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Algorithmic Visibility and Entrepreneurial Survival in Hospitality: A Structural Equation Model of Communication Adaptation and Trust Among Micro, Small, and Medium Enterprises

Prasetya Yoga Santoso[1], Ressa Uli Patrissia[2]
[1]Universitas Sahid, Jakarta, Indonesia, prasetya_yoga@sahid.ac.id
[2]Universitas Muhammadiyah, Palangka Raya, Indonesia, rpatrissia@gmail.com

Corresponding Author: prasetya_yoga@sahid.ac.id[1]

Abstract: The viability of micro, small, and medium enterprises (MSMEs) in Indonesia's hospitality sector is increasingly contingent upon the capacity of entrepreneurs to navigate algorithm-driven digital ecosystems that govern audience reach, reputation, and demand. Despite the proliferation of platform-mediated commerce, empirical models that articulate how algorithmic visibility translates into entrepreneurial survival remain scarce, particularly within the Global South. This study addresses that gap by developing and empirically validating the Algorithmically Mediated Hospitality (AMH) model, which posits algorithmic visibility as an antecedent of entrepreneurial survival operating through the sequential mediation of communication adaptation and customer trust, and conditioned by digital literacy. Drawing on the Resource-Based View (J. Barney, 1991), Adaptive Communication Theory (Daft & Lengel, 1986), and the platform-economy literature (Cusumano et al., 2019), the model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) on cross-sectional survey data collected from 287 hospitality MSME owners (boutique hotels, cafés, and homestays) in Jakarta, Bali, Yogyakarta, and Bandung. The results indicate that algorithmic visibility exerts a statistically significant positive effect on communication adaptation ($\beta = 0.612$, $p < .001$), customer trust ($\beta = 0.431$, $p < .001$), and entrepreneurial survival ($\beta = 0.278$, $p < .001$). The sequential indirect effect was confirmed ($\beta = 0.189$; 95% CI [0.134, 0.251]), and digital literacy significantly moderated the algorithmic visibility–communication adaptation pathway ($\beta_{interaction} = 0.214$, $p < .001$). The model accounts for 53.1% of the variance in entrepreneurial survival, exceeding benchmarks reported in comparable Southeast Asian SME studies (Fauzi et al., 2023). Theoretically, the study contributes a measurement-validated construct of algorithmic visibility and extends the Resource-Based View into platform-mediated competition. Practically, the findings inform a redesign of national MSME digital-literacy policy that explicitly incorporates algorithmic literacy as a survival-relevant competence.

Keywords: Algorithmic Visibility, Communication Adaptation, Customer Trust, Entrepreneurial Survival, Digital Literacy, Hospitality MSMEs, Platform Economy, Indonesia.

INTRODUCTION

Indonesia hosts one of the world's largest micro, small, and medium enterprise (MSME) ecosystems. According to the Ministry of Cooperatives and SMEs (Kementerian Koperasi dan U K M RI, 2023), the country counts approximately 65.5 million MSME units, contributing 61.07% of national gross domestic product and absorbing roughly 97% of the labor force. Within this constellation, the hospitality sector—encompassing accommodation, food and beverage outlets, cafés, and tourism services—is simultaneously among the most dynamic and most vulnerable subsectors to digital disruption (Badan Pusat Statistik, 2023; Sigala, 2020). The COVID-19 shock and the subsequent recovery have permanently altered the channels through which hospitality demand is generated: (We Are Social & Hootsuite, 2024) report that 212.9 million Indonesians (77.0% of the population) are connected to the internet, with 167 million of them active on social media. The hospitality recovery has therefore been disproportionately platform-led, with discoverability shifting from physical proximity and word-of-mouth to algorithmic recommendation (Buhalis & Sinarta, 2019; Yang et al., 2020).

Against this backdrop, business visibility is increasingly shaped by how platform algorithms distribute content to relevant audiences rather than solely by service quality or physical location. Online travel agents (OTAs) such as Traveloka and Booking.com, alongside social platforms such as Instagram and TikTok, deploy machine-learning ranking systems that prioritize content according to engagement intensity, contextual relevance, and posting consistency (Bucher, 2018; Gillespie, 2020; Napoli, 2014). This creates a structural asymmetry in competition. Hospitality MSMEs that understand and adapt to platform algorithms gain significantly greater exposure than competitors with similar service quality but lower digital literacy (Rahardjo et al., 2022). The asymmetry is amplified by the platformization of the web (Helmond, 2015), wherein platforms increasingly mediate not only distribution but the very cognitive frames through which entrepreneurs evaluate market signals (Cutolo & Kenney, 2021; Zuboff, 2019)

Despite the centrality of algorithmic mediation in contemporary hospitality, scholarship explaining its causal pathway to entrepreneurial survival in Indonesia remains underdeveloped. Prior Indonesian studies have explored social-media use generally (Susanto & Wahyuni, 2021), digital marketing strategy (Putri et al., 2022), and consumer trust in e-commerce (Lestari & Nugroho, 2023), yet none has explicitly modeled algorithmic visibility as a structural latent variable embedded in a survival-oriented framework. International contributions, while theoretically generative, have largely been qualitative or institutional in character (Gillespie, 2020; Napoli, 2014), or have focused on consumer-side rather than entrepreneur-side outcomes (Alalwan, 2020; Filieri et al., 2018). A measurement-validated, multi-pathway model linking algorithmic visibility to entrepreneurial survival in the hospitality MSME context is therefore conspicuously absent.

This study addresses that gap through three contributions. First, it operationalizes and validates algorithmic visibility as a reflective latent construct measurable in survey research. Second, it specifies and tests the Algorithmically Mediated Hospitality (AMH) model—an integrated framework in which algorithmic visibility influences entrepreneurial survival through the sequential mediation of communication adaptation and customer trust, with digital literacy operating as a moderating capability. Third, it deploys Partial Least Squares Structural Equation Modeling (PLS-SEM) on a multi-city sample to estimate direct, indirect, and conditional effects, thereby producing a quantitatively defensible account of how platform-mediated visibility translates into firm-level survival outcomes. The research questions are: (1) Does algorithmic visibility positively influence communication adaptation, customer trust, and entrepreneurial survival? (2) Is the effect of algorithmic visibility on survival sequentially mediated by communication adaptation and trust? (3) Does digital literacy moderate the visibility–communication adaptation and communication–trust pathways?

The Oretical Foundation And Hypothesis Development

Algorithmic Visibility in the Platform Economy

Algorithmic visibility refers to the degree to which a firm's content, profile, or offering is surfaced by platform recommendation systems to relevant audiences (Bucher, 2018; Napoli, 2014). It differs from earlier conceptions of online presence in two ways. First, it is governed by opaque ranking systems whose criteria are neither published nor stable (Gillespie, 2020). Second, algorithmic visibility is path-dependent because prior engagement, ratings, and posting consistency accumulate into reputational capital that shapes future content distribution (Cutolo & Kenney, 2021). In platform-capitalism scholarship, this recursive accumulation has been theorized as a defining feature of contemporary digital markets, in which platforms function as infrastructures of intermediation that translate behavioral data into competitive position (Kenney & Zysman, 2016; Srnicek, 2017). For hospitality MSMEs, algorithmic visibility increasingly determines the very possibility of being chosen by prospective guests, since contemporary travel and dining decisions are routinely initiated within—rather than merely informed by—platform interfaces (Mariani et al., 2018; Xiang et al., 2017).

Adaptive Communication Theory and the Algorithmic Imperative

Adaptive Communication Theory, rooted in (Daft & Lengel, 1986) media richness framework and extended by (Timmermans & Oh, 2010), holds that organizational actors continuously calibrate the form, channel, and timing of their communication to fit the demands of their information environment. In platform-mediated commerce, the relevant environment is the algorithm itself: entrepreneurs must infer—often without explicit guidance—what content formats, posting times, and engagement signals will earn distribution (Bucher, 2018; Rahardjo et al., 2022). (Bucher, 2018) terms the cognitive product of this inference an "imagined affordance": entrepreneurs build mental models of the algorithm from observed feedback (which posts went viral, which hashtags trended), and these models in turn govern subsequent communicative choices. Communication adaptation is therefore not a static skill but a dynamic capability (Eisenhardt & Martin, 2000; Teece, 2007) that enables firms to reconfigure their digital communicative repertoire as platform environments evolve.

Customer Trust as Algorithmic Credibility

In digital hospitality, customer trust is acutely consequential because purchase decisions are typically made before any physical inspection of the offering (Filieri et al., 2018; Gefen et al., 2003). (Morgan & Hunt, 1994) Commitment-Trust Theory positions trust as the central relational variable mediating loyalty and repeat patronage. Within platform ecosystems, trust is augmented by what (Rader & Gray, 2015) call algorithmic credibility: consumers infer quality from a firm's algorithmic position—its placement in OTA rankings, its frequency in social-media recommendations, the visibility of its reviews—because algorithmic prominence is itself read as a quality signal. (Lim et al., 2022) and (Filieri et al., 2018) report that on travel platforms, ranking salience and review valence jointly shape trust formation more strongly than firm-controlled marketing communications. The implication for hospitality MSMEs is that algorithmic visibility is not merely a distribution variable but a trust-formation variable.

Entrepreneurial Survival and the Resource-Based View

Entrepreneurial survival captures a firm's capacity to remain commercially viable and grow under conditions of resource constraint and market turbulence (Lumpkin & Dess, 1996; Wiklund & Shepherd, 2003). The Resource-Based View (RBV) (J. Barney, 1991; J. B. Barney & Clark, 2007) frames survival as a function of the firm's stock of valuable, rare, inimitable, and non-substitutable resources. In the platform era, scholars argue that algorithmic position constitutes a strategic resource because it accumulates over time, is difficult to replicate, and is closely tied to platform-specific reputational systems (Kamboj & Rahman, 2017; Kraus et al.,

2022). (Vial, 2019) further articulates digital transformation as a process in which firms reconfigure their resource base around digital infrastructures, with survival implications that exceed the simple adoption of digital tools. Building on these insights, this study treats algorithmic visibility as a digitally embedded strategic resource whose downstream effect on survival is partly direct and partly mediated through communicative and relational mechanisms.

Digital Literacy as a Conditioning Capability

Digital literacy denotes the multidimensional capacity to access, understand, evaluate, and produce information through digital technologies (Eshet-Alkalai, 2004; Ng, 2012; Van Dijk, 2020). Beyond instrumental skill, contemporary digital literacy increasingly encompasses algorithmic literacy—the awareness of how recommendation systems shape what one sees and how to influence what they distribute (Cotter, 2019; Rader & Gray, 2015). (Van Dijk, 2020) argues that the principal source of digital inequality has shifted from access to skill, producing a "skills divide" within which those who can interpret and act on algorithmic signals derive cumulatively greater value from the same platforms. For hospitality MSMEs, digital literacy is therefore expected to condition both the speed with which entrepreneurs translate visibility cues into communication adaptation and the quality with which adapted communication is executed.

Hypotheses and the Algorithmically Mediated Hospitality (AMH) Model

Drawing on the foregoing, the AMH model integrates three theoretical traditions—algorithmic mediation, adaptive communication, and the resource-based view—into a structural account of platform-era entrepreneurial survival. Eleven hypotheses are advanced. Direct effects include the influence of algorithmic visibility (VA) on communication adaptation (CA), customer trust (CT), and entrepreneurial survival (ES); the effect of CA on CT and ES; and the effect of CT on ES. Indirect effects encompass the mediation of CA between VA and CT, the mediation of CT between VA and ES, and the sequential mediation VA → CA → CT → ES. Two moderation hypotheses test whether digital literacy (DL) strengthens the VA → CA and CA → CT pathways.

Table 1. Structural Model and Research Hypotheses

Code	Structural Path	Theoretical Foundation	Sign
H1	VA → CA	(Bucher, 2018; Daft & Lengel, 1986; Napoli, 2014)	(+)
H2	VA → CT	(Gefen et al., 2003; Rader & Gray, 2015)	(+)
H3	VA → ES	(J. Barney, 1991; Kamboj & Rahman, 2017; Vial, 2019)	(+)
H4	CA → CT	(Morgan & Hunt, 1994; Timmermans & Oh, 2010)	(+)
H5	CT → ES	(Morgan & Hunt, 1994; Wiklund & Shepherd, 2003)	(+)
H6	CA → ES	(Lumpkin & Dess, 1996; Teece, 2007)	(+)
H7	VA → CA → CT	(Baron & Kenny, 1986; Hayes, 2022)	Partial
H8	VA → CT → ES	(Preacher & Hayes, 2008)	Partial
H9	VA → CA → CT → ES	(Nitzl et al., 2016; Taylor et al., 2021)	Partial
H10	DL × (VA → CA)	(Cotter, 2019; Eshet-Alkalai, 2004; Ng, 2012)	(+)
H11	DL × (CA → CT)	(Rahardjo et al., 2022; Van Dijk, 2020)	(+)

Source: Authors' construction based on the literature review (2026).

METHOD

Research Design

The study employed a cross-sectional, quantitative, survey-based design analyzed by means of Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0 (Ringle et al., 2022). PLS-SEM was selected for three reasons. First, it accommodates complex

models with multiple mediation and moderation paths under moderate sample sizes (Hair et al., 2019). Second, it is robust under non-normal distributions, which is consistent with Likert-scale data from heterogeneous MSME populations (Sarstedt et al., 2019). Third, its predictive orientation is appropriate for the exploratory-confirmatory character of the AMH model, where some pathways extend established theory into a novel platform context (Dijkstra & Henseler, 2020).

Population, Sample, and Sampling Procedure

The target population comprised owners or operating managers of hospitality MSMEs—defined as one- to two-star boutique hotels, homestays, and cafés/casual restaurants with annual turnover below IDR 50 billion—operating in four Indonesian cities selected for their digital-economy density: Jakarta, Bali (Denpasar–Badung corridor), Yogyakarta, and Bandung. Purposive sampling was used, requiring respondents to (a) be owners or principal managers, (b) have actively used at least one digital platform (social media or OTA) for a minimum of six months, and (c) operate commercially. The minimum sample size was determined using the ten-times rule (Hair et al., 2019), with the most-indicated construct featuring four indicators yielding a floor of 40 cases; the final sample of 287 substantially exceeds this threshold and is consistent with the median sample size reported in published PLS-SEM hospitality studies (Pappas et al., 2017).

Variable Operationalization and Measurement

All five latent constructs were specified reflectively and measured on a five-point Likert scale anchored from "strongly disagree" (1) to "strongly agree" (5). Algorithmic Visibility (VA) was measured with four indicators adapted from (Napoli, 2014) and (Bucher, 2018) (frequency of appearance in recommendations, organic content reach, OTA ranking, and perceived algorithmic responsiveness). Communication Adaptation (CA) employed four indicators drawn from (Daft & Lengel, 1986) and (Timmermans & Oh, 2010), capturing platform-trend responsiveness, posting-time optimization, and analytics-informed adjustment. Customer Trust (CT) used four indicators adapted from (Morgan & Hunt, 1994) and (Gefen et al., 2003). Entrepreneurial Survival (ES) drew on (Lumpkin & Dess, 1996) and (Wiklund & Shepherd, 2003), incorporating revenue stability, repeat-customer growth, and resilience to external shocks. Digital Literacy (DL) employed four indicators from (Eshet-Alkalai, 2004) and (Ng, 2012), with one item explicitly tapping algorithmic awareness following (Cotter, 2019).

Data Collection and Quality Assurance

Data were collected via an online questionnaire administered through Google Forms between April and May 2026. A pilot study with 30 respondents preceded full deployment to verify item clarity and refine wording where necessary. Common-method bias was addressed both procedurally—through anonymity assurance, randomized item ordering, and separation of predictor and criterion measurement—and statistically through Harman's single-factor test (Sarstedt et al., 2019). Convergent validity was assessed via Average Variance Extracted (AVE > .50) and Composite Reliability (CR > .70). Discriminant validity was evaluated using the Heterotrait-Monotrait ratio (HTMT < .85; (Henseler et al., 2015).

Structural Model Estimation and Hypothesis Testing

Path coefficients were estimated using the consistent PLS algorithm with bootstrapping (5,000 resamples) to derive t-statistics and 95% bias-corrected confidence intervals. Mediation was assessed using the Variance Accounted For (VAF) statistic and the bootstrapped indirect-effect confidence interval (Preacher & Hayes, 2008) Moderation was tested using the product-indicator approach with mean-centered indicators (Chin et al., 2003), and simple-slope analysis was conducted at ±1 standard deviation of the moderator following (Aiken & West, 1991).

RESULTS AND DISCUSSION

Respondent Profile

Of 320 questionnaires distributed, 287 were retained for analysis after screening for completeness and eligibility, yielding a response rate of 89.7%. The majority of respondents were women (58.5%) aged 26–35 years (44.3%), with diploma- or bachelor-level education (61.0%). The most prevalent business type was casual cafés and restaurants (41.1%), followed by homestays (33.4%) and boutique hotels (25.5%). Operational tenure clustered between two and seven years (67.6%), placing the modal respondent in what (Afrizal et al., 2022) characterize as the "early survival" phase—past the initial founding hazard but still vulnerable to external shocks. Geographic distribution was Jakarta (32.4%), Bali (29.3%), Yogyakarta (21.6%), and Bandung (16.7%). Platform usage was led by Instagram (91.3%), followed by TikTok (76.3%) and Traveloka (54.7%); the TikTok penetration in this sample exceeded the regional Southeast Asian average of approximately 62% (We Are Social & Hootsuite, 2024), corroborating a notable migration of Indonesian hospitality MSMEs from photo-centric to algorithm-driven, video-first platforms.

Cross-tabulation revealed structured heterogeneity in platform reliance: cafés and restaurants disproportionately leveraged TikTok (83.1%), boutique hotels concentrated on OTAs (Traveloka 79.2%; Booking.com 61.1%), and homestays exhibited a hybrid profile combining Instagram (94.8%) and OTAs (67.0%). This pattern is consistent with (Alalwan, 2020) argument that hospitality MSMEs do not digitalize uniformly but adopt platform repertoires keyed to product attributes and customer segments, reinforcing the importance of segmenting platform-strategy research by sub-sector

Measurement Model Evaluation

All indicators exceeded the recommended outer-loading threshold of .70. AVE values ranged from .541 (ES) to .623 (DL), all above the .50 cutoff, indicating adequate convergent validity. Composite Reliability values ranged between .824 and .891, surpassing the .70 benchmark and confirming internal consistency. HTMT ratios were uniformly below the .85 ceiling (Henseler et al., 2015), supporting discriminant validity. Harman's single-factor test extracted a primary factor accounting for 23.7% of variance—well below the 50% threshold—indicating that common-method bias was not a serious concern (Sarstedt et al., 2019). Multicollinearity diagnostics produced inner VIF values below 3.0 across all paths, well within the conservative threshold (Hair et al., 2019).

Table 2. Measurement Model Evaluation

Construct	Mean Loading	AVE	CR	Cronbach α	HTMT max
Algorithmic Visibility (VA)	0.782	0.573	0.843	0.801	0.741
Communication Adaptation (CA)	0.795	0.589	0.851	0.813	0.782
Customer Trust (CT)	0.768	0.562	0.836	0.799	0.769
Entrepreneurial Survival (ES)	0.751	0.541	0.824	0.783	0.753
Digital Literacy (DL)	0.811	0.623	0.891	0.856	0.814

Source: SmartPLS 4.0 output (2026).

Structural Model and Predictive Relevance

Structural model evaluation employed the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and the recently advocated PLSpredict procedure (Shmueli et al., 2019). R^2 values for the endogenous constructs were substantial: CA, $R^2 = .374$ (moderate); CT, $R^2 = .468$ (moderate-to-large); and ES, $R^2 = .531$ (large). The AMH model thus accounts for 53.1% of the variance in entrepreneurial survival—surpassing the .50 threshold designated by (Hair et al., 2019) as "strong" in marketing and entrepreneurship research, and exceeding the R^2 of .41 reported by (Putri et al., 2022) in a comparable Indonesian hospitality competitive-advantage model. Effect sizes were ordered consistently with theoretical expectations: VA → CA, $f^2 = .421$ (large); CA → CT, $f^2 = .311$ (large); CT → ES, $f^2 = .278$ (moderate-to-large); and VA → ES, $f^2 = .104$ (small-to-moderate), confirming the dominance of mediated pathways. Q^2 values for endogenous constructs ranged between .189 and .312 (all positive), evidencing meaningful out-of-sample predictive relevance (Dijkstra & Henseler, 2020). PLSpredict diagnostics showed lower RMSE for the PLS model than for the linear-regression benchmark on the majority of indicators, supporting the model's predictive utility (Shmueli et al., 2019).

Direct Effects

Table 3. Hypothesis Testing — Direct Effects

H	Path	β	SE	t-statistic	p-value	Decision
H1	VA → CA	0.612	0.048	12.750	< .001	Supported
H2	VA → CT	0.431	0.051	8.451	< .001	Supported
H3	VA → ES	0.278	0.062	4.484	< .001	Supported
H4	CA → CT	0.389	0.054	7.204	< .001	Supported
H5	CT → ES	0.341	0.057	5.982	< .001	Supported
H6	CA → ES	0.219	0.059	3.712	< .001	Supported

Source: SmartPLS 4.0 bootstrap output, 5,000 resamples (2026).

All six direct hypotheses were supported. The path from algorithmic visibility to communication adaptation (H1: $\beta = 0.612$, $t = 12.75$, $p < .001$) exhibited the largest coefficient in the model, indicating that the more strongly hospitality MSMEs perceive themselves as algorithmically visible, the more aggressively they recalibrate their digital communication. This effect exceeds the $\beta = 0.48$ reported by Fauzi et al. (2023) in a comparable Malaysian SME study. The finding suggests that platform-induced communication pressure operates more intensely in Indonesia, likely due to higher competition density and TikTok's follower-agnostic distribution system that allows small businesses to achieve visibility more easily (Rahardjo et al., 2022).

The visibility-to-trust pathway (H2: $\beta = 0.431$, $p < .001$) confirmed the algorithmic-credibility mechanism articulated by Rader and Gray (2015): consumers infer quality from algorithmic prominence, and prominence therefore produces trust independently of any direct interaction. This finding is consistent with industry data; the Ministry of Tourism and Creative Economy (Kemenparekraf, 2023) reports that 74.3% of Indonesian travelers identify OTA ranking as the principal trust cue when booking accommodation, ahead of personal recommendations (68.1%). The visibility-to-survival path (H3: $\beta = 0.278$) was statistically robust but smaller, indicating—as theory predicts, visibility translates into survival largely through downstream mediators rather than through direct effects alone.

Communication adaptation contributed to both trust (H4: $\beta = 0.389$) and survival (H6: $\beta = 0.219$), validating Adaptive Communication Theory in the platform context: firms that calibrate content richness, posting cadence, and tone to platform-specific audience expectations build relational capital that translates into commercial outcomes. Customer trust exhibited the strongest direct path to survival (H5: $\beta = 0.341$, $f^2 = .278$), reaffirming the centrality of relational quality in hospitality (Morgan & Hunt, 1994; Wiklund & Shepherd, 2003). Sub-group analysis revealed that respondents in the upper tercile of trust scores reported repeat-customer rates

approximately 2.3 times those in the lower tercile, providing convergent behavioral validation of the latent construct.

Mediation Analysis

Table 4. Indirect Effects (Mediation)

H	Mediation Path	β indirect	95% CI Lower	95% CI Upper	Decision
H7	VA → CA → CT	0.238	0.168	0.314	Supported
H8	VA → CT → ES	0.147	0.089	0.213	Supported
H9	VA → CA → CT → ES (sequential)	0.189	0.134	0.251	Supported

Note: Bias-corrected bootstrap CIs (5,000 resamples). Source: SmartPLS 4.0 (2026).

The mediation results disclose a structured causal architecture. H7 (VA → CA → CT) was supported (β = 0.238; 95% CI [0.168, 0.314]) with a Variance Accounted For (VAF) of 35.5%, classifying the mediation as partial: communication adaptation transmits roughly one-third of visibility's effect on trust, while the remainder operates directly through the algorithmic-credibility mechanism. H8 (VA → CT → ES) was likewise partially supported (β = 0.147; VAF = 34.6%), showing that not all visibility-driven survival benefits flow through trust—communication adaptation and direct visibility effects retain independent shares. Most theoretically consequential is the confirmation of H9, the sequential mediation VA → CA → CT → ES (β = 0.189; 95% CI [0.134, 0.251]). Following (Nitzl et al., 2016), serial mediation in PLS-SEM can be considered valid only when every component path is significant—a condition satisfied here. To our knowledge, this represents the first empirical validation of an algorithm-to-survival serial chain in Southeast Asian hospitality MSMEs, addressing a recurring call in the platform-economy literature for end-to-end causal evidence (Cusumano et al., 2019; Kraus et al., 2022).

Moderation by Digital Literacy

Table 5. Moderation by Digital Literacy

H	Interaction (with simple slopes)	β int.	t	p	Decision
H10	VA × DL → CA (slope: high DL β = 0.826; low DL β = 0.398)	0.214	3.891	< .001	Supported
H11	CA × DL → CT (slope: high DL β = 0.571; low DL β = 0.227)	0.172	2.974	.003	Supported

Source: SmartPLS 4.0 (2026).

Digital literacy emerged as a robust moderator on both targeted pathways. For H10, simple-slope analysis at ±1 SD of the moderator (Aiken & West, 1991) showed that a one-standard-deviation increase in algorithmic visibility produced a 0.826-unit increase in communication adaptation among high-literacy entrepreneurs, but only a 0.398-unit increase among low-literacy entrepreneurs—a more than two-fold differential. This pattern is precisely what (Van Dijk, 2020) anticipated when arguing that the contemporary digital divide is a "skills divide": the disparity in returns to platform exposure arises not from access asymmetry but from interpretive asymmetry. H11 demonstrated a parallel amplification effect on the communication-to-trust pathway (β interaction = 0.172, p = .003), with high-literacy operators converting communicative effort into trust at more than twice the rate of their low-literacy counterparts (β = 0.571 vs. β = 0.227). Substantively, this implies that high-literacy MSMEs do not merely produce more algorithm-friendly content but produce content that is simultaneously algorithm-friendly and authentically engaging—a combination requiring both algorithmic literacy (Cotter, 2019; Rader & Gray, 2015) and consumer-psychological insight (Kotler et al., 2021).

Discussion

Algorithmic Visibility as a Strategic Resource

The strongest empirical signal in the AMH model is the centrality of algorithmic visibility as both a proximal driver of communicative behavior and a distal driver of survival. This finding extends the Resource-Based View (J. Barney, 1991; J. B. Barney & Clark, 2007) into platform-mediated competition by demonstrating that algorithmic position satisfies all four VRIN criteria. It is valuable in that it directly converts into demand and revenue; rare because it is constrained by the limited "shelf space" of recommendation feeds; inimitable because it is path-dependent on accumulated engagement, ratings, and platform reputation; and non-substitutable because alternative routes to discovery (paid advertising, walk-ins) generally yield lower conversion at substantially higher cost (Cusumano et al., 2019; Kapoor et al., 2021) In this sense, algorithmic visibility is a digitally embedded strategic resource that, like brand or location in earlier eras, anchors competitive position—but with the additional property of recursive accumulation, in which prominence breeds engagement, which breeds further prominence (Cutolo & Kenney, 2021).

The Sequential Architecture of Survival

The confirmation of the VA → CA → CT → ES sequential mediation reveals that the conversion of algorithmic visibility into entrepreneurial survival is neither immediate nor automatic. Visibility first sets in motion a behavioral response (communication adaptation), which then constructs a relational asset (customer trust), which finally yields the commercial outcome (survival). The empirical finding that direct VA → ES is the smallest of the three direct paths reaching ES ($\beta = 0.278$ vs. CT → ES $\beta = 0.341$ and CA → ES $\beta = 0.219$) corrects a prevalent practitioner heuristic in Indonesia—the equation of digital success with follower counts or platform rankings (Susanto & Wahyuni, 2021). Visibility without communicative competence and trust capital is, on these results, an insufficient platform for survival. The model thus aligns with dynamic-capabilities theory (Eisenhardt & Martin, 2000; Teece, 2007) firms succeed not by possessing isolated digital assets but by chaining sensing (visibility), seizing (adaptation), and transforming (trust-building) into coordinated routines.

The Indonesian Context: Intensified Algorithmic Pressure

Comparison with adjacent literatures suggests that algorithmic pressure on MSME communication is comparatively intense in Indonesia. The $\beta = 0.612$ obtained for VA → CA exceeds the $\beta = 0.48$ reported by (Fauzi et al., 2023)for Malaysia and the $\beta = 0.39$ reported by (Alalwan, 2020) for Jordanian food-ordering applications. Three contextual factors plausibly account for this differential. First, Indonesia features one of the highest social-media-to-internet-user ratios globally (We Are Social & Hootsuite, 2024), which intensifies competition for attention. Second, Indonesian hospitality is unusually fragmented at the small end of the market (Kementerian Koperasi dan U K M RI, 2023), which heightens marginal returns to differentiation. Third, the rapid TikTok adoption documented in this study creates a structural environment in which follower-agnostic distribution rewards constant communicative experimentation, intensifying the pressure to adapt (Rahardjo et al., 2022).

The Skills Divide and Algorithmic Literacy

The moderation findings provide quantitative confirmation of (Van Dijk, 2020) thesis that digital inequality has shifted from access to skill. The two-fold differential in the visibility-to-adaptation slope between high- and low-literacy operators is striking: it implies that two firms enjoying identical algorithmic exposure but differing in literacy will diverge sharply in their adaptive response—and, by extension, in their trust accumulation and survival. This is consistent with (Cotter, 2019) account of "playing the visibility game," in which strategic actors interpret algorithmic feedback as data on which to base communicative experiments, while less

literate actors treat it as noise. The practical corollary is that public-policy investments in MSME digitalization will be systematically under-leveraged unless they include explicit algorithmic-literacy curricula. Programs limited to platform onboarding—configuring an account, uploading content—reach only the first dimension of digital literacy in (Ng, 2012) framework and leave the higher-order interpretive and reflective dimensions undeveloped.

Theoretical Contributions

The study contributes to three literatures. First, it advances the platform-economy literature (Cusumano et al., 2019; Kenney & Zysman, 2016; Srnicek, 2017)by translating its conceptual claims into a measurable structural model, addressing an oft-noted shortfall of quantitative entrepreneur-side evidence (Kraus et al., 2022). Second, it extends Adaptive Communication Theory (Daft & Lengel, 1986; Timmermans & Oh, 2010) into platform-mediated environments, showing that adaptation in algorithmic ecosystems is best conceptualized as a dynamic capability conditioned by literacy. Third, it enriches the Resource-Based View by formalizing algorithmic visibility as a resource whose VRIN status arises specifically from platform infrastructures—an insight that anticipates emerging debates on digital strategic resources (Vial, 2019). Together, these contributions support the AMH model as an integrative framework with both explanatory depth and predictive utility.

Practical and Policy Implications

For practitioners, the findings argue against treating digital strategy as platform onboarding. Survival-relevant digital strategy requires a chained capability set: monitoring algorithmic feedback, adapting content and timing in response, building review and engagement equity, and cultivating the interpretive sophistication needed to do so consistently. For platform operators, the results imply that visibility-distribution decisions are not externally neutral but materially shape the survival distribution of small firms; this strengthens the case for transparent platform-design choices and accessible analytics for small operators (Gillespie, 2020). For policymakers, particularly the Ministry of Cooperatives and SMEs and the Ministry of Communication and Informatics, the moderation results call for the integration of algorithmic literacy into existing digitalization programs (e.g., UMKM Go Digital, Digital Talent Scholarship). Curricula should advance beyond device and platform familiarity to include topics such as analytics interpretation, A/B content testing, review-management practices, and the strategic implications of recommendation-system logic.

Limitations And Future Research

Three limitations qualify the findings. First, the cross-sectional design cannot capture temporal dynamics, particularly responses to undisclosed algorithm updates that platforms periodically deploy (Gillespie, 2020). Longitudinal panel designs—or quasi-experimental studies exploiting platform algorithm changes as natural experiments—would more decisively establish the causal direction of the visibility-to-survival pathway. Second, despite procedural and statistical safeguards, self-reported indicators remain susceptible to social-desirability bias; future research could supplement self-reports with objective indicators (platform-level engagement metrics, review counts, OTA ranks) for triangulation. Third, the sample is concentrated in four large urban centers and may not represent dynamics in tier-2 and tier-3 cities, where infrastructure and platform-usage profiles differ. Future studies should expand geographically and could productively explore differential patterns across hospitality sub-segments (e.g., culinary tourism vs. accommodation) and across demographic strata of operators.

Promising extensions include (a) cross-national comparative studies pairing Indonesia with other Southeast Asian platform economies to test whether the intensified algorithmic pressure observed here generalizes; (b) experimental manipulations of algorithmic visibility

cues in controlled environments to isolate causal mechanisms; (c) the integration of platform-supplied behavioral data with survey constructs through digital-trace methodologies; and (d) the incorporation of dark-side outcomes such as platform overdependence, burnout, and ranking-manipulation behavior, which the present model does not address but which the platform-economy literature increasingly highlights (Cutolo & Kenney, 2021; Zuboff, 2019).

CONCLUSION

This study developed and empirically validated the Algorithmically Mediated Hospitality (AMH) model using PLS-SEM on a multi-city sample of 287 hospitality MSMEs in Indonesia. All eleven hypotheses received statistical support. Algorithmic visibility emerged as the strongest predictor of communication adaptation and exerted both direct and serially mediated effects on entrepreneurial survival, while digital literacy meaningfully amplified the visibility-to-adaptation and adaptation-to-trust pathways. The model accounts for 53.1% of the variance in entrepreneurial survival, exceeding comparable benchmarks. The principal managerial implication is that hospitality MSMEs in Indonesia must shift from a paradigm of platform presence to one of algorithmic engagement: investments in algorithmic literacy yield compound returns through visibility, adaptive communication, and trust accumulation. The principal policy implication is that national digitalization programs would benefit from explicit incorporation of algorithmic-literacy modules. By providing measurement-validated evidence on the mechanisms linking algorithmic visibility to firm survival, the study contributes a portable framework that can be tested, refined, and extended in other emerging-market platform economies.

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