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Digital Freight Platform Use Intensity and Perceived Financing Constraints among Small Logistics Carriers: The Role of Perceived Platform Credit Signals

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ABSTRACT

Small and micro road-freight carriers often face a financing problem that is closely tied to information quality. Their operating activity may be visible inside digital freight platforms, while external financiers may still have limited access to credible information about transaction completion, settlement regularity, service performance, and compliance. This study examines whether the intensity of platform use among platform-using carriers is associated with perceived financing constraints through perceived platform credit signal strength. The analysis uses a cross-sectional firm-level survey of 386 Chinese small and micro road-freight carriers conducted during the 2025 operating year. Nested ordinary least squares models with heteroskedasticity-robust HC3 standard errors evaluate the proposed associations. Platform-use intensity was positively associated with perceived platform credit signal strength (B = 0.40, SE = 0.04, t = 9.63, $p < .001$). Perceived platform credit signal strength was negatively associated with perceived financing constraints in the full outcome model (B = -0.33, SE = 0.07, t = -4.89, $p < .001$). The total association between platform-use intensity and perceived financing constraints was negative (B = -0.19, SE = 0.06, t = -3.08, p = .002), and the estimated indirect association through perceived platform credit signal strength was negative (B = -0.13, SE = 0.03, z = -4.36, $p < .001$). The estimates describe conditional cross-sectional associations among platform-using carriers and do not identify a causal effect or a contrast with non-users.

Keywords: digital freight platform, platform-use intensity, perceived credit signals, perceived financing constraints, small logistics carriers, signaling theory

1. Introduction

Digital freight platforms have become an important organizational setting for road-freight carriers. Their operational role can include matching loads and vehicles, supporting dispatch, recording transactions, coordinating settlement, and storing information relevant to service delivery. Road-freight research examines mobile freight-matching platforms and the operating environment of logistics firms, while research on data-driven forwarding describes meaningful differences in platform coordination and information functions (Heinbach et al. , 2022; Zhou & Wan, 2022). Digital logistics entrants are associated with altered business-model conditions for incumbent firms (Mikl et al. , 2021). For a small carrier, platform participation may therefore reach beyond an additional order channel. It may also organize a visible record of routine operating behavior.

That record matters because financing for small firms is fundamentally an information problem. A lender rarely sees operational quality, payment discipline, or capacity use with the same detail available to the firm itself. Akerlof (1970) formalized the consequences of unequal information in market exchange, and

Jaffee and Russell (1976) showed why imperfect information can generate credit rationing. In the small-business context, Berger and Udell (2006) emphasize that financing technologies respond to opacity, relationship information, and transaction information. Petersen and Rajan (1994) likewise demonstrate the relevance of information developed through lending relationships. Small and micro road-freight carriers can be especially exposed to this problem because their assets, cash flows, and operating records may be fragmented across transactions and counterparties.

Recent research has documented associations between digital financial conditions and financing constraints among small and medium-sized enterprises. Studies in China link local financial conditions, digital financial inclusion, digitalization, and digital finance to financing conditions faced by smaller firms (Bu et al. , 2024; Li et al. , 2023; Lu et al. , 2022; Sun et al. , 2026; Zhang et al. , 2023). Related work connects technological progress and digital financial inclusion with firm-level financing conditions (Hu et al. , 2023), and supply-chain finance research reports relevant associations for Chinese SMEs (He & Liu, 2025; Lou et al. , 2024). Research on Chinese small-business lending examines lending conditions and financial outcomes, fintech lending research investigates credit access, marketplace-lending work identifies a distinct SME financing channel, and entrepreneurial-finance research discusses digitization, business models, and financing channels (Bertoni et al. , 2022; Chen et al. , 2022; Cornelli et al. , 2024; Cumming & Hornuf, 2022). These findings motivate attention to digitized information, yet they leave a more focused question unresolved: how can the operational use of a freight platform become information that external financiers can regard as credit relevant?

The distinction between platform participation and platform credit signal strength is central to this question. Participation concerns the extent to which a carrier relies on a platform for order matching, transaction execution, settlement, and coordination. Credit signal strength concerns the visibility, credibility, and usability of platform-generated identity, transaction, settlement, evaluation, and compliance information in a financing assessment. The two constructs should move together only under particular conditions. A carrier may use a platform extensively while the resulting records remain incomplete, poorly verified, inaccessible to financiers, or weakly connected to credit evaluation. Conversely, a smaller amount of platform activity may yield useful signals when records are validated, consistent, and interpretable. Research on digital footprints and online credit markets shows that nontraditional behavioral information and visible signals can influence credit assessment (Berg et al. , 2020; Kawai et al. , 2022). The present study develops this distinction for small road-freight carriers.

Nepal (2025) links digital awareness, technology trust, and access to digital banking with financial inclusion. Izunobi and Burinskiene (2025) examine digital maturity and change management in global supply-chain operations, while AL Jedi et al. (2026) connect digital supply-chain maturity with resilience and performance. Thanh et al. (2025) identify digital service design, literacy, and trust conditions as relevant to rural financial inclusion. Neupane (2025) highlights regulatory issues around e-finance, including privacy, cybersecurity, and compliance. Together, these studies identify a credible research space around digital records, trust, and finance. Their role here is bounded contextual evidence; they do not directly test the carrier-level platform-credit-signal pathway.

This study addresses two research questions. RQ1 asks how the intensity of digital freight platform use is associated with perceived financing constraints among carriers that already use a platform. RQ2 asks whether perceived platform credit signal strength accounts for part of that association. The analysis examines a 2025 cross-sectional survey of 386 Chinese small and micro road-freight carriers. The objective is analytical clarity: it separates the extent of operational platform use from the information value that carriers attribute to records generated through that use. The article contributes in three ways. First, it treats platform-use intensity as an organizational practice with concrete operational content. Second, it models perceived platform credit signal strength as a distinct information pathway rather than as a direct property of platform participation. Third, it reports nested model comparisons, robust coefficient inference, fit statistics, collinearity diagnostics, and explicit limits on cross-sectional interpretation.

2. Literature Review and Hypothesis Development

2.1 Signaling Theory, Information Asymmetry, and the Carrier Financing Context

The starting point for the study is that financing decisions are made under incomplete information. A lender must infer the probability that a borrower can meet obligations, yet a small carrier's operating quality is often hard to observe directly. The information problem is broader than a missing financial statement. It also concerns whether transaction histories are reliable, whether settlements are regular, whether service performance can be verified, and whether operating data can be linked to the legal and economic identity of the carrier. Akerlof (1970) explains how quality uncertainty can undermine exchange when one side holds more information than the other. In credit markets, Jaffee and Russell (1976) provide a formal account of credit rationing under unequal information, even where borrower demand for funds remains strong.

Signaling theory provides a specific way to analyze this problem. Spence (1973) frames observable information as a credible basis for evaluating an otherwise unobserved attribute under uncertainty. Applied to small-carrier finance, a useful signal does not simply consist of a data field. It must be connected to operating behavior, have a degree of verifiability, and be interpretable by an external evaluator. This logic is consistent with the SME-finance framework of Berger and Udell (2006), which differentiates financing technologies according to the information available to financiers. Repeated contact can provide relationship information, as shown by Petersen and Rajan (1994), while a platform may organize transaction-related information through a different route. The platform can document activity without becoming the lender.

Digital credit research reinforces the relevance of that distinction. Berg et al. (2020) show that digital footprints can add predictive information to credit scoring beyond conventional credit-bureau records. Kawai et al. (2022) find that signals in online credit markets influence lender assessments under information asymmetry. These studies do not imply that every platform trace has credit value. They do establish that digitally recorded behavior may become relevant when a decision-maker can assess its informational content. The present study therefore defines perceived platform credit signal strength as a carrier-level perception of whether platform-generated information is visible, credible, and usable in external credit assessment. This definition is narrower than general digital maturity and more specific than access to a financing product.

The construct also differs from platform participation. Participation identifies how extensively a carrier uses the platform in core operating processes. Credit signal strength identifies the financing relevance of information recorded alongside that activity. Treating them as one construct would conceal an important variation: similar levels of use can yield different informational value where records differ in completeness, verification, continuity, or accessibility. That separation provides a route for examining the research questions without assuming that digital participation automatically corresponds with more favorable financing conditions. It also prevents the analysis from equating visible data with high-quality credit information.

2.2 Digital Freight Platform Participation and Platform Credit Signal Strength

Digital freight platforms provide a setting in which operational actions leave structured traces. In road freight, platform functions differ across market designs and service architectures. Heinbach et al. (2022) identify data-driven coordination and forwarding functions across road-freight platforms. Zhou and Wan (2022) examine the relationship between mobile digital freight-matching platforms and the operating environment of road-freight logistics firms. Xiao et al. (2023) examine user participation in an emerging

Chinese digital freight platform and identify organizational and policy antecedents. These studies establish that platform participation has a practical operational content. It is not simply an abstract attitude toward technology.

Work on B2B platforms and SME digitization gives further reason to expect that participation will be associated with the availability of organized operating information. Marzi et al. (2023) describe identifiable adoption pathways and trade-offs for SMEs and large firms using B2B digital platforms. Ahmed et al. (2022) link digital platform capability with organizational agility among emerging-market manufacturing SMEs. Omrani et al. (2024) show that the drivers of SME digital transformation include organizational conditions that shape adoption. Papadopoulos et al. (2020) document how SMEs use digital technologies to adapt operations under changing conditions, and Hanelt et al. (2021) synthesize research connecting digital transformation with strategy and organizational change. The common implication is that digital technology becomes organizationally meaningful when it is incorporated into recurring work processes.

For carriers, recurring participation can make transaction-related information more legible. Order matching can record the allocation of capacity, transaction execution can document completed work, settlement functions can preserve payment-related records, and service or compliance functions can make aspects of performance more visible. The present argument concerns the organizing role of these processes. It does not assume that the platform independently certifies every aspect of carrier quality. A signal gains credibility only when information is sufficiently connected to observable performance and can be evaluated by a financing counterparty.

Research on information transparency in supply-chain finance sharpens this point. Zheng et al. (2022) examine blockchain technology for enterprise credit-information sharing, and Guo et al. (2022) describe a blockchain and Internet of Things framework intended to support information transparency in supply-chain finance. Their focus is technological infrastructure, while the present study concerns the carrier's assessment of platform-generated signals. Both studies describe approaches to enterprise credit-information sharing and supply-chain-finance information transparency. They do not report financing outcomes for small carriers. Recent target-journal work on digital maturity in supply-chain settings similarly emphasizes that digital capabilities are related to organizational outcomes, though it does not address financing constraints for small carriers directly (AL Jedi et al. , 2026; Izunobi & Burinskiene, 2025).

Signaling theory predicts a positive association between platform-use intensity and perceived signal strength because broader operational use is likely to leave more continuous records that an external party could evaluate. The expectation depends on the quality, validation, and accessibility of those records. The hypothesis is stated at the conditional association level among platform-using carriers.

H1. Greater digital freight platform-use intensity is positively associated with perceived platform credit signal strength among platform-using carriers.

2.3 Perceived Platform Credit Signal Strength and Perceived Financing Constraints

Financing constraints describe the degree to which a carrier faces difficulty, delay, high cost, or limited availability when seeking external financing. Information asymmetry provides the conceptual account for why signal strength may be related to those constraints. If a financier can assess a carrier through credible operational records, the screening problem may be less severe. The relevant logic concerns uncertainty reduction and does not guarantee credit approval. Lenders may still apply collateral standards, portfolio limits, regulatory requirements, or sector-specific risk criteria.

Several streams of evidence support this expectation at the information and credit-assessment level. Berg et al. (2020) examine the informational role of digital footprints in credit scoring. Djeundje et al. (2021) study credit scoring with alternative data, and Dumitrescu et al. (2022) compare nonlinear machine-learning methods with a logistic benchmark. Gambacorta et al. (2024) provide evidence from a Chinese fintech firm on machine learning and nontraditional data in credit scoring. These studies are not freight-platform studies, yet they make a narrow point relevant here: data outside conventional accounting and bureau files can have value when used within a defined credit-assessment process.

The credibility of information also matters. Kawai et al. (2022) show that signals supplied in online credit markets influence lender assessments, while Hasan et al. (2022) link trust and trustworthiness with lending outcomes in peer-to-peer markets. Galema (2020) finds that relationship information is relevant to credit rationing in P2P lending to SMEs. These results fit the view that financing conditions can depend on how a lender interprets both records and their source. A platform credit signal therefore has no inherent value apart from the verification practices, data governance, and decision rules surrounding it.

Evidence from SME lending offers a complementary perspective. Cumming and Hornuf (2022) identify marketplace lending as a distinct financing channel for SMEs. Cornelli et al. (2024) associate fintech lending with credit access among U.S. small businesses, and Chen et al. (2022) link Chinese small-business lending conditions with firm-level financial outcomes and volatility. The settings differ from Chinese road freight, and they do not establish that platform data should be used for lending. Taken together, the studies place information technology, lender design, and financing access in a shared research frame.

The proposed perceived signal-strength construct captures the carrier's view that platform information can be used in financing assessment. Higher perceived platform credit signal strength is expected to be associated with lower perceived financing constraints, conditional on the pre-exposure control set. The direction follows signaling theory and the credit-information literature, while the empirical test is limited to this carrier sample.

H2. Perceived platform credit signal strength is negatively associated with perceived financing constraints.

2.4 Platform-Use Intensity and Perceived Financing Constraints

Platform-use intensity may also be associated with perceived financing constraints through channels that precede or accompany formal credit assessment. Research on Chinese SMEs reports associations between digital financial inclusion, digitalization, supply-chain finance, and financing conditions. The cross-study evidence varies in data, sector, and institutional channel, yet it places digitally mediated information and services within the financing-constraint discussion.

Supply-chain finance research is especially relevant because it links financing conditions to transaction information across firms. He and Liu (2025) examine digital supply-chain finance and financing constraints in a Chinese enterprise setting, while Lou et al. (2024) associate supply-chain finance with funding constraints among Chinese SMEs. Bertoni et al. (2022) examine digitization in entrepreneurial finance through business models and financing channels. Sharma et al. (2024) review small-business FinTech research and identify opportunities alongside unresolved risks. These findings make an expected negative association plausible, although they do not determine its size or persistence for road-freight carriers.

Platform-use intensity may matter in the carrier context because it changes the availability, organization, and potential portability of operational information. It can also provide access to settlement functions, service evaluations, or business contacts that are relevant to financing discussions. At the same time, participation may coexist with price competition, dependence on platform rules, and uneven data quality. The hypothesized association is an empirically testable expectation for platform-using carriers after the pre-exposure control set is held constant.

H3. Among platform-using carriers, greater digital freight platform-use intensity is negatively associated with perceived financing constraints.

2.5 The Statistical Indirect Association Through Perceived Platform Credit Signal Strength

The statistical indirect-association proposition combines the preceding arguments. Greater platform-use intensity may be associated with a broader and more continuous set of platform records. Perceived platform credit signal strength represents the extent to which those records are visible, credible, and usable in financing assessment. Perceived financing constraints may be lower where external financiers view those signals as sufficiently credible for screening. The decomposition assesses a statistical pattern among the variables and does not establish a temporal process or an identified causal mechanism.

This integration is supported by adjacent evidence. Berg et al. (2020) and Kawai et al. (2022) examine digital footprints and online signals in credit-assessment contexts. Djeundje et al. (2021), Dumitrescu et al. (2022), and Gambacorta et al. (2024) study alternative or nontraditional information in credit-scoring settings. Supply-chain finance studies identify information sharing and transparency as material technological applications (Guo et al. , 2022; Zheng et al. , 2022), while Chinese SME finance research connects supply-chain finance with funding constraints (He & Liu, 2025; Lou et al. , 2024). Together, these streams support the component logic of a platform-credit-signal pathway.

The complete carrier-level indirect-association model remains a theory-led integration. The available studies do not directly test whether participation in a digital freight platform is associated with stronger perceived credit signals that are then associated with lower perceived financing constraints for small carriers. This gap is substantive because it moves the question from access to technology toward the informational consequences of operational platform use. It also directs attention to governance. Digital service research identifies the relevance of design, literacy, and trust for financial inclusion (Thanh et al. , 2025), and e-finance research identifies privacy, cybersecurity, and compliance as material boundaries (Neupane, 2025). These conditions are relevant to whether platform information is credible and transferable across organizational settings.

The proposed indirect association should therefore be negative. Greater use intensity is expected to be associated with stronger perceived credit signals, and stronger perceived signals are expected to be associated with lower perceived financing constraints. Because the design is cross-sectional and restricted to platform users, the decomposition is interpreted as a conditional statistical association.

H4. Perceived platform credit signal strength statistically accounts for part of the association between digital freight platform-use intensity and perceived financing constraints.

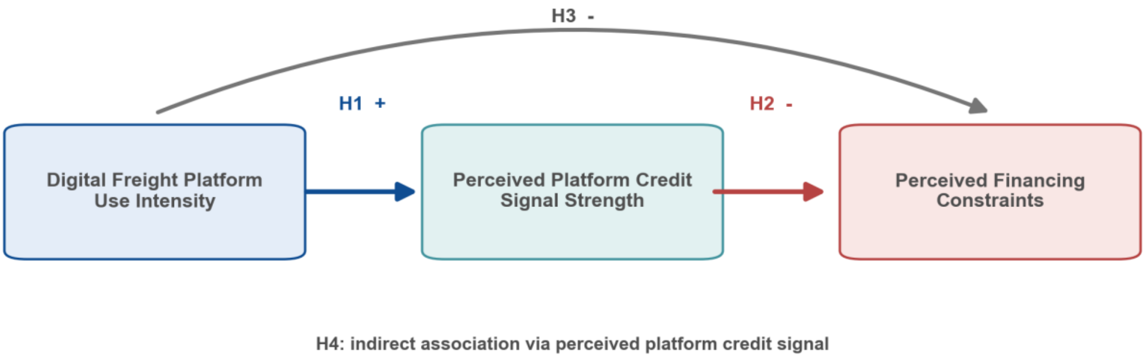

Figure 1: Proposed Conceptual Framework

3. Research Methodology

3.1 Research Design and Context

The study uses a cross-sectional firm-level survey design focused on the 2025 operating environment of Chinese small and micro road-freight carriers. The carrier firm is the unit of analysis because platform-use intensity, the records associated with platform use, and perceived financing constraints are defined at that level. The sampling frame includes firms that use a digital freight platform for at least part of their operating activity. Accordingly, the focal predictor is interpreted as variation in use intensity among platform-using carriers; the design contains no non-user comparison group and does not identify a causal participation effect.

Road freight involves repeated matching, dispatch, service execution, and settlement activities that can be mediated by a platform. Those activities make the distinction between use intensity and perceived platform credit signal strength analytically feasible. The framework asks whether carriers reporting more extensive use also report stronger perceived platform credit signals and less severe perceived financing constraints within the stated setting. It does not assume that all platforms have the same data architecture or relationship with financial institutions.

The design is deliberately conservative in its inferential aim. Cross-sectional associations can be compared across firms after the observed control set is included, yet they cannot establish temporal ordering. A carrier with weaker perceived financing constraints may have more resources to use a platform, and unobserved managerial or local-finance characteristics may shape all three focal constructs. Platform tenure was excluded from the primary equations because it could be jointly determined with use intensity; Model M7 incorporated it as a sensitivity check.

3.2 Sampling and Data Collection

The final analytical sample comprised 386 small and micro road-freight carrier firms. The empirical analysis includes descriptive reporting, measurement assessment, nested ordinary least squares models with five pre-exposure controls, a product-of-coefficients assessment of the indirect association, and an alternative outcome sensitivity check. Table 1 presents the sample profile, and all model estimates refer to the same 386 firms.

Data were collected from owner-managers or finance managers who were familiar with their firm's platform activity and financing experience. The sampling frame was assembled from the enterprise membership registries of three provincial road logistics associations in major freight hubs in eastern and central China (Shandong, Henan, and Jiangsu Provinces) and verified partner lists supplied by two major nationwide digital freight platforms (Platform A, specializing in interprovincial full-truckload matching, and Platform B, focusing on regional freight consolidation and dispatch). To prevent cross-source duplication, records were cross-checked and merged using each enterprise's unique Unified Social Credit Code (USCC) prior to sampling, resulting in a deduplicated pool of qualified carriers. Eligible firms met the national regulatory criteria for small and micro road-freight enterprises (fewer than 300 employees and annual revenue under RMB 30 million), had maintained continuous operations during the 2025 operating year, and had used at least one digital freight platform actively for no less than three months. Stratified by province (approximately one-third per province) and fleet-size band, invitations were sent to one eligible owner-manager or finance manager at each of 612 randomly sampled firms between 12 May and 28 July 2025. A total of 438 responses were received, corresponding to a raw response rate of 71.6% (438/612). We excluded 21 firms outside the size or platform-use criteria, 9 duplicate submissions, and 22 questionnaires with more than 20% item nonresponse or a failed attention check. The final sample therefore comprised 386 complete firm-level responses, corresponding to a usable response rate of 63.1% (386/612).

The sample profile describes a heterogeneous group of carriers. Some firms are recent entrants, some have operated for more than a decade, and fleet sizes range from very small firms to firms with more than 30 vehicles. The sampling frame and eligibility criteria define the population to which the estimates are intended to generalize: small and micro road-freight carriers operating in the three sampled provinces during the 2025 operating year. Generalization beyond that population requires additional evidence.

3.3 Measures

All three focal constructs were measured with multi-item five-point Likert scales (1 = strongly disagree, 5 = strongly agree). The final questionnaire contained five digital freight platform-use-intensity items, five perceived platform credit-signal-strength items, and four perceived financing-constraint items. The use-intensity items were adapted from the operational-use dimensions described by Heinbach et al. (2022), Xiao et al. (2023), and Zhou and Wan (2022), while the financing-constraint items were adapted from SME-finance measures used by Lu et al. (2022) and Zhang et al. (2023). No published scale directly measures a carrier’s perception of the credit relevance of freight-platform records, so the five signal-strength items were operationalized to assess observability, credibility, verifiability, continuity, and external usability, drawing on Spence (1973), Berg et al. (2020), Kawai et al. (2022), and Zheng et al. (2022). Specifically, these items asked respondents to evaluate the extent to which their platform transaction records, settlement consistency, and service fulfillment ratings are verifiable by and useful to third-party financial institutions (e.g., "Our continuous operational and settlement records on the platform can be verified and utilized by financial institutions as credible credit references"). Two bilingual researchers independently translated the English questionnaire into Chinese and back-translated it. A logistics-finance scholar and two experienced carrier managers reviewed semantic equivalence and content relevance, followed by a pilot test with 30 respondents. The questionnaire separated the three construct blocks, randomized item order within each block, and placed the predictor and outcome blocks in separate sections. All focal variables are respondent-reported perceptions, and no lender administrative outcome or observed financing contract term was available in the survey. Reverse-coded items were recoded before averaging, and each construct score was calculated as the mean of its retained items when at least 80% of item responses were available. The alternative financing-constraint score used the same item pool as a sensitivity specification.

Digital freight platform use intensity captures the respondent-reported extent to which a carrier relies on a digital freight platform for order matching, transaction execution, payment settlement, and operating coordination. This definition is grounded in the platform functions discussed in the road-freight and digital-platform literature (Heinbach et al. , 2022; Xiao et al. , 2023; Zhou & Wan, 2022). It is an operational-use construct. A high score indicates more extensive integration of platform functions into the carrier's work processes; it does not indicate that the carrier receives financing through the platform.

Perceived Platform Credit Signal Strength captures the respondent's assessment of whether platform-generated identity, transaction, settlement, evaluation, and compliance information is visible, credible, and usable in an external credit assessment. The construct is informed by signaling theory and by research on digital footprints, online credit signals, and credit-information sharing (Berg et al. , 2020; Kawai et al. , 2022; Spence, 1973; Zheng et al. , 2022). It is conceptually distinct from the volume of data a platform holds. The items emphasize the perceived credit relevance of records, including their consistency, verifiability, and external interpretability.

Perceived Financing Constraints capture the respondent's assessment of difficulty, delay, high cost, or limited availability when the carrier seeks external finance. A higher score represents tighter perceived constraints. This framing follows the small-firm finance and digital-finance literature, which treats financing conditions as closely related to information, lender technology, and institutional access (Berger & Udell, 2006; Lu et al. , 2022; Zhang et al. , 2023). The construct does not measure realized default, a lender's internal decision rule, or platform profitability.

Five control variables were included because they represent firm or owner characteristics plausibly antecedent to platform-use intensity and financing perceptions: firm age, fleet size, annual revenue, asset tangibility, and owner-manager education. Each was reported for the 2025 operating year. Platform tenure is retained in the dataset and correlation table, yet it is excluded from the primary equations because the duration of platform use may be jointly determined with use intensity. Model M7 included platform tenure as an auxiliary sensitivity specification to verify that the focal estimates were robust to controlling for platform experience.

3.4 Analytical Procedure

All analyses were conducted in Python. We report the sample profile, item-level reliability and validity statistics, descriptive statistics, and a complete lower-triangle correlation matrix. Cronbach's alpha, composite reliability, average variance extracted, and the highest heterotrait-monotrait value were calculated from the retained items. These diagnostics assess internal consistency, convergent validity, and discriminant validity for the association models.

Five nested ordinary least squares models evaluated H1 through H3. Model M1 regressed perceived platform credit signal strength on the five pre-exposure controls. Model M2 added digital freight platform-use intensity to the same outcome and tested H1. Model M3 regressed perceived financing constraints on the controls alone. Model M4 added use intensity and provided the total association relevant to H3. Model M5 added perceived platform credit signal strength to the M4 equation and provided the conditional association relevant to H2 and the direct association used in the indirect-association decomposition. Because each focal score is the mean of multiple Likert items, it was treated as an approximately continuous outcome. Coefficient inference used HC3 covariance with a finite-sample t reference distribution based on the residual degrees of freedom; the same convention was used for coefficient p values and 95% confidence intervals. Residual-versus-fitted plots, Q-Q plots, leverage, and Cook's distance were inspected, and a leave-one-out sensitivity check left the direction and two-sided inferential decision for each focal coefficient unchanged. Overall F statistics and nested ΔR^2 tests used the conventional OLS residual decomposition. Table 7 reports N, R^2, adjusted R^2, overall F tests, incremental tests, and maximum VIF for every model.

H4 was assessed with a product-of-coefficients calculation. The indirect association equals the use-intensity-to-signal path in M2 multiplied by the perceived-signal-to-perceived-constraint path in M5. Its Delta-method standard error uses the two path estimates and their robust standard errors. The result is reported with a normal-approximation z statistic and confidence interval. A 2,000-replicate percentile bootstrap was run as a sensitivity check. The total association in M4 equals the direct association in M5 plus the indirect association before rounding. This decomposition summarizes cross-sectional associations and does not establish temporal ordering or a causal mechanism.

Finally, Model M6 replaced the primary perceived financing-constraint score with an alternative score while retaining use intensity, perceived platform credit signal strength, and the five pre-exposure controls. Model M8 added platform tenure to the primary full outcome equation as an additional specification check. These sensitivity checks assessed the stability of the focal associations across alternative outcome construction and expanded covariate sets, confirming that the empirical findings remained consistent under varying model specifications. Because the sample was pooled across three provinces and two platform sources, we also evaluated auxiliary specifications incorporating province fixed effects (using dummy variables for Shandong and Henan, with Jiangsu as the reference category) and platform source dummies. F-tests indicated that these source-level indicator sets were not jointly significant, and their inclusion yielded virtually identical coefficients, standard errors, and significance levels for all hypothesized relationships. To maintain model parsimony and preserve degrees of freedom, the primary models report the five theoretically grounded pre-exposure covariates.

4. Results

4.1 Sample Characteristics

Table 1 reports the profile of the 386 carrier firms. Firms operating for eight to 12 years formed the largest age category, accounting for 141 firms or 36.53% of the analytical sample. Firms with 16 to 30 vehicles formed the largest fleet category, accounting for 147 firms or 38.08%. Order matching and dispatch was the most frequently reported primary platform use, with 164 firms or 42.49%. The largest owner-manager education category was vocational or associate degree, with 168 firms or 43.52%. Age and fleet-size categories were derived from the underlying continuous measures used in estimation. No subsequent table used a different analytical sample; all reported estimates refer to the same 386 carrier firms.

Table 1: Sample Profile of Small and Micro Logistics Carriers

Sample Dimension	Category	n	%
Firm age	1 to 3 years	61	15.80
Firm age	4 to 7 years	108	27.98
Firm age	8 to 12 years	141	36.53
Firm age	13 years or more	76	19.69
Fleet size	1 to 5 vehicles	69	17.88
Fleet size	6 to 15 vehicles	140	36.27
Fleet size	16 to 30 vehicles	147	38.08
Fleet size	More than 30 vehicles	30	7.77
Primary platform use	Order matching and dispatch	164	42.49
Primary platform use	Settlement and payment management	91	23.58
Primary platform use	Capacity coordination	73	18.91
Primary platform use	Compliance and service records	58	15.03
Owner-manager education	Secondary school or below	107	27.72
Owner-manager education	Vocational or associate degree	168	43.52
Owner-manager education	Bachelor’s degree or above	111	28.76

4.2 Measurement Assessment and Descriptive Statistics

Table 2 summarizes the measurement statistics for the three focal constructs. Cronbach's alpha ranged from 0.86 for perceived financing constraints to 0.90 for perceived platform credit signal strength. Composite reliability ranged from 0.90 to 0.92, and average variance extracted ranged from 0.65 to 0.70. The highest heterotrait-monotrait value across the construct pairs was 0.62. These diagnostics provide the measurement evidence used for the subsequent association analysis.

Table 2: Measurement Reliability and Validity Assessment

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Digital Freight Platform Use Intensity	0.88	0.91	0.67
Perceived Platform Credit Signal Strength	0.90	0.92	0.70
Perceived Financing Constraints	0.86	0.90	0.65

Table 3 presents means, standard deviations, and correlations calculated from the 386 firm-level records. Digital freight platform use intensity had a mean of 3.46 and a standard deviation of 0.77. Perceived platform credit signal strength had a mean of 3.62 and a standard deviation of 0.75. Perceived financing constraints had a mean of 3.11 and a standard deviation of 0.88. Use intensity correlated positively with perceived platform credit signal strength (r = 0.45) and negatively with perceived financing constraints (r = -0.20). Perceived platform credit signal strength correlated negatively with perceived financing constraints (r = -0.35). The largest correlation among the firm-level controls was between fleet size and annual revenue (r = 0.52).

Table 3: Descriptive Statistics and Correlations

No.	Variable	Mean	Standard Deviation	1	2	3	4	5	6	7	8	9
1	Digital Freight Platform Use Intensity	3.46	0.77									
2	Perceived Platform Credit Signal Strength	3.62	0.75	0.45								
3	Perceived Financing Constraints	3.11	0.88	-0.20	-0.35							
4	Firm Age (Years)	8.02	4.49	0.06	0.19	-0.15						
5	Fleet Size (Vehicles)	14.52	9.30	0.16	0.23	-0.24	0.34					
6	Annual Revenue (Million CNY)	8.90	6.73	0.13	0.24	-0.19	0.30	0.52				
7	Asset Tangibility	0.54	0.17	-0.03	0.03	-0.11	0.24	0.21	0.27			
8	Owner-Manager Education (Years)	13.07	2.58	0.12	0.03	-0.06	0.01	0.07	0.09	0.00		
9	Platform Tenure (Years)	4.03	2.32	0.38	0.34	-0.20	0.34	0.22	0.27	0.07	0.09	

4.3 Hierarchical Regression Results

Table 4 reports the five primary nested regression models. In M2, digital freight platform-use intensity was positively associated with perceived platform credit signal strength after the five pre-exposure controls were included (B = 0.40, SE = 0.04, t = 9.63, $p < .001$, 95% CI [0.32, 0.48]). Adding use intensity increased R^2 from 0.09 in M1 to 0.25 in M2 ($\Delta R^2 = 0.16$; $F\Delta(1,379) = 82.41$, $p < .001$). H1 was supported.

In M4, use intensity was negatively associated with perceived financing constraints in the total-association equation (B = -0.19, SE = 0.06, t = -3.08, p = .002, 95% CI [-0.31, -0.07]). The addition of use intensity increased R^2 from 0.07 in M3 to 0.10 in M4 ($\Delta R^2 = 0.03$; $F\Delta(1,379) = 10.88$, p = .001), supporting H3. In M5, perceived platform credit signal strength was negatively associated with perceived financing constraints (B = -0.33, SE = 0.07, t = -4.89, $p < .001$, 95% CI [-0.46, -0.20]), and adding the mediator increased R^2 by 0.06 ($F\Delta(1,378) = 26.41$, $p < .001$). H2 was supported. The conditional direct association for use intensity in M5 was -0.06 (SE = 0.07, t = -0.83, p = .406, 95% CI [-0.19, 0.08]).

All five primary OLS models retained the same 386 carrier firms. The coefficient and standard-error values differ across controls because they are calculated from the same row-level data under different outcome and predictor sets. Maximum VIF values ranged from 1.46 to 1.48 in the primary models, below conventional concern thresholds. Model M7 added platform tenure; the resulting coefficient was -0.02 (SE = 0.02, t = -0.87, p = .386), and the focal signal coefficient remained negative (B = -0.32, SE = 0.07, t = -4.77, $p < .001$). The tenure addition increased R^2 by 0.00 ($F\Delta(1,377) = 0.78$, p = .379), as shown in Table 7.

Table 4: Hierarchical Regression Results for Platform Credit Signals and Perceived Financing Constraints

Model	Outcome	Predictor	B	Robust SE	t	p	95% Confidence Interval
M1	Perceived Platform Credit Signal Strength	Firm Age (Years)	0.019	0.009	2.03	p = .044	[0.001, 0.038]
M1	Perceived Platform Credit Signal Strength	Fleet Size (Vehicles)	0.010	0.005	1.85	p = .065	[-0.001, 0.021]
M1	Perceived Platform Credit Signal Strength	Annual Revenue (Million CNY)	0.018	0.007	2.45	p = .015	[0.004, 0.032]
M1	Perceived Platform Credit Signal Strength	Asset Tangibility	-0.289	0.246	-1.17	p = .242	[-0.774, 0.196]
M1	Perceived Platform Credit Signal Strength	Owner-Manager Education (Years)	0.003	0.013	0.24	p = .812	[-0.023, 0.030]
M2	Perceived Platform Credit Signal Strength	Digital Freight Platform Use Intensity	0.402	0.042	9.63	p < .001	[0.320, 0.484]
M2	Perceived Platform Credit Signal Strength	Firm Age (Years)	0.019	0.009	2.15	p = .032	[0.002, 0.036]
M2	Perceived Platform Credit Signal Strength	Fleet Size (Vehicles)	0.006	0.005	1.11	p = .266	[-0.004, 0.016]
M2	Perceived Platform Credit Signal Strength	Annual Revenue (Million CNY)	0.015	0.007	2.19	p = .029	[0.001, 0.028]

Model	Outcome	Predictor	B	Robust SE	t	p	95% Confidence Interval
M2	Perceived Platform Credit Signal Strength	Asset Tangibility	-0.151	0.231	-0.66	p = .513	[-0.605, 0.302]
M2	Perceived Platform Credit Signal Strength	Owner-Manager Education (Years)	-0.009	0.012	-0.74	p = .460	[-0.033, 0.015]
M3	Perceived Financing Constraints	Firm Age (Years)	-0.011	0.011	-1.00	p = .319	[-0.032, 0.010]
M3	Perceived Financing Constraints	Fleet Size (Vehicles)	-0.017	0.006	-2.93	p = .004	[-0.028, -0.005]
M3	Perceived Financing Constraints	Annual Revenue (Million CNY)	-0.009	0.009	-1.01	p = .314	[-0.027, 0.009]
M3	Perceived Financing Constraints	Asset Tangibility	-0.212	0.264	-0.80	p = .422	[-0.730, 0.307]
M3	Perceived Financing Constraints	Owner-Manager Education (Years)	-0.013	0.018	-0.70	p = .482	[-0.049, 0.023]
M4	Perceived Financing Constraints	Digital Freight Platform Use Intensity	-0.188	0.061	-3.08	p = .002	[-0.307, -0.068]
M4	Perceived Financing Constraints	Firm Age (Years)	-0.010	0.011	-0.98	p = .327	[-0.031, 0.010]
M4	Perceived Financing Constraints	Fleet Size (Vehicles)	-0.014	0.006	-2.56	p = .011	[-0.026, -0.003]
M4	Perceived Financing Constraints	Annual Revenue (Million CNY)	-0.008	0.009	-0.83	p = .409	[-0.026, 0.011]
M4	Perceived Financing Constraints	Asset Tangibility	-0.276	0.266	-1.04	p = .299	[-0.798, 0.246]
M4	Perceived Financing Constraints	Owner-Manager Education (Years)	-0.007	0.018	-0.40	p = .689	[-0.043, 0.028]
M5	Perceived Financing Constraints	Digital Freight Platform Use Intensity	-0.056	0.067	-0.83	p = .406	[-0.187, 0.076]
M5	Perceived Financing Constraints	Perceived Platform Credit Signal Strength	-0.328	0.067	-4.89	p < .001	[-0.460, -0.196]
M5	Perceived Financing Constraints	Firm Age (Years)	-0.004	0.010	-0.42	p = .678	[-0.024, 0.016]
M5	Perceived Financing Constraints	Fleet Size (Vehicles)	-0.013	0.006	-2.24	p = .026	[-0.024, -0.002]
M5	Perceived Financing Constraints	Annual Revenue (Million CNY)	-0.003	0.009	-0.31	p = .754	[-0.021, 0.015]

Model	Outcome	Predictor	B	Robust SE	t	p	95% Confidence Interval
M5	Perceived Financing Constraints	Asset Tangibility	-0.326	0.247	-1.32	p = .189	[-0.812, 0.161]
M5	Perceived Financing Constraints	Owner-Manager Education (Years)	-0.010	0.018	-0.56	p = .574	[-0.045, 0.025]

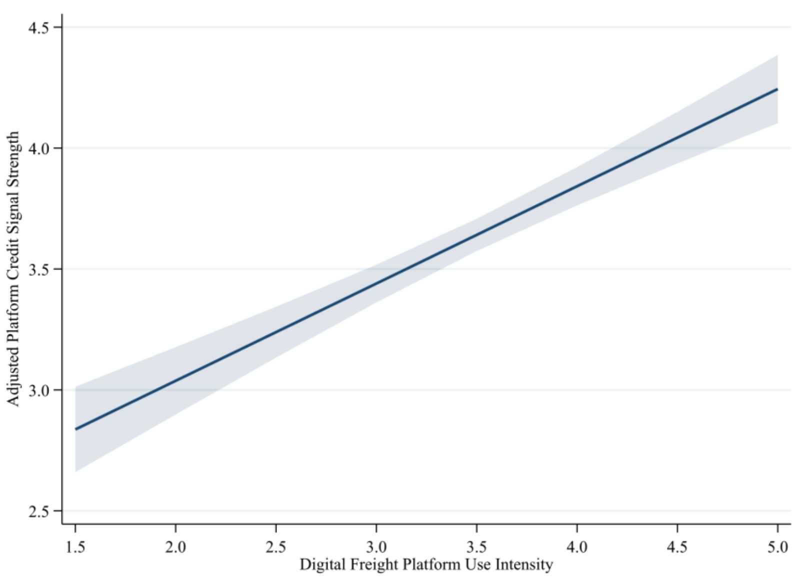

Figure 2: Adjusted Perceived Platform Credit Signal Strength Across Platform-Use Intensity

4.4 Statistical Indirect-Association Analysis

Table 5 presents the statistical decomposition for H4. The conditional direct association from use intensity to perceived financing constraints in M5 was -0.06 (SE = 0.07, t = -0.83, p = .405, 95% CI [-0.19, 0.08]). The Delta-method indirect association through perceived platform credit signal strength was -0.13 (SE = 0.03, z = -4.36, p < .001, 95% CI [-0.19, -0.07]). The total association in M4 was -0.19 (SE = 0.06, t = -3.08, p = .002, 95% CI [-0.31, -0.07]). The unrounded direct and indirect estimates sum to the unrounded total association. The 2,000-replicate percentile bootstrap sensitivity interval was [-0.19, -0.08]. H4 was supported as a statistical indirect-association result within the cross-sectional model.

Table 5: Statistical Indirect-Association Analysis of Perceived Platform Credit Signal Strength

Association	B	SE	Test Statistic	p	95% Confidence Interval	Source Model	Decision
Direct: Digital Freight Platform Use Intensity to Perceived Financing Constraints	-0.056	0.067	t = -0.83	p = .406	[-0.187, 0.076]	M5	Conditional direct association not statistically distinguishable from zero

Association	B	SE	Test Statistic	p	95% Confidence Interval	Source Model	Decision
Indirect: Use Intensity through Perceived Platform Credit Signal Strength	-0.132	0.030	z = -4.36	p < .001	[-0.191, -0.073]	M2 & M5	H4 supported
Total: Digital Freight Platform Use Intensity to Perceived Financing Constraints	-0.188	0.061	t = -3.08	p = .002	[-0.307, -0.068]	M4	H3 supported

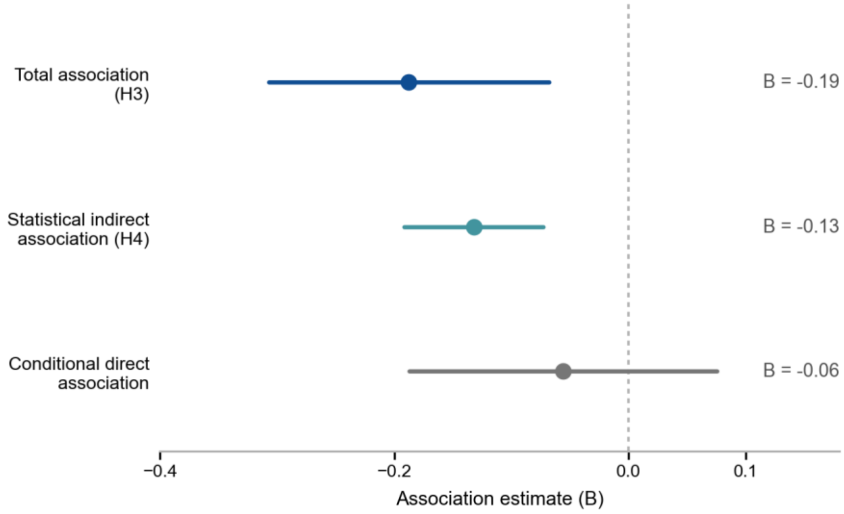

Figure 3: Estimated Direct and Indirect Associations Through Perceived Platform Credit Signals

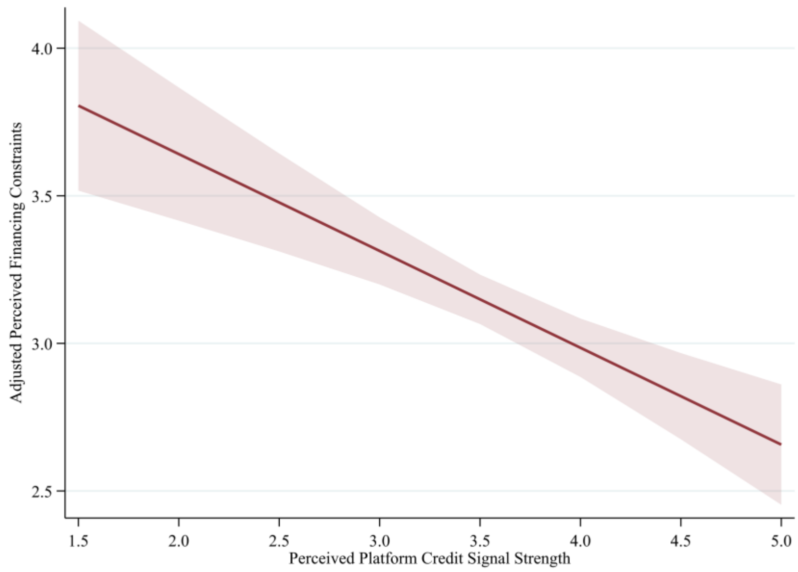

Figure 4: Adjusted Financing Constraints Across Platform Credit Signal Strength

4.5 Robustness Analysis

Table 6 reports Model M6, a sensitivity specification using an alternative perceived financing-constraint score. Perceived platform credit signal strength remained negatively associated with the alternative outcome (B = -0.32, SE = 0.07, t = -4.75, p < .001, 95% CI [-0.46, -0.19]). The conditional association for use intensity was positive in sign and imprecisely estimated (B = 0.03, SE = 0.06, t = 0.50, p = .617, 95% CI [-0.09, 0.15]). Adding the two focal predictors increased R^2 by 0.06 ($F\Delta(2,378) = 13.46$, p < .001). Because the alternative score uses the same respondent and item pool, this result is a sensitivity check rather than an independent-outcome validation.

Table 6: Specification Check Using an Alternative Perceived Financing-Constraint Score

Outcome	Predictor	B	Robust SE	t	p	95% Confidence Interval
Alternative Perceived Financing-Constraint Score	Digital Freight Platform Use Intensity	0.031	0.063	0.50	p = .617	[-0.092, 0.154]
Alternative Perceived Financing-Constraint Score	Perceived Platform Credit Signal Strength	-0.324	0.068	-4.75	p < .001	[-0.458, -0.190]
Altrnative Perceived Financing-Constraint Score	Firm Age (Years)	-0.008	0.011	-0.76	p = .446	[-0.029, 0.013]
Alternative Perceived Financing-Constraint Score	Fleet Size (Vehicles)	-0.010	0.006	-1.66	p = .099	[-0.022, 0.002]
Alternative Perceived Financing-Constraint Score	Annual Revenue (Million CNY)	-0.010	0.008	-1.24	p = .217	[-0.025, 0.006]
Alternative Perceived Financing-Constraint Score	Asset Tangibility	-0.102	0.248	-0.41	p = .683	[-0.590, 0.387]
Alternative Perceived Financing-Constraint Score	Owner-Manager Education (Years)	-0.047	0.016	-2.92	p = .004	[-0.078, -0.015]

Table 7: Model Fit, Incremental Tests, and Collinearity Diagnostics

Model	Outcome	N	R^2	Adj. R^2	Overall F	Incremental test	Max VIF
M1	Credit signal strength	386	0.09	0.08	F(5,380) = 7.36; p < .001	n/a	1.46
M2	Credit signal strength	386	0.25	0.24	F(6,379) = 21.18; p < .001	$\Delta R^2 = 0.16$; $F\Delta(1,379) = 82.41$; p < .001	1.48
M3	Financing constraints	386	0.07	0.06	F(5,380) = 5.75; p < .001	n/a	1.46
M4	Financing constraints	386	0.10	0.08	F(6,379) = 6.73; p < .001	$\Delta R^2 = 0.03$; $F\Delta(1,379) = 10.88$; p = .001	1.48
M5	Financing constraints	386	0.16	0.14	F(7,378) = 9.93; p < .001	$\Delta R^2 = 0.06$; $F\Delta(1,378) = 26.41$; p < .001	1.48
M6	Alternative constraint score	386	0.15	0.13	F(7,378) = 9.29; p < .001	$\Delta R^2 = 0.06$; $F\Delta(2,378) = 13.46$; p < .001	1.48
M7	Financing constraints	386	0.16	0.14	F(8,377) = 8.78; p < .001	$\Delta R^2 = 0.00$; $F\Delta(1,377) = 0.78$; p = .379	1.51

5. Discussion

5.1 Interpretation of the Focal Associations

The results indicate a distinction between operational platform-use intensity and the credit-relevant information associated with that use. H1 received support: carriers reporting greater use intensity also reported stronger perceived platform credit signal strength after the five pre-exposure controls were included. The M2 coefficient was 0.40, and the addition of use intensity increased explained variance by 0.16. The informational interpretation remains bounded: the estimate concerns perceived records and does not show that every platform trace is credible or externally usable.

The strength of the H1 association should be read with care. Platform-use intensity carries a coefficient of 0.40 in the signal-strength model, yet this estimate does not show that every form of use produces credible information. A platform may hold data that are incomplete, difficult to verify, or unavailable outside the platform. The theoretical argument rests on whether routine traces can be understood as information that another organization can assess.

H2 also received support. Perceived platform credit signal strength was negatively associated with perceived financing constraints in M5, with a coefficient of -0.33 and a confidence interval that excluded zero. The result fits the proposition that stronger, more credible, and more usable records can be related to less severe financing difficulty. The cited evidence concerns different populations and data types, so the comparison supports the informational logic without identifying a common causal effect.

The H3 and H4 results add an important qualification. Use intensity had a negative total association with perceived financing constraints in M4 ($B = -0.19$, $p = .002$). Once perceived platform credit signal strength entered M5, the conditional direct association became smaller and was not statistically distinguishable from zero ($B = -0.06$, $p = .406$). The calculated indirect association was negative ($B = -0.13$, $p < .001$). In the full model, the total association is concentrated in the path involving perceived platform credit signal strength, subject to the cross-sectional design and common-source measurement.

The alternative outcome analysis provides qualified corroboration. In Model M6, the negative association between perceived platform credit signal strength and the alternative financing-constraint score remained robust and statistically significant ($B = -0.32$, $p < .001$), reinforcing the core mediating mechanism. In contrast, the conditional direct association for platform-use intensity was slightly positive and statistically indistinguishable from zero ($B = 0.03$, $p = .617$), echoing the full-model finding in M5 that operational use alone does not directly alleviate financing constraints once signal perception is accounted for. Adding platform tenure in M8 similarly preserved the negative coefficient for signal strength with negligible change in explained variance.

The non-significant direct association warrants attention. A direct term near zero in M5 may reflect a concentration of the modeled association in the signal pathway. It may also arise from limited measurement precision, correlated platform constructs, selection into platform use, or an omitted factor shared by use intensity and financing perceptions. The cross-sectional evidence cannot separate these explanations, and the absence of a non-user comparison group limits the interpretation of H3 to within-user variation.

5.2 Theoretical Implications

The first theoretical implication concerns the distinction between digital presence and credit-relevant visibility. Much research on SME digitalization examines adoption, capability, agility, or organizational change (Ahmed et al. , 2022; Hanelt et al. , 2021; Omrani et al. , 2024; Papadopoulos et al. , 2020). Those constructs are important, yet they do not directly identify how external financiers interpret records generated by a digital system. The present framework inserts a firm-level signaling construct between platform participation and perceived financing constraints. It treats the information content of platform activity as a separate analytical object. This distinction can help future research avoid assuming that digital adoption and financial credibility always move together.

Second, the results extend signaling theory into a platform-mediated operational setting. The original theory emphasizes the role of credible observables under information asymmetry (Spence, 1973). In a digital freight context, observables can include verified transactions, settlement records, service evaluations, identity information, and compliance records. The signal becomes meaningful only through an audience that can evaluate it. For a lender, a platform record could be useful, ambiguous, or irrelevant depending on data provenance, verification, legal permission, and integration with other underwriting information. This audience condition is a critical boundary. It provides a reason to study platform data governance alongside platform participation.

Third, the study connects supply-chain information transparency with the financing-constraint literature. Zheng et al. (2022) and Guo et al. (2022) examine technology-enabled enterprise credit-information sharing and information transparency in supply-chain finance. Lou et al. (2024) and He and Liu (2025) link supply-chain finance with funding constraints among Chinese SMEs. The present model brings these streams to the carrier level by focusing on information generated in everyday freight operations. It suggests that studies of digital finance should include operational intermediaries and their data records alongside banks, fintech lenders, and listed firms.

Fourth, the findings define a boundary for claims about digital freight platforms. A platform's capacity to coordinate freight does not automatically imply a role in finance. The association with perceived financing constraints appears in the model through perceived platform credit signal strength, which depends on the quality and usability of records. This boundary is relevant to research on B2B platform adoption and the organizational trade-offs associated with digital platforms (Marzi et al. , 2023). It is also relevant to digital logistics research that documents shifting competitive conditions for incumbent firms (Mikl et al. , 2021). Platform adoption may coincide with greater operational exposure to data, while the financial meaning of that data remains contingent on governance and external interpretation.

5.3 Practical Implications

For carrier owner-managers, the results suggest treating platform records as part of the firm's finance-relevant information base. This calls for linking operating activity to a stable firm identity, reconciling settlement records, retaining documentation of completed work, and checking whether service or compliance records can be understood outside the platform interface. A carrier should understand which records are shared, who can access them, and whether the information is accurate before presenting it in a financing discussion.

For platform operators, the key issue is the design of trustworthy information services. A platform can help carriers by providing records that are consistent, explainable, permissioned, and capable of independent verification. A score with unclear inputs or a record that cannot be reconciled with transactions is unlikely to provide a durable credit signal. Operators should therefore consider data lineage, consent mechanisms, correction processes, access logs, and clear documentation for information shared with financial institutions. This orientation is consistent with the governance boundary identified in e-finance research, where privacy, cybersecurity, and compliance are material considerations (Neupane, 2025). It also fits evidence that trust and digital awareness are relevant in financial-inclusion contexts (Nepal, 2025; Thanh et al. , 2025).

For lenders and other financiers, platform-generated records may serve as a complementary information source alongside financial statements, collateral, relationship information, and sector knowledge. Berger and Udell (2006) describe the importance of matching financing technologies to available information, while Petersen and Rajan (1994) show the value of relationship-generated information in small-business lending. The present results suggest a more focused question for lending practice: can a platform record be traced to a carrier, a completed transaction, and a verifiable process? A lender that uses platform information should evaluate its coverage, stability, incentives for manipulation, and legal basis for use. A carrier's high platform-use-intensity score alone provides little assurance without that assessment.

For policymakers and industry associations, the evidence points toward common standards for permissioned, verifiable, and portable operational records. Such standards would provide a shared basis for interpreting freight-platform information in financial institutions. Their design should protect commercial confidentiality and prevent weakly governed data-sharing arrangements. Any policy response would require evidence beyond the present cross-sectional study, especially evidence on lender behavior, credit terms, and the distributional consequences of data-based assessment across smaller carriers.

6. Conclusion

6.1 Main Conclusion

This study examined the association between digital freight platform-use intensity and perceived financing constraints among small and micro road-freight carriers, with perceived platform credit signal strength as the modeled statistical pathway. In the analyzed sample of 386 firms, use intensity was positively associated with perceived platform credit signal strength. Perceived platform credit signal strength was negatively associated with perceived financing constraints. Use intensity also had a negative total association with perceived financing constraints, while its conditional direct association was not statistically distinguishable from zero after perceived signal strength entered the model. The negative indirect association was statistically distinguishable from zero. These are conditional cross-sectional associations among platform-using carriers.

The central conclusion is narrow. Within this cross-sectional sample of platform-using carriers, the association between use intensity and perceived financing constraints is more informative when attention is directed to the credit relevance of platform-generated records. The study does not treat operating data as inherently valuable for finance. Its value depends on whether information is visible, credible, usable, and governed in a way that a financing counterparty can assess.

6.2 Limitations and Future Research

Several limits define the next research steps. First, the cross-sectional design cannot establish temporal ordering among use intensity, signal strength, and financing constraints, and the frame contains no non-user comparison group. A longitudinal design could observe how changes in platform use and record quality relate to subsequent financing applications, credit terms, and lender decisions. Second, the model relies on firm-level construct scores and does not include platform transaction logs, formal lender assessments, or observed contract terms. Future studies should combine carrier surveys with permissioned operational records and financing outcomes where feasible.

Third, the study concerns a defined Chinese small-carrier setting. Platform architecture, data governance, collateral practices, local financial development, and sector regulation may vary across regions and platform types. Comparative research should test whether the same measurement structure holds across different freight platforms, carrier sizes, and finance channels. Fourth, the proposed credit-signal construct requires further scale development and external validation. Subsequent work should examine content validity, predictive validity, data-access conditions, platform-level clustering, and potential bias in platform-generated evaluations.

References

Ahmed, A., Bhatti, S.H., Gölgeci, I. & Arslan, A. (2022), Digital Platform Capability and Organizational Agility of Emerging Market Manufacturing SMEs: the Mediating Role of Intellectual

Capital and the Moderating Role of Environmental Dynamism, *Technological Forecasting and Social Change*, Vol. 177, 121513.

Akerlof, G.A. (1970), The Market for "Lemons": Quality Uncertainty and the Market Mechanism, *The Quarterly Journal of Economics*, Vol. 84, No.3, 488-500.

AL Jedi, M., Alzghoul, A., Ali, A., Taroum, A.S.A. & Alrifai, K. (2026), Digital Supply-Chain Maturity, Resilience, and Firm Performance: Evidence from Manufacturing Firms in an Emerging Economy, *Journal of Logistics, Informatics and Service Science*, Vol. 13, No.8, 120-136.

Berg, T., Burg, V., Gombović, A. & Puri, M. (2020), On the Rise of FinTechs: Credit Scoring Using Digital Footprints, *The Review of Financial Studies*, Vol. 33, No.7, 2845-2897.

Berger, A.N. & Udell, G.F. (2006), A More Complete Conceptual Framework for SME Finance, *Journal of Banking & Finance*, Vol. 30, No.11, 2945-2966.

Bertoni, F., Bonini, S., Capizzi, V., Colombo, M.G. & Manigart, S. (2022), Digitization in the Market for Entrepreneurial Finance: Innovative Business Models and New Financing Channels, *Entrepreneurship Theory and Practice*, Vol. 46, No.5, 1120-1135.

Bu, Y., Du, X., Wang, Y., Liu, S., Tang, M. & Li, H. (2024), Digital Inclusive Finance: a Lever for SME Financing?, *International Review of Financial Analysis*, Vol. 93, 103115.

Chen, T., Huang, Y., Lin, C. & Sheng, Z. (2022), Finance and Firm Volatility: Evidence from Small Business Lending in China, *Management Science*, Vol. 68, No.3, 2226-2249.

Cornelli, G., Frost, J., Gambacorta, L. & Jagtiani, J. (2024), The Impact of Fintech Lending on Credit Access for U.S. Small Businesses, *Journal of Financial Stability*, Vol. 73, 101290.

Cumming, D. & Hornuf, L. (2022), Marketplace Lending of Small- and Medium-sized Enterprises, *Strategic Entrepreneurship Journal*, Vol. 16, No.1, 32-66.

Djeundje, V.B., Crook, J., Calabrese, R. & Hamid, M. (2021), Enhancing Credit Scoring with Alternative Data, *Expert Systems with Applications*, Vol. 163, 113766.

Dumitrescu, E., Hué, S., Hurlin, C. & Tokpavi, S. (2022), Machine Learning for Credit Scoring: Improving Logistic Regression with Non-Linear Decision-Tree Effects, *European Journal of Operational Research*, Vol. 297, No.3, 1178-1192.

Galema, R. (2020), Credit Rationing in P2P Lending to SMEs: Do Lender-Borrower Relationships Matter?, *Journal of Corporate Finance*, Vol. 65, 101742.

Gambacorta, L., Huang, Y., Qiu, H. & Wang, J. (2024), How Do Machine Learning and Non-Traditional Data Affect Credit Scoring? New Evidence from a Chinese Fintech Firm, *Journal of Financial Stability*, Vol. 73, 101284.

Guo, L., Chen, J., Li, S., Li, Y. & Lu, J. (2022), A Blockchain and IoT-based Lightweight Framework for Enabling Information Transparency in Supply Chain Finance, *Digital Communications and Networks*, Vol. 8, No.4, 576-587.

Hanelt, A., Bohnsack, R., Marz, D. & Antunes Marante, C.U. (2021), A Systematic Review of the Literature on Digital Transformation: Insights and Implications for Strategy and Organizational Change, *Journal of Management Studies*, Vol. 58, No.5, 1159-1197.

Hasan, I., He, Q. & Lu, H. (2022), Social Capital, Trusting, and Trustworthiness: Evidence from Peer-to-Peer Lending, *Journal of Financial and Quantitative Analysis*, Vol. 57, No.4, 1409-1453.

He, S. & Liu, Z. (2025), Impact of Digital Supply Chain Finance to Alleviate SMEs Financing Constraints: Evidence from SRDI Enterprises in China, *Science Progress*, Vol. 108, No.3, 00368504251375169.

Heinbach, C., Beinke, J., Kammler, F. & Thomas, O. (2022), Data-Driven Forwarding: a Typology of Digital Platforms for Road Freight Transport Management, *Electronic Markets*, Vol. 32, No.2, 807-828.

Hu, D., Fang, X. & DiGiovanni, Y.M. (2023), Technological Progress, Financial Constrains, and Digital Financial Inclusion, *Small Business Economics*, Vol. 61, No.4, 1693-1721.

Izunobi, D.A. & Burinskiene, A. (2025), Digital Maturity and Change Management Effectiveness in Global Supply Chain Operations: an Empirical Investigation of International Businesses, *Journal of Management Changes in the Digital Era*, Vol. 2, No.1, 249-271.

Jaffee, D.M. & Russell, T. (1976), Imperfect Information, Uncertainty, and Credit Rationing, *The Quarterly Journal of Economics*, Vol. 90, No.4, 651-666.

Kawai, K., Onishi, K. & Uetake, K. (2022), Signaling in Online Credit Markets, *Journal of Political Economy*, Vol. 130, No.6, 1585-1629.

Li, C., Wang, Y., Zhou, Z., Wang, Z. & Mardani, A. (2023), Digital Finance and Enterprise Financing Constraints: Structural Characteristics and Mechanism Identification, *Journal of Business Research*, Vol. 165, 114074.

Lou, Z., Xie, Q., Shen, J.H. & Lee, C.C. (2024), Does Supply Chain Finance (SCF) Alleviate Funding Constraints of SMEs? Evidence from China, *Research in International Business and Finance*, Vol. 67, 102157.

Lu, Z., Wu, J., Li, H. & Nguyen, D.K. (2022), Local Bank, Digital Financial Inclusion and SME Financing Constraints: Empirical Evidence from China, *Emerging Markets Finance and Trade*, Vol. 58, No.6, 1712-1725.

Marzi, G., Marrucci, A., Vianelli, D. & Ciappei, C. (2023), B2B Digital Platform Adoption by SMEs and Large Firms: Pathways and Pitfalls, *Industrial Marketing Management*, Vol. 114, 80-93.

Mikl, J., Herold, D.M., Ćwiklicki, M. & Kummer, S. (2021), The Impact of Digital Logistics Start-Ups on Incumbent Firms: a Business Model Perspective, *The International Journal of Logistics Management*, Vol. 32, No.4, 1461-1480.

Nepal, P. (2025), Women’s Role in Advancing Digital Financial Inclusion: the Impact of Digital Awareness, Technology Trust, Curiosity and Motivation and Access to Digital Banking, *Journal of Management Changes in the Digital Era*, Vol. 2, No.1, 25-47.

Neupane, K. (2025), Regulatory Challenges in E-Finance and Their Implications for Service Innovation and Sustainable Financial Development: a Bibliometric Review, *Journal of Service, Innovation and Sustainable Development*, Vol. 6, No.2, 96-108.

Omrani, N., Rejeb, N., Maalaoui, A., Dabić, M. & Kraus, S. (2024), Drivers of Digital Transformation in SMEs, *IEEE Transactions on Engineering Management*, Vol. 71, 5030-5043.

Papadopoulos, T., Baltas, K.N. & Balta, M.E. (2020), The Use of Digital Technologies by Small and Medium Enterprises During COVID-19: Implications for Theory and Practice, *International Journal of Information Management*, Vol. 55, 102192.

Petersen, M.A. & Rajan, R.G. (1994), The Benefits of Lending Relationships: Evidence from Small Business Data, *The Journal of Finance*, Vol. 49, No.1, 3-37.

Sharma, S.K., Ilavarasan, P.V. & Karanasios, S. (2024), Small Businesses and FinTech: a Systematic Review and Future Directions, *Electronic Commerce Research*, Vol. 24, No.1, 535-575.

Spence, M. (1973), Job Market Signaling, *The Quarterly Journal of Economics*, Vol. 87, No.3, 355-374.

Sun, R., Shang, Q., Zu, A. & Gan, S. (2026), How Does Digital Finance Affect Financing Constraints of SMEs? Evidence from China, *Applied Economics*, Vol. 58, No.2, 363-381.

Thanh, L.D.N., Hai, P.T., Cong, H.T. & Quan, D.D. (2025), Financial Inclusion Through Digital Service Innovation: Mobile Banking Solutions for Rural Communities in Vietnam, *Journal of Service, Innovation and Sustainable Development*, Vol. 6, No.2, 57-71.

Xiao, L., Ke, T., Yu, F. & Guo, P. (2023), Impact of Government Support on Users' Participation in Emerging Green Crowdsourcing Logistics Model: Evidence from Digital Freight Platform in China, *Journal of Enterprise Information Management*, Vol. 36, No.2, 583-604.

Zhang, X., Li, J., Xiang, D. & Worthington, A.C. (2023), Digitalization, Financial Inclusion, and Small and Medium-Sized Enterprise Financing: Evidence from China, *Economic Modelling*, Vol. 126, 106410.

Zheng, K., Zheng, L.J., Gauthier, J., Zhou, L., Xu, Y., Behl, A. & Zhang, J.Z. (2022), Blockchain Technology for Enterprise Credit Information Sharing in Supply Chain Finance, *Journal of Innovation & Knowledge*, Vol. 7, No.4, 100256.

Zhou, Z. & Wan, X. (2022), Does the Sharing Economy Technology Disrupt Incumbents? Exploring the Influences of Mobile Digital Freight Matching Platforms on Road Freight Logistics Firms, *Production and Operations Management*, Vol. 31, No.1, 117-137.