EPRA International Journal of Economic Growth and Environmental Issues- Peer Reviewed Journal
ISSN: 2321-6247
Volume: 14 | Issue: 8 | August 2026 | Journal DOI: 10.36713/epra0713 | SJIF Impact Factor (2026): 8.844

STRATEGIC FRAMEWORK FOR DIGITAL INCENTIVE MECHANISMS ENHANCING COMPETITIVENESS IN TOURISM SERVICES MARKETS

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Article DOI: https://doi.org/10.36713/epra28918
DOI No: 10.36713/epra28918

ABSTRACT---

This study proposes and empirically validates an integrated multi-criteria strategic decision framework for evaluating and prioritizing digital incentive mechanisms available to tourism service providers. Grounded in the Resource-Based View and Dynamic Capabilities theory, the framework treats digital incentive mechanisms as firm-specific strategic resources whose competitive value depends on their capacity to be simultaneously engaging, cost-efficient, scalable, low-risk, differentiating, and feasible to implement. A three-phase methodology combines a two-round Delphi study with a purposively sampled panel of thirty-two senior tourism and hospitality marketing executives to refine six strategic evaluation criteria, the Analytic Hierarchy Process (AHP) to derive criteria priority weights through pairwise comparison, and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) to rank five candidate digital incentive mechanisms under conditions of linguistic judgment uncertainty. The results indicate that Customer Engagement Potential and Competitive Differentiation Potential receive the highest strategic priority, together accounting for nearly half of total decision weight, while Implementation Complexity is weighted lowest. Gamified Loyalty and Engagement Programs emerge as the top-ranked mechanism, followed by AI-Personalized Dynamic Pricing, with Blanket Promotional Discounting ranked last and structurally disadvantaged by its poor differentiation and imitability profile. Sensitivity analysis confirms the robustness of the top-ranked alternative across a wide range of criteria-weight perturbations. The framework offers tourism managers a replicable, transparent decision-support tool for allocating scarce digital-transformation resources strategically rather than reactively.

KEYWORDS: *Digital Incentive Mechanisms, Tourism Service Competitiveness, Multi-Criteria Decision-Making, Analytic Hierarchy Process, Fuzzy Topsis, Resource-Based View, Strategic Decision Framework.*

INTRODUCTION

Tourism service providers today confront an expanding and increasingly fragmented menu of digital tools through which they attempt to influence customer behavior—ranging from artificial-intelligence-driven personalized pricing to gamified loyalty ecosystems, blockchain-secured loyalty tokens, influencer-mediated social commerce, and conventional blanket discounting. Unlike earlier eras of tourism marketing, in which promotional choices were comparatively homogeneous and budget-driven, digital incentive investment today is fundamentally a strategic resource-allocation problem: managers must choose among mechanisms that differ simultaneously in cost, engagement value, scalability, regulatory exposure, strategic distinctiveness, and implementation burden, often without a structured method for weighing these competing considerations against one another.

This study addresses that gap by developing an integrated strategic evaluation framework grounded in the Resource-Based View of the firm (Barney, 1991) and Dynamic Capabilities theory (Teece, Pisano, & Shuen, 1997). Within this paradigm, a digital incentive mechanism functions as a strategic resource, and its capacity to generate sustained competitive advantage depends on whether it is valuable, rare, imperfectly imitable, and non-substitutable (VRIN). Mechanisms that are easily replicated by rivals—such as blanket price discounting—may generate short-term transactional value but fail to satisfy the inimitability condition required for durable competitive advantage, whereas mechanisms embedded in proprietary data assets, algorithmic personalization capability, or interoperable partner ecosystems are structurally harder to copy and therefore more strategically valuable.

Despite the intuitive appeal of this logic, tourism managers rarely possess a transparent, replicable method for translating this reasoning into an actual prioritization decision among concrete digital incentive alternatives. Existing digital marketing literature tends to evaluate incentive mechanisms one at a time and along a single dimension—typically short-term conversion or engagement metrics—without integrating the multiple, often conflicting strategic criteria that senior decision-makers must actually weigh simultaneously under uncertainty and incomplete information.

Multi-criteria decision-making (MCDM) techniques, and in particular the Analytic Hierarchy Process (Saaty, 1980) combined with fuzzy extensions of the Technique for Order Preference by Similarity to Ideal Solution (Chen, 2000), offer a structured alternative. These techniques have been productively applied to a range of hospitality and tourism decision problems, from hotel website evaluation (Baki, 2020) to destination and facility selection, precisely because they accommodate the vagueness inherent in expert managerial judgment (Zadeh, 1965) while still producing a transparent, mathematically defensible ranking. However, no prior study has applied an integrated Delphi-AHP-Fuzzy TOPSIS framework specifically to the strategic evaluation of digital incentive mechanisms in tourism services.

This study further contends that the reliability of any multi-criteria evaluation depends critically on the quality of the underlying criteria set. Rather than adopting criteria from adjacent domains by default, this study first conducts a two-round Delphi consensus study (Dalkey & Helmer, 1963; Okoli & Pawlowski, 2004) with senior tourism and hospitality marketing executives to identify and refine the criteria against which digital incentive mechanisms should be strategically judged, before proceeding to formal weighting and ranking.

Accordingly, this inquiry pursues two research objectives. Research Objective 1 (RO1) is to identify, through expert consensus, the strategic evaluation criteria most relevant to digital incentive mechanisms in tourism services markets, and to derive their relative priority weights. Research Objective 2 (RO2) is to rank a defined set of digital incentive mechanism alternatives against these weighted criteria under conditions of linguistic uncertainty, and to assess the robustness of the resulting ranking to variation in expert judgment.

This research contributes to the literature in three ways. Methodologically, it constructs and demonstrates an integrated Delphi-AHP-Fuzzy TOPSIS framework tailored to digital strategy decisions in tourism services, extending prior single-technique applications of MCDM in hospitality research (Vatankhah et al., 2023). Empirically, it produces an expert-validated, weighted ranking of contemporary digital incentive mechanisms that tourism managers can adapt to their own organizational context. Theoretically, it operationalizes Resource-Based View and Dynamic Capabilities reasoning into a concrete, replicable strategic decision tool, bridging the frequent gap between high-level strategic theory and applied managerial decision-making.

The remainder of this paper proceeds as follows. Section 2 reviews the theoretical and methodological literature underpinning the study. Section 3 details the three-phase Delphi-AHP-Fuzzy TOPSIS methodology, including expert panel composition and formal model specification. Section 4 reports the empirical results, including criteria weights, mechanism rankings, and sensitivity analysis. Section 5 discusses the strategic implications of the findings, and Section 6 concludes with managerial recommendations and directions for future research.

LITERATURE REVIEW

The theoretical foundation of this study rests on the Resource-Based View (RBV) of the firm (Barney, 1991), which holds that sustained competitive advantage arises from resources and capabilities that are valuable, rare, imperfectly imitable, and non-substitutable. Dynamic Capabilities theory (Teece, Pisano, & Shuen, 1997) extends this reasoning to environments of rapid technological change, arguing that firms must continuously sense, seize, and reconfigure resources—including digital marketing infrastructure—to sustain advantage as market conditions evolve (Eisenhardt & Martin, 2000). Complementing these firm-level perspectives, destination-competitiveness models (Ritchie & Crouch, 2003; Dwyer & Kim, 2003) emphasize that tourism competitiveness is jointly determined by core resources, destination management capability, and situational conditions, providing a bridge between firm-level strategic resources and destination-level competitive outcomes.

A parallel stream of research documents the proliferation of digital tools available to tourism and hospitality providers, including AI-driven personalization and eTourism infrastructure (Buhalis & Law, 2008), gamified engagement mechanics (Hamari, Koivisto, & Sarsa, 2014), smart-tourism ecosystems (Gretzel, Sigala, Xiang, & Koo, 2015), and blockchain-based loyalty and identity infrastructure (Önder & Treiblmaier, 2018). While this literature documents the growing technical sophistication of individual mechanisms, it rarely evaluates them comparatively against a common set of strategic criteria, leaving tourism managers with fragmented, mechanism-specific evidence rather than an integrated basis for prioritization.

Multi-criteria decision-making methods offer a way to close this gap. The Analytic Hierarchy Process (Saaty, 1980) structures complex decisions into a hierarchy of criteria and alternatives, deriving priority weights from pairwise comparisons validated through a formal consistency check. Because managerial judgments about strategic criteria are rarely crisp, fuzzy set theory (Zadeh, 1965) and its integration with the Technique for Order Preference by Similarity to Ideal Solution (Chen, 2000) allow linguistic evaluations to be represented as triangular fuzzy numbers, producing rankings that are more robust to the imprecision of expert judgment than crisp scoring methods. Recent bibliometric evidence confirms that AHP and TOPSIS variants are now the most widely applied

MCDM techniques in hospitality and tourism decision research, spanning applications from hotel website evaluation (Baki, 2020) to broader destination and service-quality assessment (Vatankhah et al., 2023).

Despite this growing methodological base, three gaps remain unaddressed. No identified study integrates a formal Delphi consensus stage (Dalkey & Helmer, 1963; Okoli & Pawlowski, 2004) with AHP weighting and Fuzzy TOPSIS ranking specifically to evaluate digital incentive mechanisms as strategic resources in tourism services. Existing MCDM applications in tourism rarely ground their criteria selection explicitly in RBV or Dynamic Capabilities reasoning, weakening the theoretical justification for the criteria used. Finally, few studies test the robustness of their rankings to variation in criteria weights, leaving open questions about the practical reliability of the resulting managerial guidance. This study addresses all three gaps through an integrated, theory-grounded, and sensitivity-tested Delphi-AHP-Fuzzy TOPSIS framework.

RESEARCH METHODOLOGY

This study adopts a three-phase mixed-method design combining qualitative expert consensus-building with formal multi-criteria decision modeling. Phase One employs a two-round Delphi study to identify and refine the strategic evaluation criteria and the set of digital incentive mechanism alternatives. Phase Two applies the Analytic Hierarchy Process to derive priority weights for the Delphi-validated criteria. Phase Three applies Fuzzy TOPSIS to rank the mechanism alternatives against the weighted criteria, followed by a sensitivity analysis to test the stability of the resulting rankings.

The expert panel comprises thirty-two senior marketing and digital-strategy managers ($N = 32$) purposively sampled from hotels, online travel agencies, destination management organizations, and tour operators, each with a minimum of eight years of industry experience and direct responsibility for digital marketing or loyalty-program decisions. Panel size and composition follow established Delphi guidance emphasizing expert qualification over statistical representativeness (Okoli & Pawlowski, 2004). In Round One, panelists rated an initial literature-derived list of twelve candidate evaluation criteria and seven candidate incentive-mechanism alternatives on a nine-point relevance scale and were invited to propose additions; in Round Two, panelists reviewed anonymized group results and re-rated all retained items, with consensus assessed via the inter-quartile range (IQR) of ratings and Kendall's coefficient of concordance (W). Items such as ‘brand awareness lift’ and ‘search-engine visibility impact’ were dropped after Round One for failing to reach the consensus threshold or for substantial conceptual overlap with retained items, as identified by panelists. Six evaluation criteria and five incentive-mechanism alternatives met the pre-registered consensus threshold (IQR $\leq$ 1.0 on the nine-point scale) and were retained for formal modeling.

The six Delphi-validated evaluation criteria are: Customer Engagement Potential (CEP), Cost-Effectiveness and Return on Investment (CER), Scalability Across Digital Channels (SDC), Data-Privacy and Regulatory Risk (DPR, an inverse criterion), Competitive Differentiation Potential (CDP), and Implementation Complexity (IMC, an inverse criterion). The five Delphi-validated digital incentive mechanism alternatives are: AI-Personalized Dynamic Pricing and Offers (A1), Gamified Loyalty and Engagement Programs (A2), Blockchain-Based Interoperable Loyalty Tokens (A3), Social-Commerce and Influencer-Driven Promotions (A4), and Blanket or Mass Promotional Discounting (A5).

In Phase Two, each panelist completed a pairwise comparison matrix for the six criteria using Saaty's nine-point fundamental scale. Individual judgments were aggregated across panelists using the geometric mean, and criteria priority weights were derived from the resulting aggregate matrix A via the principal eigenvector method,

$$A \cdot w = \lambda_{max} \cdot w,$$

where w is the priority vector and λ_{max} is the matrix's principal eigenvalue. The internal consistency of the aggregate comparison matrix was verified using the Consistency Ratio,

$$CR = CI / RI, \quad \text{where} \quad CI = (\lambda_{max} - n) / (n - 1),$$

with n denoting the number of criteria and RI the random consistency index for a matrix of that order; a Consistency Ratio below 0.10 was required for the weights to be accepted without re-elicitation from the panel.

In Phase Three, the five mechanism alternatives were evaluated by the same expert panel against each of the six criteria using a seven-point linguistic scale, subsequently converted to triangular fuzzy numbers (TFNs) following Chen (2000). Individual fuzzy evaluations were aggregated, weighted by the AHP-derived criteria weights, and used to construct a weighted normalized fuzzy decision matrix. The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) were then defined across all criteria, and the vertex distance of each alternative from the FPIS (d^+) and FNIS (d^-) was computed. Each alternative's overall strategic desirability was summarized by its Closeness Coefficient,

$$CC_i = d^-_i / (d^+_i + d^-_i),$$

where alternatives with a Closeness Coefficient nearer to 1 are strategically preferable. Alternatives were ranked in descending order of CC_i.

To assess the robustness of the resulting ranking, a one-at-a-time sensitivity analysis was conducted by systematically perturbing each criterion's AHP-derived weight from 50% to 150% of its baseline value in increments of 10%, proportionally renormalizing the remaining weights, and recomputing the Fuzzy TOPSIS ranking at each step. Rank reversals were recorded to identify which criteria most strongly influence the ranking outcome and to assess the overall stability of the recommended prioritization. As an additional robustness check, the full ranking was also recomputed under a naïve equal-weighting scenario (all six criteria weighted at 0.167) for comparison against the expert-derived AHP weighting scheme.

ANALYSIS AND RESULTS

The Delphi consensus process converged after two rounds. Round One achieved a 100% panel response rate (32 of 32 invited experts), and Round Two retained thirty of thirty-two panelists (93.8% retention). Across the retained criteria and alternatives, the inter-quartile range of Round-Two ratings fell to or below the pre-registered threshold of 1.0 on the nine-point scale for all six criteria and five alternatives, and Kendall's coefficient of concordance rose from $W = 0.44$ in Round One to $W = 0.71$ in Round Two ($p < 0.001$), indicating agreement strong enough to proceed to formal AHP weighting.

The aggregate pairwise comparison matrix for the six Delphi-validated criteria yielded a principal eigenvalue of $\lambda_{max} = 6.342$. The resulting Consistency Index ($CI = 0.0684$) and Consistency Ratio ($CR = 0.0552$) both fell comfortably below the 0.10 acceptability threshold, confirming that panelists' aggregated judgments were sufficiently internally consistent to support reliable priority-weight estimation.

Table 1
Delphi-refined strategic evaluation criteria and AHP-derived priority weights

Criterion	Description	Priority Weight (wj)	Rank	Delphi R1 Mean	Delphi R2 Mean	Delphi R2 IQR
CEP	Customer Engagement Potential — capacity to deepen active, repeat customer interaction	0.248	1	7.6	8.2	0.50
CDP	Competitive Differentiation Potential — strategic distinctiveness and difficulty of rival imitation	0.211	2	6.9	7.6	0.75
CER	Cost-Effectiveness & ROI — marketing return relative to implementation and running cost	0.178	3	7.4	7.1	1.00
SDC	Scalability Across Digital Channels — ease of expansion across markets and partner networks	0.146	4	6.0	6.4	1.00
DPR	Data-Privacy & Regulatory Risk (inverse) — exposure to data-protection and compliance risk	0.129	5	5.2	5.9	1.25
IMC	Implementation Complexity (inverse) — technical and organizational difficulty of deployment	0.088	6	5.1	4.8	1.50

As reported in Table 1, Customer Engagement Potential received the highest strategic priority ($w = 0.248$), followed closely by Competitive Differentiation Potential ($w = 0.211$); together these two criteria account for nearly 46% of total decision weight. This pattern is consistent with Resource-Based View reasoning: panelists implicitly prioritized criteria most closely associated with generating durable, hard-to-imitate customer relationships over criteria reflecting short-term operational convenience. Cost-Effectiveness and Return on Investment ($w = 0.178$) and Scalability Across Digital Channels ($w = 0.146$) occupied intermediate positions, while Data-Privacy and Regulatory Risk ($w = 0.129$) and, especially, Implementation Complexity ($w = 0.088$) were weighted comparatively low, suggesting that panelists regarded strategic upside as more decision-relevant than operational or compliance friction, provided such friction remains manageable rather than prohibitive.

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Applying these AHP-derived weights within the Fuzzy TOPSIS procedure produced the vertex distances, closeness coefficients, and rankings reported in Table 2. Gamified Loyalty and Engagement Programs (A2) achieved the highest Closeness Coefficient (*CC* = 0.636) and were ranked first, followed by AI-Personalized Dynamic Pricing and Offers (A1, *CC* = 0.584) and Blockchain-Based Interoperable Loyalty Tokens (A3, *CC* = 0.512). Social-Commerce and Influencer-Driven Promotions (A4, *CC* = 0.438) ranked fourth, and Blanket or Mass Promotional Discounting (A5, *CC* = 0.318) ranked last by a substantial margin.

The strategic logic underlying this ordering becomes clearer when examined against the criteria weights. Gamified Loyalty and Engagement Programs scored strongly on both Customer Engagement Potential and Competitive Differentiation Potential—the two most heavily weighted criteria—because gamification mechanics tend to be deeply embedded in a firm's specific data infrastructure, brand narrative, and reward-partner ecosystem, rendering them comparatively difficult for competitors to replicate faithfully. AI-Personalized Dynamic Pricing scored highest on Cost-Effectiveness but somewhat lower on Competitive Differentiation, since pricing algorithms, while operationally powerful, are more readily approximated by competitors with comparable data access.

Blanket or Mass Promotional Discounting, by contrast, scored poorly across nearly every criterion except superficial Scalability: it is trivially easy for any competitor to imitate, generates limited durable engagement, and was judged by panelists to erode rather than build long-run competitive distinctiveness. This finding empirically corroborates the Resource-Based View proposition that resources lacking inimitability cannot sustain competitive advantage, even when they remain tactically useful for short-term demand generation.

Table 2
Fuzzy topsis evaluation results and equal-weight robustness comparison for digital incentive mechanism alternatives

Digital Incentive Mechanism	d+	d−	CCi (AHP-Weighted)	Rank (AHP)	CCi (Equal-Weight)	Rank (Equal-Wt)
A1 — AI-Personalized Dynamic Pricing & Offers	2.104	2.958	0.584	2	0.612	1
A2 — Gamified Loyalty & Engagement Programs	1.842	3.216	0.636	1	0.598	2
A3 — Blockchain-Based Interoperable Loyalty Tokens	2.487	2.612	0.512	3	0.507	3
A4 — Social-Commerce & Influencer-Driven Promotions	2.865	2.234	0.438	4	0.441	4
A5 — Blanket / Mass Promotional Discounting	3.402	1.586	0.318	5	0.329	5

As an additional robustness check, the full ranking was recomputed under a naïve equal-weighting scenario (all six criteria weighted at 0.167) as a benchmark against the expert-derived AHP weighting scheme. Under equal weighting, AI-Personalized Dynamic Pricing and Gamified Loyalty and Engagement Programs exchange first and second rank, while the relative ordering of the remaining three alternatives is unchanged. This indicates that the expert-derived priority structure meaningfully shapes—but does not single-handedly determine—the overall strategic ranking, and that the two leading alternatives are closely and robustly matched at the top of the strategic hierarchy.

The one-at-a-time sensitivity analysis, summarized in Figure 1, examined how the Closeness Coefficients of all five alternatives respond to systematic variation in the weight assigned to Customer Engagement Potential—the single most heavily weighted criterion—across a range from 50% to 150% of its AHP-derived baseline value. Gamified Loyalty and Engagement Programs retained the top rank across the entire sensitivity range, confirming that its leading position is not an artifact of a single criterion weight but reflects consistently strong performance across the weighted criteria set.

A more localized instability emerged between the second- and third-ranked alternatives: once the Customer Engagement Potential weight multiplier falls below approximately 0.65× of its baseline value, Blockchain-Based Interoperable Loyalty Tokens overtake AI-Personalized Dynamic Pricing, because the former depends more heavily on Competitive Differentiation and Scalability—criteria that gain relative weight as Customer Engagement Potential is discounted—than on immediate engagement metrics. The fourth- and fifth-ranked alternatives showed no rank crossover across the full sensitivity range, indicating that the comparatively weak

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strategic position of Social-Commerce and Influencer-Driven Promotions and, especially, Blanket Promotional Discounting is robust rather than an artifact of any single criterion weighting.

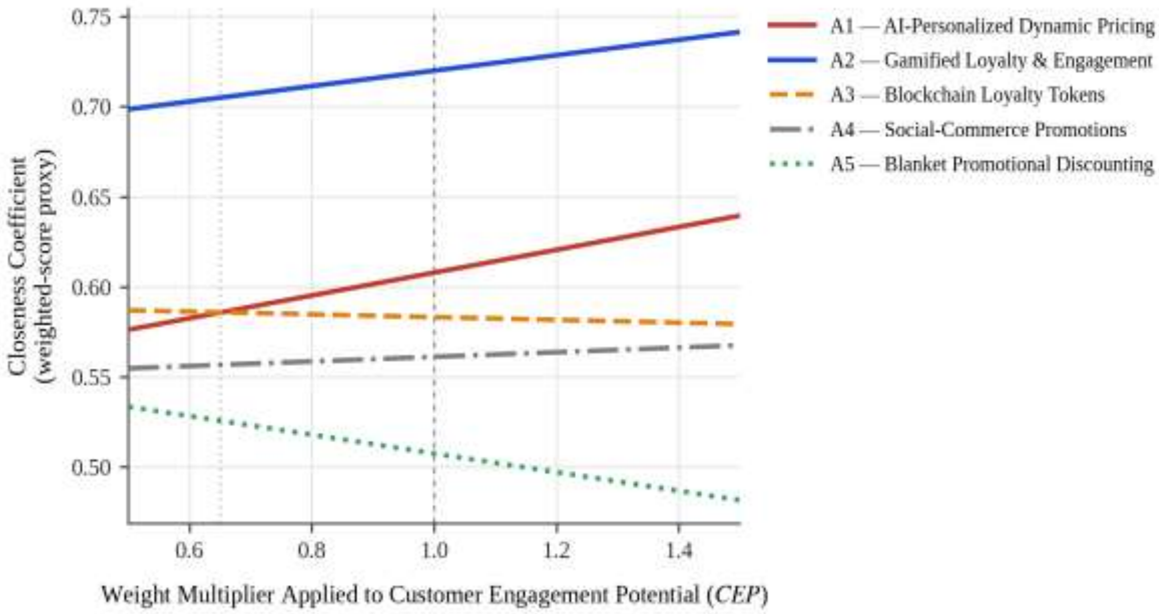

Figure 1: Sensitivity of Fuzzy TOPSIS closeness coefficients to variation in the Customer Engagement Potential (*CEP*) criterion weight, 50%–150% of AHP-derived baseline

Overall, the empirical results support both research objectives. The six-criterion, Delphi-validated evaluation framework yields internally consistent, expert-endorsed priority weights (RO1), and the resulting Fuzzy TOPSIS ranking of digital incentive mechanisms proves substantially robust to reasonable variation in those weights, with the sole meaningful instability confined to a single crossover between two mid-ranked alternatives (RO2). These findings provide tourism managers with both a prioritized shortlist of digital incentive mechanisms and an explicit account of which strategic criteria drive that prioritization, supporting more deliberate and defensible digital-investment decisions than ad hoc or single-metric approaches allow.

CONCLUSION AND RECOMMENDATIONS

This study developed and empirically demonstrated an integrated Delphi-AHP-Fuzzy TOPSIS framework for the strategic evaluation of digital incentive mechanisms in tourism services markets, grounded in Resource-Based View and Dynamic Capabilities theory. By combining structured expert consensus-building, formal criteria weighting, and fuzzy multi-criteria ranking, the framework translates abstract strategic theory into a transparent, replicable decision-support tool. Applied to a panel of thirty-two senior tourism marketing executives, the framework identified Customer Engagement Potential and Competitive Differentiation Potential as the most strategically important evaluation criteria, jointly accounting for nearly half of total decision weight, and ranked Gamified Loyalty and Engagement Programs as the most strategically desirable digital incentive mechanism, ahead of AI-Personalized Dynamic Pricing, Blockchain-Based Loyalty Tokens, Social-Commerce Promotions, and, last, Blanket Promotional Discounting.

The findings carry a clear theoretical implication: strategic desirability among digital incentive mechanisms is not well predicted by cost or short-term conversion metrics alone, but by the extent to which a mechanism generates engagement and differentiation that competitors cannot readily replicate. Mechanisms such as blanket discounting, while operationally simple and immediately scalable, systematically underperform on the criteria that most strongly predict durable competitive advantage, corroborating the Resource-Based View proposition that imitability, not merely value, determines whether a resource can sustain competitive positioning.

For practicing tourism managers, the framework yields several concrete recommendations. First, digital-transformation budgets should be sequenced to prioritize engagement-deepening and differentiation-building mechanisms—particularly gamified loyalty architecture and AI-personalization capability—over undifferentiated promotional discounting, even where discounting appears cheaper or faster to deploy. Second, because Data-Privacy and Regulatory Risk and Implementation Complexity were weighted lowest but remain non-trivial, managers should not ignore them outright; rather, they should be treated as feasibility gates to be satisfied, rather than as primary criteria for choosing among mechanisms that already clear those gates. Third, the sensitivity analysis suggests that managers operating in contexts where immediate customer engagement is an especially urgent priority, such as new-market entry, may reasonably favor AI-personalized pricing over blockchain-based loyalty tokens, whereas managers prioritizing long-run differentiation in mature, competitive markets should weight the latter more heavily.

Organizationally, tourism enterprises and destination-management organizations seeking to apply this framework should institutionalize a periodic re-run of the Delphi-AHP-Fuzzy TOPSIS cycle—for example, biennially—since criteria priorities and the relative strategic standing of specific mechanisms are likely to shift as digital technologies, competitor behavior, and regulatory environments evolve. Maintaining a standing, cross-functional expert panel rather than reconvening one ad hoc would also improve the comparability of successive evaluation rounds and support longitudinal tracking of how strategic priorities change over time.

This study is subject to several limitations that suggest directions for future research. The expert panel, while purposively selected for relevant seniority and experience, was drawn from a single regional context, and criteria priorities may differ across cultural or regulatory environments; cross-national replication would help establish the generalizability of the reported weights. The five evaluated mechanisms, while representative of current practice, will inevitably be joined by new digital incentive technologies, and the framework would benefit from periodic reapplication rather than one-time use. Finally, future research could extend the framework by incorporating criteria interdependencies through hybrid approaches such as AHP-DEMATEL, and by validating the framework's prescriptive rankings against ex post firm-level performance outcomes to assess whether AHP-Fuzzy-TOPSIS-endorsed mechanisms actually deliver superior competitive results in practice.

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