

Integrating Risk Acceptance Criteria and Collection Process to Reduce Uncollectible Receivables and Its Impact on Revenue Performance: A PLS-SEM Approach in Non-Bank B2B Trade Credit Indonesia

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Article Information:

Received: August 21, 2026, Accepted: August 28, 2026, Published: August 30, 2026

Abstract

Uncollectible receivables in Indonesia's *business-to-business* (B2B) *trade credit* industry have stagnated around 8% of total invoices, equivalent to the average profit margin of the B2B distribution sector, while 61.26% of businesses struggle to access formal bank financing, making *trade credit* the only available operational funding source despite its high risk. This study examines the influence of *Risk Acceptance Criteria* and *Collection Process* on Uncollectible Receivables, and their impact on *Revenue Performance* through a mediating mechanism, at a single *non-bank* B2B *trade credit* provider in Indonesia that underwent an extreme credit risk performance transformation during the observation period. *Longitudinal* data spanning 36 months (2023-2025) were analyzed using Partial Least Squares *Structural Equation Modeling* (PLS-SEM) with a formative *measurement model*, complemented by out-of-sample predictive validation through *PLSpredict* and the *Cross-Validated Predictive Ability Test* (CVPAT). Results show *Risk Acceptance Criteria* (beta=-0.409; p=0.0075) and *Collection Process* (beta=-0.529; p=0.0008) significantly and negatively influence Uncollectible Receivables, with *Collection Process* consistently more dominant. Uncollectible Receivables exerts a highly significant negative influence on *Revenue Performance* (beta=-0.697; p<0.0001; f²=0.945) and mediates the influence of both exogenous constructs (H4 beta=0.285, p=0.013; H5 beta=0.369, p=0.0049). All five hypotheses are supported, and the validated model significantly outperforms the Linear Model and Indicator Average benchmarks in CVPAT testing. These findings address a literature gap in which both risk mechanisms have typically been examined separately, offering an Integrated B2B *Credit Risk Management framework* for *non-bank trade credit* providers in emerging markets.

Keywords: Risk Acceptance Criteria, Collection Process, Uncollectible Receivables, Revenue Performance

JEL Classification: G32, G23, L25

Published by:

1. Introduction

Trade credit is the hidden backbone of Indonesian *business-to-business* (B2B) commerce. As much as 54% of national B2B transactions run on *trade credit* schemes, with an average payment tenor of 50 days ([Atradius, 2025](#)), meaning more than half the value of interfirm trade in this country depends on a promise to pay, not cash in hand. This structural dependence would appear unremarkable if well managed, yet industry data suggests otherwise: the average uncollectible receivable rate in this sector has stagnated around 8% of total invoices for years without meaningful improvement, a figure arithmetically equivalent to the entire average profit margin of the B2B distribution sector ([Atradius, 2025](#)). In an average year, in other words, the sector's entire operating profit is effectively erased by receivables that never return as cash.

This problem is compounded by an inelastic demand side. As many as 61.26% of Indonesian B2B businesses report difficulty accessing formal bank financing ([Atradius, 2025](#)), not because they are unwilling, but because collateral requirements, formal credit history, and conventional banking bureaucracy systematically exclude the mid-tier businesses forming the backbone of construction and manufacturing supply chains. For them, *trade credit* is not one option among several financing alternatives, but the only path remaining. The combination of these two facts, inelastic demand for *trade credit* and endemic uncollectible receivable risk, creates a paradox rarely answered conclusively by conventional financial management literature: how can a financing instrument structurally needed by the market, yet structurally high-risk, be managed sustainably without sacrificing one side, business growth or portfolio health?

This is precisely what makes this study's object worth investigating in depth. A single *non-bank* B2B *trade credit* provider serving Indonesia's construction and manufacturing sectors recorded a performance trajectory that, placed alongside the industry figures above, appears almost implausible: the firm's problematic receivables ratio (*Non-Performing Loan*) fell from 22.05% in 2023, far above the 8% industry average, to just 0.01% in 2025, alongside *Revenue Performance* growth exceeding 250% over the same period. Not a mere reasonable risk reduction, but an extreme transformation from crisis condition to near risk-free receivables status, without sacrificing, indeed while accelerating, business growth. An empirical anomaly of this kind, where a firm successfully defies the conventional risk-return *trade-off* assumption ([Brigham & Ehrhardt, 2017](#)) that regards risk control and revenue growth as conflicting objectives, is rarely documented longitudinally with monthly operational data this complete in *emerging market* B2B *trade credit* literature, making this case a revelatory one whose mechanisms warrant scientific unpacking, not mere anecdotal celebration.

This study's significance and urgency rest on three grounds. First, empirically, the gap between average industry conditions (stagnant 8% NPL) and the object firm's achievement (0.01% NPL) demands systematic explanation: what actually distinguishes firms that succeed from the majority that stagnate? Second, theoretically, prior literature tends to examine *ex-ante* credit selection mechanisms (*Risk Acceptance Criteria*) and *ex-post* collection mechanisms (*Collection Process*) separately, [Farooq et al. \(2022\)](#) and [Anggraeni et al. \(2023\)](#) focus on RAC, while [Lenz \(2023\)](#) and [Zebua et al. \(2022\)](#) focus on *Collection Process*, without any testing both simultaneously within a formal *mediation framework* explaining their shared causal pathway toward *revenue performance*. Third, practically, amid 61.26% of businesses dependent on *trade credit* for lack of alternatives, failure to manage receivables risk is not merely one firm's problem but a threat to the broader continuity of national construction and manufacturing supply chains, making "how to manage *trade credit* sustainably" a question whose impact

extends far beyond a single firm's boundaries.

This study addresses that question by simultaneously testing the influence of *Risk Acceptance Criteria* and *Collection Process* on Uncollectible Receivables, and their impact on *Revenue Performance* through a formal *mediation* mechanism. Its contribution is threefold: theoretical, through an Integrated B2B *Credit Risk Management* model uniting *ex-ante* and *ex-post* mechanisms within a single *mediation framework* unavailable in any reviewed literature; methodological, through combining formative model evaluation with out-of-sample predictive validation rarely reported in similar studies; and practical, through evidence-based managerial investment guidance for *non-bank B2B trade credit* companies facing similar structural challenges.

2. Literature Review

2.1 B2B Trade Credit and the Information Asymmetry Problem

Business-to-business (B2B) trade credit refers to deferred payment arrangements allowing buyers to receive goods or services first and pay later on an agreed date ([Petersen & Rajan, 1997](#)). Unlike bank credit, which passes through formal *underwriting* and is secured by specific collateral, *trade credit* is typically extended by providers possessing superior information about customer operational conditions compared to formal financial institutions, a position *Financial Advantage Theory* ([Petersen & Rajan, 1997](#)) describes as *trade credit* providers' comparative advantage in assessing and monitoring debtor risk unreplicable by conventional banking. This advantage becomes crucial in *emerging market* contexts: [Smith \(1987\)](#) showed *trade credit* functions as both a trust *signal* and implicit quality guarantee between firms, while [Emery \(1984\)](#) explained *trade credit* as a functional instrument balancing seller and buyer *cash flow* needs within an ongoing business relationship.

Yet this informational advantage does not eliminate risk inherent to *trade credit* itself. The theoretical foundation explaining this problem is *Information Asymmetry Theory* ([Akerlof, 1970](#)), deepened by [Stiglitz and Weiss \(1981\)](#) into the credit market context: when lenders lack perfect information about debtor quality, two pathologies emerge at different points in time. *Adverse selection* occurs before credit is granted, when high-risk debtors have greater incentive to seek credit than low-risk debtors with alternative financing. *Moral hazard* occurs after credit is disbursed, when debtors lose incentive to pay on time absent consistent oversight. Both pathologies form the conceptual foundation for the two risk-control mechanisms central to this study: Risk Acceptance Criteria, which corrects adverse selection at the selection point, and the Collection Process, which corrects *moral hazard* during post-transaction monitoring, consistent with *Delegated Monitoring Theory* ([Diamond, 1984](#)).

2.2 Risk Acceptance Criteria

Risk Acceptance Criteria refers to measurable parameters used to assess prospective debtors' creditworthiness before facility approval, encompassing documentation completeness, composite character-capacity-capital-collateral-conditions (5C) scoring, *approval matrix* consistency, and evaluation process efficiency ([Mian & Smith, 1992](#)). This concept has evolved well beyond a mere administrative checklist into a *data-driven* scoring system that actively corrects credit decision bias. [Farooq et al. \(2022\)](#), through a twelve-country *emerging market* panel study, found *data-driven* credit decisions consistently produce portfolios 40% better than decisions influenced by cognitive biases such as overconfidence and anchoring, indicating that RAC's issue is not merely which criteria are used, but how consistently those criteria are applied

without subjective judgment interference. In the Indonesian context, [Anggraeni et al. \(2023\)](#) demonstrated consistent 5C application reduces uncollectible receivable risk by up to 60%, while [Sukrianto and Lakoro \(2022\)](#) and [Widautama \(2023\)](#) separately identified the absence of formal RAC as a dominant factor in high problematic receivables among SMEs and manufacturers.

2.3 Collection Process

Collection Process encompasses post-transaction receivables monitoring and collection activities, from proactive pre-due-date reminders to direct contact, field visits, through graduated escalation toward restructuring or legal action ([Ng, Smith, & Smith, 1999](#)). What fundamentally distinguishes *Collection Process* from *Risk Acceptance Criteria* is temporal character: RAC operates once at the decision point, while *Collection Process* operates continuously throughout the receivables lifecycle, creating more contact points with ongoing risk. [Lenz \(2023\)](#), through a systematic review of forty-seven *peer-to-peer* lending studies, found reminder automation shortens *Days Sales Outstanding* by an average of ten days and reduces Non-Performing Loans by up to 25%. In the Indonesian B2B distribution context, [Zebua et al. \(2022\)](#) demonstrated that a structured *Collection Process* reduces overdue receivable ratios by up to 35%, while [Heo \(2024\)](#) showed that combining standardized RAC and a *Collection Process* keeps Non-Performing Loans below 5% even during global economic shocks.

2.4 Uncollectible Receivables

Uncollectible receivables, in this study's context, refers to a multidimensional condition encompassing long-term problematic receivables (NPL Ratio), past-due receivables (AR Overdue Ratio), permanent losses through *write-off* (*Bad Debt Write-off Ratio*), and receivables at early-stage delinquency risk (At Risk Receivable Ratio). This multidimensional operationalization matters because uncollectible receivables are not a binary condition (collected or not), but a spectrum of risk stages, each reflecting different control-mechanism effectiveness; AR Overdue reflects early-detection effectiveness, while *Bad Debt Write-off* reflects recovery failure at the final stage. [Richards and Laughlin \(1980\)](#), through *Cash Conversion Cycle Theory*, position receivables quality as a central component determining how quickly *working capital* cycles back into productive cash, a *framework* underpinning why uncollectible receivables is positioned as a mediating variable, not merely an endpoint outcome, in this study.

2.5 Revenue Performance

Revenue Performance in this study is operationalized multidimensionally, encompassing annual revenue growth, credit transaction volume growth, *customer retention* rate, and *Net Revenue Retention*, an approach deliberately transcending conventional sales growth measurement. [Jensen \(1986\)](#), through *Free Cash Flow Theory*, affirms that firm value is determined by free *cash flow* quality available for positive-value investment, not merely accrual earnings recorded on financial statements, an argument justifying why *Revenue Performance* must be measured beyond gross sales figures alone. [Deloof \(2003\)](#) provides the strongest *quantitative* evidence linking receivables quality to financial performance, showing that across 1,009 Belgian firms, every 10-day reduction in *Days Sales Outstanding* increases *profitability* by an average of 1.2%. This finding is replicated in contemporary contexts by [Endah Tri and Fanani \(2025\)](#) in Indonesia and [Lukito and Setyawan \(2024\)](#) in the Southeast Asian consumer

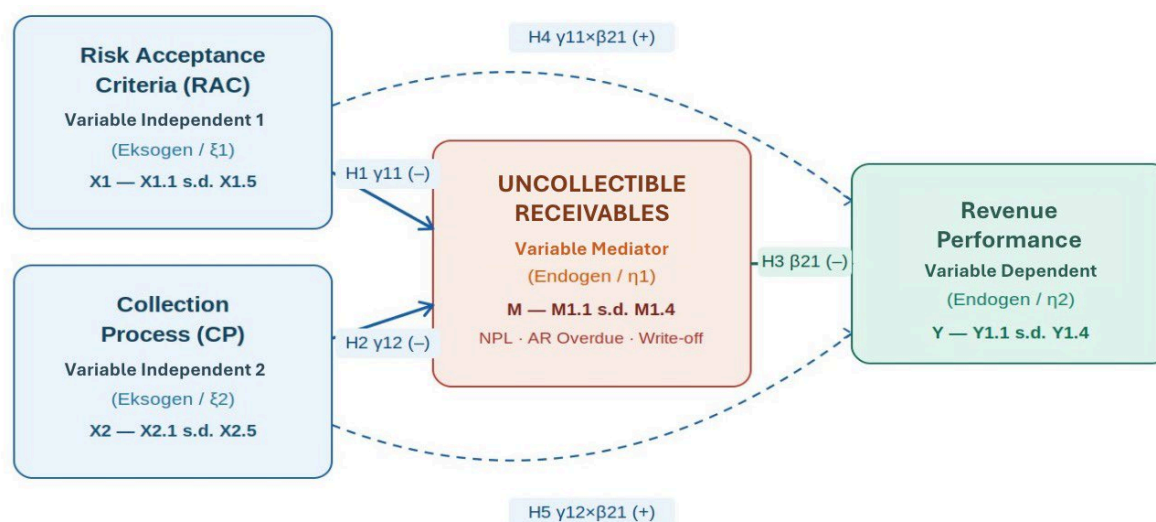
goods sector, reinforcing cross-decade, cross-geography generalization that receivables health is a prerequisite, not merely a correlate, of sustainable *revenue performance*.

2.6 Hypothesis Development

Based on the synthesis of theoretical *framework* and empirical evidence in Sections 2.1 through 2.5, this study formulates five hypotheses. The *adverse selection* argument outlined in Section 2.1, supported by empirical evidence from [Farooq et al. \(2022\)](#) and [Anggraeni et al. \(2023\)](#) in Section 2.2, suggests that better credit *screening* directly reduces the proportion of high-risk debtors entering the portfolio, leading to the first hypothesis: H1, *Risk Acceptance Criteria* has a significant negative effect on Uncollectible Receivables. The *moral hazard* and *delegated monitoring* argument in Section 2.1, reinforced by evidence from [Lenz \(2023\)](#) and [Zebua et al. \(2022\)](#) in Section 2.3, suggests that continuous post-transaction monitoring suppresses debtor payment delay incentives, leading to the second hypothesis: H2, *Collection Process* has a significant negative effect on Uncollectible Receivables.

The *Cash Conversion Cycle* and *Free Cash Flow* frameworks in Sections 2.4 and 2.5, supported by cross-decade replicated evidence from [Deloof \(2003\)](#), suggest that receivables quality directly determines a firm's capacity to generate revenue through *working capital liberation*, leading to the third hypothesis: H3, Uncollectible Receivables has a significant negative effect on *Revenue Performance*. Because *Risk Acceptance Criteria* and *Collection Process* conceptually have no mechanism to influence revenue without first affecting receivables quality, this study formulates *mediation* hypotheses: H4, Uncollectible Receivables mediates the effect of *Risk Acceptance Criteria* on *Revenue Performance*; and H5, Uncollectible Receivables mediates the effect of *Collection Process* on *Revenue Performance*.

Figure 1. Research Model



Source: Authors' own elaboration.

3. Research Method

3.1 Research Design

This study applies a descriptive-verificative approach through a *quantitative case study* design ([Yin, 2018](#)) at a single *non-bank B2B trade credit* provider serving Indonesia's construction and

manufacturing sectors. The choice of single *case study* design, rather than cross-firm surveys common in similar research, rests on specific methodological grounds: the *revelatory case* characteristic described by [Yin \(2018\)](#) requires an object undergoing a rare yet fully documented phenomenon, a condition met by this study's object through its *Non-Performing Loan* transformation from 22.05% to 0.01% within three years, alongside *Revenue Performance* growth exceeding 250%, with complete monthly operational data available since the transformation period's onset. Cross-firm *survey* designs, though superior in statistical generalization, cannot capture such temporal transformation dynamics because they only capture conditions at a single point in time.

3.1.1 Data Collection

Monthly *longitudinal* data were collected over 36 periods (January 2023–December 2025) from the company's operational information systems, comprising eighteen formative indicators forming four research constructs as presented in Table 1. The 36-month period selection was not merely a matter of following PLS-SEM minimum *sample* size convention, but deliberately encompasses the firm's entire transformation phase, from receivables crisis conditions in early 2023 to stable conditions by late 2025, ensuring the data captures sufficiently broad condition variation to detect the structural relationships tested.

3.1.2 Research Indicators

Table 1. Research Indicators

Construct	Indicator	Operational Definition
Risk Acceptance Criteria (X1)	X1.1 KYC Completeness	Completeness of legal, financial, and supporting project documentation
	X1.2 Composite 5C Score	Character, Capacity, Capital, Collateral, Conditions
	X1.3 Approval Matrix Consistency	Decision consistency according to authority tiers
	X1.4 Approval Rate	Approval percentage per risk segment
	X1.5 Turnaround Time	Speed of credit approval process (days)
Collection Process (X2)	X2.1 Collection Effectiveness Index	Percentage of due receivables successfully collected
	X2.2 Roll Rate Effectiveness	Receivables quality stability across aging buckets
	X2.3 Right Party Contact Rate	Success rate in reaching payment decision-makers
	X2.4 SOP Adherence Rate	Collection activity compliance with procedure
	X2.5 DSO Efficiency	Ratio of target to actual DSO
Uncollectible Receivables (M)	M1.1 NPL Ratio	Receivables >90 days to total receivables

	M1.2 AR Overdue Ratio	Overdue invoices to total invoices
	M1.3 Bad Debt Write-off Ratio	Written-off receivables to credit sales
	M1.4 At Risk Receivable Ratio	Receivables >30 days to total receivables
Revenue Performance (Y)	Y1.1 YoY Revenue Growth	Annual revenue growth
	Y1.2 YoY Credit Volume Growth	Annual credit transaction volume growth
	Y1.3 Customer Retention Rate	Percentage of active repeat customers
	Y1.4 Net Revenue Retention	Expansion minus churn among existing customers

Source: Processed by the author, 2026

3.2 Data Analysis

All indicators were treated as formative, not reflective, following [Hair et al. \(2022\)](#). This decision is not merely technical: each indicator in Table 1 reflects a conceptually distinct operational dimension that cannot substitute for another; documentation completeness (X1.1) cannot represent process speed (X1.5), just as debtor contact success (X2.3) cannot represent procedural compliance (X2.4). Removing a single formative indicator means permanently losing part of the construct's information, unlike reflective indicators, which can conceptually substitute for one another since they originate from the same domain; thus, the formative model choice is a logical consequence of the four constructs' multidimensional nature, not merely a methodological preference.

Data were analyzed using Partial Least Squares *Structural Equation Modeling* (PLS-SEM) via SmartPLS 4, selected on three grounds: compatibility with complex formative models without the non-convergence risk commonly faced by Covariance-Based SEM at limited *sample* sizes, a dual confirmatory-predictive orientation enabling validation beyond mere *in-sample* hypothesis testing, and flexibility toward *longitudinal* data's distributional characteristics, which tend not to satisfy *multivariate normality* assumptions. *Measurement model* evaluation covered collinearity statistics (VIF), *outer-weight significance*, and *outer loadings*. *Structural model* evaluation covered *R-Square*, *F-Square*, path coefficients, and Model Fit. Hypothesis testing was conducted through *bootstrapping* with 5,000 resamples using the bias-corrected and accelerated approach. As a complement rarely reported in similar studies, *out-of-sample* predictive validation was performed through *PLSPredict* (k-fold cross-validation, k=10) and the *Cross-Validated Predictive Ability Test* (CVPAT), comparing model performance against Linear Model and Indicator Average benchmarks ([Shmueli et al. 2019](#)), ensuring the resulting model not only explains historical data but possesses genuine *predictive relevance* toward unobserved conditions.

4. Findings and Discussions

4.1 Descriptive Statistics

Table 2 presents descriptive statistics for the eighteen research indicators across 36 observation periods.

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Table 2. Descriptive Statistics

Indicator	Mean	Std. Dev.	Min	Max
X1.1 KYC Completeness	68.81	18.09	38.77	97.25
X1.2 Composite 5C Score	63.88	19.31	30.40	93.58
X1.3 Approval Matrix Consistency	66.64	19.12	36.96	94.89
X1.4 Approval Rate	57.99	20.06	26.39	91.29
X1.5 Turn Around Time	11.77	5.35	3.56	20.75
X2.1 Collection Effectiveness Index	68.93	16.56	40.90	96.39
X2.2 Roll Rate Effectiveness	70.48	15.03	47.00	96.97
X2.3 Right Party Contact Rate	63.83	17.14	37.99	94.70
X2.4 SOP Adherence Rate	67.62	17.34	38.51	93.01
X2.5 DSO Efficiency	81.67	15.24	55.91	107.76
M1.1 NPL Ratio	15.89	9.53	1.77	31.17
M1.2 AR Overdue Ratio	24.60	12.51	5.71	47.85
M1.3 Bad Debt Write-off Ratio	7.06	3.77	0.46	13.93
M1.4 At Risk Receivable Ratio	23.54	11.18	4.15	40.39
Y1.1 YoY Revenue Growth	42.81	32.87	-3.48	90.70
Y1.2 YoY Credit Volume Growth	36.64	27.29	-8.51	87.81
Y1.3 Customer Retention Rate	70.22	14.65	46.36	96.62
Y1.4 Net Revenue Retention	93.91	23.39	57.40	130.03

Source: SmartPLS 4 output, processed ($n=36$)

Substantial variability across all indicators (standard deviation 3.77-32.87) indicates genuine business dynamics following the seasonal cycles of construction and manufacturing projects,

not an artificial linearly-moving pattern.

4.2 Measurement Model (Outer Model) Evaluation

Collinearity statistics (VIF) show all indicators below the 3.3 threshold (Hair et al., 2022), with the highest value at 3.22 (X1.2) and the lowest at 1.26 (X2.1), as presented in Table 3.

Table 3. Outer Loading and Collinearity Statistics (VIF)

Indicator	Outer Loading	VIF
X1.1 KYC Completeness	0.704	1.62
X1.2 Composite 5C Score	0.895	3.22
X1.3 Approval Matrix Consistency	0.485	1.83
X1.4 Approval Rate	0.625	2.18
X1.5 Turn Around Time	-0.804	1.74
X2.1 Collection Effectiveness Index	0.765	1.26
X2.2 Roll Rate Effectiveness	0.840	2.32
X2.3 Right Party Contact Rate	0.708	1.94
X2.4 SOP Adherence Rate	0.691	1.92
X2.5 DSO Efficiency	0.388	1.36
M1.1 NPL Ratio	0.888	1.62
M1.2 AR Overdue Ratio	0.736	2.15
M1.3 Bad Debt Write-off Ratio	0.623	1.49
M1.4 At Risk Receivable Ratio	0.750	1.98
Y1.1 YoY Revenue Growth	0.954	2.18
Y1.2 YoY Credit Volume Growth	0.585	1.64
Y1.3 Customer Retention Rate	0.769	2.06
Y1.4 Net Revenue Retention	0.597	2.01

Source: SmartPLS 4 output, processed

All outer loadings are significant at $p < 0.05$ (0.485-0.954). Indicators X1.3 and X2.5 show non-significant *outer weights* individually but are retained because *outer loading* remains substantial, consistent with formative indicator retention guidelines ([Hair et al., 2022](#)).

4.3 Structural Model (Inner Model) Evaluation

Table 4. R-Square, F-Square, and Model Fit

Construct / Path	Criterion	Value
Uncollectible Receivables (M)	R-Square	0.605
Revenue Performance (Y)	R-Square	0.486
X1 to M	F-Square	0.366

X2 to M	F-Square	0.613
M to Y	F-Square	0.945
SRMR (Estimated Model)	Model Fit	0.1115
NFI (Estimated Model)	Model Fit	0.641

Source: SmartPLS 4 output, processed

The model explains 60.5% of the variance in Uncollectible Receivables and 48.6% of the variance in *Revenue Performance*, both categorized as moderate to strong (Hair et al., 2022). All three structural paths show large effect sizes ($f\text{-square} > 0.35$ per Cohen, 1988), with M to Y (0.945) far exceeding X1 to M (0.366) and X2 to M (0.613). SRMR and NFI values fall slightly outside conventional ideal thresholds, a condition common for complex formative models with limited sample sizes; NFI is specifically designed for reflective models and tends lower in purely formative models (Henseler et al. 2015), such that this model's validity rests more heavily on collinearity, bootstrapping significance, and the predictive validation presented next.

4.4 Hypothesis Testing

Table 5. Hypothesis Testing Results (Bootstrapping 5,000 Resamples)

H	Path	Beta	t	p	Decision
H1	X1 to M	-0.409	2.675	0.0075	Supported
H2	X2 to M	-0.529	3.369	0.0008	Supported
H3	M to Y	-0.697	8.779	<0.0001	Supported
H4	X1 to M to Y	0.285	2.485	0.0130	Supported
H5	X2 to M to Y	0.369	2.817	0.0049	Supported

Source: SmartPLS 4 Bootstrapping output, processed

All five hypotheses are supported. The path coefficient of *Collection Process* on Uncollectible Receivables (beta=-0.529) consistently exceeds that of *Risk Acceptance Criteria* (beta=-0.409).

4.5 Predictive Validation (PLSpredict and CVPAT)

Table 6. PLSpredict and CVPAT Results

Construct	Q2predict	CVPAT Comparison	t	p
M	0.219	vs Linear Model	2.213	0.0335
Y	0.336	vs Indicator Average	3.261	0.0025

Source: SmartPLS 4 PLSpredict and CVPAT output, processed

Positive Q2predict values on both endogenous constructs confirm the model's predictive relevance beyond the estimation sample. CVPAT shows PLS-SEM significantly outperforms the Linear Model benchmark ($t=2.213$; $p=0.0335$) and Indicator Average benchmark ($t=3.261$; $p=0.0025$) at the overall model level.

4.6 Discussion

Risk Acceptance Criteria and Uncollectible Receivables

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H1's acceptance ($\beta = -0.409$; $p = 0.0075$) confirms that more structured credit *screening* directly reduces the proportion of high-risk debtors entering the portfolio, precisely the *adverse selection* mechanism formulated by [Stiglitz and Weiss \(1981\)](#). Yet the moderate effect magnitude, relative to other paths in the model, requires explanation deeper than simply stating the hypothesis is supported. *Risk Acceptance Criteria* operates once at the credit decision point; its influence on any given month's receivables portfolio depends on the proportion of receivables originating from customer cohorts that have passed through the latest criteria. When a firm tightens RAC in a given month, most outstanding receivables still originate from prior transactions under older criteria versions, so RAC's effect accumulates gradually as older cohorts are replaced by newer ones, rather than manifesting instantly in monthly *panel data*.

This finding aligns with [Farooq et al. \(2022\)](#) and [Anggraeni et al. \(2023\)](#), both confirming the *effectiveness of data-driven RAC and 5C criteria in reducing problematic receivables, a similarity that affirms H1's external validity across emerging market contexts*. However, this study enriches both in one important respect: neither [Farooq et al. \(2022\)](#) nor [Anggraeni et al. \(2023\)](#) tested RAC's influence in isolation, without controlling for the possibility that some observed effect actually stems from concurrent, unmeasured collection mechanism effectiveness. The -0.409 coefficient reported here is an estimate purged of this potential overlap, since *Collection Process* is simultaneously controlled within the same *structural model*, yielding a methodologically more precise RAC contribution estimate than both comparison studies.

Collection Process and Uncollectible Receivables

H2's acceptance ($\beta = -0.529$; $p = 0.0008$), with a coefficient consistently exceeding H1 across every measure, magnitude, effect size (0.613 versus 0.366), and statistical significance alike, constitutes this study's most substantive finding. The most persuasive explanation lies in the structural difference in contact frequency with ongoing risk. Unlike RAC, which operates once, *Collection Process* potentially engages repeatedly with the same receivables throughout its collection cycle: fourteen-day pre-due reminders, seven-day reminders, direct contact approaching the due date, post-due-date field visits, through graduated escalation. Each contact point is a fresh opportunity to influence the debtor's payment decision within the current month, making the *Collection Process* structurally more sensitive to monthly *panel data* than a mechanism operating once upfront. This interpretation is consistent with *Delegated Monitoring Theory* ([Diamond, 1984](#)): monitoring delegated to a specialized, continuous function yields more consistent oversight than one-time evaluation.

Supporting evidence appears in the gap between the AR Overdue Ratio (mean 24.60%) and the Bad Debt Write-off Ratio (mean 7.06%) in Table 2, indicating that most temporarily delinquent receivables were recovered before becoming permanent losses. This aligns with [Lenz \(2023\)](#), finding that *Collection Process* automation reduces NPL by up to 25% through a similar recovery mechanism in *peer-to-peer* lending, and [Zebua et al. \(2022\)](#), demonstrating a similar pattern in Indonesian B2B distribution. An important difference: both studies operate in structurally simpler contexts; P2P lending has a standardized digital customer database, while [Zebua et al. \(2022\)](#) is a single *case study* without formal statistical testing. This study enriches both by presenting formal *bootstrapping* testing in the *non-bank* B2B construction-project context, a far more complex, non-standardized domain than either comparison context, while confirming that continuous monitoring effectiveness is a universal principle, not confined to digital platforms alone.

Uncollectible Receivables and Revenue Performance

H3's acceptance with an effect size of 0.945, the largest category among all structural paths, demands explanation for why this path is so dominant. The answer lies in M's structural position as the single convergence point: both the risk that RAC fails to screen and the risk that *Collection Process* fails to control ultimately converge on the same measure, receivables quality. Its causal mechanism operates through two mutually reinforcing channels: direct *liquidity* (problematic receivables lock up *working capital* that should finance new transactions, consistent with *Cash Conversion Cycle Theory* from [Richards and Laughlin, 1980](#)) and indirect expansion capacity (locked *working capital* constrains new business opportunity capture, consistent with *Free Cash Flow Theory* from [Jensen, 1986](#)).

This finding is consistent with [Deloof \(2003\)](#) in a very different geographic context, Western European manufacturing firms in the early 2000s versus Indonesian B2B financing firms in the mid-2020s, reinforcing the generalization that the receivables quality-financial performance relationship is fairly universal. This consistency is further reinforced by [Endah Tri and Fanani \(2025\)](#) and [Lukito and Setyawan \(2024\)](#) in contemporary contexts. However, this study surpasses these three comparison studies in one important aspect: all three measure the receivables quality-performance relationship directly without situating it within a formal *mediation framework* that explains where receivables quality originates. This study fills that gap by showing that receivables quality itself is a measurable outcome of the RAC and Collection Process combination that can be intervened upon separately, not merely an exogenous variable taken as given.

Mediation Effect: Why Benefits Are Not Felt Directly

H4 ($\beta=0.285$; $p=0.013$) and H5 ($\beta=0.369$; $p=0.0049$) acceptance confirms RAC and *Collection Process* do not influence *Revenue Performance* directly without first affecting receivables quality. This model deliberately excludes direct paths from X1 to Y and X2 to Y, based on the argument that sound RAC generates a healthier receivables portfolio, and that a healthier portfolio frees capacity to generate greater revenue. The observed consistency pattern, *Collection Process mediation* exceeding RAC *mediation*, aligning with the pattern that *direct effect* X2 to M also exceeds X1 to M, provides additional evidence this *mediation* mechanism operates proportionally, not as a spurious statistical artifact. [Naumenkova, Mishchenko, and Dorosh \(2020\)](#) conceptually concluded that combining *ex-ante* and *ex-post* mechanisms most effectively mitigates credit risk, yet without *quantitative* testing of their relative contribution; this study fills that gap by demonstrating *Collection Process* contributes 49% more than RAC in suppressing problematic receivables, a comparative nuance unattainable from conceptual conclusion alone.

Boundary Condition to Conventional Risk-Return Trade-off

The finding that a 99.95% NPL decline can occur alongside *Revenue Performance* growth exceeding 250% indicates a boundary condition under which Risk-Return *Trade-off Theory* ([Brigham & Ehrhardt, 2017](#)) does not hold universally. The conventional *trade-off* assumes tightening credit criteria suppresses sales volume because screened-out customers turn to more lenient providers, a mechanism requiring a competitive capital market with accessible financing alternatives. This condition is unmet in the Indonesian *non-bank* B2B market: 61.26% of businesses lack access to formal bank financing ([Atradius, 2025](#)), a structural market characteristic independent of the H1-H5 test results, not a consequence of those findings. In a

market with such high financial exclusion, *trade credit* demand is inelastic: customers screened out by tighter RAC do not necessarily have alternative financing providers to turn to, such that tightening selection criteria does not automatically translate into lost volume as the conventional *trade-off* assumes. This claim is presented with appropriate methodological caution: as a single *case study*, this research does not intend to broadly refute [Brigham and Ehrhardt \(2017\)](#), but rather proposes market financial exclusion level as a potential moderating variable determining when that *trade-off* holds.

Synthesis: Positioning Findings within the Literature Landscape

Bringing together the five discussions above, a fairly consistent pattern emerges: at the individual relationship level, this study aligns with the majority of prior literature, [Farooq et al. \(2022\)](#), [Anggraeni et al. \(2023\)](#), [Lenz \(2023\)](#), [Zebua et al. \(2022\)](#), and [Deloof \(2003\)](#), confirming these findings are not an anomaly deviating from scholarly consensus, but a coherent synthesis of bodies of knowledge previously developed separately. One important exception is Risk-Return *Trade-off* Theory ([Brigham & Ehrhardt, 2017](#)), explicitly challenged by this study's findings under high financial exclusion conditions. At the model scope level, this study's richness lies not in discovering a previously unknown relationship, which would itself be suspicious, but in synthesis: uniting five bodies of knowledge each already solid separately (*adverse selection*, *delegated monitoring*, *cash conversion cycle*, *free cash flow*, and *risk-return trade-off*) within a single simultaneous testing *framework* unavailable in any reviewed study, including [Gunardi et al. \(2024\)](#), the most thematically related yet still treating RAC and *Collection Process* as two parallel descriptive findings, not two mechanisms operating through one shared *mediation* pathway.

5. Conclusion

This study demonstrates that the extreme receivables quality transformation, from 22.05% NPL to 0.01% within three years, is not a statistical coincidence, but a measurable outcome of two risk control mechanisms operating through different yet complementary temporal logics. *Risk Acceptance Criteria* and *Collection Process* both significantly suppress Uncollectible Receivables, yet *Collection Process* is consistently more dominant across every measure tested because its responsive, continuous nature creates more intervention points than *Risk Acceptance Criteria's ex-ante*, one-time operation at the decision point. Uncollectible Receivables, in turn, proves to be the single convergence point, explaining why improvements in both risk mechanisms ultimately translate into *Revenue Performance* growth, not through a direct pathway, but through receivables portfolio quality improvement as the single yet dominant connecting pathway, confirmed by formal *mediation* testing and further validated by the model's predictive capability toward data beyond the estimation *sample*.

This study's scientific implications extend beyond confirming five hypotheses. It shows that the risk-return *trade-off* assumption long considered universally applicable in conventional financial management carries a boundary condition determined by market structural characteristics, in markets with high financial exclusion such as Indonesian *non-bank* B2B trade, inelastic *trade credit* demand means strengthened risk criteria do not automatically sacrifice growth, as demonstrated by this study's object firm. This proposition is not merely a generalization from a single case, but a theoretical argument grounded in market characteristics independent of the hypothesis-testing results themselves, opening a new research direction on financial exclusion level as a moderating variable worth formally testing in future multi-firm designs.

For managerial practice, these findings offer precise investment priority guidance: strengthening *Collection Process*, particularly capacity to reach payment decision-makers and consistency in graduated escalation, delivers the most immediate impact on receivables quality, while *Risk Acceptance Criteria* remains essential as a longer-term investment whose effects accumulate through new customer cohorts. Future research is recommended to replicate this model across multiple *non-bank B2B trade credit* firms simultaneously to test statistical generalization of the *Collection Process* dominance pattern found here, and to incorporate macroeconomic variables and explicit direct-path designs to strengthen formal validation of the *full mediation* classification this study proposes.

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