Shirkah: Journal of Economics and Business
Vol. 11, No. 1 (2026), page 1-19
p-ISSN: 2503-4235 e-ISSN: 2503-4243
Journal homepage: http://shirkah.or.id/new-ojs/index.php/home

Research Paper

From Zero Sales to Survival: Forecast-triggered Decision-making in Ecotourism MSMEs

Singgih Purnomo[a,1*], Nurmalitasari[b,2], Nurchim[b,3], Novemy Triyandari Nugroho[a,4]

[a] Faculty of Law and Business, Universitas Duta Bangsa Surakarta, Indonesia
[b] Faculty of Computer Science, Universitas Duta Bangsa Surakarta, Indonesia
[1] singgih_purnomo@udb.ac.id*, [2] nurmalitasari@udb.ac.id, [3] nurchim@udb.ac.id, [4] novemy@udb.ac.id

*Corresponding author

ARTICLE INFO

Keywords
Ecotourism MSMEs; Sustainability; Two-stage Forecasting; Zero Sales Days

Article history
Received: 02 September 2025
Revised: 24 February 2026
Accepted: 15 March 2026
Available online: 02 April 2026

To cite in APA style
Purnomo, S., Nurmalitasari, Nurchim, & Nugroho, N. T. (2026). From zero sales to survival: Forecast-triggered decision-making in ecotourism MSMEs. *Shirkah: Journal of Economics and Business, 11*(1), 1-19.

ABSTRACT

Ecotourism micro, small, and medium-sized enterprises (MSMEs) often face highly volatile demand characterized by frequent zero-sales days, strong seasonality, and exposure to external shocks. In such conditions, sustainability depends less on forecast accuracy and more on timely, low-cost operational decisions. This study examines how forecast-triggered decision-making supports short-run viability under intermittent, zero-heavy demand. Using manually recorded daily sales data from ecotourism MSMEs in Tawangmangu, Indonesia, a two-stage approach is applied that separates sale occurrence from sales magnitude. First, a logistic model estimates the probability of a sale to generate early-warning signals. Second, conditional sales magnitude is predicted to indicate readiness levels rather than precise revenue targets. Instead of focusing on accuracy alone, the analysis evaluates decision usefulness through time-ordered backtesting, emphasizing avoidable operating days and early-warning lead time. The results show that sale-occurrence signals effectively guide daily operating decisions, while magnitude forecasts support proportional readiness. The framework identifies a substantial share of avoidable operating days and provides several days of advance warning before prolonged zero-sales periods. This enables earlier cost control and capacity adjustment. The study contributes by offering a practical, human-in-the-loop decision framework that links demand uncertainty with adaptive actions using simple, manually recorded data.

Introduction

Ecotourism MSMEs operate under highly volatile demand, as visitation patterns are shaped by seasonality, weather conditions, security issues, shifts in consumer preferences, and macro-level disruptions such as public health crises and economic slowdowns (Hu et al., 2025; Song et al., 2023). Across many destinations, this volatility gives rise to periods of "zero sales days" that are not merely temporary anomalies, but extreme indicators of demand uncertainty with direct consequences for fragile cash flows, weakened operational resilience, and an elevated risk of business discontinuation (Grau-Escolano et al., 2025; Yaşar Dinçer et al., 2024). In this context, the sustainability of ecotourism MSMEs is no longer determined solely by their ability to increase sales, but by the quality of managerial decisions in anticipating demand downturns, prioritizing expenditures, and adjusting operations and marketing before losses accumulate (Díaz-Arancibia et al., 2024; Gan et al., 2024).

Consistent with this condition, entrepreneurship and tourism management literature emphasizes adaptive decision-making capacity as a critical prerequisite for MSME resilience under environmental uncertainty (Sharabati et al., 2024; Yesuf & Fields, 2025). When demand fluctuates unpredictably and episodes of zero sales days emerge without warning, owner-managers must balance the need to preserve liquidity with the imperative to maintain service quality (Gan et al., 2024; Promnil & Polnyotee, 2023). However, in practice, such decisions are often reactive rather than anticipatory, as MSMEs typically rely on limited analytical support and delayed responses to demand changes. This condition increases the risk that temporary downturns escalate into prolonged zero-sales periods, intensifying financial pressure and weakening operational resilience. Adaptive responses typically manifest through cost control, capacity adjustments, labor scheduling, and tighter inventory management, accompanied by the reconfiguration of market approaches through digital channels, flexible service packages, segment diversification, and strengthened collaborative networks (Gan et al., 2024; Zuñiga-Collazos et al., 2025). Conceptually, this process unfolds from the recognition of early signals of change (anticipation), to immediate responses aimed at mitigating the impact of declining demand (coping), and ultimately to more structural adaptation through resource reconfiguration and strategic reorientation that enables firms to survive and recover under new conditions (Eichholz et al., 2024; Zhang et al., 2023). These conditions highlight the urgency of developing simple, timely, and actionable mechanisms that allow MSMEs to detect demand weakening earlier and respond before zero-sales periods escalate into more severe threats to business sustainability.

Despite growing attention to adaptive decision-making in tourism MSMEs, much of the existing literature remains focused on post-event strategies, digital technology adoption, or performance evaluation after crises (Promnil & Polnyotee, 2023; Zuñiga-Collazos et al., 2025). While these studies provide valuable insights, they offer limited explanation of how daily operational signals can be systematically translated into timely and actionable decisions under zero-heavy demand conditions. In particular, the absence of a clear and measurable mechanism linking forecasting signals to concrete managerial actions leaves a gap between predictive insights and practical decision-making in resource-constrained MSMEs. This gap is particularly consequential for ecotourism MSMEs, which commonly exhibit zero-heavy sales patterns, characterized by frequent days without transactions interspersed with sharp seasonal peaks and strong exposure to external factors such as weather, holiday calendars, and security conditions (Hu et al., 2025). In such settings, MSME actors require more than sales forecasts; they need practical decision triggers that indicate when demand is weakening, when risk is escalating, and which actions should be activated promptly. In the absence of clear triggers, adjustments are often made too late, allowing periods of zero sales days to evolve from temporary fluctuations into serious threats to business sustainability (Cross et al., 2023).

Existing studies on tourism MSMEs have primarily emphasized three interrelated themes. First, a substantial body of work highlights adaptive decision-making and resilience strategies, focusing on how firms respond to crises through cost control, operational adjustments, and market reconfiguration (Gan et al., 2024; Promnil & Polnyotee, 2023; Zuñiga-Collazos et al., 2025). Second, prior research has examined the role of dynamic capabilities, particularly sensing, seizing, and reconfiguring processes, in enabling firms to cope with environmental uncertainty and sustain performance (Eichholz et al., 2024; Zhang et al., 2023). Third, studies on tourism demand have documented the presence of volatility, seasonality, and external shocks, which shape fluctuating consumption patterns and business instability (Hu et al., 2025; Song et al., 2023). While these strands provide important insights into how MSMEs respond and why uncertainty matters, they remain largely descriptive or retrospective, offering limited explanation of how real-time operational signals can be translated into concrete, anticipatory decisions under zero-heavy demand conditions. This limitation underscores the need for a mechanism-based approach that links daily sales signals with actionable decision triggers.

Against this backdrop, the present study seeks to explain how owner-managers of ecotourism MSMEs construct and employ forecast-triggered decision-making to remain viable under demand uncertainty. Specifically, the study addresses three research questions: (1) which signals are monitored by MSME actors to detect demand weakening, (2) how these signals are translated into concrete decision triggers, and (3) which managerial decisions are activated during zero-sales periods to safeguard cash flow while maintaining service quality. The analysis is grounded in perspectives on entrepreneurial decision-making under uncertainty and micro-level dynamic capabilities, with particular attention to the processes of sensing, seizing, and reconfiguring in contexts of constrained resources.

This study draws on daily sales records manually compiled by ecotourism MSMEs as the primary data source to capture the demand dynamics actually faced by owner-managers. Given the zero-heavy nature of the data, a two-stage forecasting approach is applied to generate practice-oriented signals, namely the probability of a sale occurring and the expected revenue conditional on a sale (Damato et al., 2025; Sfiris & Koulouriotis, 2025). These signals are subsequently translated into decision triggers that reflect concrete managerial actions, including adjustments to operating hours, expenditure controls, modifications to service packages, and the intensification of digital promotion. The conceptual novelty of this study lies in its articulation of a micro-level mechanism that links simple, manually recorded sales-based forecasting signals with adaptive decision triggers under demand uncertainty, an area that has rarely been addressed explicitly. Accordingly, this study contributes in three ways. First, it clarifies adaptive decision-making processes in ecotourism MSMEs by linking sensing, seizing, and reconfiguring activities to observable operational signals. Second, it demonstrates the empirical use of zero-heavy manual data to generate actionable forecasting signals. Third, it provides a practical decision-trigger framework that enables MSMEs to act earlier, reduce avoidable operating days, and adjust operational capacity in response to demand uncertainty.

Literature Review

Demand Uncertainty and Sustainability Vulnerability in Ecotourism MSMEs

Ecotourism MSMEs face structurally volatile demand driven by seasonality, weather sensitivity, holiday timing, safety perceptions, and macro-shocks. This condition can be understood within the tourism demand uncertainty literature, where fluctuations in visitor flows create instability in revenue generation and business continuity (Hu et al., 2025). Policy evidence emphasizes that limited anticipatory capacity can amplify disruptions and weaken competitiveness (Hu et al., 2025). Peer-reviewed tourism research also shows that demand volatility and seasonality are associated with higher exit risk and financial fragility, indicating that uncertainty is not only a marketing issue but a survival constraint (Zhang & Xie, 2021). At the micro-firm level, constrained slack resources and dependence on daily cash inflows make shocks disproportionately damaging to liquidity, consistent with financial vulnerability perspectives in small business research. Evidence from tourism firms during COVID-19 highlights the central role of cash buffers and financial slack in resilience capacity (Wieczorek-Kosmala, 2022). In this study, zero sales days denote days with no transactions and zero revenue and are conceptualized as recurring liquidity stress signals, reflecting short-term financial strain that can accumulate and threaten operational continuity under persistent demand uncertainty.

Adaptive Decision-making and Dynamic Capabilities in Tourism MSMEs

Tourism MSME resilience depends on adaptive managerial decisions that interpret weak signals, prioritize responses, and manage trade-offs between cost control and service reliability. This adaptive capacity can be understood through the lens of dynamic capabilities, which refer to a firm's ability to sense environmental changes, seize opportunities through timely decisions, and reconfigure resources to maintain competitiveness under changing conditions (Rashed et al., 2025; Yesuf & Fields, 2025). In tourism MSMEs, these capabilities are enacted through practical and iterative actions such as monitoring demand signals, adjusting operating hours, reallocating labor, controlling variable costs, and modifying service offerings in response to fluctuating demand. Recent tourism evidence strengthens this lens by linking dynamic capabilities to staged crisis responses and organizational resilience under disruption and by operationalizing dynamic capabilities and their micro foundations (e.g., learning, environmental dynamism, digital marketing) as predictors of competitive outcomes (Prayag et al., 2023). However, resilience work in tourism MSMEs often remains strategy-descriptive: it documents coping and recovery practices but provides fewer accounts of how daily operational signals are converted into disciplined, repeatable decisions when analytics capacity is minimal. A recent synthesis also notes that MSME resilience is multi-dimensional and context-dependent, reinforcing the need to specify mechanisms that are measurable and operational at the micro level (Badoc-Gonzales et al., 2022).

Forecasting Zero-heavy (Intermittent) Sales and Managerial Signals

Daily sales records in ecotourism MSMEs commonly exhibit intermittent demand: long runs of zeros punctuated by spikes. Forecasting research demonstrates that conventional methods can be biased because the process generating zeros may differ from the process governing positive outcomes (Giannopoulos et al., 2025; Sarlo et al., 2023). Intermittent-demand approaches explicitly separate occurrence from magnitude, starting from Croston-type decompositions and subsequent refinements and show that performance can be sensitive to long zero periods and parameter choices (Sfiris & Koulouriotis, 2025; Svetunkov & Boylan, 2023). Importantly, the cross-domain transfer here is methodological rather than contextual: the justification rests on process equivalence (excess zeros and distinct occurrence magnitude dynamics), not on inventory-specific assumptions. Consequently, evaluation should emphasize decision utility (e.g., timely detection of low-sale risk and avoidance of costly overreaction) in addition to point accuracy.

From Forecast to Action: Decision Triggers and Anticipatory Action

A persistent gap concerns translating forecasts into threshold-based decision triggers that activate timely, low-cost responses. Forecast-based and anticipatory action research argues that predictive value emerges when signals are linked to predefined thresholds, action protocols, and governance that manages false alarms and missed detections (Mwangi et al., 2022). For MSMEs, this implies triggers that are computable from manual records, interpretable to owners, and suitable for human oversight. Operations research on human oversight similarly distinguishes monitoring and response modes and highlights the role of warning thresholds in enabling effective intervention (Salgado-Criado, 2025). Conceptually, decision triggers operationalize the bridge from *sensing* to *seizing*, enabling actions such as operating-hour adjustments, variable-cost tightening, targeted digital promotion, or service re-bundling.

Research Gap and Novelty

Prior research establishes: (1) tourism MSME resilience as capability-driven and context-sensitive (Prayag et al., 2023; Rastegar et al., 2025), (2) robust intermittent-demand tools for zero-heavy series (Sarlo et al., 2023; Svetunkov & Boylan, 2023), and (3) trigger-based action principles that connect forecasts to timely interventions (Badoc-Gonzales et al., 2022). However, these studies do not clearly explain how daily zero-heavy sales signals are systematically converted into consistent and actionable operational decisions in ecotourism MSMEs. To address this gap, this study develops a forecast-triggered decision-making mechanism that integrates: (1) an occurrence–magnitude signal structure, (2) dynamic capabilities as the process explanation, and (3) implementable threshold-based decision rules under resource constraints.

Proposition Development

Under zero-heavy demand conditions, the sustainability of ecotourism MSMEs is best understood in terms of short-run viability rather than sales growth alone. In tourism businesses, where daily cash inflows often matter more than long-range revenue projections, even a brief sequence of zero-sales days can put pressure on routine operations. Wieczorek-Kosmala (2022) makes this point clearly in discussing cash-based resilience, while Yesuf et al. (2025) place managerial judgment at the center of tourism resilience under uncertainty. The present study follows the same logic. Here, the main issue is not whether a forecast is statistically refined in the abstract, but whether it helps owner-managers respond early, contain exposure, and preserve operational continuity.

Proposition 1: In ecotourism MSMEs facing zero-heavy demand, the value of forecasting lies primarily in supporting short-run viability through disciplined operational decisions rather than in improving forecast accuracy alone.

This perspective also fits the dynamic capabilities view. The manuscript treats adaptation as a practical sequence of noticing change, choosing a response, and adjusting operations. That reading is consistent with Badoc-Gonzales et al. (2022) and Prayag et al. (2023), who frame resilience in tourism as capability-based and context-sensitive. In the present case, the sequence is concrete. Sale-occurrence probability acts as an early signal. The choice between lean and ready modes reflects managerial commitment. Changes in staffing, opening hours, procurement, and promotion then become the operational expression of that choice. As Yesuf et al. (2025) suggest, the crucial issue is not information alone, but whether the firm can turn information into a workable response.

Proposition 2: Sale-occurrence probability functions as the primary trigger for operating-mode adaptation, whereas conditional sales magnitude functions as readiness-intensity guidance.

A second point concerns the structure of intermittent demand itself. The manuscript rightly distinguishes between two related but different questions: whether a sale occurs, and how much is sold if it does. That distinction is well established in the forecasting literature. Sarlo et al. (2023) and Svetunkov and Boylan (2023) both show that occurrence and magnitude should not be treated as if they arise from the same process, especially in series dominated by zeros. The same line of reasoning appears in Wang et al. (2024), where the practical usefulness of forecasting depends on how closely the model reflects the structure of the demand process. A single output may be simpler, but it is often less informative. For a small firm making day-to-day operating decisions, that loss of clarity matters.

Proposition 3: A two-stage forecasting structure is more suitable than a single-regime approach for generating managerially useful signals under intermittent, zero-heavy demand.

The practical contribution of the study lies not only in signal generation, but in how those signals are linked to action. This is an important distinction. Predictive information has limited value if it remains detached from concrete decisions. Mwangi et al. (2022) argue that forecasts become useful when tied to predefined responses, and a similar view appears in Schäfers et al. (2024) and Wissuchek and Zschech (2025), both of whom emphasize the managerial value of decision-oriented analytical systems. The manuscript translates that logic into modest but realistic actions: tightening purchases of perishable inputs, shortening opening hours, relying on core staffing, and using selective promotion. These are not dramatic interventions. They are small operational adjustments, which is precisely why they are plausible in MSME settings. Their value is captured here through the identification of avoidable operating days.

Proposition 4: The practical usefulness of forecast-triggered decision-making can be assessed through its capacity to identify avoidable operating days under elevated zero-sales risk.

Timing, however, is just as important as classification. A useful signal is not simply one that identifies a likely no-sale period; it is one that does so early enough for action to remain feasible. Rather than treating timing as a technical side result, it presents lead time

as part of managerial usefulness itself. That emphasis is in line with Schäfers et al. (2024), who connect prediction to decision timing, and with Wissuchek and Zschech (2025), who show that the value of prescriptive systems often depends on when intervention becomes possible. In the present study, a lead time of several days gives owner-managers room to revise schedules, moderate operating hours, adjust procurement, and protect cash flow before losses accumulate. For resource-constrained firms, that window matters.
Proposition 5: The managerial value of forecast-triggered decision-making is reflected in its ability to provide actionable lead time before prolonged zero-sales episodes.

Method

Research Design and Study Context

This study uses a two-stage forecasting framework to examine how zero-heavy sales patterns can inform adaptive operating decisions in ecotourism MSMEs. Rather than treating forecasting as an end in itself, the analysis focuses on how forecast signals can support everyday operational judgment under conditions of demand uncertainty. Stage 1 produces sale-occurrence signals that inform daily operating-mode choices. Stage 2 then estimates conditional sales magnitude, offering a practical indication of how much readiness may be needed when sales are likely to occur. The usefulness of these outputs is assessed through time-ordered backtesting, with particular attention to avoidable operating days and early-warning lead time before prolonged zero-sales episodes.

Given the limited analytics capacity of ecotourism MSMEs, this study maps managerial decisions into simple, auditable trigger rules that can be computed from manually compiled daily sales records. Accordingly, forecasts are evaluated not only for predictive performance but also for their decision utility in activating feasible operational actions when zero-sales risk rises. Therefore, this study adopts a quantitative explanatory design with a mechanism-focused approach, in which observable sales signals are linked to decision triggers and resulting managerial actions within a structured analytical framework. This design allows the study to examine how MSME actors translate volatile daily sales patterns into forecast-triggered operational decisions under resource constraints.

The empirical setting is ecotourism MSMEs in the Tawangmangu ecotourism area, Karanganyar Regency, Indonesia, where demand closely follows tourism flows and is highly sensitive to seasonality, weekends and public holidays, weather, and access disruptions. These conditions generate zero-heavy sales patterns that heighten liquidity risk and increase the value of timely operational adjustments. Because ecotourism MSMEs face variable costs that respond quickly to demand fluctuations, such as perishables, daily labor, and utilities, trigger-based decisions are particularly relevant for balancing operational readiness and cost control. Findings are therefore most applicable to similar micro and small tourism-oriented businesses relying on manual records, while generalization to stable-demand settings or data-rich firms should be undertaken with caution.

Data, Sample, and Data Collection Procedures

The primary data consist of daily sales records (daily revenue values) compiled by MSME owner-managers using manual logs/spreadsheets or simple point-of-sale exports when available. The dataset comprises daily sales records collected from multiple ecotourism MSMEs operating within the Tawangmangu area, where each firm contributes a continuous sequence of observations over the study period. In total, the dataset includes 182 firm-day observations, representing a continuous daily time series rather than aggregated data. The observation period spans several consecutive months, allowing the identification of demand fluctuations, including zero-sales episodes and seasonal variations. The unit of analysis is the firm-day, meaning each observation reflects one MSME's daily sales condition as the basis for operational decision-making. Firms were selected purposively using three criteria: (1) availability of daily sales records with consistent dates, (2) sufficient time span to support time-ordered out-of-sample evaluation, and (3) adequate daily variation to test trigger activation under volatile demand. Data quality procedures included checking date continuity, resolving format inconsistencies, screening for duplicated entries, and flagging extreme values potentially caused by recording errors. MSME identities were anonymized and the dataset was used solely for academic purposes.

Data Analysis and Model Development

The analysis was designed to reflect the temporal reality of managerial decision-making: past information is used to guide decisions today. To enhance transparency, the analytical procedure follows three main components: (1) diagnosing demand characteristics and identifying zero-heavy patterns, (2) implementing a two-stage forecasting approach that estimates sale occurrence probability and conditional sales magnitude using time-ordered validation, and (3) translating these outputs into threshold-based decision triggers that are evaluated through time-ordered backtesting. This structured workflow ensures that forecasting outputs are consistently linked to decision-oriented evaluation.

Data Diagnostics and Demand Characterization

The study first characterizes the prevalence of zero-sales days, the length of zero runs, and revenue volatility on positive-sale days. This step confirms the intermittent and zero-heavy demand structure and motivates a forecasting architecture that separates transaction occurrence from sales magnitude.

Two-stage Forecasting for Zero-heavy Daily Sales

A two-stage forecasting architecture is implemented to distinguish the "sale occurs" process from the "how much is sold" process. Stage 1 (occurrence): transaction occurrence probability is estimated using logistic regression. Model development uses time-based validation (forward chaining/time-series cross-validation) to prevent leakage and to replicate real operational forecasting conditions (train on earlier periods, test on subsequent periods) (Dinamarca et al., 2025; Öztürk & Yiğit, 2025). Performance is assessed with metrics appropriate for imbalanced outcomes, with Average Precision as the primary criterion. Candidate pipelines may be combined through probability ensembling, and a decision threshold is selected via threshold tuning to balance false alarms and missed detections. Stage 2 (magnitude): conditional sales magnitude is predicted only for days with sufficiently high occurrence likelihood. To capture sequential dynamics in daily sales, the study applies a Deep INAR model (Popović et al., 2025) with GRU (Yang et al., 2025), using sequential windows and time-ordered validation. Overfitting is controlled through early stopping and consistent training procedures aligned with time-series data properties.

Translating Signals into Decision Triggers and Evaluating Managerial Utility

The two forecasting outputs are treated as decision-oriented signals: (1) sale occurrence probability and (2) expected sales conditional on a sale. These signals are translated into threshold-based decision triggers (Song, 2025) that activate operational actions feasible for ecotourism MSMEs (Promnil & Polnyotee, 2023), such as adjusting opening hours, tightening perishable-input purchases and other variable costs, rescheduling labor, modifying product/service bundles, and intensifying targeted digital promotion. Evaluation goes beyond forecast accuracy to assess decision utility through time-ordered backtesting, focusing on (1) timeliness of warnings, (2) stability of triggering behavior (false alarms vs late detections), and (3) implications for short-run viability proxies such as reducing avoidable operating days and improving capacity alignment under intermittent demand conditions.

Results

Demand Structure and the Empirical Footprint of Zero Sales Days

As the data presented in Table 1, we analysed 182 daily observations of sales from ecotourism MSMEs operating in the Tawangmangu ecotourism area (Karanganyar, Indonesia). The series is strongly zero-heavy: 99 days recorded zero transactions and zero revenue (54.4%), while 83 days recorded positive sales (45.6%). Conditional on having sales, revenue is highly right-skewed, with a median of IDR 160,000, a mean of IDR 366,314, and a maximum of IDR 4,350,000. Importantly, *zero sales* days are not randomly dispersed; they cluster into episodes, with the longest zero-run reaching 15 consecutive days. This pattern supports the research's central premise: in tourism-facing microbusinesses, "zero sales days" is not a temporary anomaly but a recurring liquidity stress signal that can rapidly erode cash buffers and weaken operational continuity. Figure 1 visualises the dominance of zero-sales days and the long tail of positive sales. Figure 2 shows the time-series pattern, including prolonged zero stretches and sharp spikes that are typical for tourism-linked demand.

Table 1. Descriptive Statistics (Sales in IDR)

Metric	Value
Observations (days)	182
Zero-sales days (count)	99
Zero-sales days (%)	54.40
Positive-sales days (count)	83
Mean sales (positive days)	366314
Median sales (positive days)	160000
Max sales	4350000
Max zero-run length (days)	15

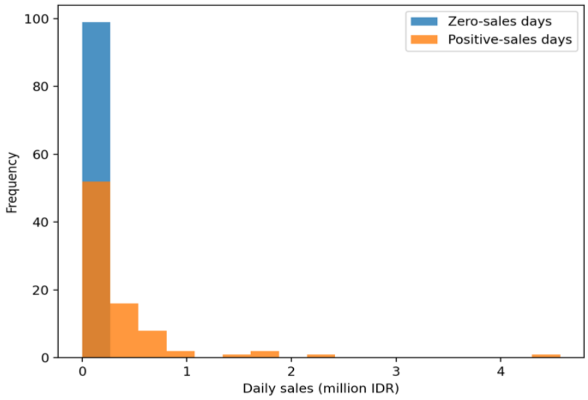

Figure 1. Distribution of daily sales (zero-heavy demand and a long positive tail)

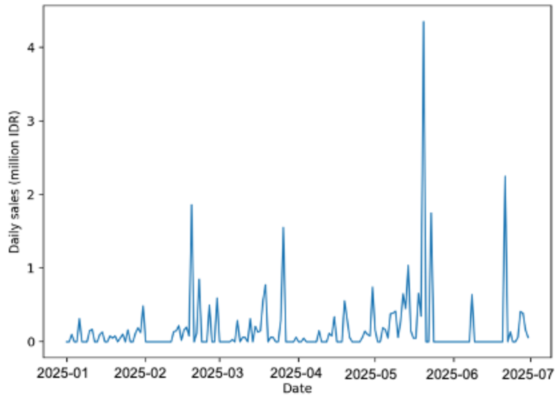

Figure 2. Daily sales time series (clusters of zero sales days and intermittent spikes)

Stage 1 (Occurrence): Forecasting the Probability of a Sale

Stage 1 estimates the daily probability of sale occurrence using a logistic model with time-ordered validation to preserve temporal realism and operational relevance. Given the zero-heavy structure of the series, model assessment prioritizes discrimination and early-warning utility rather than accuracy metrics that are sensitive to class imbalance. As reported in Table 2 (aligned sample, n = 132), the occurrence model attains an AUC of 0.736, indicating moderate yet practically meaningful discrimination for ranking days by sales likelihood under highly intermittent demand. To translate probabilistic outputs into an actionable decision rule, the trigger threshold was tuned to τ = 0.40. At this threshold, the model achieves a Recall of 0.898 and an F1-score of 0.707, indicating that most positive-sale days are correctly identified, with a balanced trade-off between precision and recall. From an operational perspective, higher recall implies that fewer potential sales days are missed, while the chosen threshold reflects a sensitivity-oriented configuration suitable for monitoring demand fluctuations under zero-heavy conditions. In practice, the threshold (τ = 0.40) functions as a trigger for activating operational responses when the predicted probability exceeds this value. Taken together, these results support Proposition 2 by showing that sale-occurrence probability functions as the primary trigger for daily operating-mode adaptation under zero-heavy demand.

Table 2. Stage 1 Performance (Occurrence) and Tuned Trigger (Aligned Sample, n = 132)

Metric	**Value**
AUC	0.736
Tuned threshold (τ)	0.40
Recall	0.898
F1-score	0.707

Stage 2 (Magnitude): Deep INAR–GRU for Conditional Sales Intensity

Stage 2 model sales magnitude conditional on a sale occurring, using a Deep INAR–GRU architecture (see Table 3). Consistent with the INAR requirement for integer-valued processes, positive daily revenue is operationalised in IDR 10,000 units (rounded). The

INAR component captures persistence in the series, while the GRU learns the innovation component that reflects volatility and contextual shifts. The estimated persistence parameter is $\alpha = 0.457$, suggesting moderate carryover from previous positive-sales days, but with a substantial innovation share, consistent with tourism demand that is heavily exposed to external conditions not recorded in manual logs. On the time-ordered validation slice for positive-sales days, Stage 2 yields MAE = 0.597 million IDR and RMSE = 0.803 million IDR. These results indicate the level of deviation between predicted and actual sales values under zero-heavy conditions. The magnitude forecasts are therefore reported as conditional estimates of sales intensity rather than exact point predictions. This pattern also supports Proposition 2 by indicating that conditional sales magnitude is more useful as readiness-intensity guidance than as a precise point-revenue target.

Table 3. Stage 2 (Deep INAR–GRU) Performance on Positive-sales Days

Component	**Value**
Unit scaling	IDR 10000 (rounded)
INAR persistence (α)	0.457
Positive-sales days in aligned sample	59
Effective validation points (time-ordered)	8
MAE (million IDR)	0.597
RMSE (million IDR)	0.803

End-to-end Comparison: Point Accuracy Versus Decision Usefulness

To avoid overstating predictive performance, we compare the two-stage, decision-calibrated signal with a simpler single-regime baseline on the tail holdout (n = 27). The results show (see Table 4) a meaningful trade-off: the two-stage approach reduces average absolute error but increases squared error due to sensitivity to spikes. Accordingly, these end-to-end results support Proposition 3 and reinforce Proposition 1 by showing that the two-stage structure is more suitable for generating managerially useful signals, even when its value lies more in decision utility than in point-forecast optimization alone.

Table 4. Point Accuracy Versus Decision Usefulness

	MAE (Million)	**RMSE (Million)**
Single-regime baseline	0.193	0.266
Two-stage decision-calibrated signal	0.136	0.431

The two-stage design is not framed as “the most accurate sales predictor,” but as a mechanism to separate sale occurrence from magnitude and to generate triggerable signals that support low-cost operational adaptation under uncertainty. Figure 3 illustrates the tail-holdout trajectories, showing how the decision-calibrated signal tracks near-zero periods differently from the baseline.

In the tail holdout (n = 27), the two-stage signal produces a lower MAE (0.136 million IDR) compared to the single-regime baseline (0.193 million IDR) (see Table 5), indicating smaller average absolute deviations. However, the RMSE is higher for the two-stage approach (0.431 million IDR vs 0.266 million IDR), reflecting greater sensitivity to extreme values. These results show differing error characteristics between the two approaches when applied to zero-heavy demand data.

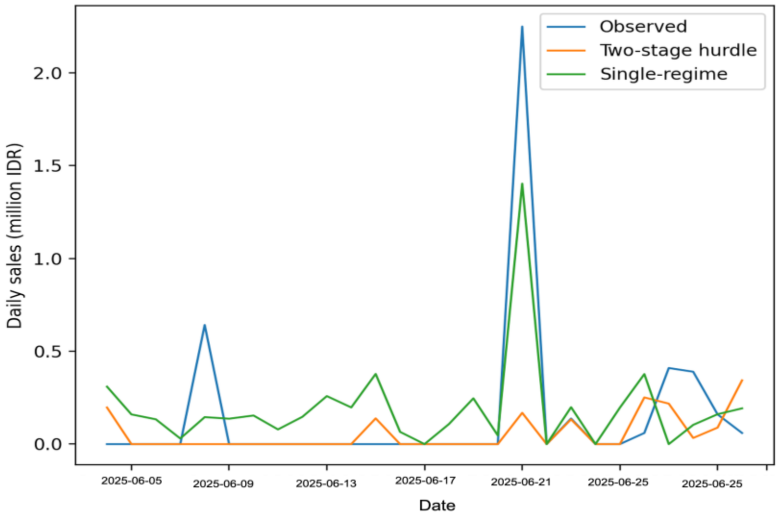

Figure 3. End-to-end Comparison on Tail Holdout (Actual Vs Baseline Vs Two-Stage Signal)

Table 5. End-to-end Performance on Tail Holdout (n = 27)

Approach	MAE (million IDR)	RMSE (million IDR)
Single-regime (linear baseline)	0.193	0.266
Two-stage (decision-calibrated signal)	0.136	0.431

Decision-trigger Outcomes: From Forecast Signals to Survival-oriented Actions

This section evaluates whether the trigger is useful for the research's stated goal, enabling survival strategies through early, disciplined, low-cost decisions.

Avoidable Operating Days as A Practical Sustainability Proxy 1

In the tail holdout, the trigger correctly identifies 17 days as "no-sale risk" (TN = 17), which represents 62.96% of the holdout window (17/27) (see Table 6). These are days where a "lean mode" recommendation is defensible: minimise perishable input purchases, operate with a core workforce, shorten opening hours, and apply targeted but low-cost promotion. While the dataset does not include cost information, the proxy is meaningful because it identifies where *zero sales days is likely*, enabling managers to reduce avoidable exposure. These results indicate that a substantial proportion of days in the holdout period are classified as no-sale risk, based on the applied trigger, supporting proposition 4.

Table 6. Avoidable operating days proxy (tail holdout)

Indicator	Value
Tail holdout length (days)	27
TN (lean-mode candidate days)	17
Share of tail holdout (%)	62.96

Early-warning Lead Time before Long Zero-sales Episodes

As presented in Table 7, we further assess the trigger's practical value by examining whether it offers usable lead time ahead of prolonged zero-sales periods (zero-run ≥ 5 days). In the aligned segment, we identify four long zero-run episodes and evaluate the trigger within a 7-day window prior to the start of each episode. The results show that the trigger provides 4–7 days of advance signals prior to the onset of each zero-run episode. This lead time is reported as the interval between the first trigger activation and the beginning of a prolonged zero-sales period. This evidence supports Proposition 5 by demonstrating that the managerial value of the trigger system also lies in its ability to provide actionable lead time before prolonged zero-sales episodes.

Table 7. Trigger Lead Time before Long Zero-run Episodes (7-day Lookback)

Episode Start	Episode End	Zero-run Length (Days)	Trigger lead Time (Days)
2025-03-01	2025-03-05	5	7
2025-04-04	2025-04-08	5	4
2025-05-24	2025-06-07	15	7
2025-06-09	2025-06-20	12	7

What the Trigger Enables and What it Cannot Guarantee

The results indicate that the trigger distinguishes between periods of higher and lower sales likelihood, with corresponding differences in operational conditions. When the trigger is not activated, the observed periods are associated with higher zero-sales incidence, while activated periods correspond to a higher likelihood of sales occurrence. The Stage 2 output provides variation in predicted sales intensity across positive-sale conditions.

We further evaluate the trigger's managerial usefulness by assessing whether it provides actionable notice before prolonged zero-sales periods (zero-run ≥ 5 days). In the aligned segment, we identify four instances of extended zero sales days and assess the signal using a 7-day lookback window prior to the start of each period. The results show that the trigger consistently provides 4 to 7 days of advance lead time across all instances. For microbusiness owner-managers, this horizon is operationally meaningful because it creates a realistic window to implement low-cost adjustments, such as tightening procurement, revising staff schedules, reducing operating hours, and reallocating promotional effort, before cash-flow pressure accumulates and reactive decisions become unavoidable. Overall, the results support the proposition-driven logic of the study by showing how forecast signals can be translated into simple, auditable, and survival-oriented operating decisions under demand uncertainty.

Discussion

This study demonstrates that under zero-heavy demand conditions, the value of forecasting lies not primarily in improving numerical accuracy but in enabling structured, timely operational decisions. The findings show that separating sale occurrence from sales magnitude produces signals that are functionally distinct and directly applicable to decision-making. In this context, forecasting serves as a mechanism for organizing managerial responses to demand uncertainty rather than as an end in itself. This shifts the analytical focus from predictive performance toward decision usefulness in supporting short-run viability.

The first substantive finding is that sustainability in tourism-oriented microbusinesses is shaped less by sales growth alone than by short-run viability. This matters because much of the tourism MSME literature, including Ramos Jesus et al. (2026) and Yulianto et al. (2025), links sustainability to volatility, seasonality, and external shocks, yet gives less attention to the operational reasoning that must come before managerial action. The present study addresses that gap by treating zero sales days not as an incidental fluctuation, but as a recurring sign of liquidity pressure. That interpretation is also in line with Wieczorek-Kosmala (2022), who emphasizes cash-based resilience in tourism firms, and with Yesuf et al. (2025), who place managerial judgment at the center of organizational response under uncertainty. What emerges here, then, is not simply a better forecast. It is a more useful basis for action. In this setting, the crucial question is not merely whether the forecast is accurate, but whether the signal arrives early enough and clearly enough to support restraint, adjustment, and continuity. That is the empirical significance of Proposition 1.

The second finding speaks directly to Proposition 2. The findings can be interpreted through the lens of dynamic capabilities by clarifying how sensing, seizing, and reconfiguring are enacted at the operational level. Sale-occurrence probability functions as a sensing mechanism by providing early signals of demand conditions. The choice between lean and ready operating modes reflects seizing, where managers commit to a course of action based on these signals. Subsequent adjustments in staffing, procurement, operating hours, and promotion represent reconfiguring, through which resources are realigned to match anticipated demand conditions. That logic is already embedded in the study's two-stage design, where sale occurrence and expected revenue conditional on sale are generated as separate signals for practical decision-making. Scientifically, this also explains why imperfect magnitude estimates may still be useful. Even when exact revenue values remain noisy, the signal can still guide proportionate preparation. The contribution, therefore, lies not in claiming that every forecast output is equally reliable, but in showing which output answers which managerial question.

The third finding supports the suitability of a two-stage structure by showing that occurrence and magnitude signals address different managerial questions and should therefore be treated separately in decision-making (Proposition 3). The reason is both conceptual and empirical. As the study notes, and as Sarlo et al. (2023) also argue, the process that determines whether a sale occurs is different from the process that determines how much is sold once it occurs. When these two processes are collapsed into a single model, the resulting forecast becomes harder to interpret operationally because it compresses distinct forms of uncertainty into one number. The present results are consistent with Wang et al. (2024), who emphasize decision-oriented forecasting under intermittent demand, but they also extend that line of work by showing what such separation means in a tourism MSME setting that relies on manually recorded daily data. In other words, the study does more than suggest that two-stage forecasting is statistically sensible. It shows why it is managerially clearer.

The fourth finding concerns avoidable operating days, which directly supports Proposition 4. At this point, the study moves beyond forecasting in the narrow sense and asks whether predictive signals can be converted into workable decision triggers. That shift is important. It also aligns closely with Schäfers et al. (2024) and Wissuchek and Zschech (2025), both of whom argue that predictive outputs become valuable only when linked to explicit action protocols. In the present study, those protocols take a modest but practical form: tightening purchases of perishable inputs, shortening operating hours, relying on core staffing, and using targeted promotion rather than fully committing resources under weak demand. The scientific interpretation is straightforward. When the sale-occurrence signal falls below the chosen threshold, continued full-intensity operation is no longer neutral; it becomes a form of avoidable exposure. That is why the identification of lean-mode candidate days is analytically meaningful. It shows that the forecasting system can strengthen cost discipline under uncertainty, rather than merely produce descriptive classification.

The fifth finding supports Proposition 5 indicating that lead time is a key dimension of decision usefulness, as earlier signals expand the feasible window for operational adjustment under resource constraints. A useful signal is not only one that identifies likely no-sale periods; it is one that does so early enough for action to remain feasible. The manuscript reports that the trigger provides several days of advance notice before prolonged zero-sales runs, creating time to revise schedules, moderate procurement, adjust operating hours, and reduce cost commitments before liquidity pressure intensifies. This result is consistent with anticipatory-action research. As Schäfers et al. (2024) argue, predictive information matters when it changes the timing of intervention, and Wissuchek and Zschech (2025) make a similar point in the prescriptive-analytics literature. Yet the present study differs from much of that work in one important respect. It shows that useful anticipatory action in MSMEs does not depend on sophisticated infrastructure. What it requires, rather, is a simple and auditable trigger system built around signals that owner-managers can monitor and use.

This study contributes to the literature by repositioning forecasting in zero-heavy demand environments as a decision-support mechanism rather than a purely predictive tool. It extends dynamic capabilities theory by demonstrating how sensing, seizing, and reconfiguring processes can be operationalized through simple, data-driven signals in resource-constrained MSMEs. Specifically, sale-occurrence probability functions as a sensing mechanism, operating-mode selection reflects seizing, and adjustments in staffing, procurement, and service delivery represent reconfiguring. In addition, the study advances intermittent-demand research by linking occurrence–magnitude forecasting structures with threshold-based decision triggers, thereby bridging the gap between predictive modelling and managerial action. This provides a measurable micro-level mechanism through which demand uncertainty is translated into structured and repeatable operational decisions.

For practitioners, the findings translate into a set of actionable guidelines for managing demand uncertainty. First, MSME owner-managers should separate two key decisions: whether a sales day is likely (based on occurrence signals) and how much operational readiness is needed (based on magnitude signals). Second, the occurrence signal can be used to trigger operating modes: a lean mode under high zero-sales risk (e.g., reduce perishable inputs, limit staffing, shorten operating hours) and a ready mode when sales are likely (e.g., maintain core inventory, deploy essential staff, apply targeted promotion). Third, responses should remain low-cost, flexible, and reversible to manage forecast uncertainty and avoid overcommitment. Finally, early-warning lead time should be actively used to adjust procurement, scheduling, and cost exposure before zero-sales periods occur.

For policymakers and support institutions, the implication is to prioritize simple data-recording practices and decision templates rather than complex analytics systems, enabling MSMEs to implement trigger-based management within existing resource constraints.

Conclusion

This study shows that under zero-heavy and highly volatile demand conditions, the sustainability of ecotourism MSMEs depends more on timely and disciplined operational decisions than on improving forecast accuracy alone. The findings demonstrate that manually recorded daily sales data can be transformed into decision-relevant signals through a two-stage approach that separates sale occurrence from sales magnitude. Sale-occurrence probability functions as an early-warning signal for determining operating modes, while conditional magnitude provides guidance on the level of operational readiness. By linking these signals to threshold-based decision triggers, the study identifies avoidable operating days and provides actionable lead time before prolonged zero-sales periods. Theoretically, the study contributes by operationalizing dynamic capabilities, sensing, seizing, and reconfiguring, within a measurable decision framework. Practically, it offers a simple and feasible human-in-the-loop approach that enables MSMEs to anticipate demand fluctuations, control costs, and adjust capacity under resource constraints.

This study is subject to several limitations. First, the analysis is based on ecotourism MSMEs within a specific destination context, which may limit generalizability to other sectors with different demand structures. Second, the use of manually recorded sales data restricts the inclusion of external variables such as weather, events, and access conditions that may influence demand patterns. Third, the magnitude forecasting component is sensitive to limited observations of positive-sales days, which affects precision in estimating sales intensity. Future research can extend this work by incorporating additional low-burden external indicators, testing alternative modelling approaches for magnitude prediction, and examining the broader impact of decision-trigger adoption on long-term business resilience, employment stability, and recovery performance across different tourism settings.

Authors' Declaration

The authors made substantial contributions to the conception and design of this study. The authors take responsibility for the data analysis, interpretation, and discussion of the results. The authors have read and approved the final manuscript.

ORCID

Singgih Purnomo https://orcid.org/0000-0001-5151-9142
Nurmalitasari https://orcid.org/0000-0002-8304-1750
Nurchim https://orcid.org/0000-0001-8921-3237
Novemy Triyandari Nugroho https://orcid.org/0009-0003-7473-9211

References

Badoc-Gonzales, B. P., Mandigma, M. B. S., & Tan, J. J. (2022). SME resilience as a catalyst for tourism destinations: a literature review. *Journal of Global Entrepreneurship Research*, *12*(1), 23–44. https://doi.org/10.1007/s40497-022-00309-1

Cross, G. R., Tozier, A., Poterie, D., Castro, E., & Rahaman, H. (2023). Anticipatory action to manage climate risks : Lessons from the Red Cross Red Crescent in Southern Africa , Bangladesh, and beyond Climate Risk Management Anticipatory action to manage climate risks : Lessons from the Red Cross Red Crescent in Southern Af. *Climate Risk Management*, *39*(January), 100476. https://doi.org/10.1016/j.crm.2023.100476

Damato, S., Azzimonti, D., & Corani, G. (2025). Forecasting intermittent time series with Gaussian Processes and Tweedie likelihood. *International Journal of Forecasting*. https://doi.org/10.1016/j.ijforecast.2025.10.001

Díaz-Arancibia, J., Hochstetter-Diez, J., Bustamante-Mora, A., Sepúlveda-Cuevas, S., Albayay, I., & Arango-López, J. (2024). Navigating digital transformation and technology adoption: A literature review from small and medium-sized enterprises in developing countries. *Sustainability (Switzerland)*, *16*(5946), 1–31. https://doi.org/10.3390/su16145946

Dinamarca, M. A., Rojas, F., Ibacache-Quiroga, C., & González-Pizarro, K. (2025). Modeling Time Series with SARIMAX and Skew-Normal and Zero-Inflated Skew-Normal Errors. In *Mathematics* (Vol. 13, Issue 11, p. 1892). https://doi.org/10.3390/math13111892

Eichholz, J., Hoffmann, N., & Schwering, A. (2024). The role of risk management orientation and the planning function of budgeting in enhancing organizational resilience and its effect on competitive advantages during times of crises. *Journal of Management Control*, *35*(1), 17–58. https://doi.org/10.1007/s00187-024-00371-8

Gan, J. E., Lim, J. P. S., Trupp, A., & Poon, W. C. (2024). State intervention and tourism business resilience: Exploring firm-level crisis responses. *Annals of Tourism Research Empirical Insights*, *5*(2), 100142. https://doi.org/10.1016/j.annale.2024.100142

Giannopoulos, P. G., Dasaklis, T. K., Tsantilis, I., & Patsakis, C. (2025). Machine learning algorithms in intermittent demand forecasting: a review. *International Journal of Production Research*, 1–43. https://doi.org/10.1080/00207543.2025.2578701

Grau-Escolano, J., Anton Clavé, S., & Borràs, J. (2025). Daily tourism demand forecasting via card transactions: a multi-source, interpretable, framework for diverse destinations and markets. *Information Technology & Tourism*, *28*(1), 11. https://doi.org/10.1007/s40558-025-00350-2

Hu, M., Liang, W., Qiu, R. T. R., & Wu, D. C. (2025). Tourism demand forecasting using compound pattern recognition. *Tourism Management*, *109*, 105138. https://doi.org/10.1016/j.tourman.2025.105138

Mwangi, E., Taylor, O., Todd, M. C., Visman, E., Kniveton, D., Kilavi, M., Ndegwa, W., Otieno, G., Waruru, S., Mwangi, J., Ambani, M., Abdillahi, H., MacLeod, D., Rowhani, P., Graham, R., & Colman, A. (2022). Mainstreaming forecast based action into national disaster risk management systems: experience from drought risk management in Kenya. *Climate and Development*, *14*(8), 741–756. https://doi.org/10.1080/17565529.2021.1984194

Öztürk, K. N., & Yiğit, Ö. E. (2025). Information-Theoretic ESG Index Direction Forecasting: A Complexity-Aware Framework. In *Entropy* (Vol. 27, Issue 11, p. 1164).

https://doi.org/10.3390/e27111164

Popović, P. M., Bakouch, H. S., & Ristić, M. M. (2025). A non-linear integer-valued autoregressive model with zero-inflated data series. *Journal of Applied Statistics*, *52*(6), 1195–1218. https://doi.org/10.1080/02664763.2024.2419495

Prayag, Girish, Jiang, Yawei, Chowdhury, Mesbahuddin, Hossain, Muhammad Ismail, & Akter, Nasrin. (2023). Building dynamic capabilities and organizational resilience in tourism firms during COVID-19: A Staged Approach. *Journal of Travel Research*, *63*(3), 713–740. https://doi.org/10.1177/00472875231164976

Promnil, N., & Polnyotee, M. (2023). Crisis management strategy for recovery of small and medium hotels after the COVID-19 pandemic in Thailand. In *Sustainability* (Vol. 15, Issue 5, p. 4194). https://doi.org/10.3390/su15054194

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2026). Building resilience in tourism firms: Evidence from COVID-19. *International Journal of Hospitality Management*, *132*, 104395. https://doi.org/10.1016/j.ijhm.2025.104395

Rashed, M., Uddin, M. K., Islam, M. F., Faisal-E-Alam, M., Tushar, H., & Ahmed, M. E. (2025). Building resilient organizations: The role of technological capability, innovation leadership, and sustainability. *Global Journal of Flexible Systems Management*, *26*(4), 963–995. https://doi.org/10.1007/s40171-025-00471-x

Rastegar, R., Seyfi, S., & Shahi, T. (2025). Tourism SMEs' resilience strategies amidst the COVID-19 crisis: the story of survival. *Tourism Recreation Research*, *50*(2), 428–434. https://doi.org/10.1080/02508281.2023.2233073

Salgado-Criado, J. (2025). Human oversight of AI: An operations management perspective. In *Lecture Notes on Data Engineering and Communications Technologies* (Vol. 239). https://doi.org/10.1007/978-3-031-82334-3_104

Sarlo, R., Fernandes, C., & Borenstein, D. (2023). Lumpy and intermittent retail demand forecasts with score-driven models. *European Journal of Operational Research*, *307*(3), 1146–1160. https://doi.org/10.1016/j.ejor.2022.10.006

Schäfers, A., Bougioukos, V., Karamatzanis, G., & Nikolopoulos, K. (2024). Prediction-led prescription: Optimal Decision-Making in times of turbulence and business performance improvement. *Journal of Business Research*, *182*, 114805. https://doi.org/10.1016/j.jbusres.2024.114805

Sfiris, D. S., & Koulouriotis, D. E. (2025). A new approach to forecast intermittent demand and stock-keeping-unit level optimization for spare parts management. In *Applied Sciences*, *15*(22), 12030. https://doi.org/10.3390/app152212030

Sharabati, A. A. A., Ali, A. A., Allahham, M. I., Hussein, A. A., Alheet, A. F., & Mohammad, A. S. (2024). The impact of digital marketing on the performance of smes: An analytical study in light of modern digital transformations. In *Sustainability* (Vol. 16, Issue 19, p. 8667). https://doi.org/10.3390/su16198667

Song, H., Qiu, R. T. R., & Park, J. (2023). Progress in tourism demand research: Theory and empirics. *Tourism Management*, *94*, 104655. https://doi.org/10.1016/j.tourman.2022.104655

Song, M. (2025). Research on intelligent decision support platform for tourism enterprises based on multi-source heterogeneous data fusion. *Scientific Reports*, *15*(1), 39810. https://doi.org/10.1038/s41598-025-23486-x

Svetunkov, I., & Boylan, J. E. (2023). iETS: State space model for intermittent demand forecasting. *International Journal of Production Economics*, *265*, 109013.

https://doi.org/10.1016/j.ijpe.2023.109013

Wang, S., Kang, Y., & Petropoulos, F. (2024). Combining probabilistic forecasts of intermittent demand. *European Journal of Operational Research*, *315*(3), 1038–1048. https://doi.org/10.1016/j.ejor.2024.01.032

Wieczorek-Kosmala, M. (2022). A study of the tourism industry's cash-driven resilience capabilities for responding to the COVID-19 shock. *Tourism Management*, *88*, 104396. https://doi.org/10.1016/j.tourman.2021.104396

Wissuchek, C., & Zschech, P. (2025). Prescriptive analytics systems revised: a systematic literature review from an information systems perspective. *Information Systems and E-Business Management*, *23*(2), 279–353. https://doi.org/10.1007/s10257-024-00688-w

Yang, M., Li, M., & Li, G. (2025). On memory-augmented gated recurrent unit network. *International Journal of Forecasting*, *41*(2), 844–858. https://doi.org/10.1016/j.ijforecast.2024.07.008

Yaşar Dinçer, F. C., Yirmibeşoğlu, G., Narin, M., & Saraç, F. E. (2024). Crisis management and sustainability in tourism industry: Obstacles and recovery strategies after the COVID-19 crisis in Antalya, Türkiye. *Sustainability*, *16*(12), 5121. https://doi.org/10.3390/su16125121

Yesuf, Y. M., & Fields, Z. (2025). Entrepreneurial decision-making and tourism resilience: Organisational crisis responses. *Acta Commercii*, *25*(1), 1–13. https://doi.org/10.4102/ac.v25i1.1439

Yulianto, E., Ali, Q. S. A., Hanafiah, M. H., Wiyata, W., & Salamah, S. N. (2025). Strengthening resilience and performance through business continuity management: insights from central java tour operators. *Quality & Quantity*. https://doi.org/10.1007/s11135-025-02285-6

Zhang, Dengjun, & Xie, Jinghua. (2021). Influence of tourism seasonality and financial ratios on hotels' exit risk. *Journal of Hospitality & Tourism Research*, *47*(4), 714–733. https://doi.org/10.1177/10963480211016038

Zhang, S., Zhang, F., Xue, B., Wang, D., & Liu, B. (2023). Unpacking resilience of project organizations: A capability-based conceptualization and measurement of project resilience. *International Journal of Project Management*, *41*(8), 102541. https://doi.org/10.1016/j.ijproman.2023.102541

Zuñiga-Collazos, A., Galvez-Albarracin, E. J., Vera-Jaramillo, F., & Patiño-Giraldo, L. V. (2025). Digitalization, innovation, sustainability and performance: A causal analysis applied to tourism MSMEs. *International Journal of Innovation Studies*, *9*(1), 46–59. https://doi.org/10.1016/j.ijis.2024.12.001