviews. The questionnaires assessed variables related to short-term capital and business performance that were developed in three stages: first stage, item adaptation from validated scales (Lusardi & Mitchell, 2014; Weber et al., 2002). Second, expert review with academics and practitioners who have competencies in fintech (Marliyah et al., 2023). The last step involved deploying pilot testing with 15 women entrepreneurs in Medan city, followed by minor revisions for clarity.

3-3. Measures and Indicators

The key constructs were operationalized using validated items from prior studies. Financial literacy (FL) was measured using three reflective indicators that assessed basic financial understanding, credit literacy, and financial management skills (Bucher-Koenen et al., 2017; Klapper & Lusardi, 2020). Risk perception (RP) was measured through two reflective indicators capturing perceived repayment risk and decision tendencies under financial pressure (Sitkin & Pablo, 1992; Weber et al., 2002).

Credit cost (CC) was operationalized as a composite construct that combines self-reported perceived cost (index), combined with actual loan terms (interest, fees, repayment cycle) (Beck et al., 2018; Geiger, 2020). The loan amount (LA) was treated as a continuous variable in Indonesian Rupiah (Indra et al., 2021).

Demographics (age, education, experience) were included as exogenous moderators, consistent with prior studies on gender-sensitive financial behavior (Kaur & Sahni, 2023; Servon et al., 2010). Credit decision (CD) was measured as a binary variable indicating whether the respondent adopted Pinjol (Sun, 2020). Business performance (BP) was measured using objective indicators of financial outcomes: return on investment (ROI) and sales growth (Klapper & Lusardi, 2020; Santos & Brito, 2012).

Reliability and validity were assessed through Cronbach's α, composite reliability (CR), and average variance extracted (AVE) for convergent validity (Creswell & Creswell, 2022; Neuman, 2014), and the HTMT ratio for discriminant validity (Henseler et al., 2015), using established guidelines for PLS-SEM (Shmueli et al., 2019).

3-4. Method of Analysis

The combined use of propensity score matching (PSM) and partial least squares structural equation modeling (PLS-SEM) reflects the dual objectives of this study. Together, these methods strike a balance between the need for causal inference and the need to understand latent mechanisms.

(a) Propensity Score Matching (PSM)

PSM has been widely used in microfinance studies; its application in fintech gender-based lending research remains limited. PSM was deployed to reduce confounding from non-random treatment assignment (Rosenbaum & Rubin, 1983). PSM addresses causal identification by reducing observable selection bias between *Pinjol* users and comparable non-users (Austin, 2009; Rosenbaum & Rubin, 1983), to estimate the treatment effect of *Pinjol* adoption on women's business outcomes under the Rubin causal model.

The first step is the propensity score estimation. A logistic regression model predicted *Pinjol* use through the following covariates: age, education, business experience, business size, loan amount, and credit cost. The second step involves a matching algorithm using kernel matching (bandwidth 0.06) with common support enforced. Third, using balance diagnostics, assessments are made with standardized mean differences (SMD), variance ratios, and pseudo-R^2. Following Austin (2009), SMD < 0.1 was taken as evidence of adequate balance. Diagnostics showed covariates were well-balanced after matching. The final step is estimating the treatment effect**.** The average treatment effect on the treated (ATT) was calculated for ROI and sales growth, with bootstrapped standard errors to reduce bias.

(b) Partial Least Squares Structural Equation Modeling (PLS-SEM)

Following PSM, PLS-SEM was conducted to analyze latent constructs and structural relationships (Hair et al., 2017; Shmueli et al., 2019), the mechanisms underlying loan choice and outcomes. This method was chosen because it is appropriate for exploratory models with multiple latent constructs. It performs well with small to moderate sample sizes and non-normal data. It emphasizes prediction and mechanism testing, aligning with our research goals.

In PLS-SEM, the study analyzes the measurement model, confirming indicator reliability (loadings > 0.70), construct reliability (α and CR > 0.70), convergent validity (AVE > 0.50), and discriminant validity (HTMT < 0.85). The structural model, which was employed by bootstrapping with 5,000 samples, yielded path coefficients, t-values, and confidence intervals. Model fit was assessed using SRMR (<0.08) and NFI (>0.90). The moderating effects of education, age, and business experience were tested to capture heterogeneity among borrowers (Hair et al., 2017; Shmueli et al., 2019).

Integrating PSM and PLS-SEM provides a two-stage validation of results, reducing endogeneity and then exploring structural relationships among latent constructs. This sequential logic allows the study to move beyond simple correlations and examine mediated and moderated pathways. The approach aligns with recent empirical recommendations for behavioral finance research in emerging markets, where quasi-experimental data structures and complex interactions frequently occur (Hair et al., 2021; Shmueli et al., 2019).

3-5. Ethical Considerations

This study followed established ethical guidelines for behavioral research (Creswell & Creswell, 2022; Neuman, 2014). All participants were informed about the study's purpose, their voluntary involvement, and their right to withdraw at any point without penalty, in accordance with the principles of respect for persons outlined in the Belmont Report. Written informed consent was obtained before the collection of data. To ensure confidentiality, no identifying information was collected, and all responses were anonymized and securely stored for research use only.

4. Results and Analysis

4-1. Descriptive

The minimum number of samples obtained from the Lemeshow formula (with an error degree of 10%) is 203. The samples obtained were 302 samples with a distribution of 2 sub-district samples (there are 151 sub-districts in Medan city). The summarized data are presented in Table 1.

Table 1 summarizes the sample. Most respondents are in the productive age group, which mirrors Indonesia's broader population structure (BPS-Statistics Indonesia, 2023). The sample's business experience also supports data reliability, as most companies have been in operation for more than five years. Monthly sales figures indicate that the businesses in this study are essentially microenterprises (Republik Indonesia, 2021).

Table 1. Sample Description

No	Age (years)	Experience	Sales /month (In million rupiah/month)	
1	< 21 = 20%	< 1 year = 5%	<10 = 33%	*Pinjol* user = 50%
2	21-30 = 41%	1-2 years =16%	10-20 = 56%	Others = 50%
3	31-35 = 22%	2-3 years =16%	21-30 = 5%	
4	36-40 = 11%	4-5 years = 13%	31-40 = 3%	
5	> 40 = 6%	> 5 years = 51%	>40 = 1%	

(Source: Processed data, 2024)

Table 2. Tests of Normality

Kolmogorov-Smirnov[a]	Statistic	df	Sig.
Business performance	.038	302	.120
a. Lilliefors Significance Correction			

(Source: Processed data, 2024)

With a sig value greater than α (0.05) and a statistical value smaller than the Lilliefors significance correction (0.051), it can be concluded that the data are normally distributed.

Table 3. Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Business performance	Based on the Mean	.008	1	300	.930

(Source: Processed data, 2024)

With a significance value greater than α (0.05), the data can be considered homogeneous. The diagnostics point to approximate normality and homogeneity, supporting the use of the planned analyses.

Baseline differences between *Pinjol* users and non-users show that adoption is systematically linked to borrower characteristics. This aligns with Lusardi and Mitchell (2014), who find that financial literacy and income jointly shape credit-seeking behavior. The younger age and higher education of adopters suggest that access is not the main barrier; instead, risk tolerance and digital familiarity appear to drive early participation (Fehr-Duda et al., 2006).

4-2. PSM Results

PSM builds upon earlier studies on Pinjol use for short-term capital needs (Darmawan & Prianto, 2021; Putu, 2022), its effects on financial management (Musdalifa et al., 2021), and the intention to use it (Apriliana et al., 2023; Indra et al., 2021). It is also built based on prior work on loan impacts (Moss & Stine, 1993; Servon et al., 2010). In the baseline comparability stage, financial literacy (FL), risk perception (RP), credit cost (CC), and loan amount serve as covariates that must be balanced between the treatment and control groups. These predictors are assessed with t-tests or standardized mean differences (SMDs) before matching, and then used to form balanced groups through PSM.

$$\text{SMD} = \frac{\bar{X}_T - \bar{X}_C}{\sqrt{\frac{1}{2}\left(\sigma_T^2 - \sigma_C^2\right)}} \tag{1}$$

where:

a) $\bar{X}_T$ = mean of the treated group (*Pinjol* users),

b) $\bar{X}_C$= mean of the control group (other credit users),
c) σ_T^2 = variance of the treated group,
d) σ_C^2= variance of the control group.

The denominator is the pooled standard deviation across the two groups, where the balance is generally acceptable when the absolute SMD is below 0.1 (Austin, 2009).

Table 4. SMD Result

Variable	SMD (Before Matching)	SMD (After Matching)
FL	-0.153	-0.010
CR	-0.111	-0.015
CC	3.654	0.065
Loan_Amount	-0.458	-0.020

(Source: Processed data, 2024)

After kernel matching, balance improved across all covariates, with most SMDs falling within the acceptable range (|SMD| below 0.10). This indicates that the treatment and control groups are comparable after matching. Table 4 shows that FL, CR, and CC achieved an acceptable balance, making the dataset suitable for estimating treatment effects without significant confounding from baseline differences.

Table 5. Treatment Effect Results

Outcome Variable	Mean (Treatment)	Mean (Control)	T-statistic	P-value
Post_ROI	36.77	30.34	5.46	1.889E-07
Post_Sales	17963322.19	16184983.18	2.97	0.0035

(Source: Processed data, 2024)

Table 5 presents the treatment effects for Post_ROI and Post_Sales, revealing significant differences between the treatment and control groups following kernel matching. The treatment group performs better, indicating a positive effect of the intervention. The mean values confirm this pattern, with the treatment group displaying higher averages, higher medians, and a wider range of outcomes.

Table 6. Treatment Effect per Group

Subgroup Variable	Subgroup	Mean (Treatment)	Mean (Control)	T-statistic	P-value
Age_Group	Old	36.774	42.166	-3.542	0.0005
Age_Group	Young	36.766	30.324	3.032	0.0044
Experience_Group	More Experienced	36.705	39.054	-1.133	0.2602
Experience_Group	Less Experienced	37.022	30.327	2.812	0.0084
Education_Group	Low Education	36.723	30.342	4.852	0.00003

(Source: Processed data, 2024)

There was no significant difference between the treatment and control groups in the more experienced group. In contrast, within the younger groups and the less experienced group, the treatment group showed significantly higher Post_ROI. In the low-education group, the treatment group also performed significantly better. The ATT results for the kernel-matched dataset are as follows:

$$\mathrm{ATT} = \frac{1}{N_T} \sum_{i \in Treated} \left(Y_i - \hat{Y}_i \right) \tag{2}$$

where:

a) N_T = the total number of treated group (*Pinjol* users),
b) Y_i= the observed outcome (e.g., ROI or sales growth) for the treated individual i,
c) $\hat{Y}_i$= the counterfactual outcome for the same individual, estimated from the matched non-treated observation(s) with similar propensity scores,
d) Y_i-$\hat{Y}_i$= the difference between the actual performance of a treated unit and its estimated performance had it not received treatment.

Table 7. ATT Result

Outcome	ATT
Post_ROI	3.51
Post_Sales	1775.34

(Source: Processed data, 2024)

The ATT Post_ROI = 3.51 and Post_Sales = 1,775.34 indicate that the treatment group experienced a significant average increase in ROI and sales compared to the synthetic control group, supporting H1. These results show that the intervention (*Pinjol* use) is positively associated with both ROI and sales performance, as reflected in Tables 5 and 7.

Table 8. Interaction Result

Moderator	Interaction Term	P-value	Effect Size (Coefficient)
Age	Treatment: Age	< 0.0001	-1.696
Experience	Treatment: Experience	1.36E-163	-2.542
Education	Treatment: Education	2.38E-203	20.869

(Source: Processed data, 2024)

Table 8 shows that the interaction terms for treatment × age and treatment × experience are negatively significant, indicating that older and more experienced individuals gain less from the treatment. In contrast, the treatment × education interaction is positively significant, suggesting more substantial effects for individuals with higher education. Education and experience, therefore, moderate the link between credit decisions and ROI.

The PSM results indicate that *Pinjol* users experience a short-term rise in ROI and sales. This improvement should be interpreted cautiously, since it occurs alongside increased repayment pressure. This is consistent with Ikram et al. (2016) that short-term gains in microcredit often conceal long-term financial stress. Therefore, while *Pinjol* expands access, its cost structure can undermine sustained growth if not supported by effective financial management.

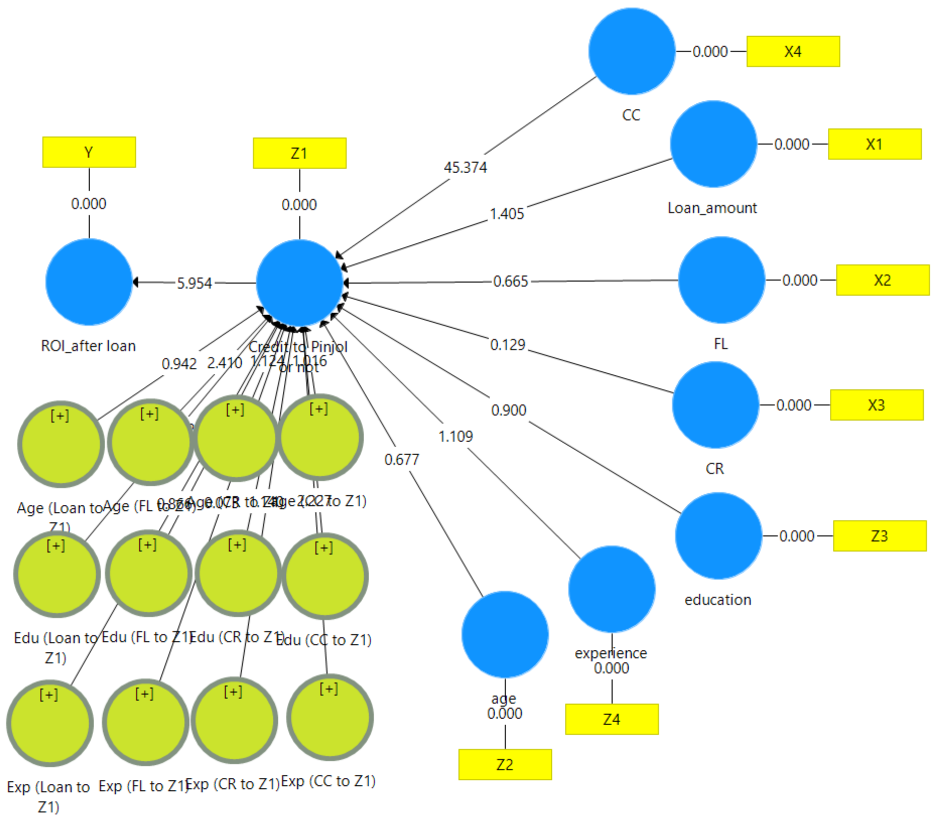

Fig. 3. PLS-SEM Result

4-2. PLS-SEM Results

The model then ran with PLS-SEM with the resulting R-squared of 0.781 (with the dependent variable being credit decision), which indicates substantial explanatory power for most social science and economic studies, suggesting that FL – CR – CC – LA and other mediating variables (age-experience-education) can predict the credit decision (whether to use *Pinjol* or not) well.

Table 9. Model-Specific Indirect Effect

Specific Indirect Effect	T Statistics	P Values
Age (FL to Z1) -> Credit decision (CD)-> ROI_after loan	2.244	0.025
Credit cost (CC) -> Credit Decision (CD)-> ROI_after loan	5.964	0.000
Edu (CR to Z1) -> Credit decision (CD)-> ROI_after loan	2.142	0.033
Exp (CC to Z1) -> Credit decision (CD)-> ROI_after loan	2.066	0.039

(Source: Processed data, 2024)

Based on Table 9, age (moderating FL → CD) indirectly affects ROI after the loan by influencing the credit decision, which in turn, affects ROI. Credit cost (CC) has also a significant effect on CD, and CD has a strong influence on post_loan ROI, indicating that CC plays a central role in determining ROI through its effects on credit choices. Education (moderating CR → CD) also indirectly influences ROI, likely by enhancing risk awareness, which in turn affects CD. Experience (moderating CC → CD) suggests that greater experience may improve the understanding of credit inclusion, particularly regarding credit costs, which influence the credit decision and ultimately affect ROI after the loan.

Table 10. Model Total Effect

Total Effect	T Statistics	P Values
Age (FL to Z1) -> Credit decision (CD)	2.410	0.016
Credit cost (CC) -> Credit decision (CD)	45.374	0.000
Credit decision (CD) -> ROI_after loan	5.954	0.000
Edu (CR to Z1) -> Credit decision (CD)	2.349	0.019
Exp (CC to Z1) -> Credit decision (CD)	2.227	0.026

(Source: Processed data, 2024)

Table 10 reinforces the findings in Table 9. Credit cost (CC) has the most substantial effect (T = 45.374) on whether someone chooses *Pinjol* or another credit source. This supports the model in Figure 2, which suggests that CC captures the credit inclusion dilemma women face when seeking short-term capital. The PLS-SEM results (Figure 3; Tables 9 and 10) show that financial literacy (FL) ($p < 0.05$), risk perception (RP) ($p < 0.05$), and credit cost (CC) have a marginal negative association ($p < 0.1$) with *Pinjol* adoption. The loan amount (LA) has a positive effect on *Pinjol* adoption ($p < 0.05$), supporting H2.

Table 8 shows strong moderating effects: education moderates the link between financial literacy and credit decision ($\beta = 20.86$), and age moderates the link between risk perception and credit decision. Experience does not significantly moderate any of the tested relationships ($p > 0.1$), thereby partially supporting H3. The total effects in Table 10 indicate that credit decisions have a significant influence on post-loan performance (T = 5.95), supporting H4 and confirming that the credit source matters for financial outcomes. Women who use *Pinjol* show short-term gains in liquidity but struggle to sustain ROI, while those using alternative credit sources report more stable results.

The PLS-SEM results offer a clearer view of the behavioral mechanisms. The effects of financial literacy and risk perception align with behavioral finance theory, highlighting that cognitive awareness has a more substantial influence on borrowing quality than income or collateral. The moderating roles of age and education show that demographic factors shape risk-taking, consistent with Fehr-Duda et al. (2006). The positive but fragile link between credit decision and business performance reflects a behavioral trade-off: short-term empowerment through liquidity versus vulnerability created by repayment burdens.

4-3. Model Evaluation

Table 11 summarizes the key PLS-SEM evaluation indicators. The R^2 value of 0.781 indicates substantial explanatory power. Among the predictors, credit cost (CC) has the most significant effect on the credit decision. The model also confirms the significance of demographic and behavioral predictors. Overall, the model exhibits a good fit with a GoF index above medium threshold standards (Tenenhaus et al., 2005), with SRMR < 0.08 and NFI > 0.90 indicating acceptable model fit (Henseler et al., 2015).

Table 11. PLS-SEM Model Evaluation Summary

Model Component	Metric	Estimated Model
Credit decision	R^2	0.781
	R^2 Adjusted	0.767
ROI after loan	R^2	0.098
	R^2 Adjusted	0.095
Model fit	SRMR	0.037
	d_ULS	0.060
	d_G	0.014
	Chi-Square	21.408
	NFI	0.959

(Source: Processed data, 2024)

5. Discussion

This study investigated the paradox of *Pinjaman Online* (*Pinjol*) as a short-term financing mechanism for women entrepreneurs in Indonesia, drawing on credit rationing theory (Stiglitz & Weiss, 1981) and behavioral finance theory (Barberis & Thaler, 2003; Kahneman & Tversky, 1979). The study evaluated the effects of *Pinjol* adoption, identified the behavioral and structural determinants of borrowing decisions, and assessed how demographic factors condition these relationships. The findings reveal both expected and nuanced patterns in how women entrepreneurs navigate digital credit markets.

5-1. *Pinjol* on Business Performance (H1)

The PSM results show that *Pinjol* adoption is significantly associated with higher sales and modest improvements in ROI. Sales benefits appear to stem from the immediate liquidity that stabilizes inventory purchases and ensures operational continuity, in line with evidence that digital credit can facilitate short-term cash flow smoothing (Darmawan & Prianto, 2021; Sun, 2020). However, ROI gains are weaker and more volatile, reflecting the strain imposed by high daily interest rates and rapid repayment schedules (Geiger, 2020).

This dual outcome reflects the classic tension described in credit rationing theory: women excluded from formal loans often accept high-cost credit to keep their businesses running, even if it compromises long-term returns (Stiglitz & Weiss, 1981). Behavioral finance further explains this pattern through present bias and liquidity preference, which drive borrowers to prioritize immediate relief over long-term financial efficiency (Fehr-Duda et al., 2006). The evidence suggests that while Pinjol provides short-term operational benefits, those gains are fragile and can erode profitability under repayment pressure. This finding reinforces the liquidity–vulnerability paradox that characterizes high-cost digital credit markets.

5-2. Determinants of Credit Decision (H2)

Financial literacy and risk perception emerge as significant deterrents to the adoption of *Pinjol*. Highly literate borrowers tend to avoid high-cost credit, consistent with prior work showing that knowledge reduces susceptibility to risky or suboptimal borrowing (Bucher-Koenen et al., 2017; Lusardi & Mitchell, 2011). Likewise, greater perceived repayment risk lowers willingness to adopt fintech loans, supporting Weber et al., (2002), who argue that risk perception governs borrowing behavior under uncertainty. These results highlight that behavioral factors, not only structural constraints, strongly influence credit choices.

Credit cost, however, exerts only a weak effect. Although high costs typically discourage borrowing (Beck et al., 2018; Geiger, 2020), many women still choose *Pinjol*, suggesting that urgency and convenience override price sensitivity. This aligns with evidence that digital credit users in emerging markets prioritize ease and speed over interest considerations (Aracil et al., 2022). The loan amount significantly increases the likelihood of adopting *Pinjol*, indicating that larger short-term financial needs prompt women to opt for faster but more expensive credit, echoing prior findings that liquidity pressures lead borrowers to seek digital microloans (Indra et al., 2021).

The international comparison supports this pattern: Kenya's M-Shwari and India's digital lending platforms show similar issues, where high-cost digital credit expands access but also elevates default risk and debt stress (Kaffenberger et al., 2018; Malladi et al., 2021). These dynamics are particularly pronounced among borrowers with weaker financial literacy, who may underestimate repayment risks or misjudge interest accrual (Leyeza et al., 2023; Saputra et al., 2020).

Overall, these results suggest that demand-side capacities (financial literacy, risk perception) are more influential than cost-awareness in shaping borrowing decisions. Liquidity urgency (loan size) remains a decisive structural driver, underscoring the need for interventions that simultaneously address knowledge gaps and short-term financial pressures.

5-3. Moderating Effects of Demographics (H3)

Demographic moderators reveal substantial heterogeneity in borrowing choices. Age strengthens the adverse effect of risk perception on *Pinjol* adoption, consistent with life-cycle theories of risk aversion, where older individuals display more conservative financial behavior (Fehr-Duda et al., 2006). Education enhances the influence of financial literacy on borrowing decisions, indicating that human capital improves financial judgment and reduces the likelihood of adopting high-cost loans (Kaur & Sahni, 2023; Servon et al., 2010).

In contrast, entrepreneurial experience does not significantly moderate credit decisions. This aligns with recent fintech research suggesting that platform use depends more on digital literacy and formal education than on years of business operation (Turiel & Aste, 2020). The implication is that educational attainment and age are far more consequential than entrepreneurial tenure in shaping how women evaluate high-cost digital loans. Policy interventions targeting financial literacy among younger and less educated entrepreneurs may therefore produce the most significant improvements in credit outcomes.

5-4. Credit Decision and Business Performance (H4)

The type of credit chosen has a substantial effect on post-loan performance. Women relying on *Pinjol* report short-term liquidity benefits but greater vulnerability to repayment stress, whereas those accessing microfinance or government-backed loans achieve more consistent and sustainable returns. This aligns with findings that the *structure* of credit: cost, repayment cycle, and flexibility, matters as much as access in determining long-term business sustainability (Lenz, 2016; Sun, 2020).

The results highlight a dual effect: *Pinjol* temporarily boosts financial performance but elevates financial stress for women entrepreneurs (Alsos & Ljunggren, 2017; Expósito et al., 2023). High borrowing costs and limited borrower protections make it less suitable for long-term financial resilience. Financial literacy emerges as a critical factor for navigating this trade-off, influencing risk management and borrowing outcomes (Achugamonu et al., 2020; Kartawinata et al., 2021).

This underscores that expanding credit access alone is insufficient. Effective borrower protection frameworks, transparent interest disclosures, and digital financial literacy initiatives are essential to prevent unsustainable debt cycles. Fintech platforms and regulators must collaborate to design gender-responsive lending models that enhance both access and financial well-being

5-5. Theoretical Contributions

This study's resulting theoretical contribution advances three main theoretical insights. First, it integrates credit rationing theory and behavioral finance theory, showing that structural exclusion drives women toward *Pinjol*, while behavioral characteristics determine which women adopt it. This combined perspective highlights that both institutional barriers and cognitive factors shape digital credit use in underserved populations.

Second, the findings refine rational borrower models by showing that cost-sensitivity is weaker than expected in high-cost digital credit markets, while urgency, literacy, and risk perception are more decisive. This nuances traditional assumptions in credit rationing and extends behavioral finance insights on present bias, overconfidence, and risk misperception (Barber & Odean, 1998; Kahneman & Tversky, 1979).

Third, the moderating effects of age and education extend gendered borrowing models by demonstrating how demographic heterogeneity conditions fintech adoption. Experience plays a limited role, suggesting that digital financial capability, rather than entrepreneurial tenure, drives decision-making in modern credit environments.

Overall, the findings deepen the behavioral finance perspective by showing how knowledge gaps heighten women's vulnerability to high-cost credit, confirming Kahneman and Tversky's (1979) argument that limited cognitive capacity leads to suboptimal financial choices. The results also reinforce risk perception theory (Rousseau et al., 1998), highlights that education and financial experience shape borrowers' ability to evaluate risk and anticipate long-term outcomes (Ediagbonya & Tioluwani, 2023). Overconfidence bias (Barber & Odean, 1998; ul Abdin et al., 2022) encourages borrowers to overestimate their repayment capacity, while present bias (Xiao & Porto, 2019) drives a preference for immediate liquidity even when future costs are high. Together, these psychological tendencies increase the likelihood of choosing high-cost fintech loans despite their long-term burden (Ediagbonya & Tioluwani, 2023).

At the same time, the findings support credit rationing theory, showing that women continue to face barriers in formal financial systems due to information asymmetry and the absence of collateral. These structural constraints push them toward digital alternatives such as *Pinjol*, consistent with broader financial inclusion debates emphasizing how fintech expands access but may also reproduce new forms of vulnerability (Beck et al., 2007, 2018).

5-6. Practical and Policy Implications

The findings carry several practical and policy implications, highlighting the interplay between accessibility and sustainability in emerging financial ecosystems (Simba et al., 2023). Although *Pinjol* provides rapid liquidity, its high cost and tight repayment cycles threaten long-term financial stability, underscoring the need for stronger borrower protection. Regulators should require more transparent disclosure of effective interest rates and standardized cost presentations so borrowers can more easily understand the actual price of credit.

Repayment schedules also need to be adjusted to align with the cash flow patterns of microenterprises, thereby reducing the likelihood of liquidity stress. In parallel, gender-sensitive financial capability programs are crucial, particularly for younger and less educated women who are more vulnerable to risky borrowing. Practical training, such as that delivered through community groups or mobile learning, should focus on comparing loan costs, understanding repayment planning, and recognizing the characteristics of predatory lending.

Beyond education, bridging mechanisms are needed to help responsible *Pinjol* users transition to safer credit options, such as government-backed or cooperative loans, using repayment histories as a basis for credit scoring. Fintech platforms also carry a responsibility, such as implementing affordability checks, early-warning systems for repeated borrowing, and safeguards against revolving debt to prevent borrowers from entering distress cycles. For practitioners, integrating simple credit-choice counselling into business mentoring can support women in using short-term liquidity more productively. Together, these measures strengthen both access and sustainability, ensuring that digital credit contributes to empowerment rather than financial vulnerability.

5-7. Limitations and Future Research

The study has several limitations. First, it relies on cross-sectional data; although PSM reduces observable selection bias, unobserved factors may remain. Second, the case study focuses on Medan city, which limits generalization to other Indonesian regions with different digital credit ecosystems. Third, performance outcomes, such as ROI and sales, were measured over a short post-loan period, which limited the ability to detect medium- or long-term effects.

Future research should adopt longitudinal designs to track debt cycles, arrears, and long-term resilience. Cross-regional comparisons will help understand variation in fintech practices and borrower vulnerability. Experiments, such as financial literacy nudges or redesigned credit disclosures, could directly test behavioural interventions aimed at improving borrowing decisions.

6. Conclusion

This study demonstrates that both behavioral and structural factors influence the adoption of short-term digital credit (*Pinjol*) among women micro-entrepreneurs. Financial literacy and risk perception significantly reduce the likelihood of using *Pinjol*, while larger loan needs increase reliance on it. Age and education further condition these relationships. Using PSM, the analysis shows that *Pinjol* users experience short-term improvements in sales and ROI compared to similar non-users. However, high borrowing costs and tight repayment schedules compress margins, introducing financial stress and limiting longer-term sustainability. The PLS-SEM results confirm that the type of credit selected, rather than merely access to credit, also plays a decisive role in shaping post-loan business performance.

The findings contribute to two key theoretical domains. First, they extend behavioral finance by illustrating how present-biased preferences, limited literacy, and risk perceptions interact to influence digital borrowing choices in vulnerable segments. Second, they refine credit rationing theory by showing that exclusion is not removed in fintech markets but transformed: formal collateral barriers are replaced by literacy-based and information-based gaps. Incorporating demographic moderators highlights how age and education create heterogeneous borrowing pathways and outcomes among women micro-entrepreneurs, enriching gender-aware perspectives on credit behavior.

From a practical and policy standpoint, the results point to the need for borrower protection and responsible product design. Fintech platforms should present effective interest rates transparently, adjust repayment schedules to match micro-enterprise cash flows, and integrate simple financial-literacy support at the point of borrowing. Regulators can strengthen these measures by implementing pricing safeguards and creating pathways from high-cost digital loans to more affordable options, such as government-backed loans or microfinance. While the study provides important insights, its cross-sectional design and single-city focus limit the generalizability of its findings. Future work should employ longitudinal data, incorporate measures of financial stress and arrears, and investigate how interface features and loan presentation shape borrower decisions. Such advances will help ensure that digital credit supports, rather than undermines, women’s entrepreneurial resilience.

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