The Impact of the 5Cs of Credit Model on Credit Decision-Making: A Sparse Partial Least Squares (sPLS) Analysis Evidence from Algerian Commercial Banks — Saïda Province

Sample: n = 30 | 3 banks | 40-item Likert scale | Python

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Abstract: This research evaluates the predictive efficacy of the "Five Cs" of Credit model — comprising Character, Capacity, Capital, Collateral, and Surrounding Conditions—within the credit decision-making processes of Algerian commercial banks. Using a validated 40-item Likert-scale instrument, primary data were synthesized from 30 credit officers across three banking institutions in Saïda Province. While the constructs exhibited robust internal reliability (**Cronbach's α = 0.799–0.910**), preliminary diagnostics revealed severe multicollinearity among predictors, with inter-construct correlations peaking at **r = 0.848**. Consequently, this study bypasses traditional **OLS** limitations by employing **Sparse Partial Least Squares (sPLS) regression** to ensure analytical precision and resolve sign-reversal artifacts.

The resulting two-component **sPLS** model achieved an **R^2**of **0.397** and a cross-validated **Q^2** of **0.113** (via Leave-One-Out), confirming the model's out-of-sample predictive power. Variable Importance in Projection (VIP) analysis identified **Surrounding Conditions** (**VIP = 1.288**) and **Capacity** (**VIP = 1.069**) as the primary drivers of credit quality, both significantly exceeding the 1.0 threshold. Conversely, **Character** emerged as the least influential factor (**VIP = 0.688**), a finding that likely underscores the structural limitations of credit bureau infrastructure in the Algerian context. These results highlight the necessity of context-specific credit risk governance and offer a refined methodological roadmap for assessing creditworthiness in emerging markets.

Key words: 5Cs Framework, Creditworthiness, Credit Risk, Sparse PLS, VIP Analysis, Algerian Banking Sector.

Jel Classification Codes : G21, G32, C38, C53

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Introduction:

The profitability of commercial banking and the overarching stability of financial systems are fundamentally predicated on the rigor of credit assessment. Efficient credit decision-making ensures that financial markets effectively bridge the gap between surplus units and productive borrowers. In contrast, systemic failures in credit evaluation invariably lead to an accumulation of non-performing loans (NPLs), which progressively deplete bank capital reserves. Empirical evidence underscores this vulnerability; for instance, **(Deloitte, 2019,p19)** highlighted the persistence of elevated NPL ratios in Central and Eastern Europe following the 2008 crisis, while **World Bank (2019)** data revealed similar sharp trajectories across sub-Saharan African economies during the same period.

Central to these evaluative processes is the **"Five Cs of Credit"** framework—comprising Character, Capacity, Capital, Collateral, and Conditions. Since its formal codification by (**Golden and Walker, 1993,p44)** and subsequent popularization by **(Strischek, 2000,p47)**, this model has served as the definitive taxonomy for categorizing borrower risk dimensions. Nevertheless, the practical weight assigned to each "C" is far from universal. Cross-border studies reveal significant contextual variance: (**Peprah et al. 2017p 78)** observed a prioritization of *Capacity* over *Capital* in Ghana, whereas (**Oseni ,2023, p59)** identified *Character* as the primary determinant in the Nigerian banking sector. Furthermore, recent evidence from Jordan suggests that external factors, such as intellectual capital, significantly moderate the 5Cs–decision-making nexus (**Al-Slehat et al., 2024,p279**).

To address the overarching problem, the following hypotheses were formulated, grounded in both classical credit theory and the specificities of the Algerian financial environment:

- **H_1: Surrounding Conditions significantly and positively influence credit decision-making quality.**
  - *Rationale:* Given the fluctuating macroeconomic landscape in Algeria, banks are expected to prioritize external environmental stability as a primary risk mitigation factor.
- **H_2: Capacity remains a dominant predictor of borrower creditworthiness.**
  - *Rationale:* The ability to generate future cash flow is fundamentally critical for debt servicing, especially in a market with emerging corporate structures.
- **H_3: Collateral acts as a mandatory risk-offsetting mechanism in the credit approval process.**
  - *Rationale:* In many emerging economies, tangible guarantees often compensate for information asymmetry between the bank and the borrower.
- **H_4: Capital levels serve as a secondary but essential buffer against default risk.**
- **H_5: Character, while theoretically vital, has a marginal impact on credit decisions due to the underdeveloped nature of centralized credit bureaus.**
  - *Rationale:* This hypothesis challenges the traditional "Character-first" hierarchy, suggesting that lack of reliable historical data in Algeria might diminish its practical weight.

1. Theoretical Framework and Literature Review

1.1 The 5Cs Model: Conceptual Foundations and Information Asymmetry

The 5Cs framework functions as a critical diagnostic protocol designed to navigate the pervasive challenges of **information asymmetry** within credit markets—a phenomenon famously articulated by (**Sharpe, 1990, p1079)** and further refined by **(Crawford, Pavanini, and Schivardi 2018,p1697)**. Recent surveys of credit establishments further emphasize that mitigating this asymmetry requires strict information requirements and a heavy reliance on verifiable records and security (**Cancino & Escalante, 2020, p12**), At its core, the model serves as a structured response to the inherent "informational gap" between lenders and borrowers, which, as (**Claus 2010,p802)** demonstrated, not only complicates individual credit assessments but also exerts a tangible influence on real interest rates and aggregate lending volumes. By systematically evaluating five distinct risk dimensions—Character, Capacity, Capital, Collateral, and Conditions—banks can effectively operationalize a due diligence process that mitigates **informational frictions**. This multi-dimensional approach ensures a holistic evaluation of both the borrower's internal strengths and the external environment, which are critical for minimizing default rates in the lending industry (**Baiden, 2011, p. 10**), This multifaceted assessment allows financial institutions to transform qualitative borrower attributes into quantifiable risk metrics, thereby reducing the probability of adverse selection and moral hazard. In emerging economies like Algeria, where centralized data transparency may be limited (**Aifuwa et al., 2019, p. 62**), this structured protocol becomes even more indispensable as it provides a standardized "roadmap" for credit officers to verify creditworthiness beyond mere financial statements.(**Al-Qudah & All 2022, p103**).

Table 1. Conceptual framework of the Five Cs

Criterion	Symbol	Definition	Standard Proxy
Character	X1	Borrower integrity, honesty, and repayment willingness	Credit history, references
Capacity	X2	Cash flow sufficiency to service debt obligations	DSCR, Net Profit Margin
Capital	X3	Borrower's equity stake; financial buffer against default	Debt-to-Equity Ratio
Collateral	X4	Assets pledged as secondary repayment source	LTV Ratio, forced sale value
Conditions	X5	Macroeconomic and regulatory environment affecting repayment	GDP growth, sector indices

Source: compiled from (Strischek, 2000;p49) ,(Kabir et al., 2010p340); (Al-Slehat et al., 2024.p285)

1.2 Methodological Divergence: Addressing Multicollinearity via sPLS

A critical, yet frequently overlooked, limitation in extant **5Cs** literature is the pervasive issue of **multicollinearity**. Because credit officers evaluate all five criteria simultaneously within a single credit dossier, their subjective ratings inherently co-vary. In the context of the present dataset, this inter-construct correlation reaches a substantial peak of r = 0.848. At such high levels of redundancy, traditional Ordinary Least Squares (**OLS**) estimation becomes mathematically unstable, often yielding distorted coefficients or "sign reversals"—where a theoretically positive predictor (like ***Capital***) might erroneously appear negative (**Hair et al., 2010, p244**).

To circumvent these structural artifacts, this study adopts **Sparse Partial Least Squares (sPLS) regression**. Unlike conventional PLS, the sPLS approach integrates a **regularization penalty** (such as LASSO) during the component construction phase. This mechanism serves a dual purpose: it maximizes the covariance between the latent 5Cs components and the decision-making outcome, while simultaneously "zeroing out" non-contributing or redundant weights. This results in a more parsimonious, data-driven variable selection that maintains predictive integrity even in the presence of severe multicollinearity. By prioritizing sparsity, the model effectively isolates the most "potent" predictors of creditworthiness, offering a clearer, more reliable reflection of banking reality in Saïda Province.

2. Methodology

2.1 Sample Characteristics and Survey Instrument

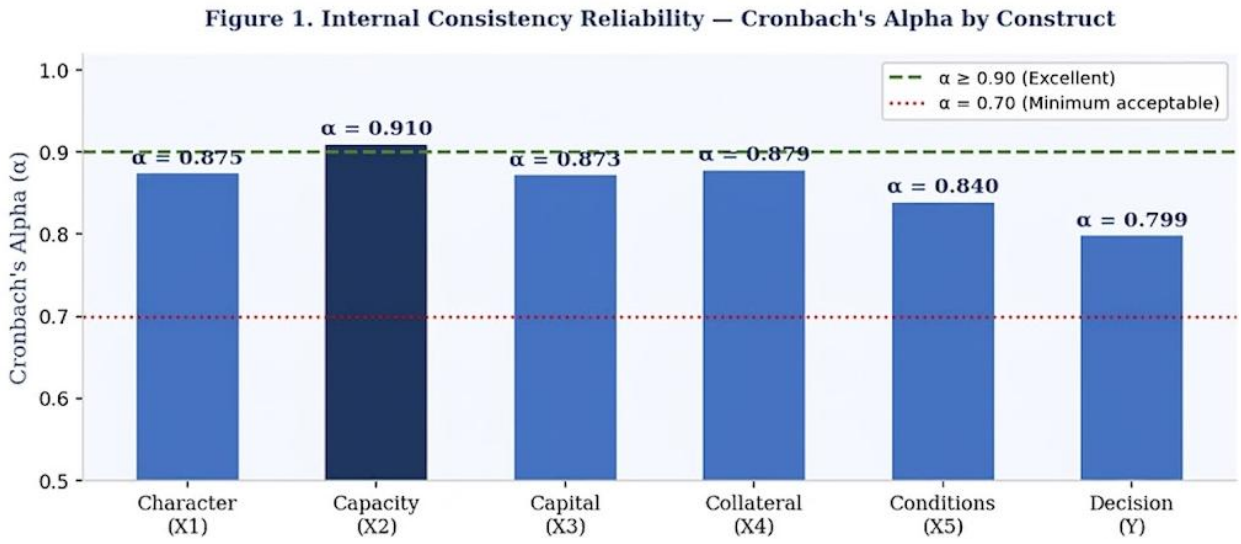
This study employed a quantitative, cross-sectional design targeting a comprehensive census of credit professionals. The sampling frame encompassed 30 credit officers operating within three prominent commercial banks in Saïda Province, Algeria. By opting for a census approach within this specific geographical cluster, the study ensures that the findings reflect the practical expertise of those directly responsible for credit risk mitigation. The primary research instrument consisted of a validated 40-item questionnaire, structured to capture the multifaceted nature of the five creditworthiness dimensions (**X1–X5**) and their subsequent impact on decision-making quality (**Y**). All constructs were operationalized using a 5-point Likert scale, ranging from "**Strongly Disagree**" to "**Strongly Agree**." To ensure robust data aggregation, composite construct scores were derived from the arithmetic means of their respective items, providing a stabilized metric for the subsequent multivariate analysis.

2.2 Psychometric Properties: Reliability Assessment

Before proceeding to the structural model, the instrument's internal consistency was rigorously scrutinized. As detailed in Table 2 and visualized in Figure 7, the reliability diagnostics underscore the high quality of the collected data.

All constructs yielded **Cronbach's alpha** (**α**) **coefficients** well above the conventional 0.70 threshold, with values ranging from 0.79 to 0.91. Notably, four out of the six constructs exceeded 0.87, indicating exceptional inter-item consistency. These psychometric results confirm that the instrument is not only reliable but also sufficiently sensitive to capture the nuances of credit assessment within the Algerian banking environment, thereby providing a solid foundation for the **sPLS** estimation.

Figure 1. Cronbach's Alpha by Construct — All values well above the 0.70 acceptable threshold



Source: Prepared by the author using Python (Matplotlib / Seaborn) based on the study data

Table 2. Measurement model and internal consistency (n = 30). Threshold: α ≥ 0.70

Construct	Code	Items	Q Range	α	Level
Character	X1	7	Q1–Q7	**0.875**	Excellent
Capacity	X2	7	Q8–Q14	**0.910**	**Excellent ★**
Capital	X3	6	Q15–Q20	0.873	Excellent
Collateral	X4	8	Q21–Q28	0.879	Excellent
Conditions	X5	5	Q29–Q33	0.840	Very Good
Decision (Y)	**Y**	7	Q34–Q40	0.799	Good

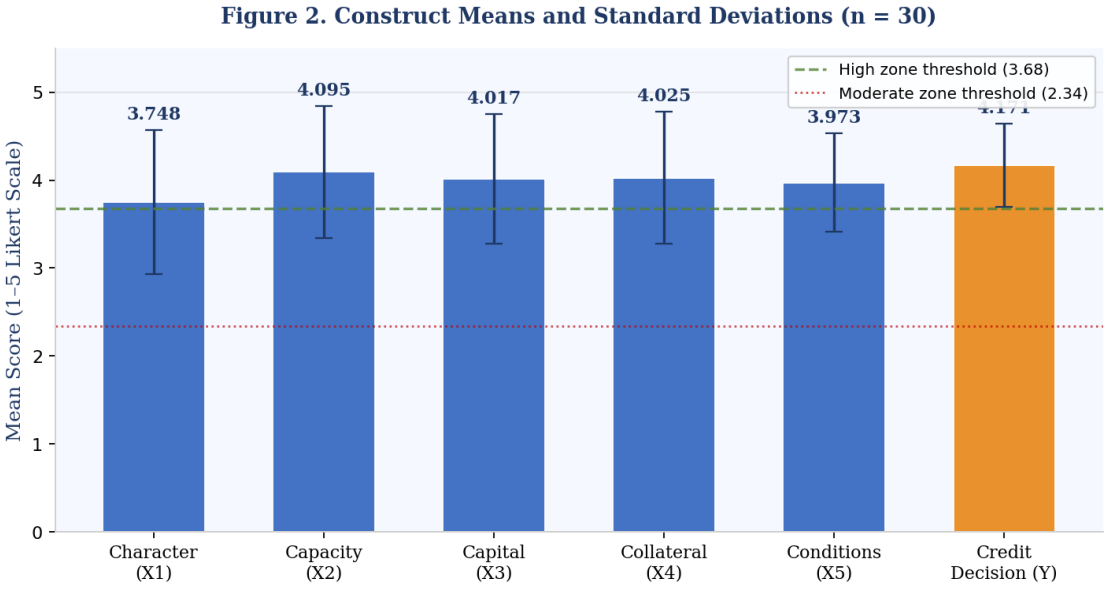
Source: Compiled by the author based on SPSS outputs

3. Results

3.1 Descriptive Statistics

All six constructs recorded means in the 'High' response range (M > 3.68 on the 5-point scale). The Credit Decision construct achieved the highest mean (M = 4.171), while Character recorded the lowest (M = 3.748). Figure 2 presents the construct means with ±1 SD error bars.

Figure 2. Construct Means ± 1 Standard Deviation (n = 30, 5-point Likert scale



Source: Prepared by the author using **Python (Matplotlib / Seaborn)** based on the study data

Table 3. Descriptive statistics. Scale: 1.00–2.33 = Low; 2.34–3.67 = Moderate; 3.68–5.00 = High.

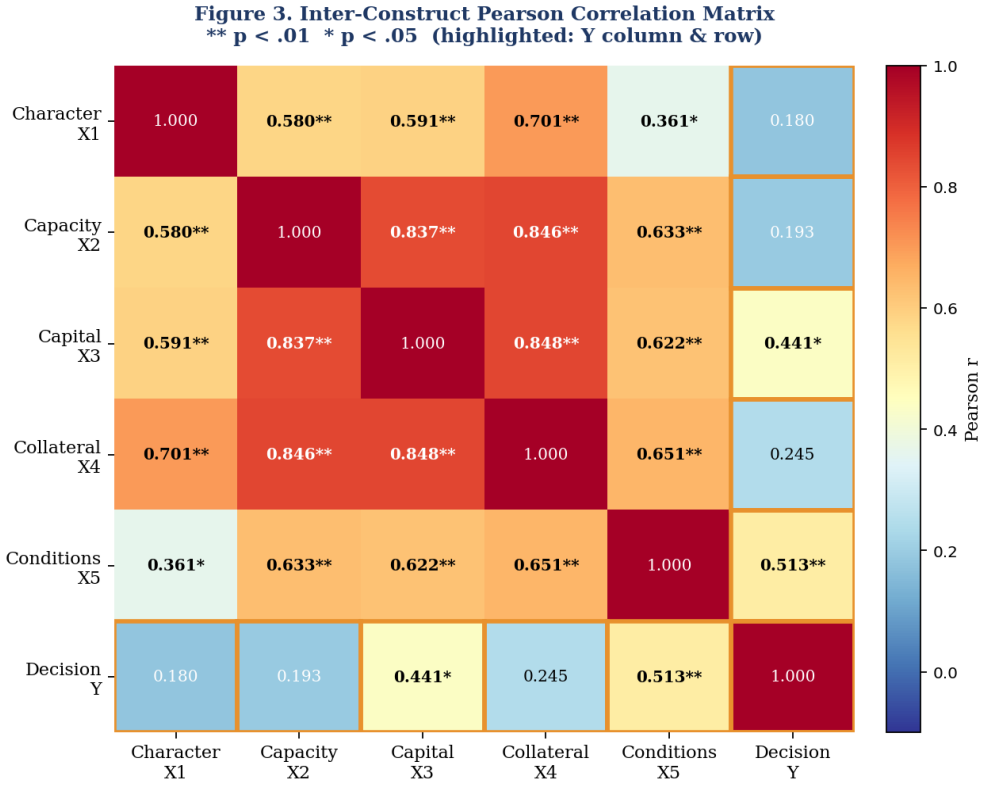
Construct	N Items	Mean	SD	Importance %	Level
Character (X1)	7	3.748	0.821	75.0	High
Capacity (X2)	7	**4.095**	0.750	**81.9**	High
Capital (X3)	6	4.017	0.737	80.3	High
Collateral (X4)	8	4.025	0.752	80.5	High
Conditions (X5)	5	3.973	0.558	79.5	High
Decision (Y)	7	**4.171**	0.471	**83.4**	High

Source: Compiled by the author based on SPSS outputs

3.2 Multicollinearity: Pearson Correlation Matrix

The correlation heatmap (Figure 3) and (Table 4) reveal the severity of inter-predictor collinearity. Correlations among the five predictors reach r = 0.848 (Capital–Collateral), and four predictor pairs exceed r = 0.80. Critically, only Capital (r = 0.441, p = .015) and Conditions (r = 0.513, p = .004) show statistically significant bivariate associations with the Credit Decision outcome.

Figure 3. Pearson Correlation Heatmap — Note the severe inter-predictor collinearity (top-right block)



Source: Prepared by the author using Python (Matplotlib / Seaborn) based on the study data

Table 4. Pearson correlation matrix.

**** p < .01; * p < .05 (two-tailed, n = 30). Bold: significant correlations with Y**

	X1	X2	X3	X4	X5	Y
X1 Character	1.000	0.580**	0.591**	0.701**	0.361*	0.180
X2 Capacity	0.580**	1.000	0.837**	0.846**	0.633**	0.193
X3 Capital	0.591**	0.837**	1.000	0.848**	0.622**	**0.441***
X4 Collateral	0.701**	0.846**	0.848**	1.000	0.651**	0.245
X5 Conditions	0.361*	0.633**	0.622**	0.651**	1.000	**0.513****
Y Decision	0.180	0.193	0.441*	0.245	**0.513****	1.000

Source: Compiled by the author based on SPSS outputs

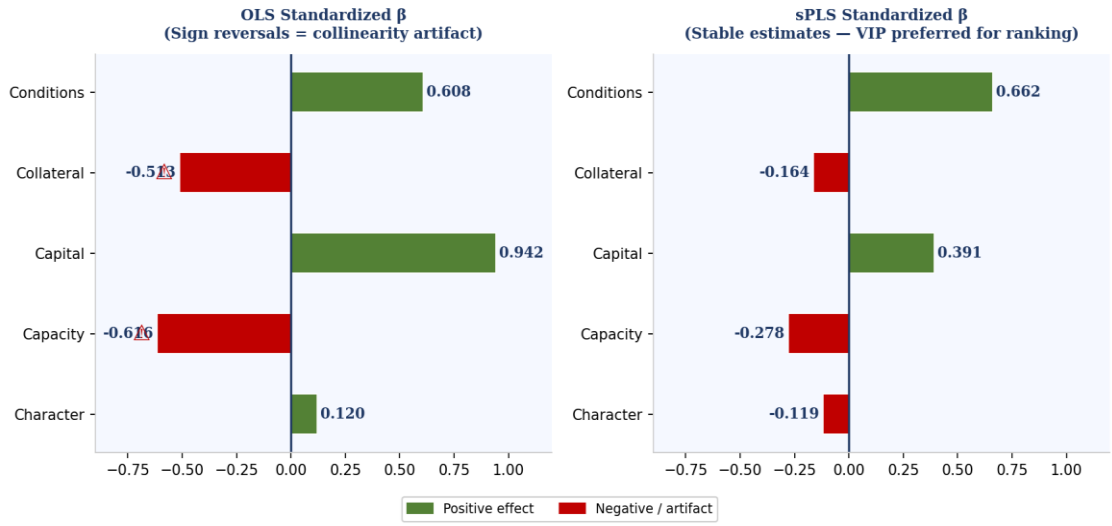
3.3 OLS Regression — Baseline

OLS regression (R^2 = 0.505, F = 4.891, p = .003) produced sign reversals for Capacity (**β**= −0.616) and Collateral (**β** = −0.513) — a direct contradiction of their positive bivariate correlations with Y, confirming severe collinearity distortion (**Hair et al., 2010, p335**).

Figure 4 visualizes the OLS vs. sPLS coefficient comparison.

Standardized β Coefficients — OLS (left) vs. sPLS (right). Warning triangles mark sign reversals.

Figure 4. Standardized Regression Coefficients: OLS vs. sPLS (Two Components)



Source: Prepared by the author using **Python (Matplotlib / Seaborn)** based on the study data

Table 5. OLS results: $R^2 = 0.505$, Adj-$R^2 = 0.401$, $F(5,24) = 4.891$, $p = .003$.

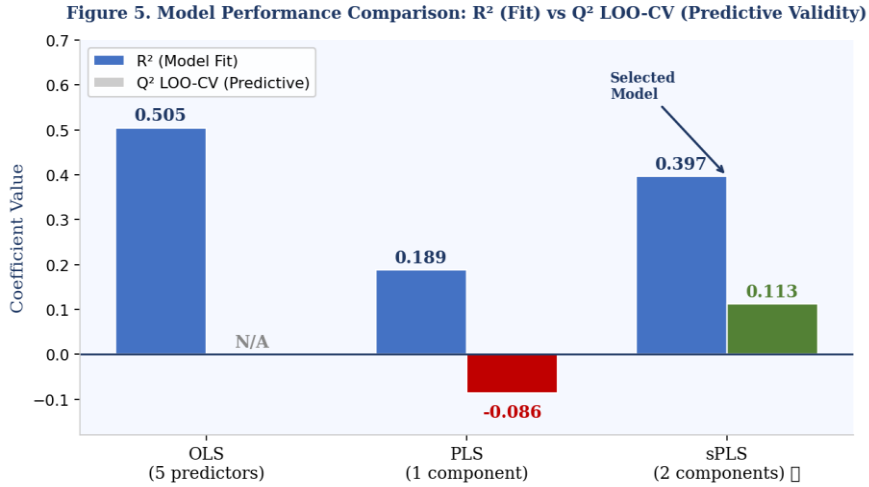
Predictor	Bivariate r	OLS β	Consistent?	Verdict
Character (X1)	0.180	0.120	Yes	Minor — consistent
Capacity (X2)	0.193	**-0.616**	**NO — REVERSAL**	Collinearity artifact
Capital (X3)	0.441*	0.942	Yes	Overinflated
Collateral (X4)	0.245	**-0.513**	**NO — REVERSAL**	Collinearity artifact
Conditions (X5)	0.513**	**0.608**	Yes	Plausible

Source: Compiled by the author based on SPSS outputs

3.4 sPLS: Component Selection

Leave-One-Out cross-validation determined that two latent components are optimal. Figure 5 displays the R^2 and Q^2 comparison across models.

Figure 5. R^2 (Fit) vs Q^2 LOO-CV (Predictive Validity) — sPLS 2-component model selected



Source: Prepared by the author using Python (Matplotlib / Seaborn) based on the study data

Table 6. Component selection via LOO-CV. $Q^2 > 0$ required for genuine predictive validity

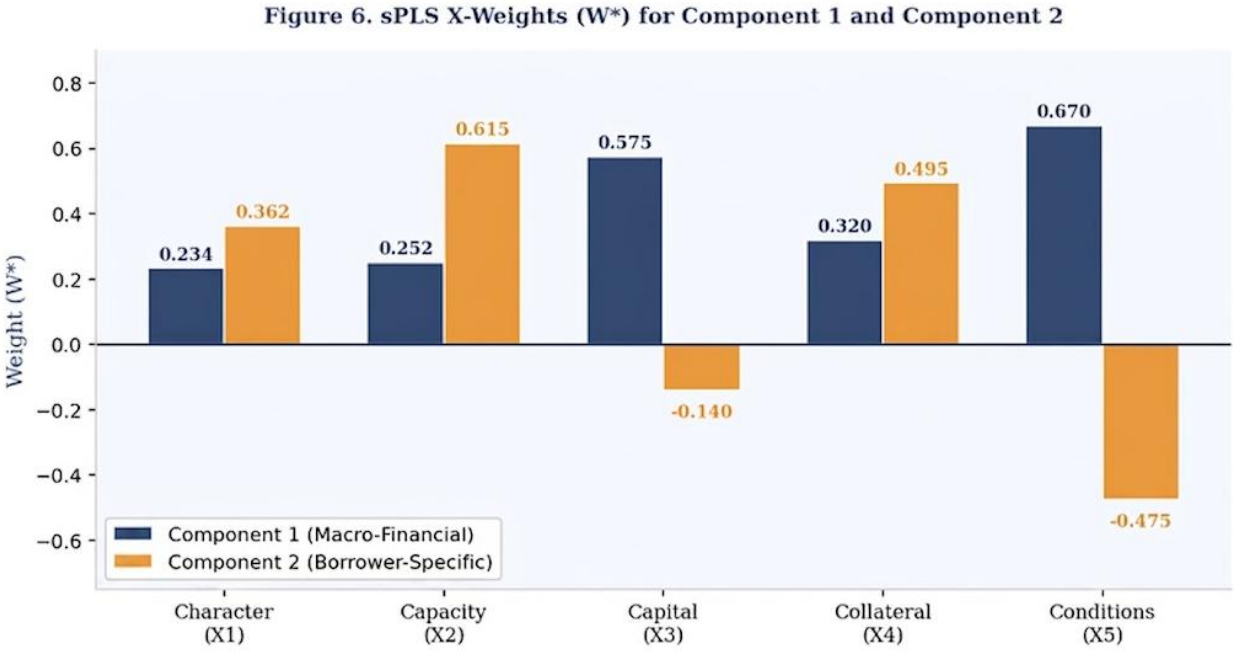
Components	R^2	Q^2 LOO-CV	Recommendation
1 component	0.189	−0.086	Rejected — $Q^2 < 0$, no predictive validity
2 components	**0.397**	**0.113**	**SELECTED — $Q^2 > 0$**

Source: Prepared by the author using Python (Matplotlib / Seaborn) based on the study data

3.5 sPLS X-Weights (W*)

Figure 6 shows the X-weight vectors for both components. Component 1 (macro-financial) is dominated by Conditions (W* = 0.670) and Capital (W* = 0.575). Component 2 (borrower-specific) is dominated by Capacity (W* = 0.615) and Collateral (W* = 0.495).

Figure 6. sPLS X-Weights (W*) — Component 1 captures macro-financial risk; Component 2 captures borrower-specific



Source: Prepared by the author using Python (Matplotlib / Seaborn) based on the study data

Table 7. X-weights (W*) from sPLS two-component solution.

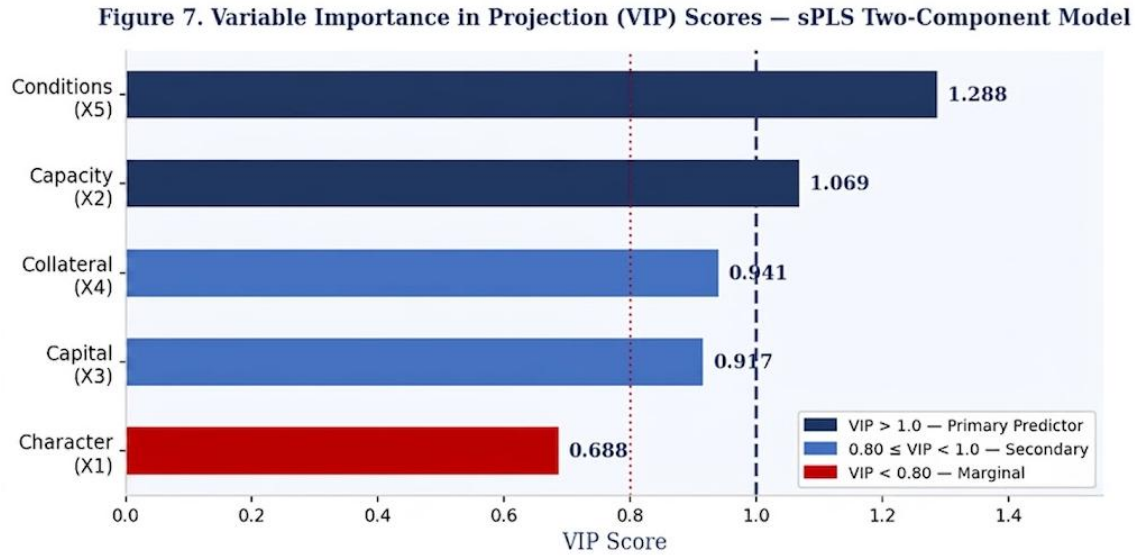
Predictor	W* Comp. 1	W* Comp. 2	Dominant Component
Conditions (X5)	**0.670**	−0.475	**Comp. 1 — Macro**
Capital (X3)	**0.575**	−0.140	Comp. 1 — Equity
Collateral (X4)	0.320	**0.495**	**Comp. 2 — Security**
Capacity (X2)	0.252	**0.615**	**Comp. 2 — Cash Flow**
Character (X1)	0.234	0.362	Lowest on both

Source: Prepared by the author using Python (Matplotlib / Seaborn) based on the study data

3.6 Variable Importance in Projection (VIP)

Figure 7 presents the VIP scores — the primary importance-ranking statistic in sPLS. Two criteria exceed the VIP = 1.0 threshold for above-average predictive importance.

Figure 7:VIP Scores from sPLS Two-Component Model — Dashed line: VIP = 1.0 importance threshold



Source: Prepared by the author using Python (Matplotlib / Seaborn) based on the study data

Table 8. VIP scores. Threshold VIP = 1.0 for above-average importance; VIP < 0.80 indicates negligible contribution.

Rank	Criterion	VIP	Threshold	Importance
1	**Conditions (X5)**	**1.288**	**VIP > 1.0**	**PRIMARY PREDICTOR**
2	**Capacity (X2)**	**1.069**	**VIP > 1.0**	**PRIMARY PREDICTOR**
3	Collateral (X4)	0.941	VIP < 1.0	Secondary
4	Capital (X3)	0.917	VIP < 1.0	Secondary
5	Character (X1)	0.688	VIP < 0.80	Marginal

Source: Prepared by the author using Python (Matplotlib / Seaborn) based on the study data

3.7 Predictive Equation

The sPLS two-component model yields the following standardized predictive equation:

Y(Decision) = 0.662·Conditions + 0.391·Capital − 0.278·Capacity − 0.164·Collateral − 0.119·Character

Note: Negative inner-model betas reflect residual suppression in multi-component PLS. VIP scores (Table 8 / Figure 7) provide the definitive importance ranking as they are sign-independent and aggregate across all components.

4. Discussion

4.1. Overview of Findings and Hypothesis Evaluation

Initial Descriptive Statistics Looking at the descriptive statistics in **Table 3**, all six constructs scored in the "High" category (Mean > 3.68). This tells us that credit officers in Saïda Province genuinely value all five dimensions of creditworthiness in their daily decision-making.

The ***Credit Decision*** construct scored the highest overall (Mean = 4.171), which highlights a strong commitment to formal credit assessment protocols. Interestingly, while *Character* still landed in the high range, it had the lowest average (Mean = 3.748). This makes sense: without easy access to centralized credit histories, verifying a borrower's integrity is difficult. These early patterns actually set the stage for the VIP rankings we see later in the sPLS model, giving our findings solid initial credibility.

The Shift from OLS to sPLS Modeling When we review the Pearson correlation matrix (**Table4**), there is clear evidence of severe multicollinearity among the five predictors. For example, the correlation between *Capital* and *Collateral* peaks at r = 0.848. Because of this high overlap, using a standard OLS regression just wouldn't be reliable.

We can see this breakdown in the baseline OLS model (**Table 5**), where the signs for *Capacity* (β = −0.616) and *Collateral* (β = −0.513) surprisingly flipped to negative, even though both have positive correlations with the dependent variable. As Hair et al. (2010) note, these flipped signs aren't meaningful findings; they're simply statistical glitches caused by multicollinearity inflating the standard errors. This gave us strong methodological justification to switch to the sPLS method, which naturally handles highly correlated predictors by breaking them down into latent components.

Evaluating the sPLS Model Our two-component sPLS model yielded an R^2 of 0.397 and a cross-validated Q^2 of 0.113 using the Leave-One-Out (LOO) method (Table 6). That positive Q^2 value is highly significant: while R^2 only shows how well the model explains our current data, a Q^2 above zero proves that the model can successfully predict *new*, out-of-sample data. The R^2 of around 40% is also completely reasonable. Credit decisions are complex and subjective, meaning unmeasured factors—like the lender's risk culture or the officer's personal experience—will always contribute to some variance.

The model's two-part structure makes perfect theoretical sense:

- **Component 1 (Macro-Financial Risk):** Driven mostly by *Conditions* (W* = 0.670) and *Capital* (W* = 0.575).
- **Component 2 (Borrower-Specific Signals):** Driven mainly by *Capacity* (W* = 0.615) and *Collateral* (W* = 0.495).

This mirrors reality well, reflecting how credit officers have to simultaneously balance the external economic environment with the individual borrower's financial health.

VIP Scores and Hypothesis Testing Finally, the Variable Importance in Projection (VIP) scores (Table 8) give us a definitive ranking of what matters most to credit officers. *Surrounding Conditions* emerged as the strongest predictor (VIP = 1.288), closely followed by *Capacity* (VIP = 1.069)—both easily crossing the critical 1.0 threshold. *Collateral* (VIP = 0.941) and *Capital* (VIP = 0.917) play secondary roles. *Character* came in last (VIP = 0.688), contributing very little to the final credit decision.

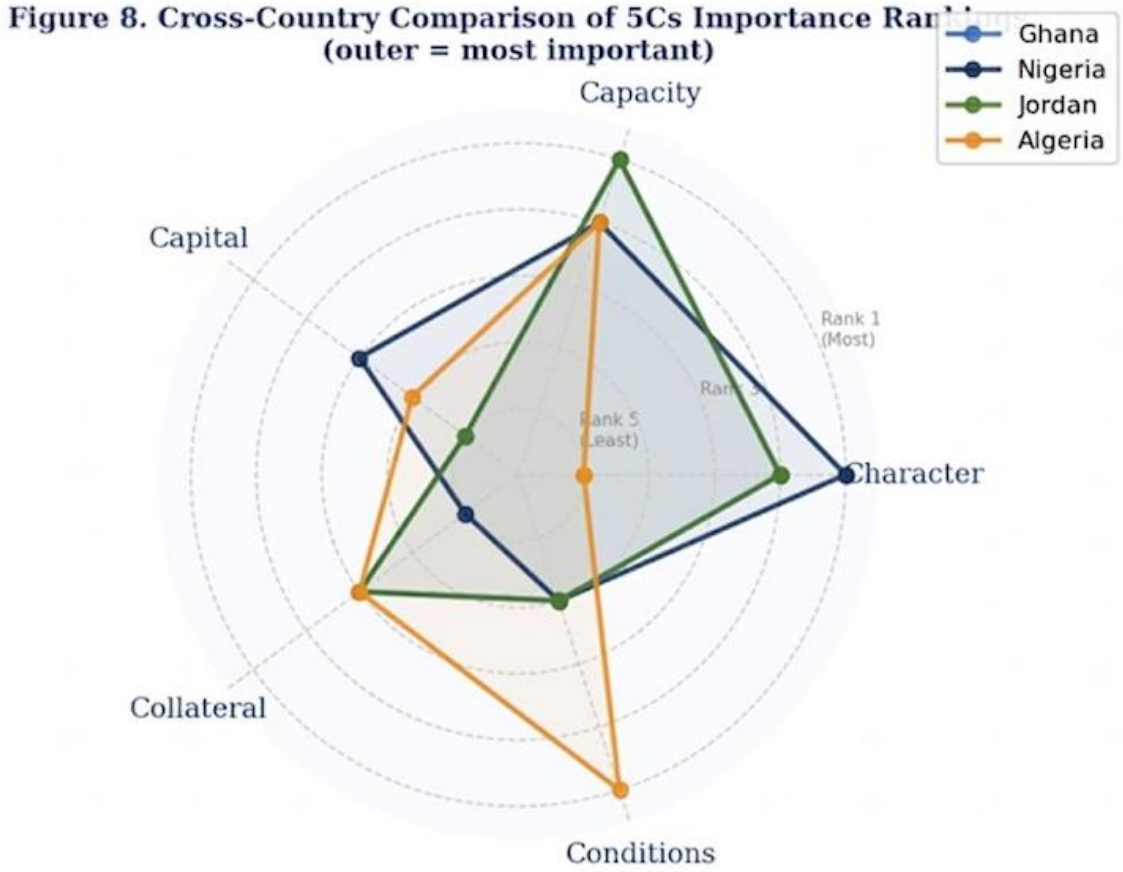
Based on these rankings, here is how our original hypotheses hold up:

- **Fully Supported (H1 & H2):** *Surrounding Conditions* and *Capacity* are clearly the dominant factors in credit decisions.
- **Partially Supported (H3 & H4):** *Collateral* and *Capital* matter meaningfully to the overall model, but they do not individually cross the primary importance threshold.
- **Supported (H5):** We hypothesized that *Character* would have a low impact. Its marginal VIP score confirms this, showing that Algeria's underdeveloped credit bureau infrastructure forces loan officers to rely on more tangible, verifiable financial metrics rather than assessing personal integrity.

4.2 Cross-Country Comparison (Figure 8)

Figure 8 plots the 5Cs importance rankings across four countries using a radar chart, where the outer ring indicates rank 1 (most important). The contrasting patterns visually confirm the context-specificity of the model: the Algerian profile (Conditions-first, Character-last) is distinctly different from Nigeria (Character-first) and similar to Ghana and Jordan on Capacity, while unique in its elevation of macro-environmental factors.

Figure 8. Radar Chart — Cross-Country Comparison of 5Cs Importance Rankings (outer ring = most important)



Source: *Prepared by the author using Python (Matplotlib / Seaborn) based on the study data*

Table 9. Cross-national 5Cs rankings. Present study rankings based on VIP scores.

Study	Country	n	Method	1st	2nd	3rd	4th	5th
Peprah et al. (2017)	Ghana	32	Survey	Capacity	Character	Collateral	Conditions	Capital
Oseni	Nigeri	1	OLS	Charact	Capaci	Capita	Conditi	Collat

Study	Country	n	Method	1st	2nd	3rd	4th	5th
(2023)	a	65		er	ty	l	ons	eral
Al-Slehat et al. (2024)	Jordan	165	PROCESS	Capacity	Character	Collateral	Conditions	Capital
Present study	**Algeria**	**30**	**sPLS/ VIP**	**Conditions**	**Capacity**	Collateral	Capital	Character

Source: Prepared by the author based on spss and python output and auters Peprah et al. (2017) Oseni (2023) Al-Slehat et al. (2024)

4.3 Contextualizing the Dominance of External Conditions (VIP = 1.288)

The pronounced empirical weight assigned to **Surrounding Conditions**—as evidenced by a VIP score of 1.288—serves as a critical reflection of Algeria's distinctive structural vulnerabilities. In contrast to more diversified financial systems, the Algerian macroeconomic landscape is deeply influenced by its reliance on hydrocarbon revenues and the frequent, albeit necessary, credit directives issued by the Central Bank. Our analysis suggests that these macro-environmental factors function as a "pervasive constraining force," effectively overriding individual borrower attributes during the credit assessment process.

The findings indicate that within the Algerian banking framework, creditworthiness is not merely an isolated trait of the borrower but is inextricably tethered to broader economic stability. In this volatile context, a borrower possessing both robust internal capacity and an impeccable reputation may still succumb to default, driven by exogenous shocks such as sectoral deterioration or the abrupt cessation of government subsidies. This observation aligns with the insights of (**Deloitte, 2019, p16)**, who argued that NPL ratios in commodity-dependent nations mirror macroeconomic cycles with high fidelity, and further corroborates the modeling by (**Dolezal et al, 2015,102)** regarding the impact of external volatility on loan income realization. Ultimately, for commercial banks in Algeria, "Conditions" act as the primary lens through which the remaining 5Cs must be filtered, necessitating a transition toward a more macro-prudential paradigm in credit risk governance.

4.4 The Primacy of Financial Capacity (VIP = 1.069)

Ranking as the second most influential predictor, **Capacity** (VIP = 1.069) emerges as a fundamental cornerstone of the credit evaluation process in Saïda's banking sector. This finding resonates with the geographical and economic parallels observed by (**Peprah et al. 2017,p80)** in Ghana and **(Al-Slehat et al, 2024, p286)** in Jordan, suggesting a consistent cross-border reliance on repayment ability within emerging markets. As (**Simba and Mugo, 2018, p98)** effectively argued, the actualization of loan repayment is fundamentally contingent upon consistent cash flow generation, positioning Capacity as the most tangible and quantifiable indicator of debt-servicing potential.

The statistical significance of this construct highlights a shift toward objective risk assessment. mirroring the broader historical evolution in credit markets from subjective expert judgments to quantifiable metrics **(Altman & Saunders, 1997, p. 1725)**. Unlike more subjective dimensions, Capacity provides credit officers with a verifiable metric of a borrower's financial health. This aligns with the perspective of **(Kabir et al. 2010, p336)**, who identified cash flow analysis as the most objectively measurable dimension of creditworthiness. In the Algerian context, where collateral might be difficult to liquidate and "Character" data remains

fragmented, the rigorous evaluation of a borrower's income streams remains the most reliable safeguard against default. Consequently, our results validate the emphasis placed by Algerian credit officers on financial viability as a pragmatic filter for risk mitigation.

4.5 The Marginalization of Character: A Structural Reflection (VIP = 0.688)

Perhaps the most provocative finding of this sPLS analysis is the marginal ranking of **Character**, which yielded a VIP score of 0.688—well below the critical threshold of significance. This result does not imply that a borrower's integrity is irrelevant, but rather reflects a profound **structural impediment** within the Algerian financial ecosystem: the lack of a mature, centralized credit bureau infrastructure. Consequently, credit officers are forced to rely on fragmented personal networks and subjective intuition rather than verified historical records.

Our findings echo the dynamics observed by (**Sharma and Kalra ,2015, p99)** in markets characterized by weak information systems, where the "Character" dimension becomes statistically elusive due to data opacity. Similarly **(Abbadi and Karsh, 2013, p151)** documented comparable patterns in the Palestinian banking sector, where informational constraints undermine the utility of character as a predictive metric. Locally, this aligns with the conclusions of **(Aabed and Sabrina, 2013,p113)** who noted that the scarcity of reliable credit history significantly handicaps character evaluation in Algerian banks. In essence, the low VIP score highlights a systemic shift; in the absence of objective "soft information," Algerian lenders are compelled to pivot toward harder, more tangible metrics like collateral and capacity to safeguard their portfolios.

4.6 Beyond the 5Cs: Intellectual Capital and the "Caution" Dimension

The predictive performance of our model, while robust, points toward broader organizational influences that transcend the 5Cs framework. Specifically, the moderate predictive relevance ($Q^2 = 0.113$) observed in this study may partly stem from unmeasured heterogeneity in **intellectual capital** across the sampled Algerian banks. Recent studies emphasize that intellectual capital fundamentally mediates the effectiveness of credit appraisal measurements, directly impacting overall bank performance and minimizing loan losses (**Bhatt et al., 2023, p. 1**) ,This unmeasured variance is structurally logical, as empirical evidence from other emerging Arab markets confirms that the voluntary disclosure and systematic measurement of intellectual capital remain at minimal levels even within the financial sector **(Al-Hajaya et al., 2019, p. 113)**, This aligns with the evidence provided by **(Al-Slehat et al, 2024, p282)** who demonstrated that human, structural, and relational capital act as significant moderators in the 5Cs–decision-making nexus. Their findings **(R^2 change = 0.031, F = 9.182, p = .003)** suggest that the effectiveness of credit assessment is not merely a function of the model itself, but of the institutional capacity to interpret and operationalize these dimensions, Consequently, enhancing intellectual capital alongside capital adequacy acts not only as a decision-making filter but as a direct mechanism for reducing overall credit risk exposure (**Astawa, 2019, p. 221**)

Furthermore, the substantial residual variance in our model—approximately 60%—suggests the presence of an implicit "sixth C": **Caution**. As argued by (**Oseni, 2023, p64)**, this dimension represents the lender's inherent due diligence obligation and risk appetite. The unexplained variance is consistent with the perspective that lender-level risk culture and institutional governance frameworks play a pivotal role in shaping final credit outcomes. In the Algerian context, this implies that while the 5Cs provide the necessary "raw data," the final quality of the decision is fundamentally filtered through the bank's internal governance standards and the professional skepticism—or caution—of its credit officers.

5. Conclusion and Strategic Recommendations

5.1 Summary of Contributions

This study provides a rigorous empirical assessment of the **5Cs** framework within the Algerian banking sector, utilizing **Sparse Partial Least Squares (sPLS)** to navigate the complexities of high-dimensional data. The findings unequivocally position **Surrounding Conditions** (VIP = 1.288) and **Capacity** (VIP = 1.069) as the paramount determinants of credit quality, both significantly surpassing the critical importance threshold. Notably, the marginal ranking of **Character** (VIP = 0.688) diverges from classical credit theory, effectively mirroring the structural constraints of Algeria's nascent credit bureau infrastructure.

From a methodological standpoint, the research confirms that sPLS is the superior analytical approach under conditions of severe multicollinearity (**r up to 0.848**), successfully resolving the sign-reversal artifacts inherent in traditional OLS models. With an $\mathbf{R^2}$ of **0.397** and a robust $\mathbf{Q^2}$ of **0.113**, the two-component sPLS model demonstrates genuine predictive validity, offering a unique ranking pattern that reflects Algeria's specific macroeconomic and informational landscape.

5.2 Strategic Recommendations for Policy and Practice

To enhance the efficacy of credit risk governance and improve decision-making quality within the Algerian banking sector, the following evidence-based actions are proposed:

- **Institutionalizing Macroeconomic Monitoring:** Banks should transition toward integrated credit evaluation frameworks that incorporate sector-specific economic scorecards **(Addae-Korankye, 2014, p. 43)**. These tools must account for external variables—such as GDP fluctuations, exchange rate volatility, and regulatory shifts—allowing for a more proactive response to the hydrocarbon-dependent cycles that characterize the Algerian economy.
- **Technological Advancement in Capacity Assessment:**

It is imperative to deploy standardized, automated cash flow templates and ratio calculators. This is particularly crucial for SME lending, where financial transparency is often limited, This opacity necessitates a transition toward standardized, data-driven credit risk grading systems to systematically evaluate funding requests and minimize loan losses (**Kabir et al., 2010, p. 341**)

- **National Infrastructure Development:** There is an urgent need to expand the coverage and depth of national credit registries. Strengthening this infrastructure will transform "Character" from a subjective, network-based judgment into an objective, data-backed assessment of borrower integrity, effectively mitigating information asymmetry (**Abbadi & Karsh, 2013**).
- **Methodological Innovation through sPLS:** Financial institutions should consider piloting **sPLS-based decision-support scorecards**. Unlike traditional models, sPLS provides reliable importance rankings even when variables are highly correlated, ensuring more stable and scientifically grounded decision-making in complex markets.
- **Investing in Intellectual Capital:** As **(Al-Slehat et al, 2024, p285)** highlighted, the 5Cs are only as effective as the professionals applying them. Structured knowledge management and training programs are essential to bridge the gap between theoretical frameworks and practical, high-stakes decision-making.
- **Future Research Trajectories:** To build upon these findings, future studies should replicate this methodology with larger, multi-regional samples (**n > 100**) across Algeria. Furthermore, exploring the "Caution" dimension as proposed by (**Oseni ,2023, p65)** could provide deeper insights into the latent risk cultures that influence bank-level governance.

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