INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VII July 2026

Data Analytics Utilization and Credit Collection Management in Selected Retail Banks in Muntinlupa: Inputs to Performance Optimization

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DOI: https://doi.org/10.51244/IJRSI.2026.1307000242

Received: 19 July 2026; Accepted: 24 July 2026; Published: 09 August 2026

ABSTRACT

This study responds to a set of editorial revisions requiring a clarified unit of analysis, full re-analysis from raw respondent-level data, a defensible theoretical framework, and transparent reporting of sampling, reliability, and common-method-bias safeguards. It re-examines data analytics capability and credit collection management as they are perceived by bank employees — not as bank-level analytics capability and not as objective collection performance, which were not measured in this dataset and are flagged as a direction for future research rather than inferred. Fifty employees (27 Collection Officers, 13 Branch Managers, and 10 Data Analysts) of retail banks operating in Muntinlupa City, Philippines, completed a 127-item structured questionnaire between February 23 and March 24, 2026. Bank affiliation was identifiable for 24 respondents across ten named banks; the remaining 26 (52.0%) did not record a bank affiliation, a data-completeness gap that is reported openly rather than masked. All descriptive statistics, composite means, ANOVA results, post hoc comparisons, and correlations were recalculated directly from the 50-respondent raw dataset. The twelve capability and practice dimensions demonstrated strong internal consistency ($\alpha = .880$ to $.936$; corrected item-total correlations .51 to .86) and were rated Highly Evident overall, ranging from Real-Time Reporting and Monitoring ($M = 4.13$, $SD = 0.61$) to Data Security and Confidentiality ($M = 4.35$, $SD = 0.50$). One-way ANOVA indicated role-based differences in ten of twelve dimensions at the conventional $\alpha = .05$, but after Holm-Bonferroni correction for multiple comparisons only Data-Driven Decision Making ($F = 6.87$, $p = .002$, holm-$p = .027$, $\eta^2 = .23$) and Payment Reminder Systems ($F = 7.16$, $p = .002$, holm-$p = .023$, $\eta^2 = .23$) remained significant, with Tukey post hoc tests locating the difference between Collection Officers and Data Analysts. All 36 correlations between analytics-capability and collection-management dimensions were positive and remained significant after Holm correction ($r = .439$ to $.823$), and the overall composite correlation was very high ($r = .909$, 95% CI [.844, .947]). Harman's single-factor test extracted 43.7% of variance on one unrotated factor, and a dimension-level principal-components analysis found a single dominant component (68.4% of variance, loadings .70 to .88) rather than two separable constructs — evidence that favors an integrated data-driven collection-capability framework over the Technology Acceptance Model, which was not retained because its core constructs (perceived usefulness and perceived ease of use) were not measured. An exploratory intraclass correlation computed on the bank-identified subsample (ICC(1) ≈ 0, $\bar{k} = 2.08$ across 10 banks) could not detect reliable bank-level clustering, a result attributed to the incomplete bank identifiers and small, unbalanced cluster sizes rather than to an absence of institutional effects. Respondents reported moderate-to-high challenges in both analytics utilization ($M = 3.72$) and collection management ($M = 4.02$), and rated proposed performance-optimization inputs as highly acceptable ($M = 4.10$). The study concludes that, at the level of employee perception, data analytics practices and collection-management practices are strongly and positively associated, while cautioning that this evidence is perceptual, single-method, and drawn from an incompletely documented sampling frame, and recommending that future iterations capture objective collection indicators, complete bank identifiers, and a larger, cluster-balanced sample suitable for multilevel analysis.

Keywords: data analytics capability, credit collection management, employee perceptions, retail banking, common method bias, Philippines

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INTRODUCTION

Data analytics is increasingly positioned as a strategic lever for strengthening credit collection performance in retail banking, yet much of the supporting evidence in the Philippine setting rests on studies that do not clearly separate what is actually being measured: how employees perceive their institution's analytics practices, how capable the institution actually is at generating and using analytics, and how collection accounts objectively perform. Conflating these levels risks overstating what a perception survey can support. This study addresses that concern directly by re-scoping the inquiry to what the available data can defensibly speak to — employee perceptions — while being explicit about what it cannot: bank-level analytics capability as an organizational property, and objective collection outcomes such as delinquency, recovery, cure, or collection-cost measures, none of which were captured in the underlying instrument.

Unit of Analysis and Scope of the Study

The unit of analysis in this study is the individual employee respondent — a Collection Officer, Branch Manager, or Data Analyst — and the outcome measured is that employee's perception of the extent to which data-driven practices and collection-management practices are implemented in their workplace. This is an important distinction for three reasons. First, employee perception is not equivalent to bank-level analytics capability: capability is an organizational property that would typically be assessed through IT infrastructure audits, documented governance practices, or aggregated performance across an institution's full complement of relevant staff, none of which this survey was designed to capture. Second, employee perception is not equivalent to objective collection performance: no delinquency, recovery, cure-rate, or collection-cost data were collected, so any statement about “effectiveness” in this paper refers to perceived, self-reported implementation rather than verified financial outcomes. Third, because respondents are nested within banks (with considerable clustering evident in the roster, and with 26 of 50 respondents not reporting a bank affiliation at all), perceptions cannot automatically be pooled as if they were 50 independent observations of a single population; the clustering question is examined explicitly in Section 4.7, and its limitations are reported rather than glossed over. Throughout the paper, findings are therefore worded as employee-perceived data analytics capability and employee-perceived credit collection management, and claims about organizational-level capability or objective performance are avoided unless directly evidenced.

Research Gap

Existing literature on analytics-enabled credit collection in Philippine retail banking tends to report high, uniformly favorable composite means and significant relationships without disclosing whether those figures were recomputed from raw respondent data, whether multiple-comparison corrections were applied, whether the instrument's reliability and factor structure were examined, or whether common method variance was assessed — despite the entire dataset being collected through a single self-report instrument administered to a single source of respondents at one point in time. In addition, studies in this space frequently adopt the Technology Acceptance Model (TAM) as a theoretical anchor without actually measuring its core constructs of perceived usefulness and perceived ease of use, using it instead as a general reference to “technology adoption” rather than as a testable model. This study addresses these gaps by (a) recalculating every descriptive and inferential statistic directly from the 50-respondent raw dataset; (b) reporting assumption checks, effect sizes, confidence intervals, and Holm-Bonferroni corrected p-values for every comparison and correlation; (c) assessing common method bias procedurally and statistically; (d) examining whether the hypothesized two-construct structure (analytics capability versus collection management) is empirically distinguishable through dimension-level factor analysis; and (e) adopting an organizational data-analytics-capability framework in place of TAM, whose constructs this instrument does not measure.

Objectives of the Study

This study aimed to examine employee-perceived data analytics capability and credit collection management practices among retail bank employees in Muntinlupa City, Philippines, as inputs to performance optimization. Specifically, it sought to:

1. Describe the demographic and institutional profile of respondents, including the extent to which bank affiliation could be identified from the available records;

2. Assess employee-perceived data analytics capability across six dimensions: data accuracy and integrity, real-time reporting and monitoring, predictive analytics for default risk, dashboard visualization and automation, data-driven decision-making, and data security and confidentiality, including the reliability and item-level validity of each dimension;

3. Assess employee-perceived credit collection management practices across six dimensions: customer segmentation and profiling, payment reminder systems, incentive and penalty programs, debt restructuring and negotiation, digital payment channels, and collection staff competency and training, including the reliability and item-level validity of each dimension;

4. Determine whether respondents' assessments differ significantly by organizational role (Collection Officer, Branch Manager, Data Analyst), applying assumption checks, effect sizes, and correction for multiple comparisons;

5. Determine the strength, direction, and significance of the relationship between data analytics capability and credit collection management dimensions, applying correction for multiple comparisons and reporting confidence intervals;

6. Evaluate the extent of common method bias and the empirical factor structure underlying the twelve capability and practice dimensions;

7. Examine, on an exploratory basis, whether perceptions cluster by participating bank, and report the limitations of this analysis given the available data;

8. Identify the challenges employees encounter relative to data analytics utilization and credit collection management; and

9. Determine the acceptability of proposed inputs to performance optimization, developed from the study's findings.

Theoretical Framework

The original conception of this study anchored on the Technology Acceptance Model (TAM; Davis, 1989) alongside Credit Risk Management Theory. On review, TAM was judged unsuitable as a retained framework because its defining constructs — perceived usefulness and perceived ease of use, and the behavioral-intention pathway that connects them to technology use — were not measured by the instrument; the questionnaire instead asks respondents to rate the extent to which specific analytics and collection practices are implemented, which is a capability-implementation judgment rather than an acceptance or intention judgment. Retaining TAM without measuring its constructs would have created a nominal rather than a substantive theoretical link. This section therefore substitutes an organizational data-analytics-capability framework, grounded in the Resource-Based View, for the analytics side of the study, and retains Credit Risk Management Theory as the domain-specific anchor for the collection-management side.

Data Analytics Capability Framework

Drawing on the Resource-Based View, big data and analytics capability is conceptualized as an organizational capability built from tangible resources (data and technology infrastructure), human resources (analytical and managerial skills), and intangible resources (a data-driven culture) that together allow a firm to convert data into decisions and, ultimately, into performance (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016). Mikalef, Krogstie, Pappas, and Pavlou (2020) extend this view by showing that analytics capability operates through dynamic and operational capabilities to influence competitive performance, rather than translating directly into outcomes. Applied here, the six analytics-side dimensions in the instrument — data accuracy and integrity, real-time reporting and monitoring, predictive analytics, dashboard visualization and automation, data-driven

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decision-making, and data security — map onto this capability view: the first and last describe foundational data-infrastructure resources, the middle dimensions describe the technical and managerial capability to convert data into usable insight, and data-driven decision-making describes the behavioral outcome of that capability being exercised in practice. This framing treats the six dimensions as facets of a single underlying analytics capability rather than as independent variables, a treatment that is examined empirically in Section 4.6.

Credit Risk Management Theory

Credit Risk Management Theory, as synthesized by Naili and Lahrichi (2022) in their review of the determinants of banks' credit risk, holds that effective management of credit exposure depends on systematic borrower assessment, continuous monitoring, timely intervention, and differentiated recovery strategies across the loan lifecycle. This provides the domain-specific anchor for the six collection-management dimensions examined here — customer segmentation and profiling, payment reminder systems, incentive and penalty programs, debt restructuring and negotiation, digital payment channels, and staff competency and training — each of which corresponds to an operational mechanism through which banks are expected to identify, monitor, and resolve delinquency risk.

Integration and Testable Expectation

Read together, the data-analytics-capability framework and Credit Risk Management Theory generate a specific, testable expectation for this study: if analytics capability functions as a resource that supports collection-management practice, then employees who perceive stronger analytics capability in their bank should also perceive more effective collection-management practice, and the two sets of dimensions may not be empirically separable at the perception level because both are manifestations of the same underlying, technology-enabled collection capability. This expectation is tested directly through the correlation and factor analyses reported in Sections 4.5 and 4.6, rather than assumed.

METHODOLOGY

Research Design

This study employed a cross-sectional, descriptive-correlational research design using a single structured self-report questionnaire. The descriptive component characterizes the extent to which respondents perceive data analytics capability and collection-management practices to be implemented; the correlational component examines the statistical association between these perceptions. Because both sets of variables were collected from the same respondents, at the same time, using the same instrument, the design is explicitly single-source and cross-sectional, which bears on the interpretation of common method bias discussed in Section 3.7 and Section 4.6, and on the correlational (non-causal) nature of every relationship reported.

Research Setting and Data-Collection Period

The study was conducted among retail bank branches operating in Muntinlupa City, Philippines. Response timestamps in the raw dataset indicate that data collection occurred between February 23, 2026 and March 24, 2026 (approximately four weeks). This window is reported here because it was not clearly documented in the earlier draft and is reconstructed directly from the survey platform's recorded timestamps rather than from memory or estimate.

Participants and Sampling

Fifty employees directly involved in credit collection and analytics use completed the questionnaire: 27 Collection Officers (54.0%), 13 Branch Managers (26.0%), and 10 Data Analysts (20.0%). Respondents were asked to record their employing bank; this field was completed by 24 respondents, identifying ten named banks (Security Bank Corporation, Bank of the Philippine Islands, Banco de Oro, Rizal Commercial Banking Corporation, Metropolitan Bank and Trust Company, Robinsons Bank, Development Bank of the Philippines, Philippine Savings Bank, Land Bank of the Philippines, and Philippine National Bank), while 26 respondents (52.0%) left the field blank. This is reported as a data-completeness limitation rather than resolved by

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assumption: the total number of participating banks, the sampling frame from which respondents were drawn, and the response rate relative to an eligible population cannot be verified from the records available for this analysis. Because the original sampling documentation could not be located, the sampling technique is best described post hoc as availability/purposive sampling of employees who were accessible and willing to respond during the collection window, rather than the total enumeration or probability design that would be needed to support a formal response-rate calculation. Future data collection for this line of research should make bank identification a mandatory field, log an explicit sampling frame (e.g., a roster of eligible staff per participating branch), and record retrieval counts so that a response rate can be reported.

Research Instrument

Data were collected using a structured questionnaire comprising five parts: (1) demographic and institutional profile; (2) 48 items across six dimensions assessing perceived data analytics capability; (3) 48 items across six dimensions assessing perceived credit collection management practices; (4) 12 items across two dimensions assessing challenges encountered relative to analytics utilization and collection management; and (5) 6 items assessing the acceptability of proposed performance-optimization inputs. All 114 substantive items were rated on a five-point Likert scale, with higher scores indicating greater perceived implementation, greater frequency of challenges encountered, or greater acceptability, depending on the section. The complete item pool, response scale, and section instructions are reproduced in Appendix A (to be finalized by the author); the underlying construct definitions used to interpret the twelve dimensions in this report were derived from the content of the items themselves, as summarized in Table 1.

The record available to this analysis does not document the original source of each item, the adaptation procedure from any prior instrument, or a formal panel expert-validation report with a content validity index. This is acknowledged directly: the reviewers' request that the complete questionnaire be provided together with item sources, adaptation procedures, expert validation, and pilot-testing documentation cannot be satisfied from the materials available for this reanalysis, and doing so is identified as a required next step before the manuscript is resubmitted, not something this reanalysis can retroactively supply. What this reanalysis can and does supply is empirical reliability and item-level validity evidence computed directly from respondent data (Section 3.5), which is a necessary complement to, but not a substitute for, documented content and expert validation.

Table 1. Working Definitions of the Twelve Capability and Practice Dimensions

Dimension	**Working Definition (derived from item content)**
Data Accuracy and Integrity	Extent to which customer and loan records are perceived to be accurate, verified, and free of duplication or error.
Real-Time Reporting and Monitoring	Extent to which dashboards, alerts, and reports are perceived to reflect current account and portfolio status.
Predictive Analytics for Default Risk	Extent to which predictive models and risk scoring are perceived to inform default-risk identification and prioritization.
Dashboard Visualization and Automation	Extent to which collection data are perceived to be visualized and automatically compiled for interpretation and reporting.
Data-Driven Decision Making	Extent to which collection strategy, resourcing, and policy decisions are perceived to be guided by analytical evidence.
Data Security and Confidentiality	Extent to which access controls, encryption, and security practices are perceived to protect customer financial data.
Customer Segmentation and Profiling	Extent to which borrowers are perceived to be classified and prioritized according to payment behavior and risk.

Payment Reminder Systems	Extent to which automated, multi-channel reminders are perceived to be used before and during delinquency.
Incentive and Penalty Programs	Extent to which incentive and penalty mechanisms are perceived to encourage timely payment.
Debt Restructuring and Negotiation	Extent to which flexible repayment and restructuring options are perceived to be offered and consistently applied.
Digital Payment Channels	Extent to which secure, convenient digital payment options are perceived to be available and integrated with collection records.
Collection Staff Competency and Training	Extent to which staff are perceived to be trained in analytics tools, negotiation, and ethical collection practice.

Validity and Reliability

Internal consistency was assessed using Cronbach's alpha computed directly on the raw item responses for each of the twelve substantive dimensions plus the challenge and acceptability scales. All fourteen scales exceeded the conventional .70 threshold, ranging from .880 to .957 (Table 4, Table 9, Table 10, and Table 11). Corrected item-total correlations, computed for every one of the 96 substantive capability/practice items, ranged from .51 to .86, all comfortably above the .30 minimum typically used to flag a weak item (Nunnally, 1978), indicating that no item is a candidate for removal on internal-consistency grounds. This constitutes the reliability evidence requested by the reviewers; it does not substitute for the content-validity and expert-panel documentation noted in Section 3.4, which remains outstanding.

Statistical Treatment of Data

All analyses were computed directly on the 50-respondent raw dataset (no statistic in this report was derived from a prior draft or estimated). The following techniques were applied:

Frequency and percentage distributions described the demographic and institutional profile of respondents.

Composite (weighted) means and standard deviations described the extent of each dimension, interpreted using the ranges: 4.20–5.00 (Highly Evident), 3.40–4.19 (Evident), 2.60–3.39 (Moderately Evident), 1.80–2.59 (Least Evident), 1.00–1.79 (Very Least Evident), with the corresponding Encountered/Acceptable labels used for the challenge and acceptability scales.

Cronbach's alpha and corrected item-total correlations assessed internal consistency and item-level validity for each of the fourteen scales.

One-way analysis of variance (ANOVA) tested whether composite scores differed significantly across the three respondent groups for each of the twelve dimensions. Levene's test assessed homogeneity of variance and the Shapiro-Wilk test assessed normality of residuals for each dimension; where variance homogeneity was in question, Welch's ANOVA (robust to heterogeneity of variance) was computed alongside the classical F-test as a robustness check. Eta-squared (η^2) quantified effect size for every ANOVA.

Holm-Bonferroni correction was applied across the twelve ANOVA tests and, separately, across the thirty-six correlation tests, to control the family-wise error rate under multiple testing; both uncorrected and Holm-corrected p-values are reported so that the effect of the correction is transparent.

Tukey's Honestly Significant Difference (HSD) test, using the studentized range distribution, was computed as post hoc comparison for dimensions that remained statistically significant after Holm correction.

The Pearson product-moment correlation coefficient quantified the strength and direction of association between each analytics-capability dimension and each collection-management dimension (36 pairings) and between the

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VII July 2026

two overall composites. Fisher's z-transformation was used to compute 95% confidence intervals for every correlation.

Harman's single-factor test (an unrotated principal-components analysis of all 96 substantive items) assessed the risk of common method bias.

A separate principal-components analysis of the twelve dimension-level composite scores, with Bartlett's test of sphericity, examined whether the hypothesized two-construct structure (six analytics dimensions versus six collection dimensions) is empirically distinguishable, or whether a single general factor better describes the data.

An intraclass correlation coefficient, ICC(1), was computed on the subsample of 24 respondents with identified bank affiliation, as an exploratory check for bank-level clustering; this analysis is reported with explicit caveats given the small, unbalanced cluster sizes and the 52% missingness in bank identification.

All statistical tests were interpreted at $\alpha = .05$ prior to correction, with Holm-adjusted significance reported alongside.

Common Method Bias: Procedural and Statistical Safeguards

Because every construct in this study was measured through the same self-report instrument administered to the same respondents at a single point in time, common method bias is a material threat to the correlational findings (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Procedurally, the analytics-capability and collection-management sections were presented as conceptually distinct parts of the questionnaire with separate instructions, and items were written as concrete behavioral descriptions rather than evaluative or abstract statements, both of which are standard procedural remedies. Statistically, Harman's single-factor test and a dimension-level factor analysis were used to gauge the extent of shared method variance (Section 4.6). No objective, non-self-report indicator (such as bank-reported delinquency or recovery data) was available to cross-validate the self-reports, which remains the most important unaddressed source of potential bias and is carried forward as a limitation and a specific recommendation for future data collection.

Ethical Considerations

The study adhered to established ethical principles governing research involving human participants. Respondents were informed of the study's objectives, the voluntary nature of participation, and their right to withdraw at any stage without penalty; consent was obtained prior to questionnaire administration. No personally identifiable information beyond broad demographic categories and (where volunteered) employing bank is reported, and all data were treated confidentially and used solely for academic purposes. Formal institutional or panel ethical-approval documentation is referenced in the Declarations section; where such documentation could not be located for this reanalysis, that gap is stated rather than assumed.

RESULTS AND DISCUSSION

Demographic and Institutional Profile of Respondents

Table 2. Distribution of Respondents by Role, Demographic Profile, and Identified Bank (N = 50)

Category	f	%
Type of Respondent		
Collection Officer	27	54.0
Branch Manager	13	26.0
Data Analyst	10	20.0

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Sex		
Female	30	60.0
Male	20	40.0
Age Bracket		
25 years old and below	8	16.0
26–30 years old	4	8.0
31–35 years old	13	26.0
36–40 years old	10	20.0
41–45 years old	8	16.0
46–50 years old	5	10.0
51 years old and above	2	4.0
Highest Educational Attainment		
Bachelor's Degree	39	78.0
Master's Degree	3	6.0
With Master's Degree Units	2	4.0
Doctorate Degree	3	6.0
With Doctorate Degree Units	2	4.0
College Undergraduate	1	2.0
Civil Status		
Married	27	54.0
Single	20	40.0
Widow/Widower	2	4.0
Legally Separated	1	2.0

Table 3. Identified Bank Affiliation (n = 24 of 50; 26 respondents did not report a bank)

Bank	**f**	**% of identified**
Security Bank Corporation	10	41.7
Bank of the Philippine Islands	3	12.5
Banco de Oro	2	8.3
Rizal Commercial Banking Corporation	2	8.3
Metropolitan Bank and Trust Company	2	8.3

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Robinsons Bank	1	4.2
Development Bank of the Philippines	1	4.2
Philippine Savings Bank	1	4.2
Land Bank of the Philippines	1	4.2
Philippine National Bank	1	4.2
Total identified	24	100.0

Note. Percentages for identified banks are computed on the 24 respondents who reported an affiliation, not on the full sample of 50. Bank name variants (e.g., "SBC," "Security Bank," "Security Bank Corporations") were consolidated to a single entity prior to tabulation.

The sample is predominantly composed of Collection Officers, followed by Branch Managers and Data Analysts, broadly consistent with the frontline-heavy staffing structure typical of retail collection units. More importantly for this reanalysis, fewer than half of the respondents (24 of 50) can be tied to a specific bank; the remaining 26 are analyzed as ungrouped individual respondents throughout this report rather than assigned to an inferred institution. This is treated as a primary limitation rather than smoothed over, and it materially constrains the bank-clustering analysis reported in Section 4.7.

Employee-Perceived Data Analytics Capability

Table 4. Composite Means, Reliability, and Rank of Data Analytics Capability Dimensions

Dimension	**CO (n=27)**	**BM (n=13)**	**DA (n=10)**	**Composite Mean**	**SD**	**α**	**VI**	**Rank**
Data Accuracy and Integrity	4.12	4.49	4.35	4.260	.550	.880	HE	5
Real-Time Reporting and Monitoring	3.88	4.39	4.45	4.128	.613	.895	E	6
Predictive Analytics for Default Risk	4.00	4.25	4.59	4.183	.630	.929	E	4
Dashboard Visualization and Automation	4.00	4.40	4.56	4.215	.678	.936	HE	3
Data-Driven Decision Making	4.06	4.43	4.65	4.272	.523	.908	HE	2
Data Security and Confidentiality	4.25	4.39	4.59	4.353	.502	.902	HE	1

Note. CO = Collection Officer; BM = Branch Manager; DA = Data Analyst; VI = Verbal Interpretation (HE = Highly Evident, 4.20–5.00; E = Evident, 3.40–4.19). Overall mean across all six dimensions = 4.235 (Highly Evident).

Employee-perceived data analytics capability was rated Highly Evident overall (M = 4.24), with Data Security and Confidentiality rated highest (M = 4.35) and Real-Time Reporting and Monitoring rated lowest, though still within the Evident range (M = 4.13). Across all six dimensions, Data Analysts and Branch Managers consistently reported higher perceived implementation than Collection Officers — a pattern consistent with the Resource-Based View's expectation that capability is most visible to the personnel closest to the technology and its outputs,

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while frontline staff experience analytics capability indirectly, through the tools and prioritized account lists it produces (Akter et al., 2016; Mikalef et al., 2020).

Employee-Perceived Credit Collection Management Practices

Table 5. Composite Means, Reliability, and Rank of Credit Collection Management Dimensions

Dimension	CO (n=27)	BM (n=13)	DA (n=10)	Composite Mean	SD	α	VI	Rank
Customer Segmentation and Profiling	4.14	4.23	4.64	4.265	.523	.907	HE	6
Payment Reminder Systems	4.07	4.53	4.70	4.317	.564	.911	HE	2
Incentive and Penalty Programs	4.09	4.57	4.36	4.270	.577	.910	HE	4
Debt Restructuring and Negotiation	4.04	4.52	4.36	4.228	.531	.921	HE	5
Digital Payment Channels	4.09	4.53	4.51	4.287	.608	.932	HE	3
Collection Staff Competency and Training	4.10	4.41	4.44	4.250	.539	.929	HE	1*

Note. Rank is by composite mean; "1" marks the closeness between Collection Staff Competency and Training and Data Accuracy and Integrity from Table 4 when all twelve dimensions are ranked together (see Table 6). Overall mean across all six collection dimensions = 4.270 (Highly Evident).*

Employee-perceived credit collection management was likewise rated Highly Evident overall (M = 4.27), marginally higher than the analytics-side composite (M = 4.24). Payment Reminder Systems and Digital Payment Channels ranked highest among collection-management dimensions, while Customer Segmentation and Profiling ranked lowest, though still Highly Evident. As with the analytics dimensions, Data Analysts and Branch Managers reported higher perceived implementation than Collection Officers across every dimension, a consistent role-based pattern examined formally in Section 4.4.

Table 6. All Twelve Dimensions Ranked by Composite Mean

Rank	Dimension	M	SD	α
1	Data Security and Confidentiality	4.353	.502	.902
2	Payment Reminder Systems	4.317	.564	.911
3	Digital Payment Channels	4.287	.608	.932
4	Data-Driven Decision Making	4.272	.523	.908
5	Incentive and Penalty Programs	4.270	.577	.910
6	Customer Segmentation and Profiling	4.265	.523	.907
7	Data Accuracy and Integrity	4.260	.550	.880
8	Collection Staff Competency and Training	4.250	.539	.929

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9	Debt Restructuring and Negotiation	4.228	.531	.921
10	Dashboard Visualization and Automation	4.215	.678	.936
11	Predictive Analytics for Default Risk	4.183	.630	.929
12	Real-Time Reporting and Monitoring	4.128	.613	.895

Differences in Assessment by Respondent Role

To determine whether Collection Officers, Branch Managers, and Data Analysts differed significantly in their perceptions, one-way ANOVA was computed for each dimension, followed by Levene's and Shapiro-Wilk assumption checks, Welch's ANOVA as a robustness check, and eta-squared as an effect size. Because twelve separate ANOVA tests were run on the same sample, Holm-Bonferroni correction was applied across all twelve to control the family-wise error rate; both the uncorrected and Holm-corrected p-values are reported in Table 7 so that the effect of the correction is visible rather than hidden.

Table 7. One-Way ANOVA on the Twelve Dimensions by Respondent Role, with Assumption Checks, Effect Size, and Holm-Bonferroni Correction (df = 2, 47)

Dimension	F	p	Holm-p	η^2	Levene p	Welch F/p	Interpretation (Holm-corrected)
Data Accuracy and Integrity	2.319	.110	.322	.090	.065	3.428/.050	Not significant
Real-Time Reporting and Monitoring	5.518	.007	.070	.190	.085	5.880/.008	Not significant[b]
Predictive Analytics for Default Risk	3.625	.034	.269	.134	.014*	5.521/.010	Not significant[b]
Dashboard Visualization and Automation	3.578	.036	.269	.132	.056	3.892/.034	Not significant[b]
Data-Driven Decision Making	6.867	.002	.027*	.226	.028*	7.441/.003	Significant
Data Security and Confidentiality	1.816	.174	.322	.072	.112	2.117/.141	Not significant
Customer Segmentation and Profiling	3.651	.034	.269	.134	.250	6.395/.005	Not significant[b]
Payment Reminder Systems	7.161	.002	.023*	.234	.165	8.162/.002	Significant
Incentive and Penalty Programs	3.448	.040	.269	.128	.007*	5.772/.009	Not significant[b]
Debt Restructuring and Negotiation	4.621	.015	.133	.164	.022*	5.279/.011	Not significant[b]
Digital Payment Channels	3.486	.039	.269	.129	.017*	3.844/.035	Not significant[b]
Collection Staff Competency and Training	2.342	.107	.322	.091	.539	2.439/.108	Not significant

*Note. Holm-p < .05 is marked with an asterisk in the Holm-p column and used as the interpretation criterion. [b] indicates the dimension was significant at the uncorrected α = .05 but not after Holm correction — reported so the effect of correction is transparent, not to imply the uncorrected result should be relied upon. Levene p < .05 (marked *) indicates heterogeneity of variance, for which the Welch F/p is the more appropriate robustness check.*

At the conventional, uncorrected $\alpha = .05$, ten of the twelve dimensions showed statistically significant differences across respondent groups — the pattern that a report relying only on unadjusted p-values would highlight. After Holm-Bonferroni correction for the twelve simultaneous tests, however, only two dimensions remained significant: Data-Driven Decision Making ($F = 6.87$, $p = .002$, Holm-p = .027, $\eta^2 = .23$, a large effect) and Payment Reminder Systems ($F = 7.16$, $p = .002$, Holm-p = .023, $\eta^2 = .23$, a large effect). This divergence between uncorrected and corrected conclusions is itself a substantive finding: role-based differences in perception are real and large for the two dimensions most closely tied to visible managerial decision-making and to reminder-system operation, but the evidence for role-based differences on the remaining ten dimensions is not strong enough to survive correction for multiple testing, and those uncorrected results should not be treated as confirmed differences. Levene's test flagged heterogeneous variances for five dimensions (Predictive Analytics, Incentive and Penalty Programs, Debt Restructuring, Digital Payment Channels, and marginally Data-Driven Decision Making); the Welch F-statistics computed for these dimensions were consistent in direction and significance pattern with the classical F-test, indicating the ANOVA conclusions are not an artifact of variance heterogeneity.

Table 8. Tukey HSD Post Hoc Comparisons for Dimensions Significant After Holm Correction

Dimension	**Comparison**	**Mean Diff.**	**95% CI**	**p**	**Interpretation**
Data-Driven Decision Making	Collection Officer vs. Branch Manager	−0.377	[−0.761, 0.007]	.055	n.s.
	Collection Officer vs. Data Analyst	−0.594	[−1.015, −0.174]	.004	Significant
	Branch Manager vs. Data Analyst	−0.217	[−0.695, 0.261]	.519	n.s.
Payment Reminder Systems	Collection Officer vs. Branch Manager	−0.455	[−0.867, −0.043]	.028	Significant
	Collection Officer vs. Data Analyst	−0.626	[−1.078, −0.174]	.005	Significant
	Branch Manager vs. Data Analyst	−0.171	[−0.685, 0.342]	.701	n.s.

For both dimensions that survived correction, the significant contrast is between Collection Officers and Data Analysts, with Payment Reminder Systems also showing a significant Collection Officer–Branch Manager gap. Branch Managers and Data Analysts did not differ significantly from each other on either dimension. This suggests the perceptual gap is concentrated between frontline collection staff and the more technically specialized or managerial roles, rather than being a uniform three-way split, and is broadly consistent with Credit Risk Management Theory's emphasis on monitoring and decision-support functions being more visible to roles with direct oversight of analytics outputs and reminder-system configuration.

Relationship Between Data Analytics Capability and Credit Collection Management

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VII July 2026

Pearson correlations were computed between each of the six analytics-capability dimensions and each of the six collection-management dimensions (36 pairings), with Holm-Bonferroni correction applied across all 36 tests and 95% confidence intervals computed via Fisher's z-transformation.

Table 9. Pearson Correlations Between Data Analytics Capability and Credit Collection Management Dimensions (N = 50)

Analytics Dimension	**CSP**	**PRS**	**IPP**	**DRN**	**DPC**	**CSCT**
Data Accuracy and Integrity	.565	.684	.663	.715	.642	.688
Real-Time Reporting and Monitoring	.439	.751	.718	.584	.635	.739
Predictive Analytics for Default Risk	.620	.763	.713	.762	.701	.708
Dashboard Visualization and Automation	.505	.724	.823	.600	.634	.682
Data-Driven Decision Making	.696	.707	.606	.644	.665	.669
Data Security and Confidentiality	.559	.569	.484	.527	.619	.569

Note. CSP = Customer Segmentation and Profiling; PRS = Payment Reminder Systems; IPP = Incentive and Penalty Programs; DRN = Debt Restructuring and Negotiation; DPC = Digital Payment Channels; CSCT = Collection Staff Competency and Training. All 36 correlations were statistically significant (uncorrected $p < .01$ in every cell) and all 36 remained significant after Holm-Bonferroni correction (Holm-$p < .05$ in every cell); 95% confidence intervals (not shown per cell for space) ranged narrowly from [.183, .639] for the weakest pairing to [.706, .896] for the strongest. Overall composite correlation: $r = .909$, 95% CI [.844, .947], $p < .001$.

Every one of the 36 pairings was positive and remained significant after correcting for multiple comparisons, confirming a broad, consistent association between employee-perceived analytics capability and employee-perceived collection-management practice rather than an association driven by one or two dimensions. The strongest relationship was between Dashboard Visualization and Automation and Incentive and Penalty Programs ($r = .823$), and the weakest, though still significant, was between Real-Time Reporting and Monitoring and Customer Segmentation and Profiling ($r = .439$). Data Security and Confidentiality showed the most consistently moderate correlations with collection-management dimensions ($r = .484$ to $.619$), mirroring the earlier draft's observation that secure data-handling functions as an enabling condition for collection practice rather than a direct decision-support lever in the way dashboards and predictive models appear to be. The overall composite correlation ($r = .909$) is very high; given that both composites were built from Likert items answered by the same respondents in the same sitting, this figure should be read together with the common-method-bias evidence in Section 4.6 rather than in isolation, since general-factor or halo-type response patterns can inflate such correlations.

Common Method Bias and Factor-Analytic Evidence

Harman's single-factor test — an unrotated principal-components analysis of all 96 substantive capability and practice items — extracted a first factor accounting for 43.7% of total variance (eigenvalue = 41.99 of 96 possible; 20 components had eigenvalues greater than 1). Because this figure falls below the commonly cited 50% threshold used to flag severe common method bias (Podsakoff et al., 2003), the result does not indicate that a single method factor accounts for the majority of covariation in the data; however, at nearly 44%, it is high enough that common method variance cannot be ruled out as a contributor to the strength of the correlations reported in Section 4.5, and this qualification is carried into the study's conclusions rather than discounted.

A separate, purpose-built analysis examined whether the twelve dimension-level composite scores empirically separate into the hypothesized two constructs (six analytics dimensions, six collection dimensions) or instead form a single general factor. Bartlett's test of sphericity confirmed the twelve composites are suitable for factor

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VII July 2026

analysis ($\chi^2(66) = 538.58$, $p < .001$). The principal-components analysis extracted only one component with an eigenvalue greater than 1 (eigenvalue = 8.21, accounting for 68.4% of variance among the twelve composites); the second component's eigenvalue (0.85) fell below the conventional retention threshold. All twelve dimensions loaded strongly and positively on this single component (loadings ranging from .70 to .88), with no dimension showing a markedly higher loading on a hypothetical second axis. This is an important and honestly reported finding: at the level of these twelve composite scores, the data are more consistent with a single, general "data-driven collection capability" factor than with two cleanly separable constructs of "analytics capability" and "collection management." This result should temper any causal or even strictly two-construct correlational reading of Section 4.5, and it directly supports the decision in Section 2 to adopt an integrated organizational-capability framework rather than a two-construct TAM-plus-outcome model: the empirical structure of the data, not only the instrument's content, points toward a unified underlying construct.

Because full item-level exploratory factor analysis of the 96 individual items would require a substantially larger sample than N = 50 to produce stable loadings (Fabrigar, Wegener, MacCallum, & Strahan, 1999, recommend samples of 100 or more under favorable conditions), item-level EFA was not attempted here; the dimension-composite analysis above is offered as the factor-analytic evidence that this sample size can support, and full item-level EFA or confirmatory factor analysis is recommended as a next step once a larger sample is available.

Exploratory Check for Clustering by Participating Bank

Because respondents are nested within banks, pooling all 50 perceptions as though they were independent draws from a single population risks understating the true standard error if perceptions cluster strongly by employer. This was examined, on an exploratory basis, using the one-way random-effects intraclass correlation, ICC(1), computed on the 24 respondents with an identified bank affiliation across 10 named banks (average cluster size $\bar{k} = 2.08$, with several banks represented by a single respondent). The resulting estimates were effectively zero or negative for both the analytics composite (ICC(1) = −0.44, bounded at 0 for interpretation) and the collection-management composite (ICC(1) = −0.24, bounded at 0), indicating no detectable bank-level clustering in this subsample.

This null result should not be read as evidence that bank identity has no bearing on employee perceptions; with only 24 clustered observations spread thinly across 10 banks — several of them singletons that contribute no within-cluster variance information at all — the analysis is severely underpowered, and a true clustering effect of moderate size would likely go undetected. Combined with the 52% missingness in bank identification (Section 4.1), this analysis cannot responsibly support either a multilevel model or a cluster-robust standard-error adjustment for the present dataset; both are recommended for a future round of data collection in which bank identification is mandatory and cluster sizes are large enough (a minimum of roughly 5 respondents per bank across at least 15–20 banks is a common rule of thumb for stable multilevel estimation) to support formal multilevel or cluster-robust analysis.

Challenges Encountered

Table 10. Challenges Encountered Relative to Data Analytics Utilization (Ranked; α = .957)

Indicator	M	SD	Rank
Concerns regarding data privacy, cybersecurity risk, and regulatory compliance	3.80	.90	1
Poor data quality (incomplete, inconsistent, or outdated records)	3.76	.92	2
Limited financial resources for advanced analytics infrastructure	3.70	.84	3.5
Inadequate technical expertise among staff	3.70	.86	3.5
Integration difficulties between analytics platforms and core banking systems	3.70	.93	3.5

Resistance to adopting data-driven practices	3.68	.89	6

Overall composite mean = 3.723 (Encountered).

Table 11. Challenges Encountered Relative to Credit Collection Management (Ranked; α = .915)

Indicator	**M**	**SD**	**Rank**
Limited use of analytics insights weakens prioritization of high-risk accounts	4.10	.74	1
Difficulty reaching borrowers due to outdated contact information	4.06	.74	2
High delinquency rates increase workload and strain collection resources	4.04	.76	3
Regulatory restrictions and compliance requirements limit flexibility	4.02	.71	4
Customer resistance or unwillingness to negotiate repayment terms	3.96	.64	5.5
Insufficient staff training affects negotiation effectiveness	3.96	.83	5.5

Overall composite mean = 4.023 (Encountered).

Consistent with the earlier draft, concerns about data privacy, cybersecurity, and regulatory compliance and poor data quality ranked as the foremost analytics-side challenges, while the limited translation of analytics insight into account prioritization ranked as the foremost collection-side challenge. The recalculated composite means are close to, though not identical to, the previously reported figures, which is expected given that they are now computed on the actual 50-respondent dataset rather than reproduced from an earlier, unverified draft.

Acceptability of Proposed Inputs to Performance Optimization

Guided by the dimensions that ranked lowest (Real-Time Reporting and Monitoring, Predictive Analytics for Default Risk) and by the challenges most frequently reported (data privacy/cybersecurity, data quality, and the limited operational use of analytics insight), proposed inputs to performance optimization were organized around strengthening predictive analytics and real-time monitoring, formalizing data-quality audit routines, closing the cybersecurity and access-control gap employees themselves identified, and better connecting analytics output to account-prioritization workflow. Acceptability of these proposed inputs was rated by all respondents.

Table 12. Acceptability of the Proposed Inputs to Performance Optimization (Ranked; α = .953)

Indicator	**M**	**SD**	**Rank**
The plan improves efficiency, compliance, and customer satisfaction.	4.20	.78	1
The proposed optimization plan aligns with organizational goals.	4.10	.74	2.5
Employees and management are willing to adopt the plan.	4.10	.86	2.5
The plan is supported by reliable data findings.	4.08	.78	4
Implementation costs are reasonable relative to benefits.	4.06	.82	5
The recommendations are practical within current operations.	4.04	.76	6

Overall composite mean = 4.097 (Acceptable).

The proposed inputs were rated Acceptable overall (M = 4.10), with the item concerning improved efficiency, compliance, and customer satisfaction rated highest. This indicates general employee readiness for the proposed direction, though acceptability by respondents is not itself evidence that the plan will produce the intended objective improvements in collection performance — a distinction that follows directly from the unit-of-analysis clarification in Section 1.1.

INTEGRATED DISCUSSION

Taken together, the reanalysis confirms that employees of the participating retail banks perceive both data analytics practices and collection-management practices as Highly Evident, that the two sets of perceptions are strongly and consistently associated, and that role-based differences in perception are genuine for two specific dimensions (Data-Driven Decision Making and Payment Reminder Systems) but not statistically defensible, after correction, for the other ten. The dimension-level factor analysis further suggests these perceptions may be better understood as facets of one general, technology-enabled collection capability than as two independently varying constructs — a reading that is consistent with, and provides empirical support for, the decision to replace the Technology Acceptance Model with an integrated data-analytics-capability framework grounded in the Resource-Based View. At the same time, three qualifications limit how far these findings can be pushed: the evidence is entirely perceptual and single-source, so a moderately high common-method-bias signal (43.7% on Harman's test) cannot be excluded as a contributor to the observed associations; more than half the sample cannot be tied to a specific bank, which forecloses a reliable clustering or multilevel analysis; and no objective collection-performance indicator was available to validate whether stronger perceived analytics capability corresponds to actual improvement in delinquency, recovery, cure, or cost outcomes. Each of these qualifications is carried forward explicitly into the conclusions, limitations, and recommendations below, rather than resolved by assumption.

CONCLUSIONS

1. At the level of employee perception, data analytics practices are Highly Evident among the participating retail banks in Muntinlupa City, with data security and confidentiality perceived as the most strongly institutionalized dimension and real-time reporting and monitoring perceived as comparatively less developed, though still evident.

2. Employee-perceived credit collection management practices are likewise Highly Evident overall, with payment reminder systems and digital payment channels perceived most favorably and customer segmentation and profiling perceived comparatively less favorably.

3. After correcting for the twelve simultaneous ANOVA tests, statistically defensible role-based differences in perception exist for only two of twelve dimensions — Data-Driven Decision Making and Payment Reminder Systems — concentrated between Collection Officers and Data Analysts; differences reported at the uncorrected significance level alone should not be treated as confirmed.

4. A strong, statistically significant, and Holm-corrected-robust positive relationship exists between every pairing of analytics-capability and collection-management dimensions, and between the two overall composites (r = .909), consistent with the theoretical expectation that these are related, technology-enabled organizational practices.

5. Dimension-level factor analysis indicates the twelve dimensions are better represented by a single general capability factor than by two empirically distinct constructs, providing empirical support for the study's adoption of an integrated data-analytics-capability framework in place of the Technology Acceptance Model.

6. Common method bias, assessed through Harman's single-factor test (43.7% of variance on one factor), cannot be ruled out as a partial contributor to the strength of the observed associations, given the single-source, single-occasion, self-report design.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VII July 2026

7. Bank-level clustering could not be reliably assessed: 52% of respondents did not report a bank affiliation, and the identified subsample's cluster sizes were too small and unbalanced to support a conclusive intraclass-correlation estimate.

8. Employees report moderate-to-high challenges in both analytics utilization and collection management, most notably data privacy/cybersecurity concerns, data-quality gaps, and the limited operational translation of analytics insight into account prioritization.

9. Proposed inputs to performance optimization, developed from these findings, were rated Acceptable overall by all three respondent groups, indicating employee readiness for the proposed direction while not, by itself, evidencing that the plan will improve objective collection outcomes.

RECOMMENDATIONS

1. Prior to any further submission, append the complete questionnaire, including construct definitions, the source or adaptation basis for each item, the expert-validation (content validity index) report, and any pilot-testing results; these documents could not be located for the present reanalysis and cannot be reconstructed from respondent data alone.

2. Make bank identification a mandatory, validated field in future data collection (e.g., a fixed drop-down list rather than free text) so that the number and identity of participating banks, and any bank-level analysis, can be reported without the 52% missingness encountered here.

3. Maintain and report an explicit sampling frame (a roster of eligible staff by branch and role), the data-collection period, and retrieval counts sufficient to compute a response rate; the present reanalysis could only reconstruct the collection window (February 23–March 24, 2026) from platform timestamps.

4. In the next data-collection cycle, pair employee-perception items with objective, bank-reported collection indicators (e.g., delinquency rate, recovery rate, cure rate, or collection cost per account) so that perceived analytics capability can be validated against actual performance rather than left at the level of self-report.

5. Increase the sample size and ensure adequate, balanced representation per participating bank (a minimum of approximately five respondents per bank across at least fifteen to twenty banks is a reasonable target) to support multilevel or cluster-robust analysis of the nested data structure, and to support full item-level exploratory or confirmatory factor analysis.

6. Continue applying Holm-Bonferroni (or an equivalent) correction for multiple comparisons in any future ANOVA or correlation battery, and continue reporting both uncorrected and corrected results so that reviewers and readers can see the effect of the correction directly.

7. Strengthen procedural common-method-bias remedies in future rounds (e.g., temporal or source separation between the analytics-capability and collection-management sections, or supplementing self-report with a small independent-rater or archival-data check) given the 43.7% Harman's single-factor result obtained here.

8. Prioritize the two capability areas employees themselves rated lowest and identified as most challenging — real-time reporting/monitoring and predictive analytics, alongside data-quality auditing and cybersecurity controls — in the performance-optimization plan's implementation sequencing.

Limitations of the Study

This study is limited to employee perceptions and does not measure bank-level analytics capability as an organizational property or objective collection performance; no delinquency, recovery, cure-rate, or cost data were available. The cross-sectional, single-source, self-report design leaves the correlational findings vulnerable to common method bias, which the Harman's single-factor result (43.7%) suggests is a plausible, though not necessarily dominant, contributor. Bank affiliation was unrecorded for 52% of respondents, preventing a reliable bank-level clustering, multilevel, or cluster-robust analysis; the exploratory ICC estimates reported here are likely underpowered rather than definitive. The sample size (N = 50) is adequate for the dimension-composite analyses reported but is below the threshold typically recommended for stable item-level exploratory factor analysis of the full 96-item pool. Documentation of the instrument's item sources, adaptation procedure, expert validation, and pilot testing could not be located for this reanalysis and remains an outstanding requirement rather than a resolved one. Finally, the original sampling frame and response rate could not be verified from available records, so the sampling technique is described here as availability/purposive rather than as the total enumeration that would support a formal response-rate calculation.

Declarations

Ethical Approval

The study adhered to accepted ethical standards governing research involving human participants. Respondents were informed of the study's objectives, procedures, and voluntary nature prior to data collection. Formal institutional review or panel ethical-clearance documentation should be attached as an appendix in the resubmitted manuscript; it is referenced here but was not part of the materials available for this statistical reanalysis.

Informed Consent

Informed consent was obtained from all respondents prior to questionnaire administration. Participants were assured that responses would remain confidential, would be reported only in aggregate or de-identified form, and would be used solely for academic and research purposes. No personally identifiable information is disclosed in this report.

Data Availability

The respondent-level dataset underlying every statistic in this report is retained by the author and can be made available to editors or reviewers for verification upon request.

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ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VII July 2026

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