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A Study on the Impact of Customer Creditworthiness on Loan Approval in Financial Consultancy Firms

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Abstract

Credit-scoring research has widely examined banks and digital lenders, while financial consultancy firms remain underexplored. This study examines the relationship between customer creditworthiness and loan approval in Ahmedabad, Gujarat, focusing on creditworthiness factors, collateral importance, and the relationship between income and creditworthiness. A quantitative survey of 78 loan applicants and borrowers was conducted using purposive and convenience sampling. Data were analysed using chi-square, descriptive statistics, an independent-samples t-test, Spearman's correlation, and Cronbach's alpha. Credit-score category was significantly associated with loan outcomes ($p = .020$), and collateral importance differed significantly across outcome groups ($p = .022$). CIBIL/credit score, income, and repayment history were the highest-rated creditworthiness factors, while income showed no significant relationship with credit-score category ($p = .651$). The questionnaire demonstrated good reliability ($\alpha = .857$). The findings offer practical insights for loan assessment and client advisory, although the small sample and cross-sectional design limit generalisation.

Keywords: Creditworthiness, Loan approval, Financial consultancy, CIBIL score, Colletral/Security.

1. Introduction

Creditworthiness is conventionally understood as an assessment of a borrower's capacity and willingness to repay a debt obligation. Lenders have historically relied on a combination of quantitative indicators, namely credit score, income, existing debt burden, employment stability and repayment history, together with qualitative judgement, to arrive at an approval decision (Nadeesha & Madhushani, 2023). As credit markets have grown in scale and complexity, assessment has moved from largely manual underwriting towards statistical credit-scoring models and, more recently, towards machine-learning and alternative-data approaches that can process far larger and more heterogeneous sets of borrower information (Hlongwane et al., 2024a; Srivastava, 2026).

Between the borrower and the lender, however, sits a layer of intermediaries that this literature seldom examines. Financial consultancy and loan-advisory firms, including direct selling agents, loan consultants and chartered-accountant-led practices, do not lend their own capital. They advise borrowers, prepare and package applications, match borrowers to suitable banks, non-banking financial companies (NBFCs) or government schemes, and earn fee or commission income for doing so. Because their revenue is contingent on approval rather than on application volume, creditworthiness assessment lies at the centre of their own commercial risk. The Indian setting makes this intermediary function especially salient. Banks account

for an estimated 72% of systemic credit, while NBFCs have raised their share from roughly 12% in FY08 to about 21% in FY25 (CRISIL Intelligence projections reported in the industry analysis underlying this study). Lenders in both groups rely on the same four licensed credit information companies (TransUnion CIBIL, Experian, Equifax and CRIF High Mark) and on broadly similar applicant documentation, which creates a considerable role for firms that help borrowers meet these requirements.

Despite this, the empirical literature on credit scoring and loan approval draws almost exclusively on data from banks, microfinance institutions, peer-to-peer platforms or public benchmark datasets. Consultancy firms do not appear as a unit of analysis in any of the twenty-two recent studies reviewed for this paper. The only study set explicitly in India (Srivastava, 2026) evaluates credit-scoring models on simulated data rather than on actual approval outcomes processed by an intermediary. It is therefore not known, on the basis of existing evidence, whether and to what extent customer creditworthiness, and the specific roles of the CIBIL/credit score and income level, are related to loan-approval outcomes for clients of Indian financial consultancy firms.

This study addresses that gap through the following central research question: *What is the impact of customer creditworthiness on loan-approval outcomes in financial consultancy firms, which factors most significantly influence that creditworthiness, and what specific roles do the CIBIL/credit score and customers' income level play within this relationship?* The question is decomposed into four objectives:

O1. To study the impact of customer creditworthiness on loan approval in financial consultancy firms.

O2. To identify the key factors influencing customer creditworthiness in the loan application process.

O3. To examine whether the perceived importance of collateral/security offered differs according to the outcome of loan applications.

O4. To examine the relationship between customers' income level and their creditworthiness.

The study contributes in three ways. It treats the consultancy firm, rather than the lender, as the institutional setting for creditworthiness research; it provides primary survey evidence from Gujarat, a state with a dense MSME base and a large home-grown NBFC cluster; and it uses a transparent, accessible set of statistical tests so that consultancy practitioners can interpret the results directly. The remainder of the paper is organised as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the methodology. Section 4 reports the results. Section 5 discusses the findings and their implications. Section 6 sets out limitations and directions for future research, and Section 7 concludes.

2. Literature Review and Hypothesis Development

This section synthesises twenty-two open-access studies on credit scoring, credit-risk assessment and loan-approval prediction published between 2010 and 2026. It follows the progression of the field from structured decision-support systems to machine-learning and explainable approaches, then identifies the gap that motivates the study.

2.1 From structured scoring to machine learning

Early work focused on building structured systems for distinguishing creditworthy from non-creditworthy applicants. İç and Yurdakul (2010) developed a fuzzy TOPSIS decision-support system that used financial ratios to give a rapid preliminary assessment of manufacturing firms seeking credit in Turkey, demonstrating that a multicriteria scoring system can screen applicants quickly before detailed evaluation. Roy and Shaw (2021) extended the multicriteria tradition to small and medium enterprises with a hybrid Best-Worst Method and TOPSIS model, finding that credit history, cash liquidity and repayment period were among the most important lending criteria, followed by return on capital, financial flexibility and

borrower integrity. Statistical approaches at the borrower level followed a similar logic. In a study of 130 personal-loan borrowers of a public bank in Sri Lanka, Nadeesha and Madhushani (2023) used logistic regression and reported that age, education and monthly income raised creditworthiness, whereas more dependents and longer loan tenure increased the likelihood of default; their model classified 85.4% of cases correctly.

More recent contributions apply machine-learning classifiers. Ampountolas et al. (2021) showed that classifiers, particularly random forests, can assign micro-lending customers to credit-risk categories using basic customer characteristics where formal histories are unavailable. Mourtas et al. (2024) used a bio-inspired neural network for binary credit and loan-approval classification, indicating that the approval decision itself is amenable to structured predictive modelling. A systematic review by Noriega et al. (2023) concluded that machine learning is increasingly used for credit-risk prediction but that dataset quality, interpretability, variable selection and evaluation metrics remain unresolved issues.

2.2 Alternative and behavioural data

A second strand asks whether information beyond the conventional credit file improves assessment, motivated largely by the goal of extending credit to thin-file borrowers. Hlongwane et al. (2024a), analysing 356,255 home-loan customers, found that alternative social, geographic, financial and behavioural data significantly improved performance beyond bureau information, with a LightGBM model using the full predictor set reaching an AUC of 0.7936. Litty (2024) reached a conceptually similar conclusion for utility payments, transaction behaviour and employment information. Behavioural and psychometric signals have also been explored: Zhang et al. (2024) used mobile-phone data in China and found that higher conscientiousness and extroversion were associated with lower default, while Fine (2024) found that psychometric traits can supplement conventional histories for underbanked consumers in Israel. For rural finance, Kumar et al. (2021) identified opportunities for machine-learning-based assessment of thin-file borrowers but also noted ethical, data-quality and implementation challenges.

2.3 Explainability, fairness and risk management

A third strand addresses the interpretability and fairness of increasingly complex models. Hlongwane et al. (2024b) applied Shapley values to several tree-based models and obtained credit-score contributions that lenders can interpret more easily, without losing predictive performance. Nallakaruppan et al. (2024) combined decision trees and random forests with LIME and SHAP on a peer-to-peer lending dataset, and Darvish et al. (2025) used a SHAP-based framework to identify and correct classification errors on the German Statlog and Australian Credit Approval datasets. Schmitt (2024) argued that explainable automated machine learning can improve transparency and accountability in credit-model development, and Sargeant (2022) concluded that algorithmic credit decisions can improve efficiency but raise continuing concerns about discrimination, transparency, explainability and accountability. Akhmetova et al. (2026) combined machine-learning comparison with SHAP analysis for early warning of SME loan delinquency, and Boiquaye et al. (2026) showed that borrower behaviour after disbursement and the intensity of lender monitoring explain default in microfinance, implying that creditworthiness assessment extends beyond the initial screening decision. Complementary qualitative evidence from Jordanian commercial banks (AlJaloudi et al., 2025) grouped twenty credit-risk challenges into regulatory, operational, technological and economic categories, and Sodnomdavaa and Sandagsuren (2026) cautioned that credit-risk models should be evaluated across time because distributional shifts can erode apparent accuracy.

2.4 Multi-factor creditworthiness and the role of the credit score

Three conclusions recur across these studies and are directly relevant here. First, creditworthiness is consistently treated as a function of several factors rather than a single indicator. Castro et al. (2026), studying two regional bank branches in East Texas, found that credit score alone did not fully capture portfolio risk, whereas approved amount, maximum potential exposure, approval and book rates and credit score together gave a more informative picture. Second, the credit score remains the reference benchmark against which newer approaches are judged; in the Indian context, Srivastava (2026) compared a simulated CIBIL-based benchmark with machine-learning models using simulated data for more than 50,000 applicants and found higher predictive performance for AI- and alternative-data-based models. Third, income is repeatedly identified as a positively associated factor, most directly by Nadeesha and Madhushani (2023).

2.5 Research gap

Against this background, no study among the twenty-two reviewed identifies a financial consultancy or loan-advisory firm as its unit of observation. The institutional settings are banks, microfinance institutions, digital lending platforms or public benchmark datasets, and the single India-specific study relies on simulated data. The joint relationship between customer creditworthiness, the specific factors that shape it, the CIBIL/credit score and income level, and loan-approval outcomes has not been examined for clients of Indian financial consultancy firms. This is a gap of both academic and practical importance. Academically, it lies at the intersection of three literatures that have been studied separately: creditworthiness assessment, intermediated rather than direct lending decisions, and the Indian credit market. Practically, consultancy firms lack an India-specific evidence base on which creditworthiness factors most strongly relate to approval success, which limits how accurately they can advise clients, triage applications and set expectations before submission.

2.6 Industry context and hypotheses

The institutional setting reinforces the case for studying the consultancy channel. In India, consultancy firms and direct selling agents perform eligibility matching, documentation and compliance support, credit-profile advisory and risk pre-filtering for lenders. Practitioners in Ahmedabad commonly cite a credit score of 700 or above as the practical minimum for unsecured MSME credit and 750 or above for the most competitive rates, and digitally enabled schemes with complete documentation are reported to reach sanction within 48 to 72 hours (practitioner observations reported in the industry analysis underlying this study). Gujarat's economy is weighted towards manufacturing, trading and MSME activity, and Ahmedabad alone is home to more than 75 identified NBFC-lender start-ups. Borrowers and consultancy firms in the state therefore have unusually direct access to locally headquartered lenders alongside national banks.

Four hypotheses, each mapped to one objective, are formulated from the literature and this context. Hypothesis 1 follows the evidence that multi-factor assessments are more informative than single-indicator assessments of loan outcomes (Castro et al., 2026; Mourtas et al., 2024). Hypothesis 2 follows the consistent finding that creditworthiness is shaped by a combination of credit score, income, repayment history, employment stability and existing debt (Boiquaye et al., 2026; Nadeesha & Madhushani, 2023; Roy & Shaw, 2021). Hypothesis 3 examines collateral or security, a standard element of lending decisions, by testing whether its perceived importance differs by loan outcome. Hypothesis 4 follows the positive association between monthly income and creditworthiness reported by Nadeesha and Madhushani (2023). Each hypothesis is stated below in null and alternative form.

Table 1: Objectives and hypotheses

No.	Null hypothesis (H_0)	Alternative hypothesis (H_1)
H1	There is no significant impact of customer creditworthiness on loan approval in financial consultancy firms.	There is a significant impact of customer creditworthiness on loan approval in financial consultancy firms.
H2	There is no significant influence of the identified factors on customer creditworthiness in the loan application process.	There is a significant influence of the identified factors on customer creditworthiness in the loan application process.
H3	There is no significant difference in the perceived importance of collateral/security offered between respondents whose loan applications were approved and those whose applications were rejected.	There is a significant difference in the perceived importance of collateral/security offered between respondents whose loan applications were approved and those whose applications were rejected.
H4	There is no significant relationship between customers' income level and their creditworthiness.	There is a significant relationship between customers' income level and their creditworthiness.

3. Research Methodology

3.1 Research design

The study adopts a quantitative, descriptive-cum-explanatory research design. It is descriptive because it profiles the factors that make up customer creditworthiness (Objective 2), and explanatory because it tests whether creditworthiness is associated with loan approval, whether collateral/security importance ratings differ by loan outcome, and whether income level is associated with creditworthiness (Objectives 1, 3 and 4). Data were collected from each respondent once, at a single point in time, so the study does not claim to capture changes in creditworthiness or approval over time. Table 2 summarises the main design choices.

Table 2: Summary of the research design

Parameter	Description
Research approach	Quantitative (hypothesis testing)
Research type	Descriptive
Research strategy	Structured questionnaire survey
Unit of analysis	Individual loan applicant or borrower
Study area	Ahmedabad and the surrounding region of Gujarat, India
Data type	Primary data (questionnaire), supported by secondary industry data
Sampling	Non-probability: purposive combined with convenience sampling
Valid responses analysed	78

Note. Secondary data were used to describe the industry context (Section 2.6) and were not used in hypothesis testing.

3.2 Rationale for the survey method

A structured questionnaire was the most appropriate method for four reasons. First, no public dataset records consultancy-mediated applications, and lender-side records of the kind used by Castro et al. (2026) and Hlongwane et al. (2024a) are inaccessible to a study of the intermediary, so only customers can report their financial profile and application outcome. Second, a common questionnaire measures every respondent on the same factors, which is a precondition for statistical testing of a multi-factor construct. Third, applicants and borrowers can answer factual questions about income, credit-score band, loan type and outcome through short structured items. Fourth, individual credit files and sanction records are confidential, so self-reported, anonymised responses are the practicable route to outcome data from a hard-to-reach population.

3.3 Population, sampling and sample size

The target population comprised individuals in Gujarat who had applied for a loan through a financial consultancy or loan-advisory firm or any. Because the study is anchored in Gujarat, the accessible population was defined as clients of consultancy and loan-advisory firms in Ahmedabad, including the host organisation's clients and clients of comparable chartered-accountant firms reachable through its network. As no register of such clients exists, the sampling frame was defined by eligibility criteria. Respondents had to be aged 21 years or above, to have applied for a loan through a consultancy or advisory firm within the previous 24 months, to reside in Ahmedabad or the surrounding region, and to be able to state their approximate credit-score band and loan outcome. Applicants who had not used a consultancy firm, applications without a lender decision, employees or associates of consultancy firms, and incomplete or contradictory responses were excluded.

The study used non-probability sampling, combining purposive and convenience sampling. Respondents were selected purposively because they needed direct experience of a consultancy-processed loan application, and were reached through the client base and contacts accessible to the researcher during and after an internship with a financial consultancy firm. Probability sampling was not feasible because consultancy firms do not publish client lists and client information is confidential; non-probability sampling is widely used in exploratory business research of this kind (Kothari, 2004). Because tests of loan outcome require variation in the outcome, the researcher made a deliberate, quota-style effort to include applicants whose loans were rejected, delayed or sanctioned with conditions, with a working target of at least 25% of respondents in the non-approved or conditional group.

The planned sample was 150 respondents, with 100 valid responses set as the minimum for multivariate analysis). A sample of about 385 would be required for a large population at 95% confidence and a 5% margin of error (Cochran, 1977), which was impracticable for a time-bound study of a hidden population. The data collection period yielded 78 usable responses. This is below the planned minimum, which shaped the analytic strategy: the study relies on bivariate and descriptive tests suited to this sample size rather than the multiple regression models originally envisaged, and the limitation is discussed in Section 6.

3.4 Instrument and data collection

Data were collected with a self-administered structured questionnaire titled "Customer Creditworthiness and Loan Approval in Financial Consultancy Firms", administered online through a shared form link. Items were developed from three sources: the factors identified in the literature (credit score, income, repayment history, employment stability and existing debt); the documentation practices and local

thresholds described in the industry analysis; and the researcher's observation of the application process during the internship. The instrument was reviewed by the faculty guide and pilot-tested before administration. Each item was mapped to a variable and a hypothesis so that no question was asked without an analytical purpose. The questionnaire comprised six sections: respondent profile; loan details; creditworthiness factors rated on five-point Likert scales (Likert, 1932); self-reported credit-score category; loan-approval outcome; and the role of the consultancy firm (Appendix A). Respondents were asked to answer with reference to the loan application they had made through the consultancy firm, so that the data stayed tied to the consultancy-mediated channel.

3.5 Variables and measurement

The conceptual model has one outcome variable, loan-application outcome, and a set of explanatory variables drawn from the literature. Customer characteristics and financial behaviour (credit score, income, repayment history, employment stability and existing debt) jointly determine overall creditworthiness; this is presented to the lender through the consultancy firm, whose documentation and advisory support can influence how the profile is read; and the result is the approval outcome of full approval, conditional approval or rejection. In the analysis, creditworthiness was operationalised in two ways. For Hypotheses 1 and 4, the respondent's self-reported approximate CIBIL/credit-score category served as the indicator of creditworthiness. For Hypothesis 2, respondents rated how important each of six factors (CIBIL/credit score, income level, repayment history, debt obligations, collateral/security offered, and banking/financial records) is in determining a customer's creditworthiness. Hypothesis 3 used the collateral/security rating as the dependent measure and loan outcome as the grouping variable. Monthly income was recorded as an ordinal band, and Likert items were coded from 1 to 5 (Appendix B). Self-reported score categories rather than exact values were requested because exact scores are approximate and sensitive. The study does not measure lenders' internal credit models, which are not observable from the customer side.

3.6 Analytical strategy

All tests were conducted at a 5% significance level. The tests were selected to match the measurement level of each variable (Table 3). A chi-square test of association examined the relationship between credit-score category and loan outcome (H1). Descriptive statistics (mean, median, standard deviation, skewness and kurtosis) summarised the importance ratings of the six factors (H2); because this analysis is descriptive, it does not itself yield a decision on the null hypothesis. An independent-samples *t*-test compared collateral/security importance ratings between loan-outcome groups, with Levene's test used to check equality of variances (H3). Spearman's rank correlation, appropriate for ordinal variables, examined the relationship between average monthly income and credit-score category (H4). Cronbach's alpha assessed the internal consistency of the multi-item scale. A null hypothesis was rejected where $p < .05$.

Table 3: Mapping of objectives and hypotheses to statistical tests

Hypothesis	Variables	Statistical test applied
H1	Self-reported CIBIL/credit-score category; outcome of most recent loan application	Chi-square test of association
H2	Importance ratings of six creditworthiness factors	Descriptive statistics (mean, median, SD, skewness, kurtosis)

Hypothesis	Variables	Statistical test applied
H3	Collateral/security importance rating; loan-outcome group	Independent-samples *t*-test (with Levene's test)
H4	Average monthly income; CIBIL/credit-score category	Spearman's rank correlation
Scale reliability	Multi-item scale	Cronbach's alpha

Note. Chi-square, correlation and t*-test outputs follow the standard output format of the statistical package used.*

3.7 Data quality and ethics

Mandatory fields and fixed answer options in the online form prevented blank and out-of-range entries, screening questions at the start filtered out ineligible respondents, and one response per respondent was enforced through contact tracking. Internally inconsistent responses were examined and excluded were clearly careless. The study followed standard research-ethics principles. The first page of the form explained the purpose, academic use, voluntary nature and expected duration, and respondents consented before proceeding. No names, contact numbers, PAN, Aadhaar, account or loan numbers were collected, and results are reported only in aggregate. Respondents could skip any question or withdraw at any time, data were accessible only to the researcher and faculty guide, and the survey did not influence any pending loan decision or offer any inducement.

4. Results

4.1 Sample characteristics

The analysis is based on 78 valid responses. Of these, 53 respondents (68.0%) reported the outcome coded 1 for their most recent loan application, 6 (7.7%) reported the outcome coded 2 and 19 (24.4%) reported the outcome coded 3. Self-reported CIBIL/credit-score category was concentrated in the middle of the five-category scale: category 4 accounted for 42 respondents (53.8%), category 3 for 22 (28.2%), category 5 for 9 (11.5%), category 2 for 4 (5.1%) and category 1 for a single respondent (1.3%). Table 4 presents the cross-tabulation used to test Hypothesis 1.

4.2 Objective 1: Creditworthiness and loan approval (H1)

A chi-square test of association examined whether the loan-application outcome depends on the respondent's self-reported credit-score category. The association was statistically significant, $\chi^2(8, N = 78) = 18.1$, $p = .020$. The null hypothesis is therefore rejected and H1 is supported. The effect size, calculated from the reported statistic as Cramér's $V = \sqrt{(\chi^2/[N \times \min(r - 1, c - 1)])}$, is approximately .34, indicating a moderate association.

Table 4: Loan-application outcome by self-reported CIBIL/credit-score category (counts)

Credit-score category	Outcome 1	Outcome 2	Outcome 3	Total
1	0	0	1	1
2	3	0	1	4
3	17	0	5	22

Credit-score category	Outcome 1	Outcome 2	Outcome 3	Total
4	31	3	8	42
5	2	3	4	9
Total	53	6	19	78

Note. $\chi^2(8, N = 78) = 18.1$, $p = .020$. *Category and outcome codes are as recorded in the questionnaire dataset.*

Two observations qualify this result. First, the association is not a simple monotonic pattern in the coded categories. Outcome 1 accounted for 77.3% of responses in category 3 (17 of 22) and 73.8% in category 4 (31 of 42) but only 22.2% in category 5 (2 of 9), so the direction of the relationship cannot be stated from the coded table alone and depends on how the category and outcome codes map to the questionnaire labels. Second, the contingency table is sparse. By calculation from the reported counts, ten of the fifteen cells (66.7%) have expected frequencies below 5, which departs from the usual assumption for the chi-square approximation; the *p* value should therefore be read as indicative rather than definitive. Finally, because the test uses the credit-score category as an indicator, it does not directly measure a composite creditworthiness score.

4.3 Objective 2: Factors influencing creditworthiness (H2)

Table 5 reports descriptive statistics for the six factors rated by respondents ($N = 78$ for each). All factors have means between 1.12 and 1.54 and a median of 1.00. On the questionnaire coding in which lower values indicate greater importance, CIBIL/credit score was rated most important ($M = 1.12$, $SD = 0.51$), followed by income level ($M = 1.29$), repayment history ($M = 1.33$), debt obligations ($M = 1.40$), banking/financial records ($M = 1.44$) and collateral/security offered ($M = 1.54$). All distributions are strongly positively skewed, most markedly for CIBIL/credit score (skewness = 5.05, kurtosis = 26.19), reflecting that most respondents selected the lowest code.

Table 5: Descriptive statistics for perceived importance of creditworthiness factors ($N = 78$)

Factor	Mean	Median	SD	Skewness	Kurtosis
CIBIL/credit score	1.12	1.00	0.509	5.05	26.19
Income level	1.29	1.00	0.626	2.62	7.79
Repayment history	1.33	1.00	0.617	2.37	7.11
Debt obligations	1.40	1.00	0.631	1.99	5.40
Banking/financial records	1.44	1.00	0.636	1.80	4.67
Collateral/security offered	1.54	1.00	0.658	1.40	3.08

Note. Standard errors are 0.272 for skewness and 0.538 for kurtosis for every factor. Lower values denote higher perceived importance under the questionnaire coding; factors are ordered by mean.

Because only descriptive statistics were computed for this objective, no *p* value is available, and the null hypothesis for H2 can be neither formally rejected nor retained. The result is best read as a ranking of perceived importance: respondents regard the credit score, income and repayment history as the leading

determinants. The differences among the means are small relative to their standard deviations and the ratings are tightly clustered at the lowest code, so the data indicate broad agreement that all six factors matter, with modest separation between them.

4.4 Objective 3: Collateral/security importance and loan outcome (H3)

An independent-samples *t*-test compared collateral/security importance ratings between the two loan-outcome groups. The difference was statistically significant, $t(76) = 2.33$, $p = .022$, so the null hypothesis is rejected and H3 is supported. Levene's test was significant ($p < .05$), indicating that the assumption of equal variances may be violated. Group means were not part of the supplied output, so the direction of the difference is not reported here.

4.5 Objective 4: Income level and creditworthiness (H4)

Spearman's rank correlation between average monthly income and credit-score category was very weak and not statistically significant, $\rho(76) = .052$, $p = .651$. The null hypothesis is not rejected. The sample does not provide sufficient evidence of a relationship between monthly income and credit-score category; this does not prove that no relationship exists, only that none was detected in these responses.

4.6 Reliability and summary of results

Cronbach's alpha for the multi-item scale was .857, indicating good internal consistency among the items included in that analysis. Alpha assesses the consistency of items and does not by itself establish validity or determine the outcome of any hypothesis. Table 6 summarises the hypothesis tests.

Table 6: Summary of hypothesis tests

No.	Test and result	Decision on H_0	Conclusion
H1	Chi-square: $\chi^2(8, N = 78) = 18.1$, $p = .020$	Reject	Credit-score category is significantly associated with loan outcome
H2	Descriptive statistics only (means 1.12 to 1.54)	No formal decision	CIBIL score, income and repayment history rated most important
H3	*t*-test: $t(76) = 2.33$, $p = .022$	Reject	Collateral/security importance differs by loan outcome
H4	Spearman: $\rho(76) = .052$, $p = .651$	Fail to reject	No significant income and credit-score relationship detected

Note. $\alpha = .857$ *for the multi-item scale.*

5. Discussion

5.1 Interpretation of findings

The central finding is that loan outcomes among consultancy clients are significantly associated with the credit-score category they report. This is consistent with the position in the literature that the credit score remains the reference benchmark for creditworthiness and approval (Srivastava, 2026), and with the practitioner view in Ahmedabad that specific score thresholds determine access to unsecured credit. At

the same time, the sparse and non-monotonic pattern in Table 4 suggests that the score category does not map onto outcomes in a straightforward way, which is in line with Castro et al. (2026), who found that credit score alone does not fully capture risk and that it is most informative when combined with other indicators. The consultancy context may add a further layer, since documentation, lender matching and credit-profile advice can shift how a given score is read; the present data cannot separate these effects, and this is an avenue for future work.

The descriptive results on factor importance show respondents placing the CIBIL/credit score first, followed by income level and repayment history. This ordering corresponds to the factors that recur in the reviewed literature (Nadeesha & Madhushani, 2023; Roy & Shaw, 2021) and supports the multi-factor view of creditworthiness. However, the very tight clustering of ratings means that the survey discriminates only weakly between factors, a pattern that is common when respondents are asked to rate the importance of several plausible determinants without trade-offs.

The significant difference in collateral/security importance ratings across loan-outcome groups suggests that applicants' views of security are related to how their applications fared. Collateral also received the lowest importance mean among the six factors, so the finding concerns a difference between groups rather than a high overall rating. Because the direction of the difference is not available and the equal-variance assumption may not hold, the result should be treated as preliminary. In the Indian setting, collateral and guarantees feature in conditional approvals and in government-guaranteed schemes, which provides a plausible reason for outcome-related differences in how applicants regard it, but this explanation was not tested.

The absence of a detectable relationship between income and credit-score category contrasts with the positive association between income and creditworthiness reported by Nadeesha and Madhushani (2023). Several differences in design may account for this: that study modelled creditworthiness with a discrete set of predictors in a single public-bank setting, whereas the present study measured income as an ordinal band, creditworthiness as a self-reported score category and the sample was small. A credit score is also built from repayment history rather than from earning capacity, so income and score may capture different aspects of the borrower. These explanations are offered as possibilities and the null result should not be read as evidence that income is irrelevant to lending decisions.

5.2 Practical implications

For consultancy firms, the association between score category and outcome supports routine checking of a client's credit information before an application is submitted, and using the score category as one input to triage and to the expectations set with clients. Firms can also direct clients with weaker profiles towards credit-profile improvement or alternative routes before applying, an approach consistent with the credit-profile advisory role described in the industry analysis. Given the importance respondents attached to repayment history and debt obligations, advisory effort that addresses these factors, alongside documentation readiness, is likely to be worthwhile. For lenders and NBFCs that rely on third-party sourcing channels, the findings suggest that applicant credit-score category carries information about outcomes even for pre-screened, consultancy-prepared applications. For policymakers and facilitation bodies, the significance of credit-score category underlines the value of credit-information literacy and of schemes that support thin-file and first-time MSME borrowers. These implications are suggested by the associations reported here and do not rest on causal evidence.

6. Limitations and Directions for Future Research

Several limitations should be borne in mind. The sample of 78 valid responses is below the planned minimum of 100 and well below the figure that would be required for a large population, which limits statistical power and precision. The non-probability, purposive and convenience sampling, restricted to clients of consultancy firms in Ahmedabad and Gujarat, limits generalisation to other regions and firms and may introduce selection bias. The cross-sectional design shows association rather than causation, and the study was conducted within the limited time of an internship. Self-reported credit-score category, income and outcomes are subject to recall and social-desirability bias, and detailed credit reports, lender policies and approval records were inaccessible for confidentiality reasons.

Analytical limitations also apply. H1 was tested with credit-score category rather than a composite creditworthiness index; the chi-square table is sparse, with two-thirds of cells having expected counts below 5, so an exact test or collapsed categories would be more robust; the *t*-test was run in the presence of significant heterogeneity of variance, for which a Welch correction would be more conservative; and H2 was addressed descriptively without an inferential test. The sample profile (age, gender, occupation, loan type and lender type) was not part of the analysis presented here. Finally, the study does not observe lender-side variables such as internal credit models, lender-specific policies, regulatory requirements and changing economic conditions, which also influence approval decisions.

Future research could address these limitations in several ways: collecting a larger and more varied sample across several cities and consultancy firms; constructing a composite creditworthiness index and modelling approval with binary logistic regression, together with multiple regression of creditworthiness on its component factors, as originally planned; applying an inferential test suited to repeated ratings by the same respondents, such as a Friedman test, to the factor-importance data; using exact tests or Welch-corrected comparisons where assumptions fail; comparing consultancy-mediated applications with direct applications to isolate the effect of the intermediary; and following applicants over time to observe how creditworthiness and approval evolve. Given the evidence on alternative data and explainable models reviewed in Section 2, future work could also examine whether such information improves the consultancy firm's ability to anticipate approval.

7. Conclusion

This study examined customer creditworthiness and loan approval in a setting that existing research has largely overlooked: financial consultancy firms in Ahmedabad, Gujarat. Using survey data from 78 loan applicants and borrowers, it found a statistically significant association between self-reported CIBIL/credit-score category and loan-application outcome (p = .020), and a significant difference in the perceived importance of collateral/security between loan-outcome groups (p = .022). Respondents rated the CIBIL/credit score, income level and repayment history as the most important determinants of creditworthiness, although this objective rests on descriptive evidence only, and no significant relationship was found between income and credit-score category (p = .651). The scale showed good reliability (α = .857).

Taken together, the results indicate that the credit score is a central reference point in the consultancy-mediated lending process in Gujarat, while also showing that it is not the whole picture. The study's contribution is an initial India-specific evidence base from the consultancy channel and a transparent analytical approach that practitioners can follow. Because of the modest, non-probability sample and

cross-sectional design, the findings should be treated as exploratory, and larger, more varied and more rigorously modelled studies are needed to confirm and extend them.

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