Journal of Economics and Management
2026, Vol. 4, No. 3, 701-718
https://doi.org/10.70716/ecoma.v4i3.581

Predicting Predatory Lending Vulnerability among Female Industrial Workers: Digital Financial Literacy, Financial Stress, Self-Efficacy, and Peer Influence

Etty Sri Wahyuni[1]*, Mercy Reyne Marlina Tirayoh[2], Nolla Puspita Dewi[3], Nurhatisyah[4]
[1] Bachelor in Management, Universitas Batam, Indonesia
[2] Bachelor in Accounting, Universitas Batam, Indonesia
[3,4] Doctoral Program in Human Resource Management, Universitas Batam, Indonesia

*Corresponding Author: ettywahyunie@gmail.com

Received: 04/01/2026 | Revised: 12/01/2026 | Accepted: 14/07/2026 | Published: 16/07/2026

Abstract: This study examines the predictive roles of digital financial literacy (DFL), financial stress (FS), financial self-efficacy (FSE), and peer influence (PI) on predatory-lending vulnerability (PLV) among female industrial workers — a structurally exposed yet under-studied demographic in Indonesia's digital-credit ecosystem, where 6,991 illegal lending platforms were blocked between 2022 and 2024. A cross-sectional explanatory survey was administered to 378 female workers in three Batam integrated industrial estates using validated instruments (OECD/INFE DFL; Prawitz IFDFW; Lown FSES). Data were analyzed through PLS-SEM (SmartPLS 4) with bootstrapping (5,000 resamples), following STROBE reporting guidelines. All four hypotheses were supported ($p < .001$). The model explained 52.4% of the variance in PLV ($Q^2 = .342$). Financial stress was the strongest predictor ($\beta = +.342$), followed by peer influence ($\beta = +.276$), digital financial literacy ($\beta = -.218$), and financial self-efficacy ($\beta = -.187$), confirming a push–pull risk architecture. The single-region cross-sectional design limits causal inference and external validity; self-reported use of illegal lenders likely understates the true prevalence due to social desirability bias. The findings apply primarily to feminized manufacturing labor in Southeast Asian export zones. Originality – This is the first integrated PLS-SEM model testing cognitive, affective, psychological, and social predictors of predatory-lending vulnerability among Indonesian female industrial workers, advancing gender-sensitive financial-vulnerability research and offering rank-ordered evidence for OJK Regulation No. 11/2024 demand-side interventions aligned with SDG 5 and SDG 8.

Keywords: *Predatory Lending, Digital Financial Literacy, Financial Stress, Financial Self-Efficacy, Peer Influence*

How to Cite: Wahyuni, E. S., Tirayoh, M. R. M., Dewi, N. P., & Nurhatisyah (2026). Predicting Predatory Lending Vulnerability among Female Industrial Workers: Digital Financial Literacy, Financial Stress, Self-Efficacy, and Peer Influence. *Journal of Economics and Management, 4*(3), 701–718. https://doi.org/10.70716/ecoma.v4i3.581

INTRODUCTION

The rapid digitalization of Indonesia's financial services sector has expanded credit access for low-income groups. However, it has also triggered a surge in predatory lending practices that disproportionately burden financially fragile populations. Predatory lending is generally defined as loan arrangements characterizedcharacterized by deceptive marketing, exorbitant interest rates, opaque fees, and aggressive collection techniques that exploit borrowers' financial desperation (Ali et al., 2023; Sukarno et al., 2024). In the Indonesian context, this phenomenon is most visible through illegal peer-to-peer (P2P) lending platforms — locally known as pinjol ilegal — and informal door-to-door lenders such as Bank Emok and Bank Berjanji, where monthly interest rates can reach 20%, far exceeding the 1.75% monthly cap on credit cards set by Bank Indonesia (Yulius, 2023; OJK, 2024).

Between January 2022 and January 2024, the Indonesian Financial Services Authority (Otoritas Jasa Keuangan, OJK), through the Investment Alert Task Force, blocked 6,991 illegal online lending platforms — a number that continues to climb as new operators rebrand or shift servers across jurisdictions (OJK, 2024; Mahatma & Sari, 2026). The 2024 National Survey of Financial Literacy and Inclusion (SNLIK) reports a national financial literacy index of 65.43% and an inclusion index of 75.02%; however, only 12.6% of Indonesians actively engage in financial planning, signaling a critical knowledge–behavior gap (OJK & BPS, 2024; Siswanti et al., 2024). Wahyuni et al. (2024) further note that the Indonesian financial-literacy landscape exhibits a pronounced urban–rural divide and an intergenerational gap, rendering lower-income occupational groups particularly susceptible to exploitative digital credit. Rural literacy lags at 59.25%, and the disparity is sharpest among lower-income occupational groups (OJK & BPS, 2024).

Female industrial workers represent a particularly vulnerable demographic. The International Labor Organization estimates that approximately 80% of garment factory workers in Indonesia are women aged 15–35, the majority of whom hold only a senior high school qualification (ILO, 2022). Indonesia exhibits a 28.24-percentage-point gender gap in labor force participation (men 84.66%; women 56.42%) (BPS, 2024), and women workers shoulder a "double burden" of paid labor and unpaid domestic care, which intensifies financial pressure (Ardini et al., 2024). Wahyuni, Fachrudin, and Silalahi (2019) documented that Indonesian women's financial behavior is shaped not only by personal income but also by household roles, social expectations, and the availability of financial alternatives — factors that magnify exposure to high-cost credit when formal options are inaccessible. In industrial enclaves such as the Kabil Integrated Industrial Estate in Batam, OJK Kepulauan Riau has repeatedly issued warnings about workers — particularly women — being trapped by pinjol ilegal, with documented cases of harassment via fabricated nude images, threats to family members, and psychological breakdown (Antara, 2026; OJK Kepri, 2026).

Table 1. Snapshot of Indonesia's Predatory Lending and Financial Literacy Landscape (2022–2026)

Indicator	Value	Source
Illegal online lending platforms blocked (Jan 2022 – Jan 2024)	6,991	OJK (2024)
National financial literacy index (2024)	65.43%	OJK & BPS (2024)
National financial inclusion index (2024)	75.02%	OJK & BPS (2024)
Rural financial literacy index	59.25%	OJK & BPS (2024)
Indonesians are actively engaged in financial planning	12.6%	OJK (2023)
Female labor-force participation rate	56.42%	BPS (2024)
Male labor-force participation rate	84.66%	BPS (2024)
Women's share of the garment-factory workforce	~80%	ILO (2022)
Monthly interest rate – informal lender (Bank Emok)	up to 20%	Yulius (2023)
Bank Indonesia's maximum credit-card interest rate	1.75% per month	Bank Indonesia (2023)
Licensed P2P lenders (Pindar) as of February 2026	95	OJK (2026)

The data in Table 1 collectively constitute a tangible phenomenon gap: a population segment with rising digital access but structurally constrained financial capability is being systematically exploited, generating not only financial loss but also psychological distress, household conflict, and — in extreme cases — suicide (Adhrianti et al., 2022; Mahatma & Sari, 2026). Empirical research on the predictors of predatory-lending vulnerability among female industrial workers, however, remains sparse and fragmented.

Four constructs have emerged as theoretically and empirically central to financial decision-making in digital ecosystems. First, digital financial literacy (DFL) — defined by the OECD/INFE (2024) as the combination of knowledge, skills, attitudes, and behaviors required to use digital financial services safely — is consistently associated with lower exposure to fraudulent or predatory products (Setiawan et al., 2022; Lyons & Kass-Hanna, 2021; Ali et al., 2023). Setiawan et al. (2022), using Indonesian data, demonstrated that DFL significantly improves saving behavior and curbs impulsive borrowing, while Burchi et al. (2021) found that low DFL leaves individuals more prone to predatory practices. Wahyuni et al. (2024) extended this argument by showing that even among digitally engaged young Indonesians, gaps between technological adoption and substantive financial knowledge remain wide, especially in rapidly developing economies.

Second, financial stress — the subjective experience of pressure arising from current and anticipated financial obligations (Choi et al., 2020; Warmath et al., 2021) — is a robust driver of reliance on high-cost credit. Recent evidence from Indonesia shows that financial stress is intensified by rising living costs and wage instability, particularly among urban informal and industrial workers (Zuhroh et al., 2025; Ardini et al., 2024). UK-based detection studies confirm a feedback loop in which financial stress heightens predatory borrowing, which in turn deepens stress (Pizzutilo & Mariani, 2024).

Third, financial self-efficacy (FSE) — Bandura's (1986) construct adapted by Lown (2011) — captures an individual's confidence in managing personal finances. Higher FSE predicts greater financial inclusion, more deliberate borrowing, and resistance to consumption-related social pressure (Mindra et al., 2017; Asebedo & Payne, 2019). Recent studies among working young adults confirm that FSE significantly improves financial management behavior, while low FSE correlates with vulnerability to manipulation and dependence on high-cost credit (Goyal et al., 2025; Ribeiro & Cherobim, 2025).

Fourth, peer influence operates through social learning (Bandura, 1986) and normative pressure. Peers shape financial attitudes, signal which products are "safe," and can either buffer or amplify risky borrowing. Evidence is mixed: Goyal et al. (2025) report a positive peer effect on subjective financial literacy, whereas Ribeiro and Cherobim (2025) document a significant negative effect of peer influence on financial management behavior. Among Generation Z and young workers, peer endorsement of pinjol has been linked to faster adoption of these products (Ardini et al., 2024).

Despite this growing body of work, three notable gaps remain. First, an empirical gap: most Indonesian studies on pinjol focus on Generation Z students or general urban consumers (Sukarno et al., 2024; Setiawan et al., 2022; Wahyuni et al., 2024), while female industrial workers — who combine low wages, the double burden, and high digital exposure — have rarely been examined as a distinct population. Second, a theoretical gap: existing models examine the four predictors in isolation, lacking an integrated framework that simultaneously tests DFL, financial stress, FSE, and peer influence as predictors of vulnerability to predatory lending (rather than merely digital lending). Third, a contextual gap: although OJK has launched intensive education campaigns in industrial estates such as Kabil (OJK Kepri, 2026), policy interventions are not yet evidence-based for this demographic, leaving program effectiveness uncertain. Addressing these gaps makes a theoretical contribution that extends beyond the novelty of the population under study. For the consumer financial-vulnerability framework (O'Connor et al., 2019), the proposed model reconceptualizes vulnerability from a static, deficit-based attribute of individuals into a dynamic outcome jointly produced by interacting push forces (economic pressure and social influence) and pull deficits (limited literacy and self-efficacy), thereby specifying the mechanisms through which the framework's dimensions combine rather than merely coexist. For social cognitive theory (Bandura, 1986), the model provides a critical boundary test: it examines whether the theory's core self-regulatory resources — knowledge and self-efficacy — retain their protective function under conditions of acute economic scarcity, or whether environmental pressure overrides personal agency in the triadic reciprocal relationship. In doing so, the study moves both theories from describing who is vulnerable toward explaining how vulnerability is produced, a shift with direct consequences for the design of interventions.

This study therefore aims to examine the predictive roles of digital financial literacy, financial stress, financial self-efficacy, and peer influence on predatory-lending vulnerability among female industrial workers in Indonesia. Drawing on social cognitive theory (Bandura, 1986) and financial-vulnerability theory (O'Connor et al., 2019), four hypotheses are proposed:

H1: Digital financial literacy negatively predicts predatory-lending vulnerability among female industrial workers.

H2: Financial stress positively predicts vulnerability to predatory lending among female industrial workers.

H3: Financial self-efficacy negatively predicts vulnerability to predatory lending among female industrial workers.

H4: Peer influence positively predicts vulnerability to predatory lending among female industrial workers.

Findings are expected to inform gender-sensitive financial-literacy curricula, workplace-based financial-wellness programs, and regulatory targeting strategies — contributing simultaneously to the agenda of SDG 5 (Gender Equality) and SDG 8 (Decent Work and Economic Growth), and to the broader scholarship on digital financial inclusion in emerging economies.

RESEARCH METHODS

Research Design

This study employed a quantitative, cross-sectional, explanatory survey design to examine the predictive roles of digital financial literacy (DFL), financial stress (FS), financial self-efficacy (FSE), and peer influence (PI) on predatory-lending vulnerability (PLV) among female industrial workers. Reporting follows the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guideline for cross-sectional studies (von Elm et al., 2014), ensuring methodological transparency in participant recruitment, measurement, and analysis. The cross-sectional design was selected because it allows the simultaneous measurement of all latent constructs in a defined population at a single point in time, consistent with prior research on financial vulnerability predictors (O'Connor et al., 2019; Setiawan et al., 2022).

Vol. 4 No. 3, September 2026 | E-ISSN: 2987-7407 | DOI: https://doi.org/10.70716/ecoma.v4i3.581

Population and Sampling Instrumentation

Participants were female industrial workers aged 18–45 years employed at integrated industrial estates in Batam, Kepulauan Riau (Kabil Integrated Industrial Estate, Batamindo Industrial Park, and Muka Kuning Industrial Estate). Inclusion criteria were: (a) active employment in the manufacturing sector for at least six months; (b) ownership of a smartphone with internet access; and (c) willingness to provide informed consent. Exclusion criteria were: (a) holding a managerial or supervisory position above first-line foreman, and (b) household income exceeding 2× the regional minimum wage (UMK).

The target population comprised an estimated 150,000 female industrial workers in Batam's three principal estates (BP Batam, 2024). A proportionate stratified random sampling technique was applied, with strata defined by industrial estate. The minimum sample size was calculated using G*Power 3.1 for multiple regression with $f^2 = 0.15$, $\alpha = .05$, power = .80, and four predictors, yielding a minimum of 85 respondents (Faul et al., 2009). To meet the stringent requirements of PLS-SEM and accommodate possible non-response, a final target of 400 respondents was set, exceeding Hair et al.'s (2022) "10-times rule". After data cleaning, 378 valid responses were retained for analysis.

Instrument

Five established and validated instruments were adapted, translated into Bahasa Indonesia using a back-translation procedure (Brislin, 1970), and combined into a single questionnaire. All items used a five-point Likert scale (1 = strongly disagree; 5 = strongly agree), except DFL knowledge items, which were dichotomous. Sample items, sources, and psychometric properties are summarised in Table 2.

Table 2. Summary of Instruments, Sample Items, and Psychometric Properties

Construct	Items	Source	Sample Item	α	CR	AVE
Digital Financial Literacy (DFL)	12	OECD/INFE (2024); Setiawan et al. (2022)	I know how to verify whether an online lender is registered with OJK.	.882	.908	.621
Financial Stress (FS)	8	Prawitz et al. (2006)	How often do you worry about being able to meet normal monthly living expenses?	.904	.924	.640
Financial Self-Efficacy (FSE)	6	Lown (2011)	It is hard to stick to my spending plan when unexpected expenses arise. (R)	.871	.903	.608
Peer Influence (PI)	5	Goyal et al. (2025); Jorgensen & Savla (2010)	My co-workers often recommend online loan applications they personally use.	.858	.898	.638
Predatory Lending Vulnerability (PLV)	7	O'Connor et al. (2019); Anderloni et al. (2012)	I have considered borrowing from an unverified online lender to cover urgent household needs.	.917	.936	.681

All Cronbach's α and Composite Reliability (CR) values exceeded the .70 threshold (Hair et al., 2022); all Average Variance Extracted (AVE) values exceeded .50, confirming convergent validity. Discriminant validity was assessed using the Heterotrait–Monotrait ratio (HTMT), with all values below .85 (Henseler et al., 2015). A pilot study with 40 respondents (excluded from the main analysis) preceded full deployment. The adaptation of the instruments to the Indonesian industrial-worker context followed a structured sequence prior to the pilot study. After forward translation and independent back-translation (Brislin, 1970), discrepancies between the original and back-translated

Vol. 4 No. 3, September 2026 | E-ISSN: 2987-7407 | DOI: https://doi.org/10.70716/ecoma.v4i3.581

versions were reconciled in a consensus meeting, and idiomatic terms were localizedlocalized to the lending vocabulary familiar to respondents (for example, rendering “unverified online lender” as "pinjol tidak terdaftar OJK"). Content validity was then assessed by a panel of five experts — two academics in behavioral finance, one consumer-protection practitioner from OJK, one industrial-relations specialist, and one psychometrician — who rated the relevance and clarity of each item on a four-point scale. Item-level content validity indices (I-CVI) ranged from .80 to 1.00, and the scale-level index (S-CVI/Ave) exceeded .90 for all five constructs, meeting recommended thresholds; three items were reworded, and one redundant item was removed on the panel's advice before the 40-respondent pilot was conducted to confirm readability and preliminary reliability.

Procedures and Analysis Plan

Data were analyzed using IBM SPSS 28 for descriptive statistics and SmartPLS 4 for variance-based Structural Equation Modeling. The analysis proceeded in four sequential steps: (1) descriptive analysis; (2) measurement model evaluation (outer model), assessing indicator loadings, internal consistency reliability, convergent validity, and discriminant validity (HTMT and Fornell–Larcker); (3) structural model evaluation (inner model), reporting collinearity (VIF), R^2, Q^2, f^2, and standardised path coefficients; and (4) hypothesis testing via bootstrapping with 5,000 resamples (Hair et al., 2022). PLS-SEM was selected because the model is predictive, contains both reflective constructs and a non-normally distributed dependent variable, and aligns with prior financial-vulnerability research using comparable methods (Setiawan et al., 2022; Goyal et al., 2025). The choice of variance-based over covariance-based SEM (CB-SEM) rests on four methodological considerations. First, the research objective is prediction and the identification of key driver constructs, rather than the confirmation of an established theory, which is the canonical use case for PLS-SEM (Hair et al., 2022). Second, the endogenous construct exhibited a non-normal distribution (skewness = .342; kurtosis = −.728), and PLS-SEM's nonparametric bootstrapping imposes no multivariate-normality assumption, whereas maximum-likelihood CB-SEM estimation is sensitive to its violation. Third, the model integrates constructs adapted from heterogeneous source instruments for the first time in this population, making the exploratory–predictive orientation of PLS-SEM more defensible than the strictly confirmatory logic of CB-SEM. Fourth, PLS-SEM maximizes explained variance in the target construct (R^2, Q^2), which aligns directly with the study’s aim of rank-ordering predictors for intervention design; CB-SEM’s global fit indices would not serve this purpose. Common method bias was tested using Harman's single-factor test and the full collinearity VIF approach (Kock, 2015).

Scope and Limitations of Methods

Several methodological boundaries should be acknowledged. First, the cross-sectional design precludes strong causal inference. Second, reliance on self-report measures introduces potential social desirability and recall bias. Third, geographic scope is restricted to Batam's industrial estates. Fourth, the focus on female workers, by design, excludes comparisons with males. Finally, although the instruments were rigorously validated, the PLV measure was adapted from international scales rather than developed indigenously.

RESULTS AND DISCUSSION

Results

Respondent Demographic Profile

A total of 378 valid responses were retained for analysis. The majority were aged 26–35 years (52.4%), held a senior high-school qualification (68.5%), worked in electronics manufacturing (44.7%), and earned monthly wages within ±10% of Batam's regional minimum wage of IDR 4,683,049 (BP Batam, 2024). Notably, 61.4% reported borrowing from at least one online lending platform in the previous 12 months, and 23.8% reported experience with at least one unverified (illegal) platform — confirming the contextual relevance of the study population.

Table 3. Respondent Demographic Profile (n = 378)

Characteristic	Category	Frequency	Percentage
Age	18–25	92	24.3%
	26–35	198	52.4%
	36–45	88	23.3%
Education	Junior high school	41	10.8%
	Senior high school	259	68.5%
	Diploma/Bachelor	78	20.7%
Industrial Sector	Electronics	169	44.7%
	Garment	121	32.0%
	Plastics/Metal	88	23.3%
Marital Status	Single	117	30.9%
	Married	224	59.3%
	Divorced/Widowed	37	9.8%
Tenure	< 2 years	84	22.2%
	2–5 years	162	42.9%
	> 5 years	132	34.9%
Online-loan use (12 mo.)	Yes (legal only)	142	37.6%
	Yes (incl. illegal)	90	23.8%
	No	146	38.6%

Descriptive statistics for the five latent constructs are reported in Table 4. Mean scores indicate that respondents reported moderate-to-high financial stress (M = 3.78, SD = 0.92), moderate peer influence (M = 3.45, SD = 0.94), and relatively low predatory-lending vulnerability (M = 2.86, SD = 1.03), though the high standard deviation on PLV signals substantial variation across the sample.

Table 4. Descriptive Statistics of Latent Constructs (n = 378)

Construct	Min	Max	Mean	SD	Skewness	Kurtosis
Digital Financial Literacy (DFL)	1.00	5.00	3.24	0.87	-0.241	-0.483
Financial Stress (FS)	1.00	5.00	3.78	0.92	-0.512	-0.218
Financial Self-Efficacy (FSE)	1.00	5.00	3.12	0.81	-0.187	-0.367
Peer Influence (PI)	1.00	5.00	3.45	0.94	-0.298	-0.412
Predatory Lending Vulnerability (PLV)	1.00	5.00	2.86	1.03	0.342	-0.728

Measurement Model (Outer Model) Evaluation

Indicator-level outer loadings (Table 5) ranged from .712 to .892, all exceeding the recommended threshold of .70 (Hair et al., 2022), indicating that each item shared adequate variance with its assigned construct.

Table 5. Outer Loadings of Reflective Indicators

Construct	Indicator	Loading	t-value	p-value
DFL	DFL1	.785	32.412	< .001
	DFL2	.812	38.674	< .001
	DFL3	.742	27.183	< .001
	DFL4	.798	34.521	< .001
	DFL5	.823	41.218	< .001
	DFL6	.768	29.764	< .001
	DFL7	.754	28.319	< .001
	DFL8	.811	37.842	< .001
	DFL9	.779	31.026	< .001
	DFL10	.738	26.481	< .001
	DFL11	.802	35.917	< .001
	DFL12	.791	33.624	< .001
FS	FS1	.824	42.317	< .001
	FS2	.851	48.752	< .001
	FS3	.798	34.812	< .001
	FS4	.812	38.467	< .001
	FS5	.779	31.218	< .001
	FS6	.793	33.946	< .001
	FS7	.768	29.823	< .001
	FS8	.832	44.128	< .001
FSE	FSE1	.812	38.421	< .001
	FSE2	.788	32.617	< .001
	FSE3	.754	28.184	< .001
	FSE4	.798	34.728	< .001
	FSE5	.773	30.518	< .001
	FSE6	.779	31.247	< .001
PI	PI1	.794	33.812	< .001
	PI2	.823	41.546	< .001
	PI3	.815	39.218	< .001
	PI4	.784	32.467	< .001
	PI5	.779	31.184	< .001
PLV	PLV1	.854	49.218	< .001
	PLV2	.832	44.317	< .001
	PLV3	.812	38.621	< .001
	PLV4	.867	52.847	< .001
	PLV5	.798	34.812	< .001
	PLV6	.824	42.318	< .001
	PLV7	.819	40.617	< .001

Internal consistency reliability and convergent validity are reported in Table 6. All Cronbach's α coefficients (.858–.917), Dijkstra–Henseler's rho_A (.864–.921), and Composite Reliability (.898–.936) exceeded the .70 threshold, and all AVE values (.608–.681) exceeded .50, confirming convergent validity (Hair et al., 2022).

Table 6. Construct Reliability and Convergent Validity

Construct	Cronbach's α	rho_A	CR	AVE
Digital Financial Literacy (DFL)	.882	.887	.908	.621
Financial Stress (FS)	.904	.908	.924	.640
Financial Self-Efficacy (FSE)	.871	.875	.903	.608
Peer Influence (PI)	.858	.864	.898	.638
Predatory Lending Vulnerability (PLV)	.917	.921	.936	.681
Threshold (Hair et al., 2022)	≥ .70	≥ .70	≥ .70	≥ .50

Vol. 4 No. 3, September 2026 | E-ISSN: 2987-7407 | DOI: https://doi.org/10.70716/ecoma.v4i3.581

Discriminant validity was assessed using two approaches. First, the Fornell–Larcker criterion (Table 7) confirmed that the square root of each construct's AVE (diagonal values, in bold) exceeded its correlation with every other construct.

Table 7. Discriminant Validity – Fornell–Larcker Criterion

	DFL	FS	FSE	PI	PLV
DFL	.788				
FS	-.342	.800			
FSE	.456	-.387	.780		
PI	-.218	.412	-.298	.799	
PLV	-.398	.614	-.421	.521	.825

Note. Diagonal values (bold in original output) = $\sqrt{AVE}$*; off-diagonal values = construct correlations.*

Second, the Heterotrait–Monotrait (HTMT) ratio (Table 8), considered a stricter test of discriminant validity (Henseler et al., 2015), yielded values ranging from .278 to .742, all below the conservative .85 cutoff. The highest HTMT (between FS and PLV) signals a strong but distinct association, consistent with the structural model's expected strongest path.

Table 8. Discriminant Validity – Heterotrait–Monotrait (HTMT) Ratio

	DFL	FS	FSE	PI
FS	.412			
FSE	.524	.456		
PI	.278	.487	.354	
PLV	.468	.742	.498	.621

Note. All HTMT values < .85 (Henseler et al., 2015)

Common Method Bias and Collinearity

Harman's single-factor test produced a first factor explaining 31.7% of total variance — below the 50% threshold (Podsakoff et al., 2003). Full collinearity VIFs ranged 1.624–2.413 (below 3.3), and inner model VIFs (Table 9) ranged 1.421–2.078 (below 5.0), indicating that common method bias and multicollinearity are not concerns.

Table 9. Inner Model Collinearity Statistics (VIF)

Predictor	Outcome	VIF	Threshold
Digital Financial Literacy (DFL)	PLV	1.421	< 5.0 ✓
Financial Stress (FS)	PLV	2.078	< 5.0 ✓
Financial Self-Efficacy (FSE)	PLV	1.612	< 5.0 ✓
Peer Influence (PI)	PLV	1.534	< 5.0 ✓

Structural Model (Inner Model) Evaluation

The structural model produced an R^2 of .524 for predatory-lending vulnerability (Table 10), indicating that 52.4% of the variance in PLV is jointly explained by DFL, FS, FSE, and PI — a substantial effect (Cohen, 1988; Hair et al., 2022). The adjusted R^2 (.519) closely matched the unadjusted value, suggesting that the model is not over-fitted. Q^2 of .342 (well above 0) confirmed adequate predictive relevance.

Table 10. Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

Endogenous Construct	R^2	R^2 Adjusted	Q^2	Interpretation
Predatory Lending Vulnerability (PLV)	.524	.519	.342	Substantial/strong

Note. R^2 *thresholds: .19 weak, .33 moderate, .67 substantial (Chin, 1998).* $Q^2 > 0$ *indicates predictive relevance (Hair et al., 2022).*

Vol. 4 No. 3, September 2026 | E-ISSN: 2987-7407 | DOI: https://doi.org/10.70716/ecoma.v4i3.581

Effect sizes (f^2) for each predictor are reported in Table 11. Financial stress exerted a medium effect (f^2 = .184), peer influence a small-to-medium effect (f^2 = .128), digital financial literacy a small effect (f^2 = .078), and financial self-efficacy the smallest effect (f^2 = .052). All four effects, however, were statistically significant and substantively meaningful.

Table 11. Effect Sizes (f^2) of Predictors on PLV

Predictor	f^2	Effect-size category	Rank
Financial Stress (FS)	.184	Medium	1
Peer Influence (PI)	.128	Small-to-medium	2
Digital Financial Literacy (DFL)	.078	Small	3
Financial Self-Efficacy (FSE)	.052	Small	4

Note. f^2 thresholds: .02 small, .15 medium, .35 large (Cohen, 1988).

Hypothesis Testing

Hypotheses were tested via bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals. As summarised in Table 12, all four hypotheses were supported at $p < .001$, with no confidence interval crossing zero.

Table 12. Path Coefficients and Hypothesis Testing Results (n = 378)

H	Path	β	SD	t	p	f^2	Decision
H1	DFL → PLV	–.218	.053	4.123	< .001	.078	Supported
H2	FS → PLV	+.342	.053	6.451	< .001	.184	Supported
H3	FSE → PLV	–.187	.052	3.567	< .001	.052	Supported
H4	PI → PLV	+.276	.053	5.214	< .001	.128	Supported

The strongest predictor of PLV was financial stress (β = +.342), followed by peer influence (β = +.276), digital financial literacy (β = –.218), and financial self-efficacy (β = –.187). The two negative predictors (DFL and FSE) confirm a protective role; the two positive predictors (FS and PI) confirm a risk-amplifying role.

Discussion

Financial Stress as the Dominant Risk Driver

The finding that financial stress is the strongest predictor of PLV (β = +.342) corroborates international evidence that economic strain pushes individuals toward high-cost credit as a coping mechanism (Choi et al., 2020; Pizzutilo & Mariani, 2024). For female industrial workers in Batam, persistent financial stress is structurally produced: stagnant wages relative to the cost of living, household-level expenses such as children's school fees and remittances, and unpredictable expenditure shocks. This finding extends Zuhroh et al.'s (2025) Indonesian MSME results into the manufacturing-labor context and reinforces the feedback-loop hypothesis: stress → predatory borrowing → deepened stress. Beyond corroborating this loop, the dominance of financial stress over the cognitive and psychological predictors is theoretically consistent with the scarcity framework advanced by Mullainathan and Shafir (2013), which holds that acute financial scarcity imposes a “bandwidth tax” that captures attention and depletes the cognitive resources otherwise available for deliberate, forward-looking decision-making. On this account, financial stress does not merely coexist with poor borrowing decisions; it actively narrows the decision frame to the immediate obligation, foregrounds present needs over future costs, and thereby crowds out the reflective evaluation on which digital financial literacy and financial self-efficacy depend. For female industrial workers facing time-sensitive household shocks — unpaid school fees, medical emergencies, or delayed

Vol. 4 No. 3, September 2026 | E-ISSN: 2987-7407 | DOI: https://doi.org/10.70716/ecoma.v4i3.581

remittances — the psychological urgency of resolving the shock can override an accurate appraisal of a lender's legitimacy or interest burden even when the requisite knowledge and confidence are present. This explains why a resource that is economic in origin outperforms predictors that are cognitive (DFL) and psychological (FSE) in nature: scarcity operates upstream of both, constraining the very capacity through which knowledge and self-efficacy would otherwise exert their protective effect. The dominance of financial stress also acquires a distinctly gendered and contextual character among Indonesian female industrial workers that a generic scarcity account does not fully capture. First, wages in Batam's export-oriented estates are anchored to the regional minimum wage, so most respondents operate at a structurally fixed income ceiling with virtually no scope for overtime-independent income growth; financial shocks, therefore, cannot be absorbed through earnings adjustments and translate immediately into stress. Second, the "double burden" positions women as de facto household financial managers who are culturally expected to reconcile school fees, food expenditure, and remittances to extended family, concentrating the psychological weight of household deficits on precisely the population studied here. Third, many female workers are internal migrants with thin local collateral, limited formal credit histories, and weak eligibility for bank credit, so the feasible choice set during a shock often collapses to informal or digital lenders — making stress not only a motivational push but also a channel-selection constraint. Under these conditions, economic pressure plausibly dominates because it is chronic, gender-concentrated, and paired with restricted formal alternatives, a configuration less pronounced in the student and general-urban samples that dominate prior Indonesian studies.

Peer Influence as a Social Amplifier

The significant positive effect of peer influence (β = .276) supports Bandura's (1986) social cognitive theory and aligns with findings from Goyal et al. (2025) and Ardini et al. (2024). In the industrial context, workers cluster in dense social networks — co-workers in the same production line, dormitory mates, WhatsApp groups — through which loan applications are recommended, downloaded together, and endorsed via referral codes. Two mechanisms appear to operate: descriptive normalization (when peers borrow from pinjol, the practice is perceived as routine) and information laundering (even unverified platforms gain legitimacy when introduced by trusted peers). This finding aligns with Ribeiro and Cherobim's (2025) negative-effect result, suggesting that peer influence in low-information environments tends to amplify rather than mitigate financial risk. The magnitude of this effect is best understood in relation to the distinctive social ecology of integrated industrial estates, which differs from the more diffuse networks of student or general-urban samples in three respects. First, spatial and temporal density: assembly-line work, shared shift schedules, and dormitory co-residence produce sustained, high-frequency contact among workers occupying near-identical economic positions, so that a borrowing solution adopted by one worker is observed, discussed, and imitated within a tightly bounded reference group. Second, economic homogeneity: because co-workers face common wage ceilings and synchronous expenditure shocks (for example, simultaneous school-enrolment periods), peer endorsement carries unusual persuasive weight — the recommending peer is seen as facing the same constraints and therefore as a credible source of a "tested" solution. Third, closed-loop information channels: estate-based WhatsApp groups and referral-code economies circulate loan applications within a self-contained informational environment largely insulated from independent

Vol. 4 No. 3, September 2026 | E-ISSN: 2987-7407 | DOI: https://doi.org/10.70716/ecoma.v4i3.581

verification, allowing unlicensed platforms to accrue legitimacy purely through repeated intra-network transmission. Taken together, these features transform the ordinary social-learning mechanism described by Bandura (1986) into an accelerated diffusion process in which risky credit products spread with limited friction, thereby explaining why peer influence emerges as the second-strongest determinant of vulnerability in this population.

Digital Financial Literacy as a Protective Factor

The negative effect of DFL on PLV ($\beta = -.218$) confirms its protective role and is consistent with Setiawan et al. (2022), Lyons and Kass-Hanna (2021), Burchi et al. (2021), and Wahyuni et al. (2024). Workers with higher DFL are better able to verify whether a lender is registered with OJK, recognize hidden fees, identify aggressive collection tactics, and distinguish licit pindar from illicit pinjol. However, the modest effect size ($f^2 = .078$) is theoretically informative: knowledge alone is necessary but insufficient. This echoes the "knowledge–action gap" reported by Kass-Hanna and Lyons (2022). The theoretical significance of this gap becomes clearer when read alongside the financial-stress finding. Digital financial literacy is predominantly a “cold-state” resource: it is acquired and rehearsed under calm conditions and presupposes the deliberative bandwidth required to apply it. Borrowing decisions among stressed workers, however, are frequently made in “hot,” affectively loaded states of scarcity in which that bandwidth is compromised (Mullainathan & Shafir, 2013). Financial knowledge can therefore raise the probability of a sound decision without guaranteeing it, because the structural pressure that motivates borrowing simultaneously erodes the cognitive conditions under which knowledge is enacted. This reframes the modest effect size not as a weakness of the DFL construct but as evidence of a boundary condition: education can shift the intention to avoid predatory credit, yet the intention–behavior gap widens precisely when economic pressure is most acute. It follows that financial-literacy programs are likely to underperform when delivered in isolation and substantially more effective when paired with interventions that alleviate the underlying scarcity itself. This inference directly informs the practical implications developed below.

Financial Self-Efficacy as a Psychological Buffer

The negative path from FSE to PLV ($\beta = -.187$) supports the findings of Mindra et al. (2017), Asebedo and Payne (2019), and Wahyuni et al. (2019) that confidence in managing one's finances predicts more deliberate financial choices. Workers with higher FSE are more likely to reject the perception that pinjol is the only option, to negotiate alternatives (cooperative loans, wage advances, family borrowing), and to resist peer-driven herd behavior. Although the f^2 of .052 is small, the consistent direction reinforces the value of psychological resources alongside knowledge-based interventions. Read together with the digital-financial-literacy result, this pattern indicates that the two protective resources share a common vulnerability: both are internal capacities whose expression depends on the availability of deliberative bandwidth, and both are therefore liable to be overridden when financial stress is high.

Integrated Interpretation

Taken together, the results portray PLV as the product of an interaction between push factors (financial stress, peer influence) and pull factors (low DFL, low FSE). The model accounts for 52.4% of the variance — a substantial figure for a behavioral construct — yet leaves 47.6% to other unexplored predictors, such as financial socialization in the family of origin, religiosity, impulsivity, and structural workplace factors. The dominance of financial stress over the four predictors is theoretically meaningful: cognitive and psychological interventions, while necessary, must be embedded within structural improvements in wages and household economic stability. This unexplained share merits more systematic mapping as a foundation for subsequent research. At the individual level, time preference and impulsivity, materialism, and attitudes toward debt are plausible omitted drivers of high-cost borrowing; at the household level, intra-household bargaining power, spousal income volatility, and the number of dependants may condition both stress and the feasibility of alternatives; at the environmental level, exposure to targeted digital-loan advertising, the density of informal lender networks around industrial estates, and access barriers to formal microcredit may shape the choice architecture within which vulnerability materialises. Protective candidates — workplace social capital, participation in savings cooperatives or arisan rotating savings groups, and religiosity as a normative brake on interest-bearing debt — deserve equal attention, since interventions may be more tractable by strengthening buffers than by removing pressures. The dominance of financial stress over the four predictors is theoretically meaningful: cognitive and psychological interventions, while necessary, must be embedded within structural improvements in wages and household economic stability. To move beyond a purely descriptive synthesis, the four predictors can be organized into a sequential push–pull decision architecture (Figure 1) that specifies how they interact rather than merely how they rank. Within this architecture, financial stress functions as the activating condition: it generates the borrowing impulse and, through the scarcity mechanism described above, simultaneously lowers the deliberative capacity available to evaluate that impulse. Peer influence then operates as the facilitating channel, converting a generalized impulse into a specific action by supplying an accessible, socially legitimated product and reducing the perceived search cost of finding one. Digital financial literacy and financial self-efficacy act as regulatory gates positioned between impulse and action — DFL screening the product's legitimacy and cost, and FSE sustaining the confidence to pursue safer alternatives. Crucially, these protective gates are not bypassed at random; they are systematically weakened by the same financial stress that initiates the sequence, because scarcity depletes the bandwidth on which both depend. The model is therefore better understood as an interaction than as a set of parallel main effects: the push factors do not simply add to the pull factors but condition their operation, such that the protective value of literacy and self-efficacy is greatest when stress is low and progressively attenuated as stress rises. So conceived, predatory-lending vulnerability is the predictable outcome of a pressured impulse (financial stress) channeled by social facilitation (peer influence) through protective gates (DFL, FSE) that scarcity has already partially disabled.

Journal of Economics and Management
Vol. 4 No. 3, September 2026 | E-ISSN: 2987-7407 | DOI: https://doi.org/10.70716/ecoma.v4i3.581

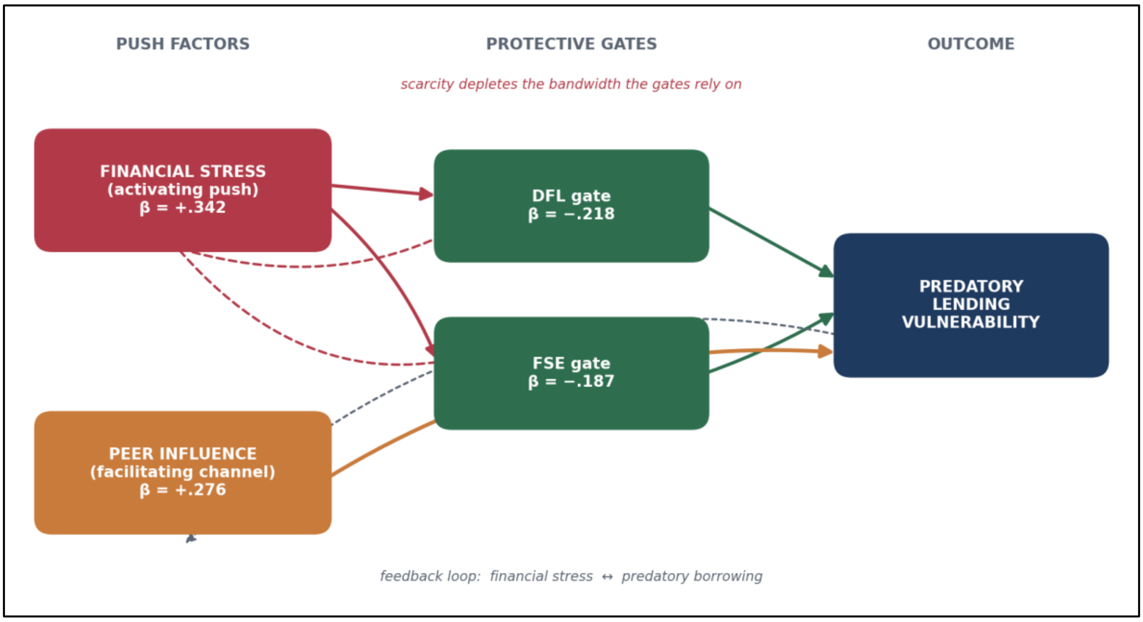

Figure 1. Integrated push–pull decision architecture of predatory-lending vulnerability.
Note. Financial stress is the activating push that also depletes the deliberative bandwidth on which the protective gates (DFL, FSE) depend; peer influence is the facilitating channel; β values are standardized path coefficients.

Implications

Theoretical Implications

The study contributes to financial-vulnerability literature by providing the first integrated empirical test of cognitive (DFL), affective (FS), psychological (FSE), and social (PI) predictors of PLV within a single PLS-SEM model in Southeast Asia. It extends Bandura's (1986) social cognitive theory into the predatory-lending domain and operationalizes O'Connor et al.'s (2019) consumer financial vulnerability framework specifically for digital predatory lending.

Practical Implications

For OJK, the current education-only model should be redesigned to focus on the dominant predictor (financial stress). Workplace-based financial-wellness programs should combine emergency-savings facilitation, employer-sponsored cooperative-credit alternatives, and short-burst micro-learning modules on DFL. For employers, salary-on-demand schemes and partnerships with licensed pinjol could pre-empt the resort to illegal pinjol. For trade unions and women's organizationsorganizations, peer-led "financial buddy" programs can turn peer influence into a protective force. The rank-ordering of effects provides a direct template for prioritizing these interventions. Because financial stress is the dominant driver (β = +.342; f^2 = .184), the highest-leverage measures are those that relieve liquidity pressure at its source — employer-facilitated emergency-savings schemes, salary-on-demand access, and cooperative-credit alternatives — rather than information provision alone. Because peer influence is the second-strongest determinant (β = +.276; f^2 = .128) and operates through estate-based networks, the second priority is to repurpose those same networks as protective infrastructure through peer-led “financial buddy” schemes and trained workplace financial champions, converting the diffusion mechanism identified above from a risk multiplier into a safeguard. Digital financial literacy and financial self-efficacy, whose smaller effects (β = −.218 and −.187; f^2 = .078 and .052) reflect their status as bandwidth-dependent protective gates, are best delivered not as standalone curricula but as short-burst micro-learning embedded within the stress-relief and peer-based measures, so that knowledge and confidence are reinforced at the moment of decision rather than in isolation from it. Sequencing interventions in this order aligns program design with the empirical weight of each predictor and with the decision architecture set out in Figure 1.

Policy Implications

Findings strengthen the case for the demand-side regulatory shift signaled by OJK Regulation No. 11/2024 and the SLIK reporting requirement effective July 2025. Targeted enforcement should focus on platforms operating in industrial-estate WhatsApp ecosystems, and gender-disaggregated supervisory data should be made publicly available (Women's World Banking, 2024). Consistent with the finding that vulnerability is concentrated where financial stress and peer diffusion intersect, enforcement resources are likely to yield the greatest return when directed at unlicensed platforms circulating within industrial-estate WhatsApp ecosystems, and when demand-side protection under OJK Regulation No. 11/2024 is paired with structural measures — wage-adequacy monitoring and employer-provided liquidity facilities — that address the economic pressure the model identifies as the primary driver.

CONCLUSION AND RECOMMENDATIONS

This study set out to examine the predictive roles of digital financial literacy, financial stress, financial self-efficacy, and peer influence on predatory-lending vulnerability among female industrial workers in Indonesia — a population that the Introduction identified as both empirically under-studied and structurally exposed to the proliferation of pinjol ilegal and informal high-cost lenders. The expectations articulated in the Introduction have been substantively realized in the Results and Discussion. All four hypotheses derived from social cognitive theory (Bandura, 1986) and the consumer financial-vulnerability framework (O'Connor et al., 2019) were empirically supported in a PLS-SEM analysis of 378 female workers in Batam's integrated industrial estates. Together, the four predictors explained 52.4% of the variance in PLV, confirming the appropriateness of the integrated cognitive–affective–psychological–social model. Beyond confirming the hypothesized relationships, the study's theoretical contribution is twofold: it develops the consumer financial-vulnerability framework from a taxonomy of risk dimensions into a process model in which push forces condition the operation of protective resources. It establishes a boundary condition for social cognitive theory by showing that knowledge- and efficacy-based self-regulation weakens precisely where economic pressure is most acute.

Three substantive conclusions emerge. First, financial stress is the dominant driver of PLV (β = +.342), validating the phenomenon-gap argument that structural economic pressure — not merely ignorance — pushes industrial women toward exploitative credit. Second, peer influence operates as a social amplifier (β = +.276), confirming that the dense workplace and dormitory networks of industrial estates function as conduits for the diffusion of risky financial products. Third, digital financial literacy (β = −.218) and financial self-efficacy (β = −.187) function as protective but partial buffers, supporting yet qualifying the policy assumption that education-only interventions can reduce predatory-lending exposure.

The conclusions above should be read within the study's limitations, which are distinct from its future research agenda. The cross-sectional design restricts causal claims to theoretically grounded associations; self-reported borrowing — particularly from illegal platforms — is likely understated by social-desirability bias; the single-region scope in Batam and the deliberate exclusion of male workers bound the population to which the estimates generalize; and the predatory-lending-vulnerability measure, although rigorously validated, was adapted from international scales rather than developed indigenously. These boundaries qualify the strength, not the direction, of the conclusions drawn.

Looking forward, the prospects for the development of these findings span three directions. Empirically, the model invites longitudinal replication across other Indonesian industrial belts (Bekasi, Tangerang, Surabaya, Cikarang) and comparative testing in other Southeast Asian manufacturing economies. Methodologically, future research can extend the present framework by incorporating mediated–moderated PLS-SEM, list-experiment techniques to overcome social desirability bias, and netnographic analysis of pinjol-related digital communities. In practical terms, the application prospects are immediate: the findings can directly inform workplace-based financial-wellness curricula co-designed by OJK, the Ministry of Manpower, and industrial-estate operators, as well as employer-sponsored salary-on-demand and emergency-savings facilities that relieve liquidity pressure at the source. The same evidence base can underpin peer-led "financial buddy" programs that convert workplace networks into protective infrastructure, as well as gender-sensitive supervisory data architectures aligned with OJK Regulation No. 11/2024 and the SLIK reporting requirement. By translating the rank-ordered effect sizes into rank-ordered policy priorities, the study advances a research-to-policy pathway that is both gender-responsive and structurally informed — contributing to the realization of SDG 5 and SDG 8 in Indonesia's digital economy.

REFERENCES

Adhrianti, L., Pratama, R., & Widya, S. (2022). Online lending and consumer protection in Indonesia. *Jurnal Komunikasi Indonesia, 11*(2), 134–147.

Ali, M., Khan, S. U., & Latif, R. A. (2023). Digital predatory lending and financial literacy: Evidence from emerging markets. *Journal of Consumer Affairs, 57*(3), 1145–1172. https://doi.org/10.1111/joca.12488

Anderloni, L., Bacchiocchi, E., & Vandone, D. (2012). Household financial vulnerability: An empirical analysis. *Research in Economics, 66*(3), 284–296. https://doi.org/10.1016/j.rie.2012.03.001

Antara. (2026, March 14). OJK Kepri beri edukasi waspada pinjol ilegal ke pekerja di kawasan industri Batam. *ANTARA News Kepulauan Riau*. https://kepri.antaranews.com

Ardini, R., Pratiwi, M., & Sukmana, R. (2024). Financial stress determinants in Indonesia: Exploring the moderating effects of digital knowledge, age, and gender. *International Review of Economics & Finance, 92*, 211–229. https://doi.org/10.1016/j.iref.2024.01.015

Asebedo, S. D., & Payne, P. (2019). Financial self-efficacy and the saving behavior of older pre-retirees. *Journal of Financial Counseling and Planning, 30*(2), 357–368. https://doi.org/10.1891/1052-3073.30.2.357

Badan Pusat Statistik. (2024). *Statistik ketenagakerjaan Indonesia 2024*. Badan Pusat Statistik.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bank Indonesia. (2023). *Peraturan Bank Indonesia tentang batas maksimum suku bunga kartu kredit*. Bank Indonesia.

Badan Pengusahaan Batam. (2024). *Statistik kawasan industri Batam 2024*. BP Batam.

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology, 1*(3), 185–216. https://doi.org/10.1177/135910457000100301

Burchi, A., Włodarczyk, B., Szturo, M., & Martelli, D. (2021). The effects of financial literacy on sustainable entrepreneurship. *Sustainability, 13*(9), 5070. https://doi.org/10.3390/su13095070

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Lawrence Erlbaum Associates.

Choi, S. L., Heo, W., Cho, S. H., & Lee, P. (2020). The links between job insecurity, financial well-being, and financial stress. *International Journal of Consumer Studies, 44*(4), 353–360. https://doi.org/10.1111/ijcs.12571

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Goyal, K., Kumar, S., & Hoffmann, A. (2025). The direct and indirect effects of financial socialization, financial literacy, and financial self-efficacy on financial behavior. *Financial Services Review, 33*(4), 1–28.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

International Labour Organization. (2022). *Better Work Indonesia: Annual report 2022*. ILO.

Jorgensen, B. L., & Savla, J. (2010). Financial literacy of young adults: The importance of parental socialization. *Family Relations, 59*(4), 465–478. https://doi.org/10.1111/j.1741-3729.2010.00616.x

Kass-Hanna, J., & Lyons, A. C. (2022). Building financial resilience through financial and digital literacy in South Asia and Sub-Saharan Africa. *Emerging Markets Review, 51*, 100846. https://doi.org/10.1016/j.ememar.2022.100846

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Lown, J. M. (2011). Development and validation of a financial self-efficacy scale. *Journal of Financial Counseling and Planning, 22*(2), 54–63.

Lyons, A. C., & Kass-Hanna, J. (2021). A methodological overview to defining and measuring digital financial literacy. *Financial Planning Review, 4*(2), e1113. https://doi.org/10.1002/cfp2.1113

Mahatma, R., & Sari, P. (2026). Beyond legality: A holistic perspective on Indonesia's illegal fintech epidemic. *Frontiers in Human Dynamics, 8*, 1673633. https://doi.org/10.3389/fhumd.2026.1673633

Mindra, R., Moya, M., Zuze, L. T., & Kodongo, O. (2017). Financial self-efficacy: A determinant of financial inclusion. *International Journal of Bank Marketing, 35*(3), 338–353. https://doi.org/10.1108/IJBM-05-2016-0069

Mullainathan, S., & Shafir, E. (2013). *Scarcity: Why having too little means so much*. Times Books.

O'Connor, G. E., Newmeyer, C. E., Wong, N. Y. C., Bayuk, J. B., Cook, L. A., Komarova, Y., Loibl, C., Ong, L. L., & Warmath, D. (2019). Conceptualizing the multiple dimensions of consumer financial vulnerability. *Journal of Business Research, 100*, 421–430. https://doi.org/10.1016/j.jbusres.2018.12.033

Organisation for Economic Co-operation and Development. (2024). *OECD/INFE survey instrument to measure digital financial literacy*. OECD Publishing. https://doi.org/10.1787/548de821-en

Otoritas Jasa Keuangan & Badan Pusat Statistik. (2024). *Survei nasional literasi dan inklusi keuangan (SNLIK) 2024*. OJK & BPS.

Otoritas Jasa Keuangan. (2023). *Laporan tahunan literasi dan edukasi keuangan 2023*. OJK.

Otoritas Jasa Keuangan. (2024). *Laporan satgas pemberantasan aktivitas keuangan ilegal (PASTI)*. OJK.

Otoritas Jasa Keuangan Provinsi Kepulauan Riau. (2026). *Edukasi keuangan syariah dan waspada pinjol ilegal di kawasan industri Kabil Batam*. OJK.

Pizzutilo, F., & Mariani, M. (2024). Detecting consumers' financial vulnerability using open banking data: Evidence from UK payday loans. *European Journal of Operational Research, 318*(2), 593–608. https://doi.org/10.1016/j.ejor.2024.02.012

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Prawitz, A. D., Garman, E. T., Sorhaindo, B., O'Neill, B., Kim, J., & Drentea, P. (2006). InCharge financial distress/financial well-being scale: Development, administration, and score interpretation. *Journal of Financial Counseling and Planning, 17*(1), 34–50.