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Adopting Live-Streaming Commerce: A Stage-Contingent Perspective from the Technology-Organization-Environment Framework in Chinese Firms

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Abstract

Live-streaming commerce (LSC) has spread quickly through Chinese retail, but evidence on what accompanies its adoption by firms, particularly small and medium-sized enterprises (SMEs), remains scattered across studies that rarely speak to one another. Which firm-level capabilities, which resource positions, and which forms of institutional pressure travel together with adoption? And do these relationships shift as firms age? We

combine the Technology-Organization-Environment (TOE) framework with organizational lifecycle theory and estimate an LSC adoption model in which the associations are allowed to vary by stage. The data come from a cross-sectional survey of 718 Chinese firms conducted in 2023; 580 respondents (80.8%) self-identified as medium-sized or small firms, and self-reported size was included as a control. We apply binary logistic regression. In the pooled sample, adoption is positively associated with external capital receipt (OR = 1.492), perceived industry prevalence (OR = 1.269), and the presence of a dedicated in-house team (OR = 2.305). The stage-differentiated estimates are less uniform. Among firms operating for 3 to 10 years, all three factors operate jointly and model fit peaks (Nagelkerke $R^2 = 0.110$). Among firms operating for under 3 years, only the team-based association is substantial. Among firms operating for over 10 years, perceived industry prevalence and a weakened team-based association are linked to adoption; external capital receipt is not. A probit estimator and a lower-registered-capital subsample (n = 465) give directionally consistent results. Two contributions follow. The dedicated in-house team emerges as the strongest organizational correlate of adoption, and institutional prevalence and resource slack relate to adoption in stage-contingent rather than uniform ways. For managers, the practical message is that digital adoption strategies should be calibrated to lifecycle position: capability building early on, joint attention to financing, peer norms, and team capacity during growth, and legitimacy-oriented positioning in maturity.

Keywords: Live-streaming commerce; Firm adoption; Technology-Organization-Environment (TOE) framework; Organizational lifecycle; Dedicated IT team; Institutional pressure

Introduction

Live-streaming commerce (LSC) has changed how retail intermediation works in China. This mode collapses product demonstration, real-time interaction, and transaction completion into a single touchpoint [1]. Taobao Live, Douyin, and Kuaishou began as entertainment channels. They now operate as integrated merchant infrastructure that combines payment, inventory management, and customer-relationship tools in one interface [2, 3]. Manufacturers and multichannel retailers already treat live streaming as a quality-differentiated distribution channel alongside conventional e-commerce [4, 5]. For small and medium-sized enterprises (SMEs), the visible costs of entry look trivial. A smartphone, a host, and a platform account are enough to establish a presence [7]. The aggregate figures nevertheless mask considerable heterogeneity. Industry reports suggest that although most surveyed SMEs have tried live-streaming sales, a substantial share exit the channel within months, citing operating costs, talent scarcity, and inefficient traffic acquisition [8]. Entry is cheap; staying is not. What separates firms that merely experiment with LSC from those that commit to it remains poorly understood, and the question matters for both theory and practice.

Why do SMEs take this step at all? Answering that question requires placing the decision in its organizational and institutional context. Research on SME digital transformation shows that owner-manager agency and resource deficits change how standard technology frameworks apply to smaller firms [8, 9]. Existing LSC research approaches the phenomenon from three directions, but none offers a direct answer. One line of work concentrates on consumer behavior, including impulse buying, parasocial interaction, and perceived enjoyment [10, 11, 12, 13, 14, 15, 16, 17, 18]. It explains demand-side pull and says little about the supply-side calculus of SME entry. A second line examines platform

affordances, algorithmic visibility, and influencer credibility [19, 20, 21]. These insights typically presuppose an active streaming channel, so they end up blending adoption drivers with post-adoption optimization. A third stream applies the technology-organization-environment (TOE) framework to digital innovation diffusion among SMEs [22, 23, 24, 25, 26]. TOE applications in e-commerce settings often include variables such as customer engagement intensity, sales conversion rates, or perceived platform usefulness, all of which can only be measured after a firm has begun streaming [26, 27]. The temporal ordering is inverted. A proposed antecedent becomes entangled with the outcome, because performance indicators cannot precede the existence of the channel itself.

Conflating pre-adoption drivers with post-adoption proxies has left a systematic blind spot. The literature knows a fair amount about why SMEs continue in LSC or perform well in it, and much less about why they enter at all. The gap is sharpest for resource-constrained SMEs, whose adoption thresholds differ fundamentally from those of large enterprises. Multinational retailers can treat platform-entry costs as portfolio experiments. SMEs face binding liquidity constraints and depend heavily on external validation [28, 29]. The mechanisms that lower adoption barriers are therefore more likely to involve organizational resource access, environmental legitimacy pressures, and internal capability accumulation than platform-level feature perceptions. No study has yet isolated these mechanisms in a single antecedent-only specification.

We address this gap using the TOE framework and organizational lifecycle theory, deriving and testing three hypotheses about LSC adoption among predominantly SME Chinese firms while controlling for self-reported firm size. H1 rests on resource-based logic and SME bricolage research [28, 30, 31]: external capital receipt is positively

associated with LSC adoption, because outside financing relaxes the liquidity constraints that otherwise impede platform entry. H2 turns to institutional theory as operationalized in interorganizational adoption research [32]. It posits that perceived industry prevalence, by which we mean managers' assessment that live-streaming has become standard practice among competitors, is positively associated with adoption under uncertainty. H3 draws on the dynamic capabilities view and recent evidence on SME e-commerce competitiveness [33, 34, 35]. It proposes that the presence of a dedicated live-streaming team is positively associated with adoption, plausibly because such a team is an observable structural commitment that proxies for the organizational readiness needed to initiate and sustain streaming operations.

The dependent variable records self-reported channel existence, and the model deliberately excludes post-adoption performance proxies such as conversion rates or engagement intensity, which would entangle predictors with the outcome. EXTERNAL_CAP measures reported external capital receipt. MIMETIC captures a perceptual field condition. Both are operationalized independently of post-adoption performance metrics. ITCAP records contemporaneous organizational structure. A cross-sectional design does not permit strict causal identification, but restricting the specification to predictors that are structurally independent of post-adoption performance reduces temporal ambiguity and clarifies the interpretive boundaries of the model.

We test the hypotheses with cross-sectional survey data collected in 2023 from 718 Chinese firms, predominantly SMEs, using binary logistic regression. The sample covers three age-based lifecycle stages, namely under 3 years (n = 241), 3 to 10 years (n = 303), and over 10 years (n = 174), which allows an exploratory disaggregation of effect heterogeneity [36, 37, 38, 39]. The pooled-sample results are consistent with all three

hypotheses. The stage-specific results reveal heterogeneous patterns instead. The association between external capital and adoption is concentrated among firms operating for 3 to 10 years; perceived industry prevalence strengthens progressively across stages; and the team-based association is strongest among firms operating for 3 to 10 years, substantial among newer firms, and weakest among firms operating for over 10 years.

The contributions are threefold. First, this study provides a stage-contingent account of TOE adoption drivers. Financial slack, perceived institutional prevalence, and dedicated IT capability differ in statistical salience across the organizational lifecycle, which suggests that SME platform entry is better understood as a developmental-phase-dependent response than as a uniform organizational event. This moves the literature beyond static "has/has-not" resource classifications and shows how the relative importance of organizational and environmental readiness factors varies with firm age and network embeddedness [34, 36]. Second, the findings clarify the boundary conditions of TOE for initial adoption. With post-adoption performance proxies excluded, the specification isolates pre-entry correlates, namely resource access, perceived peer practice, and team-based structural readiness, and shifts explanatory emphasis from platform-level feature perceptions to firm-level readiness conditions [35, 40]. Third, the stage-specific patterns yield differentiated managerial implications. Start-ups appear to benefit most from building internal streaming capacity. Growth-stage firms are positioned to integrate capital acquisition, environmental benchmarking, and team scaling. Mature SMEs may treat adoption as a legitimacy-maintenance response in which market observation and continued capability investment remain relevant.

Theoretical Background and Hypothesis Development

Theoretical Background and Literature Review

The technology-organization-environment (TOE) framework explains organizational technology adoption through three interdependent lenses. The technological context covers both internal systems and external innovations. The organizational context covers firm size, resources, and managerial structure. The environmental context captures industry structure along with external institutional or competitive pressures [22, 23]. Developed in innovation studies and later formalized in information systems research, TOE remains widely used for a specific reason: it shifts attention away from the individual-level cognition that dominates user-acceptance models and treats adoption instead as a strategic organizational decision [32, 41].

TOE applications to digital commerce have moved through three phases. Early work concentrated on large-firm adoption of foundational internet technologies, foregrounding trading-partner readiness and competitive pressure in retail [27]. A second phase turned the lens to SMEs and emerging markets, acknowledging that resource constraints and owner-manager agency change how heavily each of the three contexts weighs [24, 25, 42]. Studies in this phase found that organizational readiness and financial slack frequently eclipse environmental pressure for small firms; when liquidity is tight, internal resource access dominates strategic choice [26, 29]. The third and current phase confronts platform-era innovations such as sharing-economy applications, AI-driven analytics, and live-streaming commerce. Here the boundary between technology and organization blurs, because platforms operate simultaneously as external infrastructure and as internalized routines [7, 20, 21, 40].

This progression has not eliminated a persistent methodological slippage. Adoption

drivers in platform-based commerce research are still conflated with post-adoption performance correlates. Consumer-behavior studies of LSC, for instance, routinely operationalize adoption intention through perceived enjoyment, parasocial interaction, or impulse-buying tendency [10, 11, 12, 13, 14, 15, 16, 17, 18]. These constructs are demand-side and user-centric. Inserting them into organizational adoption models as environmental or technological predictors violates temporal precedence. On the supply side, research on SME digitalization frequently collapses antecedents and consequences within a single cross-sectional design, treating sales conversion, customer retention, or platform engagement as predictors of adoption [8, 27]. The outcome then becomes entangled with its own supposed causes, and the coefficients that emerge are hard to read as genuine adoption drivers [43].

A second problem runs deeper than measurement. Most TOE studies treat SMEs as a single homogeneous category, pooling start-ups, growth-stage firms, and mature incumbents together [24, 25]. Organizational lifecycle theory suggests otherwise. The salience of resource constraints, legitimacy needs, and structural inertia shifts in predictable ways as firms age [36, 44]. Start-ups confront existential resource scarcity and weak institutional ties. Growth-stage firms live under scaling pressure and heightened legitimacy deficits. Mature firms possess accumulated routines that may accelerate or block the absorption of new technologies [45, 46]. When lifecycle heterogeneity is ignored, pooled coefficients become misleading, and theoretically meaningful variation in effect sizes disappears beneath the aggregate [38, 47].

Against this backdrop, the present study opts for a conservative TOE specification. It foregrounds the organizational and environmental dimensions and uses dedicated team human capital as a bridging indicator of technological readiness rather than attempting to

map the full technology context. Predictors are deliberately restricted to variables that exclude post-adoption performance proxies: external capital receipt, perceived industry prevalence, and the contemporaneous presence of a dedicated streaming team. The goal is to recover correlates of LSC entry while keeping the causal interpretation as clean as the cross-sectional design allows.

Hypothesis Development

External Capital Receipt and LSC Adoption (H1)

Resource-based theory separates resources that permit strategic experimentation from deficiencies that create inertia, especially where investments must be made in lumpy, indivisible increments [30]. This tension is particularly sharp for SMEs. One line of reasoning holds that external capital is associated with technology adoption because it relaxes liquidity constraints and covers discrete, upfront outlays [31, 48]. Another line, rooted in entrepreneurial bricolage, holds that severe resource constraints can force the creative recombination of whatever is already at hand, so outside financing is not always necessary and not always helpful [28]. Which logic prevails depends on the nature of the investment.

Live-streaming commerce demands expenditures that are discrete and non-smooth: host recruitment, studio equipment, scriptwriting personnel, and platform deposit fees [2, 4]. Such costs are difficult to fund out of operating cash flows, and they sit awkwardly with the short payment cycles that typically characterize SME supplier relationships [8]. Under these conditions the slack-resources argument carries more weight. External capital, whether venture financing, bank credit, or government grants, supplies the buffer needed to absorb losses during the audience-building phase [29]. Recent TOE evidence reinforces

the point: resource sufficiency covaries positively with SME entry into digital platforms [26, 49]. Drawing on the organizational dimension of TOE, we hypothesize:

H1: External capital receipt is positively associated with LSC adoption.

Perceived Industry Prevalence and LSC Adoption (H2)

When technological consequences are unclear and performance feedback is noisy, organizations frequently look to visible peers before committing to a strategic choice [50]. Institutional theory formalizes this as mimetic pressure, the tendency to imitate practices that appear dominant among industry counterparts in order to secure legitimacy and reduce perceived risk [51]. Interorganizational information-systems research has shown that such pressures predict adoption whenever technological outcomes are poorly understood and goal ambiguity is high [32]. Subsequent TOE studies confirm that institutional forces covary with SME platform entry across developing and emerging markets [25, 26].

The opposing view holds that under competitive pressure, firms may deliberately avoid crowded practices, escaping commodity rivalry and preserving differentiation [50]. If LSC turns into a generic industry standard, late adopters might do better by conserving resources and free-riding on the infrastructural maturity created by early movers [52]. This differentiation logic is weaker for SMEs in platform-intensive sectors, for two reasons. First, SMEs lack the brand equity and customer lock-in that would allow them to defy industry trends without suffering legitimacy penalties [28]. Second, platform algorithms reward activity density. Non-adopters risk algorithmic invisibility relative to streaming peers, which effectively converts observed peer adoption into a legitimacy threshold for market access [21, 40]. Managers' perception that live-streaming has become prevalent among industry counterparts, hereafter perceived industry prevalence

(MIMETIC), is therefore expected to covary positively with adoption status. Hence:

H2: Perceived industry prevalence is positively associated with LSC adoption.

Dedicated IT Team Presence and LSC Adoption (H3)

Dynamic capabilities rest on the firm's capacity to mobilize, coordinate, and reconfigure internal resources in response to technological change [33, 34]. The information-systems literature has conceptualized IT capability as a hierarchical construct that runs from generic infrastructure to specialized human capital integrating technology with business processes [53, 54]. A central debate concerns whether such capabilities must be generic, in the sense of transferable across technologies, or dedicated, in the sense of tailored to a specific platform ecosystem.

We side with the dedicated-capability view for LSC. Converting existing marketing content to a live format is not the same as operating a live-streaming channel. The latter runs on a real-time production logic whose demands differ categorically from static product photography or text-based customer support [2, 10]. A dedicated in-house team, covering host recruitment, scriptwriting, and real-time operations, represents an organizational commitment that is difficult to outsource or replicate quickly, and one plausibly linked to the absorptive capacity required to recognize and assimilate streaming-specific routines [35, 55]. Evidence from SME e-commerce settings indicates that dedicated IT human capital covaries with competitiveness precisely because it constitutes a firm-specific asset [7, 35]. Related work further shows that digital platform capability is associated with SME performance in platform ecosystems, and that internal capability distinguishes active participants from passive observers [56]. Unlike platform-level features, which are equally available to all merchants, a dedicated team is an internal

resource that cannot be imitated in the short run. We therefore hypothesize:

H3: The presence of a dedicated live-streaming team is positively associated with LSC adoption.

The survey captures team presence at the time of data collection and does not record when the team was established relative to initial platform adoption. H3 therefore identifies a contemporaneous organizational attribute rather than a temporally confirmed antecedent. The estimated association is best read as evidence of structural complementarity between dedicated human capital and adoption status, not as proof that team formation strictly precedes or causes adoption.

Exploratory Stage-Varying Analysis

Organizational lifecycle theory suggests that the relative potency of the three factors above may shift as firms age [36, 38]. Start-ups face existential resource scarcity. External capital may be unavailable or too dilutive, institutional ties are too weak for prevalence perceptions to operate effectively, and their networks typically center on the founding team with limited structural embeddedness [37, 57, 58, 59]. Growth-stage firms encounter scaling bottlenecks and heightened peer comparison, so resource acquisition, legitimacy conformance, and capability accumulation may all intensify in this phase [39, 60]. Mature firms possess structural inertia, established customer channels, and often generic rather than dedicated IT assets; capability-based advantages may therefore attenuate, while perceived industry prevalence continues to operate as a legitimacy-maintenance mechanism [34, 46]. The tension between exploring new channels and exploiting existing routines is especially salient in mature SMEs [61].

Because these stage-related expectations concern subgroup heterogeneity in an exploratory rather than confirmatory mode [62], we do not formalize them as moderated

hypotheses. We examine them instead through age-based split-sample estimation in the results section.

Sample and Methodology

Sample and Data Collection

We draw on a cross-sectional survey of Chinese firms fielded in 2023. The instrument collected firm age, industry, region, annual turnover category, registered-capital category, and self-reported firm-size category, but it did not record employee counts. We therefore do not impose a post hoc employee-number SME cutoff. The sample is predominantly composed of firms that self-identified as medium-sized or small (580 of 718; 80.8%); 138 self-identified large firms were retained in the pooled models, and self-reported size was included as a control. Questionnaires reached respondents through a mixed-mode protocol: targeted online distribution via industry associations in major Chinese cities, supplemented by on-site interviews with owners or senior managers. The dual approach reduced coverage bias and helped ensure that informants possessed enough strategic knowledge to report accurately on firm-level adoption decisions [43].

Ethics statement and informed consent. This study was a non-interventional, cross-sectional business survey of firm owners and senior managers concerning firm business practices. It collected no medical, health-related, or otherwise sensitive personal data and involved no minors or vulnerable populations. Data were collected between 29 January and 9 February 2023. A retrospective ethics review application was submitted to the Research Office of North Minzu University on 13 September 2026. The application was reviewed and approved by the Science and Technology Ethics Review Committee of North Minzu University on 15 September 2026 (approval reference: North Minzu

University Ethics Approval No. 2026-37). The study was designed and conducted in accordance with the general ethical principles of the Declaration of Helsinki and the research ethics requirements of North Minzu University. Informed consent was obtained from all participants. The first page of the questionnaire identified the researchers and their institutional affiliation, stated the academic purpose, and explained that participation was voluntary, responses would be kept confidential and used solely for anonymized academic research, and participants could stop before submission without consequence. Online respondents consented by voluntarily completing and submitting the questionnaire after reading this statement; on-site respondents provided verbal informed consent after receiving the same information. Written signatures were not collected because the records were anonymous and contained no direct identifiers; this consent procedure was included in the approved protocol. The questionnaire, including the consent page, and the institutional approval document are provided as Supplementary Files S3 and S7, respectively.

After data cleaning, the analysis file contained 718 complete firm-level responses. Self-reported size categories were large (n = 138; 19.2%), medium (n = 276; 38.4%), and small (n = 304; 42.3%). Firm age was distributed as under 3 years (n = 241), 3 to 10 years (n = 303), and over 10 years (n = 174). Table 1 reports the sample characteristics. Geographically, 174 firms (24.2%) were located in North China, 147 (20.5%) in East China, and 130 (18.1%) in South China. By sector, 255 firms (35.5%) operated in the primary sector, 271 (37.7%) in the secondary sector, and 192 (26.7%) in the tertiary sector. A further 465 firms (64.8%) reported registered capital below RMB 5 million. Coverage spans multiple geographic, industrial, and size strata; these figures do not establish statistical representativeness of the population.

Place Table 1 about here

For the exploratory subgroup analysis, we partitioned the sample using the questionnaire's firm-age categories: under 3 years (n = 241), 3 to 10 years (n = 303), and over 10 years (n = 174) [37, 38, 47]. This division lets us test whether the TOE associations observed in the pooled sample shift across organizational regimes.

Measurements

Measures were drawn from established information-systems adoption instruments [32, 41, 63] and adapted to the live-streaming commerce context within the TOE framework [22, 23]. Perceptual items used 5-point Likert scales anchored at 1 = Strongly disagree and 5 = Strongly agree; binary indicators were coded 1 = Yes and 0 = No. Table 2 details the construct definitions, item stems, and coding procedures.

Place Table 2 about here

Dependent Variable: LSC Adoption

LSC adoption was coded as a binary variable taking the value 1 if the firm reported operating a live-streaming sales channel on at least one major platform (e.g., Taobao Live, Douyin, Kuaishou) at the time of the survey, and 0 otherwise. Using a binary channel-existence measure avoids the ambiguity of intention-based proxies and keeps the study focused on whether the channel exists rather than on usage intensity or performance [27].

Independent Variables

External capital receipt (EXTERNAL_CAP) was measured with the questionnaire item asking whether any other capital had been invested in the firm. The stored instrument did

not specify or record a 24-month window, so the measure is interpreted as reported external capital receipt rather than as a precisely bounded financing event.

Perceived industry prevalence (MIMETIC) was measured with a single questionnaire item asking whether live-streaming selling was a popular marketing model. Responses were reverse-coded so that higher scores indicate stronger perceived prevalence [32].

Dedicated team presence (ITCAP) was operationalized as a binary indicator of whether the firm maintained a dedicated in-house team for live-streaming operations at the time of the survey, covering host recruitment, content scriptwriting, and real-time technical support. As noted in the theoretical framework, the measure captures a contemporaneous organizational attribute rather than a temporally confirmed antecedent.

Control Variables

Three variables were entered as single numeric controls, matching the reported models: self-reported firm-size category (FirmType; 1 = large, 2 = medium, 3 = small), the seven-category region code (Region), and the registered-capital category (Scale; 1-4). These controls were not dummy-coded. The region code is not strictly ordinal, which is acknowledged as a modelling limitation.

Analytical Procedure and Model Specification

The dependent variable is binary, so we model the probability of LSC adoption with binary logistic regression. The estimating equation for the pooled sample is:

$$\ln\left(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}\right)$$

$$= \beta_0 + \beta_1 \text{EXTERNAL_CAP}_i + \beta_2 \text{MIMETIC}_i + \beta_3 \text{ITCAP}_i$$

$$+ \sum_{k=1}^{K} \gamma_k \, \text{Control}_{ki} + \varepsilon_i$$

$Y_i i \beta_1 \beta_2 \beta_3 \text{Control}_{ki} K \gamma_k \varepsilon_i$Here Y_i is the self-reported adoption status of firm i, taking the value 1 if the firm operates a live-streaming channel and 0 otherwise; β1, β2, and β3 capture the change in the log-odds of adoption associated with a one-unit change in each predictor, with the control variables held constant; X_i is a vector containing the three numeric controls (self-reported firm-size category, region code, and registered-capital category); γ is the corresponding control coefficient vector; and ε_i is the disturbance term.

We obtain odds ratios (OR) by exponentiating the estimated coefficients, $\text{OR}_j = \exp(\hat{\beta}_j)$, and report them alongside unstandardized logit coefficients and robust standard errors. We preferred logistic regression to a linear probability model because probabilities are bounded, which makes linear approximations inefficient near the tails and heteroskedastic by construction [66].

In the exploratory lifecycle analysis, the model is re-estimated separately within each stage s∈{start-up,growth,mature}:

$$\ln\left(\frac{P(Y_{si} = 1)}{1 - P(Y_{si} = 1)}\right)$$

$$= \beta_{0s} + \beta_{1s} \text{EXTERNAL_CAP}_{si} + \beta_{2s} \text{MIMETIC}_{si} + \beta_{3s} \text{ITCAP}_{si}$$

$$+ \sum_{k=1}^{K} \gamma_{ks} \, \text{Control}_{ksi} + \varepsilon_{si}$$

This split-sample approach allows the effect sizes β_{js} to vary flexibly across lifecycle

414 regimes, without imposing restrictive interaction structures or assuming common slopes
415 [62].
416 Estimation proceeds in four steps. The first step is a baseline model containing only the
417 control variables, which establishes the variance attributable to structural factors. In the
418 second step, the three TOE predictors enter simultaneously to test H1–H3 in the pooled
419 sample. The third step reflects the exploratory nature of the lifecycle analysis and the
420 moderate within-stage sample sizes: we rely on split-sample estimation rather than
421 saturating the pooled model with stage-interaction terms, which would risk
422 overparameterization [62]. The fourth step assesses robustness through alternative
423 estimators and subsample replication, as detailed in Section 4.4.
424
425 **Common Method Bias and Measurement Diagnostics**
426 **Common Method Variance**
427 $\chi^2 = 4240.138$All variables came from a single survey administered to one respondent
428 per firm, so common method variance (CMV) is a potential threat to validity [43]. The
429 questionnaire did not randomize item order, so no procedural randomization remedy is
430 claimed. As a statistical diagnostic, we ran Harman's single-factor test. The first unrotated
431 component explained 26.94% of total variance, below the 40% level usually read as
432 evidence of severe CMV. Kaiser-Meyer-Olkin sampling adequacy was 0.912, and
433 Bartlett's test of sphericity was significant ($df = 253$, $p < 0.001$). These diagnostics reduce,
434 but do not eliminate, concern about common-source bias.
435
436 **Multicollinearity and Correlation Diagnostics**
437 Variance inflation factors for all predictors were below 1.1, and the maximum absolute

pairwise correlation was 0.247. Multicollinearity therefore does not threaten coefficient stability. The full correlation matrix appears in Table 5.

Place Table 3 about here

Place Table 4 about here

Place Table 5 about here

Endogeneity Considerations

The cross-sectional design precludes strong causal claims. External capital receipt and adoption status were both recorded in the same survey, and the questionnaire did not impose a 24-month recall window; the measure therefore cannot establish the temporal ordering of financing and adoption. The dependent variable is a self-reported binary channel-existence item rather than a post-adoption performance measure, which avoids direct entanglement with performance outcomes but does not remove common-source concerns [43].

EXTERNAL_CAP may correlate with unobserved entrepreneurial intent, and ITCAP is measured contemporaneously. All estimates should therefore be read as conditional associations within a conservative TOE specification, not as causal effects identified through experimental or quasi-experimental variation [62]. Causal claims would be firmer with instrumental variables, panel data on adoption transitions, or regression-discontinuity designs. Following [35], the binary indicator operationalizes IT capability at its structural threshold. The presence of a dedicated team is treated as a minimal, observable proxy for the absorptive capacity needed to initiate and sustain live-streaming operations, not as a continuous measure of competence depth.

Lifecycle Stage Specification

$n_{\text{start-up}} = 241 n_{\text{growth}} = 303 n_{\text{mature}} = 174$We examined lifecycle heterogeneity through split-sample estimation rather than continuous interaction terms, for two reasons. First, organizational lifecycle theory treats stages as discrete regimes marked by qualitatively different dominant problems and resource configurations, not as smooth gradations along a single age dimension [36, 57]. Second, the within-stage sample sizes (241, 303, and 174) are large enough for stable logit estimation yet modest enough that fully saturated interactive models would risk overfitting. Stage classification follows the questionnaire's firm-age categories: under 3 years, 3 to 10 years, and over 10 years [38, 47]. Effect-size differences across stages are reported as exploratory findings rather than as formally hypothesized moderated effects.

Results

Descriptive Statistics, Correlation Matrix, and Measurement Diagnostics

We examined the distributional properties of the variables and the correlational structure of the data before estimating the multivariate models; this work formed part of the measurement validation reported in the preceding section. The full diagnostics are not reproduced here. Only the key features relevant to interpreting the regression estimates are summarized briefly.

The pooled sample (n = 718) shows an LSC adoption rate of 58.8%; 53.6% of firms reported external capital receipt, and 58.1% maintained a dedicated live-streaming team (Table 4). The mean perceived-industry-prevalence score is 3.680 (SD = 1.192, median = 4.0, on a 1-5 scale). The typical firm in this sample thus perceives at least moderate peer prevalence of live-streaming commerce, consistent with the view that environmental

signals are salient in this setting.

Bivariate correlations (Table 5) are uniformly modest. The strongest pairwise association is $r = 0.21$ ($p < .001$) between ITCAP and adoption. The maximum absolute correlation is 0.247, and all variance inflation factors in the logistic specification remain below 1.1, so multicollinearity is unlikely to threaten coefficient stability [66]. The Harman single-factor test (Table 3) further indicates that common method variance does not dominate the measurement structure; the first principal component explains only 26.94% of total variance [43].

Overall, these diagnostics indicate that the data are suitable for binary logistic regression. The dependent variable varies sufficiently, intercorrelations among predictors are low to moderate, and neither severe common-method nor multicollinearity contamination is present.

Main Effects

Table 6 presents the binary logistic regression estimates for the pooled sample ($n = 718$). The specification enters the three TOE predictors simultaneously alongside three numeric controls: self-reported firm-size category, region code, and registered-capital category. The model attains statistically significant fit (LR $\chi^2 = 54.42$, $df = 6$, $p < .001$), with a Nagelkerke pseudo R^2 of 0.098, a Cox & Snell pseudo R^2 of 0.073, and a classification accuracy of 62.0%. None of the individual controls reaches conventional significance (FirmType: $p = .103$; Region: $p = .468$; Scale: $p = .230$). Structural firm characteristics alone, in other words, do not discriminate adopters from non-adopters in this specification. All three associations predicted in H1-H3 receive support.

External capital receipt (EXTERNAL_CAP) is positively and significantly associated

with the log-odds of LSC adoption (β = 0.400, SE = 0.161, p = .013; OR = 1.492, 95% CI: 1.088-2.045). Holding the remaining variables constant, reported external capital receipt corresponds to an estimated 49.2% higher odds of adoption than for firms without such inflows. The result supports H1. It suggests that organizational resource slack covaries with adoption propensity when upfront investments are lumpy and difficult to smooth through operating cash flows [26, 30].

Perceived industry prevalence (MIMETIC) is likewise positively associated with adoption (β = 0.238, SE = 0.067, p < .001; OR = 1.269, 95% CI: 1.112-1.449). A one-unit increase in perceived peer popularity corresponds to a 26.9% increase in the odds of adoption, ceteris paribus. The finding supports H2 and accords with institutional-theoretic arguments that environmental legitimacy pressures dominate firm-level differentiation strategies under technological uncertainty [32, 50].

Dedicated team presence (ITCAP) carries the largest coefficient of the three predictors (β = 0.835, SE = 0.163, p < .001; OR = 2.305, 95% CI: 1.676-3.170). Firms with a dedicated live-streaming team show an estimated 2.305-fold difference in the odds of adoption compared with firms relying on ad hoc or outsourced arrangements. This pattern supports H3. Specialized human capital, it appears, is a salient organizational attribute distinguishing adopters from non-adopters in this sample.

Place Table 6 about here

Lifecycle-Stage Heterogeneity

We split the sample using the questionnaire's firm-age categories, under 3 years (n = 241), 3 to 10 years (n = 303), and over 10 years (n = 174), and re-estimated the three TOE predictors within each stratum. To preserve degrees of freedom within the smaller stage

534 samples and match the originally reported stage models, these models did not include the
535 three numeric controls; Table 7 therefore reports unadjusted stage-specific associations.
536 This exploratory split-sample design allows the associations to vary by organizational age
537 without imposing restrictive interaction structures [36, 38, 62].
538 Among firms operating for under 3 years, only ITCAP attains conventional statistical
539 significance ($\beta = 0.802$, SE = 0.287, $p = .005$; OR = 2.230). External capital receipt carries
540 a positive but statistically imprecise coefficient ($\beta = 0.363$, SE = 0.278, $p = .192$; OR =
541 1.438), and perceived industry prevalence is directionally consistent yet indistinguishable
542 from zero ($\beta = 0.153$, SE = 0.114, $p = .179$; OR = 1.165). This imprecision is consistent
543 with theoretical expectations. Nascent enterprises typically face restricted variance in
544 external financing accessibility, and their peer-network embeddedness is comparatively
545 weak [37, 57]; both conditions compress the measurable influence of the two factors. The
546 Nagelkerke pseudo R^2 is 0.075.
547 Among firms operating for 3 to 10 years, all three predictors attain independent statistical
548 significance and explanatory power peaks across the three stages (Nagelkerke pseudo R^2
549 = 0.110). External capital receipt is positive and significant at the 10% level ($\beta = 0.445$,
550 SE = 0.247, $p = .071$; OR = 1.560). Perceived industry prevalence is positive and
551 significant at the 5% level ($\beta = 0.258$, SE = 0.105, $p = .014$; OR = 1.295). ITCAP is
552 positive and significant at the 1% level ($\beta = 0.922$, SE = 0.246, $p < .001$; OR = 2.514).
553 Growth-stage firms simultaneously confront scaling pressures and heightened peer
554 visibility [39, 60], and it is under these conditions that the TOE specification reaches its
555 maximal explanatory power.
556 Among firms operating for over 10 years, perceived industry prevalence remains positive
557 and significant ($\beta = 0.331$, SE = 0.142, $p = .020$; OR = 1.392). ITCAP also remains

positive and significant, though its coefficient attenuates relative to the growth stage (β = 0.717, SE = 0.319, p = .025; OR = 2.049). Dedicated human capital still matters at this stage, but may yield diminishing marginal returns once organizational routines are established. External capital receipt is statistically indistinguishable from zero (β = 0.261, SE = 0.315, p = .407; OR = 1.299). Read together, the persistent significance of perceived prevalence alongside the fading of capital effects suggests that mature firms treat live-streaming less as a growth-acceleration mechanism driven by internal readiness than as a legitimacy-maintenance or defensive necessity [34, 46].

Place Table 7 about here

Robustness Checks

We estimated three auxiliary specifications to probe the sensitivity of the main findings.

Alternative estimator. To check robustness to functional form, we re-estimated the pooled model with a probit estimator. Average marginal effects (AMEs) are +0.0903 (SE = 0.0355, p = .011) for EXTERNAL_CAP, +0.0536 (SE = 0.0146, p < .001) for MIMETIC, and +0.1884 (SE = 0.0343, p < .001) for ITCAP (Table 8). Signs and significance levels agree with the baseline logit estimates, so the directional findings do not depend on the choice of link function [66]. For reference, the probit specification yields a McFadden pseudo R^2 of 0.056, a likelihood-ratio $\chi^2(6)$ of 54.48 (p < .001), LogL = -459.33, and AIC = 932.66.

Place Table 8 about here

Reduced control set. We re-estimated the pooled specification without the single region-code control. The sign, magnitude order, and significance of the three TOE predictors were materially unchanged. This corroborates what the full specification already shows: the

controls do not alter the significance or sign of the TOE predictors.

Subsample replication by registered-capital category. Firms in registered-capital categories 1-2 dominate the sample (64.8% of observations), so we re-estimated the baseline model on this lower-registered-capital subsample (n = 465) to check whether the pooled findings are artifacts of the broader sample composition. Table 9 reports the coefficients alongside the full-sample estimates. In the lower-registered-capital subsample, all three TOE predictors remain positive and statistically significant: external capital receipt ($\beta = 0.520$, SE = 0.211, $p = .014$; OR = 1.682), perceived industry prevalence ($\beta = 0.277$, SE = 0.092, $p = .003$; OR = 1.319), and ITCAP ($\beta = 1.072$, SE = 0.210, $p < .001$; OR = 2.922). Each coefficient is larger in absolute magnitude than its full-sample counterpart, and the Nagelkerke pseudo R^2 rises from 0.098 to 0.147. The TOE associations are therefore not weaker in this capital-constrained segment.

Place Table 9 about here

Discussion and Conclusions

Summary of Results

We paired the Technology-Organization-Environment framework with organizational lifecycle theory to ask which organizational and environmental conditions covary with live-streaming commerce adoption in a predominantly SME sample of Chinese firms, while controlling for self-reported firm size. Pooled binary logistic regression on the 2023 cross-sectional sample of 718 firms identifies three TOE factors positively associated with adoption probability: external capital receipt, a dedicated in-house live-streaming team, and perceived industry prevalence.

The estimates line up with H1, H2, and H3. ITCAP displays the strongest association (OR

606 = 2.305), followed by external capital receipt (OR = 1.492) and perceived industry
607 prevalence (OR = 1.269). Platform adoption in this sample does not trace back to a single
608 dominant driver. It covaries with financial slack, internal human-capital commitment, and
609 perceived peer practice [28, 33, 51].

610 Split-sample estimation across the questionnaire's firm-age categories, under 3 years, 3 to
611 10 years, and over 10 years, exposes patterns that the pooled estimates conceal. Among
612 firms operating for under 3 years, only ITCAP attains conventional significance; external
613 capital receipt and perceived industry prevalence are positive but statistically imprecise.
614 The noise is consistent with credit rationing that compresses variance in observable
615 capital access, and with weaker network embeddedness among newer firms [37, 57].
616 Among firms operating for 3 to 10 years, all three TOE predictors are simultaneously
617 significant, and the model achieves its highest explanatory power in this stratum
618 (Nagelkerke $R^2 = 0.110$). Among firms operating for over 10 years, perceived industry
619 prevalence remains positively associated with adoption, ITCAP retains significance with
620 an attenuated coefficient, and external capital receipt is indistinguishable from zero.
621 These patterns point to a shifting decision calculus: adoption early in a firm's life is most
622 tightly linked to dedicated internal capability, multiple levers operate jointly during
623 growth, and perceived peer prevalence remains salient in maturity even as the association
624 with capital weakens [34, 46].

625 Growth-stage firms present a fuller picture: all three TOE predictors are significant at
626 once, and the model reaches its highest explanatory power in this stratum (Nagelkerke R^2
627 = 0.110). One plausible reading is that mid-life firms have enough slack that financial
628 resources, peer legitimacy signals, and dedicated human capital each move adoption
629 propensity along its own margin [39, 60].

Mature firms show yet another configuration. Perceived industry prevalence stays positively associated with adoption, ITCAP remains significant though with a smaller coefficient, and external capital receipt is statistically indistinguishable from zero. Seen together, the stage-specific patterns point to a decision calculus that shifts over the firm's life: adoption tracks dedicated internal capability early on, several organizational and environmental forces operate at once in mid-life, and perceived peer prevalence still covaries with adoption in maturity even as the association with external capital weakens [34, 46].

Robustness of Findings

Auxiliary specifications support the direction of these results. A probit estimator produces consistent signs and significance levels. Re-estimation on the lower-registered-capital subsample (n = 465, 64.8% of the data) yields larger coefficient magnitudes and improved model fit (Nagelkerke $R^2 = 0.147$). The pooled associations therefore do not appear to be artifacts of sample composition by registered capital (Table 9).

Theoretical Implications

Stage-contingent TOE micro-foundations. Dedicated in-house team presence shows a stronger adoption association in the lower-registered-capital subsample (OR = 2.922, Table 9) and retains statistical significance across the lifecycle. The association peaks among firms operating for 3 to 10 years (OR = 2.514) and is also substantial among newer firms and firms operating for over 10 years (OR = 2.230 vs. 2.049, Table 7). This pattern extends the TOE micro-foundations literature by identifying a lifecycle boundary condition. Prior work has often treated technological readiness as a relatively homogeneous organizational asset [27]; the present analysis suggests instead that its

observed magnitude depends on firm size and stage. Where resource fungibility is lower, capability heterogeneity acts as a binding constraint that most sharply separates adopters from non-adopters [33].

Contingent institutional and resource mechanisms. The stage-varying pattern of perceived industry prevalence, insignificant among firms operating for under 3 years ($p = .179$) yet significant among firms operating for 3 to 10 years and over 10 years (OR = 1.295, $p = .014$ and OR = 1.392, $p = .020$, respectively; Table 7), suggests that legitimacy-seeking behavior requires a minimum threshold of network observability before it operates as an adoption correlate. This qualifies the institutional-isomorphism logic by showing that mimetic pressure is not universal but contingent on organizational age and market embeddedness [32]. The association between external capital and adoption, similarly, is concentrated among firms operating for 3 to 10 years (OR = 1.560, $p = .071$, Table 7), consistent with the reading that scaling pressure, rather than general resource slack, drives the empirical link between financing and platform entry.

Implications for adoption theory. These findings also speak to how the TOE framework itself should be conceptualized when the outcome is initial platform adoption by an SME. Read together, they point toward treating TOE as a set of conditional propositions rather than a universal variance model. All three predictors reach significance, whether at conventional or marginal levels, only in the growth stage, and model fit peaks in that same stratum (Nagelkerke $R^2 = 0.110$, Table 7). A pooled-sample design can thus overstate the relevance of some factors and understate others, depending on how the sample is composed across lifecycle stages. Theory work that follows should consider stage-calibrated TOE specifications in which effect magnitudes are allowed to vary with organizational maturity.

Managerial and Policy Implications

Managers of smaller firms should read the lifecycle patterns as a call for differentiated digital strategy. Newer firms gain the most from building dedicated in-house streaming teams first. At this stage, perceived industry prevalence carries no discernible association with adoption; peer imitation without foundational IT human capital appears insufficient for entry. Firms operating for 3 to 10 years operate in a decision environment where external financing, peer benchmarking, and team building each covary independently with adoption, and investments along these dimensions are likely complementary rather than substitutable. Among firms operating for over 10 years, adoption propensity is more tightly linked to perceived peer prevalence and to the continued presence of dedicated IT teams, even though the estimated association with external capital receipt weakens.

For policymakers and ecosystem architects, uniform subsidization is unlikely to work. Financial grants and loan guarantees show the strongest association with adoption when aimed at growth-stage SMEs, whereas start-ups may benefit more from technical training, incubation services, and talent subsidies that directly target the capability constraints visible at this stage. Industry associations that seek to accelerate LSC diffusion should recognize that peer-pressure campaigns and benchmark dissemination resonate most strongly with established, network-embedded firms rather than with newly founded ventures.

Limitations and Future Research

These findings should be interpreted in light of several limitations. First, the cross-

sectional design precludes strict causal identification. External capital receipt and adoption status were measured in the same survey, and the stored questionnaire did not record a bounded 24-month recall window; unobserved heterogeneity, entrepreneurial orientation, or unmeasured industry demand shocks may therefore confound the estimated relationships. Quasi-experimental or longitudinal panel designs would strengthen causal claims [62].

Second, the binary operationalization of adoption (1 = adopted, 0 = not adopted) captures the extensive margin of LSC engagement but not its intensive margin. Future work could model adoption depth, for instance the frequency of live-streaming events, revenue share, or team size, to examine whether the TOE drivers covary differently with initiation than with scaling.

Third, although the sample spans multiple industries and regions, the data come from a single point in time (2023) within one national context. Platform ecosystems and SME financing environments evolve rapidly. Replication in other institutional settings, or at different phases of the diffusion cycle, would test the generalizability of the lifecycle-contingent patterns reported here.

Conclusion

Live-streaming commerce is a rapidly evolving digital channel. It requires firms to allocate scarce internal resources while navigating uncertain environmental signals. Adoption, this study suggests, is not a monolithic event tied to a single dominant factor. It is a stage-contingent outcome in which capital receipt, perceived institutional prevalence, and dedicated team capability assume differential salience across the

723 organizational lifecycle. Parsing these contingencies moves the literature beyond one-
724 size-fits-all explanations and offers a theoretically grounded account of how, when, and
725 why firms step onto the live-streaming platform.
726

727 **Declarations**

728 **Data availability**

729 All data and materials supporting the findings of this study are available as Supplementary
730 Files accompanying this article. Supplementary File S1 contains the anonymized dataset
731 (raw item responses and constructed analysis variables; N = 718). Supplementary File S2
732 is the complete variable codebook documenting definitions, coding schemes, and
733 transformations. Supplementary File S3 is the original survey questionnaire, including
734 the informed-consent page. Supplementary File S4 is the complete Stata do-file
735 reproducing the descriptive statistics and regression results. Supplementary File S5 is the
736 data-reconciliation note that verifies Table 1, control-variable coding, and lifecycle
737 boundaries against the raw records. Supplementary File S6 documents the data-collection
738 protocol and data-management procedures; a separate S4 verification summary records
739 successful execution of the analysis code. The shared files contain no IP addresses,
740 submission timestamps, referral-source information, or direct identifiers. No third-party
741 or proprietary data were used; all data were collected by the authors.

742 **Ethics approval and consent to participate**

743 This study was a non-interventional, cross-sectional business survey of firm owners and
744 senior managers and collected no medical, health-related, or otherwise sensitive personal
745 data. Data were collected in 2023. A retrospective ethics review application was

submitted to the Research Office of North Minzu University on 13 September 2026. The application was reviewed and approved by the Science and Technology Ethics Review Committee of North Minzu University on 15 September 2026 (approval reference: North Minzu University Ethics Approval No. 2026-37). The study was designed and conducted in accordance with the general ethical principles of the Declaration of Helsinki and the research ethics requirements of North Minzu University. Informed consent was obtained from all participants. The questionnaire's first page identified the researchers and institutional affiliation, stated the academic purpose, and explained that participation was voluntary, responses would be kept confidential and used solely for anonymized academic research, and participants could stop before submission without consequence. Online respondents consented by voluntarily completing and submitting the questionnaire after reading this statement; on-site respondents provided verbal informed consent after receiving the same information. Written signatures were not collected because the records were anonymous and contained no direct identifiers; this consent procedure was included in the approved protocol. The institutional approval document is provided as Supplementary File S7.

Consent for publication

Not applicable. This manuscript contains no individual person's data in any form (including individual details, images, or videos).

Competing interests

The authors declare no competing interests.

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Table 1. Sample Distribution by Region, Industry, Self-Reported Firm Size, and Registered Capital

Region	Sample size	(%)	Industry type	Sample size	(%)
North China	174	24.2 %	Primary Sector	255	35.5%
East China	147	20.5 %	Secondary Sector	271	37.7%
South China	130	18.1%	Tertiary Sector	192	26.7%
Central China	78	10.9%	Self-reported firm size	n	%
Northeast China	62	8.6%	**Large**	138	19.2%
Northwest China	68	9.5%	Medium	276	38.4%
Southwest China	59	8.2%	Small	304	42.3%
Registered capital			Category	n	%
			< RMB 5 million	465	64.8%
			≥ RMB 5 million	253	35.2%

Notes: Total N = 718. Self-reported firm-size categories are used descriptively and as a numeric control; they are not a formal employee- or revenue-based SME eligibility classification. Percentages may not sum to 100% because of rounding.

Table 2. Variable Definitions and Measurement

Dimension	Specific Mechanism	Quantitative Indicator	Abbreviation	Operationalization
Dependent Variable	Adoption of LSC	Adoption status	LSC	Binary: 1 = Adopted, 0 = Not
Organizational	External Resource Access	Received external capital	EXTERNAL_CAP	Binary: 1 = Yes, 0 = No
	IT Capability (human capital)	Professional team	ITCAP	Binary: 1 = Yes, 0 = No
Environmental	Mimetic Institutional Pressure	Perceived popularity of LSC (single item)	MIMETIC	Ordinal 1-5; reverse-coded so higher values indicate stronger perceived prevalence
Controls	Self-reported firm size, region code, registered-capital category	FirmType; Region; Scale	—	Single numeric controls in reported models: FirmType (1=large, 2=medium, 3=small), Region (1-7), Scale (1-4). Not dummy-coded.

MIMETIC (Mimetic Pressure): Single-item measure on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), reverse-coded so that higher scores indicate stronger perceived mimetic pressure.

Table 3. Harman Single-Factor Test for Common Method Variance (CMV, n=718)

Test Statistic	Value
KMO Measure of Sampling Adequacy	0.912
Bartlett‘s Test of Sphericity	$\chi^2 = 4240.14$ (df = 253)
Factors Extracted (Eigenvalue > 1)	4
First Principal Component	26.94%
Cumulative Variance (Rotation)	46.421%

Interpretation: KMO > 0.9 = Excellent; Bartlett's $p < 0.001$ = Correlated variables; First factor < 40% = No serious CMV [43].

Table 4. Descriptive Statistics (n=718)

Variable	Mean	SD	Min	Max	Median
LSC (Adoption)	0.588	0.493	0	1	1.0
EXTERNAL_CAP	0.536	0.499	0	1	1.0
MIMETIC	3.680	1.192	1	5	4.0
ITCAP	0.581	0.494	0	1	1.0

Notes: LSC: 1 = Adopted, 0 = Not adopted. MIMETIC is reverse-coded (1 = Strongly disagree = weak pressure, 5 = Strongly agree = strong pressure). Binary variables (EXTERNAL_CAP, ITCAP) are coded as 1 = Yes, 0 = No. For binary variables, the reported mean is the proportion coded 1; multiply the mean by 100 to obtain the percentage reported in the text.

Table 5. Pearson Correlation Matrix (n=718)

Variable	1	2	3	4
1. EXTERNAL_CAP	1.00	0.04	0.10***	0.11***
2. MIMETIC		1.00	0.02	0.14***
3. ITCAP			1.00	0.21***
4. LSC				1.00

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. Maximum absolute correlation = 0.21.

Table 6. Binary Logistic Regression (Direct Entry, Full Sample, n=718)

Hypothesis	Variable	beta	OR	95% CI Lo	95% CI Hi	SE	p-value	Wald
—	const	-1.2937***	0.274	0.113	0.668	0.454	0.004	8.11
H1	EXTERNAL_CAP	+0.3998**	1.492	1.088	2.045	0.161	0.013	6.16
H2	MIMETIC	+0.2383***	1.269	1.112	1.449	0.067	<0.001	12.48
H3	ITCAP	+0.8350***	2.305	1.676	3.170	0.163	<0.001	26.37
—	FirmType (self-reported size category)	+0.1777	1.194	0.965	1.479	0.109	0.103	2.66
—	Region	−0.0305	0.970	0.893	1.053	0.042	0.468	0.53
—	Scale	−0.0939	0.910	0.781	1.061	0.078	0.230	1.44

Model Fit: Nagelkerke $R^2 = 0.098$; Cox & Snell $R^2 = 0.073$; LR $\chi^2 = 54.42$ (df = 6, $p < 0.001$); Model accuracy = 62.0%; VIF all < 1.1 (no multicollinearity). Coefficient significance: *p < 0.10, **p < 0.05, ***p < 0.01. Source: Survey of 718 Chinese firms (2023), predominantly SMEs.

Table 7. Binary Logistic Regression Results by Organizational Lifecycle Stage (n=718)

Variable/Driver	Under 3 years (n=241)	3 to 10 years (n=303)	Over 10 years (n=174)
EXTERNAL_CAP	+0.363 (0.278)	+0.445* (0.247)	+0.261 (0.315)
	OR=1.438 p=0.192	OR=1.560 p=0.071	OR=1.299 p=0.407
MIMETIC	+0.153 (0.114)	+0.258** (0.105)	+0.331** (0.142)
	OR=1.165 p=0.179	OR=1.295 p=0.014	OR=1.392 p=0.020
ITCAP	+0.802*** (0.287)	+0.922*** (0.246)	+0.717** (0.319)
	OR=2.230 p=0.005	OR=2.514 p<0.001	OR=2.049 p=0.025
Nagelkerke R^2	0.075	0.110	0.088

*p < 0.10, **p < 0.05, ***p < 0.01. Unstandardized β with SE in parentheses; OR shown. MIMETIC is reverse-coded (1 = strongly disagree = weak pressure, 5 = strongly agree = strong pressure). Stage-specific models include the three TOE predictors and omit the three numeric controls to preserve degrees of freedom within the stage subsamples.

Table 8. Probit Model Marginal Effects (Robustness Check, Full Sample n=718)

Variable	AME	SE	95% CI	p
EXTERNAL_CAP	+0.0903**	0.0355	[0.021, 0.160]	0.011
MIMETIC	+0.0536***	0.0146	[0.025, 0.082]	<0.001
ITCAP	+0.1884***	0.0343	[0.121, 0.256]	<0.001

Model Fit: McFadden $R^2 = 0.056$; LR $\chi^2(6) = 54.48$ ($p < 0.001$); LogL = -459.33; AIC = 932.66. Signs are consistent with Logit. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 9. Subsample Robustness: Coefficients Comparison (Lower-Registered-Capital Firms vs. Full Sample)

Variable	Lower-Registered-Capital Subsample (Categories 1-2, n=465)	Full Sample (n=718)
EXTERNAL_CAP	0.520** (0.211) OR=1.682 p=0.014	0.400** (0.161) OR=1.492 p=0.013
MIMETIC	0.277*** (0.092) OR=1.319 p=0.003	0.238*** (0.067) OR=1.269 p<0.001
ITCAP	1.072*** (0.210) OR=2.922 p<0.001	0.835*** (0.163) OR=2.305 p<0.001
Nagelkerke R^2	0.147	0.098

Notes: DV = LSC (1 = adopted). Lower-registered-capital subsample = registered-capital categories 1-2 (n = 465; 64.8%). *p < 0.10, **p < 0.05, ***p < 0.01.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- S2VariableCodebook.xlsx
- S4VerificationSummary.txt
- S4AuditChecklist.txt
- S4ReproducedTables.xlsx
- S3SurveyQuestionnaireOriginalChinese.docx
- S4AnalysisCode.do
- S6DataCollectionProtocolandDataManagement.docx
- S5DataReconciliationandTable1Audit.docx
- S4AnalysisCode.log
- S1DatasetSMELSCanonymized.xlsx