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Review Article

Predictive decision support for underutilization risk in public sector tourism: Evidence mapping and a design science roadmap

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Abstract. Publicly funded tourism assets can become stranded when utilization persistently falls below a reasonable level relative to capacity or policy-defined potential. Yet tourism analytics research largely forecasts demand or composite performance and seldom formalizes underutilization as a governance outcome, nor evaluates decision quality within planning and budgeting workflows. This study (i) maps recent evidence and research gaps and (ii) proposes a conceptual artefact in the form of a policy-ready methodology and roadmap for developing a predictive decision support system (DSS) to mitigate underutilization risk. An evidence-mapping review of 117 Scopus-indexed studies (2021–2026) reveals a critical gap: 0% of the analyzed studies explicitly formalize "underutilization" as a policy outcome in their titles. Furthermore, evaluation procedures remain opaque, with 79.5% of studies failing to clearly specify their methodologies. In response, we outline a design-science roadmap for an auditable predictive DSS that operationalizes underutilization through two complementary metrics: the Underutilization Gap (UG) and the Utilization Ratio (UR). The proposed architecture integrates heterogeneous tourism, spatial, and socio economic data while providing traceable audit trails via Explainable AI (XAI) to ensure scores are logically defensible in public budgeting. Crucially, the framework introduces a two-layer evaluation that couples technical predictive performance (E1) with decision-utility metrics (E2), such as rank agreement and allocation efficiency. This methodology equips local governments with a practical, theoretically grounded instrument to justify prioritization, optimize resource allocation, and reduce the likelihood of underutilization-related policy failure.

Keywords: Underutilization; Public Sector Tourism; Predictive Decision Support; Predictive Decision Support; Explainable AI; Design Science Research.

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1. Introduction

Local governments invest heavily in tourism infrastructure and services, yet destination utilization often departs from expected levels because of seasonality and external shocks. When assets are publicly financed, persistent underutilization can imply inefficient capital spending and foregone local socio-economic returns. This governance challenge motivates analytics that can anticipate underutilization risk rather than reacting after performance declines [1], [2], [3], [4].

Recent advances in tourism analytics and decision support systems (DSS) show how predictive models and decision engines can improve the timeliness and consistency of planning. However, most tourism applications remain demand-centric: they forecast visits or competitiveness indicators rather than operationalizing underutilization as a policy risk that can be monitored, predicted, and acted upon through prioritization and resource allocation [1], [5], [6], [7].

In accountable public administration, transparency and justification are mandatory: model outputs must be interpretable, traceable, and defensible in budgeting and audit processes. Explainable AI (XAI) for example, local surrogate explanations and Shapley based attributions can create an auditable decision trail by linking each risk score to its dominant drivers and underlying data sources [8], [9], [10], [11].

Against this backdrop, this study addresses four research questions. RQ1 asks how to define and measure underutilization in a way that is feasible for government data and suitable as a predictive target. RQ2 examines which multidimensional drivers contribute most to underutilization risk. RQ3 evaluates whether predictive models outperform demand-only baselines on real-world datasets. RQ4 investigates to what extent a predictive DSS improves decision quality for prioritization and intervention allocation, including auditability and interpretability.

This study contributes in three ways. First, it provides an evidence map of 117 Scopus-indexed studies to characterize dominant outcomes, data sources, DSS outputs, and evaluation practices. Second, it synthesizes the implications of these patterns for building a policy-ready predictive DSS. Third, it proposes a Design Science Research Methodology (DSRM) roadmap to develop and evaluate a predictive DSS for underutilization risk in public-sector tourism destinations [12], [13], [14], [15].

The primary contribution of this work lies in the systematic mapping of evidence to identify governance gaps and the procedural design of a DSRM based roadmap, providing a conceptual and architectural foundation for future empirical implementations of predictive DSS in the public sector.

This DSRM based roadmap serves as a robust conceptual artefact, bridging the gap between theoretical risk framing and the practical system architecture required for future empirical implementation. By prioritizing this foundational design, we ensure that the system meets rigorous transparency and accountability standards prior to full scale deployment.

2. Literature Review

This literature review explores the theoretical foundations of public-sector tourism management, specifically focusing on the policy risk of asset underutilization. It examines the critical role of predictive analytics and Explainable Artificial Intelligence (XAI) in fostering anticipatory and accountable governance. By synthesizing current research on decision support systems (DSS), this section identifies existing governance gaps and justifies the need for a novel conceptual architecture grounded in Design Science Research Methodology (DSRM) to effectively prioritize resources and mitigate underutilization risks.

Underutilization as a public sector policy risk

We frame underutilization as realized utilization below a reasonable level relative to capacity or policy-defined potential,. Two complementary operationalizations are typically feasible in government settings: (i) an Underutilization Gap (UG), which measures deviation from an expected or benchmark demand level; and (ii) a Utilization Ratio (UR), which compares realized use with available capacity,. These metrics link performance monitoring to critical governance concerns such as sustainability constraints, destination management capacity, and competitiveness [4], [7], [16]. By moving beyond descriptive metrics, this operationalization provides mathematically measurable predictive targets that align with bureaucratic benchmarking, effectively transforming static performance data into actionable risk signals for annual planning. Figure 1 provides a schematic operationalization of UG and UR used as target outcomes.

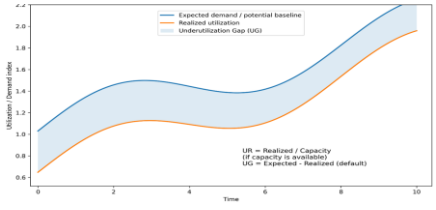


Figure 1. Operationalization of underutilization outcomes: Underutilization Gap (UG) and Utilization Ratio (UR).

Predictive analytics and explainable artificial intelligence in accountable decision making

Predictive analytics serves as a cornerstone for anticipatory governance by allowing public-sector entities to estimate the likelihood and magnitude of adverse outcomes before they materialize. In the context of tourism management, this approach shifts the focus from reactive performance monitoring to the proactive identification of underutilization risk. By moving beyond descriptive metrics, predictive modeling provides mathematically measurable targets that align with bureaucratic benchmarking, effectively transforming static data into actionable risk signals for annual planning and resource allocation.

However, within the framework of accountable public administration, predictive accuracy is a necessary but insufficient condition for effective decision-making. In high-stakes environments such as government budgeting and infrastructure planning, transparency and justification are mandatory requirements; thus, model outputs must be interpretable, traceable, and defensible during both budgeting and official audit processes. Decision-makers do not merely require a risk score; they must understand the causal logic of why a destination is classified as high-risk and identify which policy levers are plausibly controllable to mitigate that risk.

Explainable Artificial Intelligence (XAI) addresses these critical needs by producing stakeholder-facing explanations of complex model behaviors and identifying dominant drivers [8], [9], [10], [11]. By integrating XAI frameworks such as Shapley-based attributions (SHAP) or local surrogate explanations (LIME) the system can create an auditable decision trail. This technical layer links each risk score back to its underlying data sources and feature importance, providing the logical justification required to defend resource allocation decisions. Ultimately, the inclusion of an XAI-enabled traceability layer ensures that the predictive decision support system (DSS) meets rigorous public-sector accountability standards, bridging the gap between technical predictive success and practical policy impact.

Decision support outputs: from descriptive insights to prioritization and intervention design

Tourism Decision Support Systems (DSS) research currently spans a broad spectrum of applications, ranging from descriptive dashboards and multi-criteria decision analysis (MCDA) to sophisticated spatial decision support for regional planning. Within public-sector budgeting workflows, ranking and allocation serve as the central outputs, as government officials must strategically prioritize limited resources across a multitude of competing destinations and diverse intervention options [5], [6], [17], [18], [19], [20], [21]. However, evidence mapping reveals a critical misalignment in the current literature: while methodological development in demand forecasting and spatial analytics is robust, most applications remain demand-centric and fail to operationalize underutilization as a policy risk that can be systematically monitored or predicted.

Furthermore, current DSS frameworks often emphasize technical predictive accuracy but lack an explicit focus on decision quality within bureaucratic workflows. Bridging the gap between technical success and practical policy impact requires an architectural shift toward decision engines that can transform raw predictive risk scores into auditable prioritization rankings and specific intervention rationales. In an accountable public administration context, these outputs must be more than just numerical rankings; they must be supported by traceable reports and XAI-based justifications to defend the logic behind resource allocation during official audit processes. Consequently, a policy-ready DSS must integrate a decision layer that not only identifies high-risk areas but also provides the technical and administrative justifications necessary to reduce the likelihood of underutilization-related policy failure.

Synthesis and implications for the proposed study

Overall, the literature shows strong methodological development in tourism forecasting, spatial analytics, and destination competitiveness analysis, but it reveals a critical disconnect from the practical requirements of public-sector governance. Our evidence mapping of 117 Scopus-indexed studies (2021–2026) highlights a significant "governance blind spot": while demand-centric research is ubiquitous, not a single study (0%) explicitly formalizes "underutilization" as a policy outcome or risk target. Furthermore, current evaluation practices remain largely model-centric, with 79.5% of studies failing to clearly report evaluation procedures, and even fewer assessing the downstream decision quality necessary for budgeting and planning workflows.

In accountable public administration, predictive accuracy is a necessary but insufficient condition for effective intervention. When tourism assets are publicly financed, persistent underutilization implies not only inefficient capital spending but also foregone socio economic returns for the local community. This governance challenge necessitates a shift from reactive performance monitoring to anticipatory governance, where underutilization

risk is identified, measured, and acted upon before assets become stranded. However, bridging the gap between technical success and policy impact requires more than just better algorithms; it requires an architectural framework that ensures transparency and auditability.

This motivates the development of a conceptual artefact specifically a Design Science Research Methodology (DSRM) roadmap that provides a robust structural foundation for a policy ready Decision Support System (DSS). This roadmap explicitly couples prediction (identifying risk levels), prioritization (ranking destinations for intervention), and accountability requirements (providing defensible justifications) [1], [7], [11], [12], [13], [14], [15]. A central feature of this proposed architecture is the integration of Explainable AI (XAI), such as SHAP or LIME, to create an auditable decision trail. By linking risk scores back to their dominant drivers, the system provides the logical justification required for officials to defend resource allocation decisions during official audit and budgeting processes. Ultimately, this design science approach ensures that the system meets rigorous transparency standards, offering a theoretically grounded blueprint for future empirical implementation in the public sector.

3. Proposed Method

This methodology section outlines a comprehensive approach comprising two main analytical stages. First, the study conducts a systematic evidence mapping using a PRISMA-inspired flow to analyze 117 Scopus-indexed studies published between 2021 and 2026, aiming to extract data and identify critical research gaps in public-sector tourism governance. Second, the findings from this mapping serve as the foundation for designing a conceptual artefact through the Design Science Research Methodology (DSRM). This methodology follows six structured stages to develop the architecture for a transparent and auditable predictive Decision Support System (DSS).

Evidence mapping design

This study employs a comprehensive evidence mapping approach to systematically summarize and quantify evolving patterns within the research domain of public sector tourism analytics, utilizing structured data extraction from the abstracts and metadata of 117 Scopus-indexed studies published between 2021 and 2026. Adhering to rigorous systematic mapping principles and a PRISMA inspired flow, we meticulously categorize and code variables across four primary dimensions outcome operationalization, data source integration, DSS output types, and evaluation practices while maintaining total transparency by documenting all inclusion and exclusion decisions to provide a robust empirical foundation for identifying critical governance gaps, such as the complete lack of formalization for underutilization risk in current literature [22].

Screening and data extraction

The screening process followed a PRISMA inspired flow and reporting principles [23]. Records were deduplicated, screened by title and abstract, and then assessed for eligibility. A structured extraction form captured (i) outcome operationalization, (ii) data sources and integration level, (iii) modelling or decision methods, (iv) DSS outputs, and (v) evaluation procedures. When evaluation was not reported in the abstract or metadata, the study was coded as 'not specified' to avoid over inference [22], [23]. A simplified PRISMA style screening flow is reported in Figure 2**.**

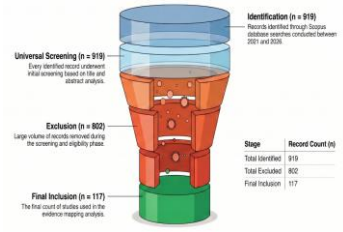


Figure 2. Simplified PRISMA-style flow for study selection (Scopus, 2021–2026).

Coding framework for evidence mapping

We coded four primary dimensions: Outcome, Data sources, DSS outputs, and Evaluation. Outcome categories included demand proxies (arrivals, visits), performance/competitiveness indicators, and composite indices that could plausibly proxy underutilization risk. Data sources were coded as government-internal systems and official statistics, surveys, GIS/remote sensing, social media/digital traces, or multi-source integration. DSS outputs were coded as policy/scenario guidance, ranking/prioritization, or

an explicit operational artefact. Evaluation was coded as prediction performance, decision quality (e.g., rank agreement or allocation efficiency), user validation, or not specified [5], [6], [16], [17], [22].

Coding framework for evidence mapping

Following Design Science Research Methodology (DSRM), the proposed artefact development follows six stages: problem identification, objective definition, design and development, demonstration, evaluation, and communication. In accordance with Design Science Research principles, the roadmap and architecture proposed in this study are presented as a conceptual artefact. This artefact provides the necessary theoretical and structural foundation for auditable decision-making before full-scale empirical deployment. The DSS is conceived as an auditable pipeline that integrates data acquisition and quality control, predictive modelling, and decision-support outputs (risk scoring and prioritization), with XAI-based explanations to support traceability and accountability in public decision making [8], [24], [25], [26], [27]. The DSRM stages and expected artefacts are summarized in Figure 3.

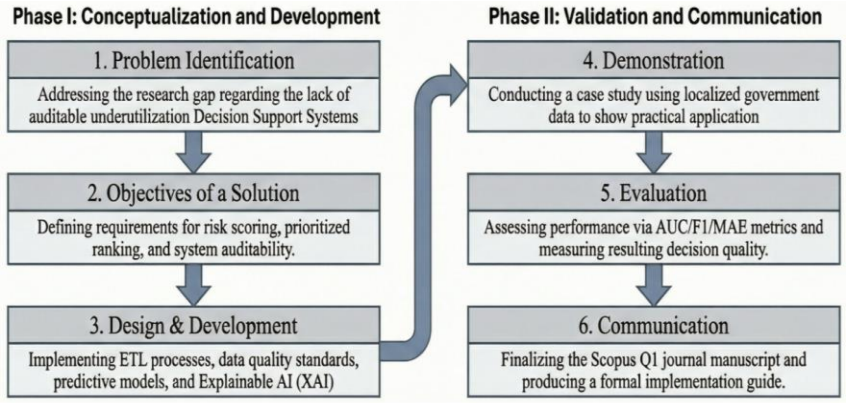


Figure 3. DSRM stages and expected artefacts for the proposed predictive DSS (adapted from Peffers et al.).

4. Results and Discussion

Results

Descriptive overview of the evidence base

Across the 117 included studies, outcome definitions were dominated by demand proxies and general performance indicators. Government-internal data sources and multi-source integration were comparatively rare, and most studies emphasized model-centric metrics without explicit decision-quality assessment. These patterns echo the broader tourism analytics literature, where demand forecasting is common while policy risk formalization and auditable prioritization remain less developed [1], [5], [6], [7]. Figure 4 and Table 1 summarize the evidence mapping across key dimensions, while tourism demand forecasting is ubiquitous, our evidence mapping reveals a critical governance blind spot: not a single study among the 117 analyzed (0%) explicitly formalizes 'underutilization' as a policy outcome. Furthermore, with 79.5% of studies failing to clearly report evaluation procedures, this highlights a significant disconnect between available analytical metrics and the accountability requirements of the public sector. This synthesis provides the empirical justification for the design requirements discussed in the following section.

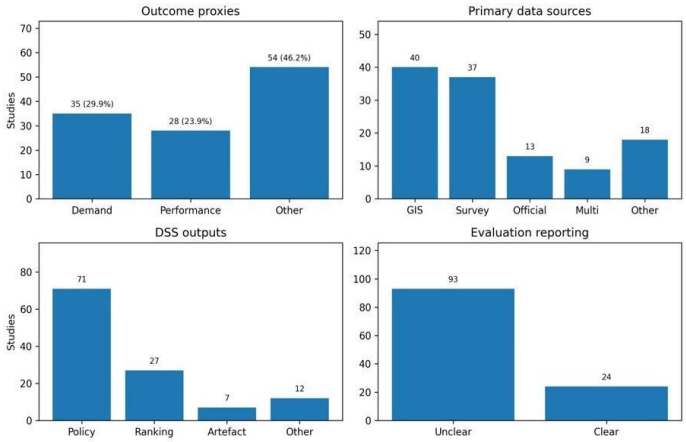


Figure 4. Evidence mapping summary (N = 117) across outcome proxies, data sources, DSS outputs, and evaluation reporting.

The patterns visualized in Figure 4 indicate that the current evidence base remains dominated by demand- and performance-oriented studies, while explicit operational DSS artefacts, decision-quality evaluation, and government-relevant data integration remain limited. To make these trends more precise and measurable, Table 1 presents the numerical summary across the four coded dimensions—outcome, data sources, DSS outputs, and evaluationthereby clarifying the empirical basis for the proposed policy-ready DSS design.

Table 1. Evidence mapping summary across key dimensions (N = 117)

Dimension	Summary findings and implications (n; % of total)
Outcome	0/117 studies used the term 'underutilization' in the title. Underutilization-relevant outcomes were mainly proxied by demand indicators (35; 29.9%) or performance/competitiveness (28; 23.9%).
Data sources	Remote sensing/GIS (40; 34.2%) and surveys/questionnaires (37; 31.6%) were prevalent; local government/internal or official statistics were limited (13; 11.1%). Multi-source integration appeared in 9 studies (7.7%).
DSS outputs	Policy/scenario insights dominated (71; 60.7%). Ranking/prioritization outputs appeared in 27 studies (23.1%). Explicit DSS artefacts were reported in 7 studies (6.0%).
Evaluation	Evaluation procedures were not clearly described in 93 studies (79.5%) based on abstract/metadata coding. Decision-quality evaluation was uncommon.

Implications of the evidence mapping for DSS design

The mapping reveals a misalignment between what is frequently reported (demand or composite performance metrics) and what local governments need to operationalize (auditable risk scores, ranked priorities, and intervention rationales). Bridging the gap between technical success and practical impact requires an artefact that couples prediction with a decision engine. Recognizing that model accuracy does not equate to policy effectiveness, our framework introduces a two-layer evaluation: Layer E1 assesses technical performance (e.g., AUC/F1), while Layer E2 measures decision utility through rank agreement with experts and simulated allocation efficiency [5], [6], [11], [12], [13], [14], [15]. This two-layer evaluation framework, as illustrated in Figure 5, ensures that the system provides both statistical rigor and practical value for public sector resource allocation.

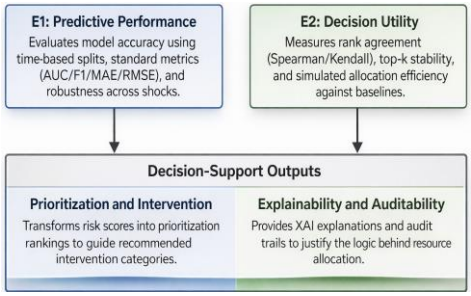


Figure 5. Two-layer evaluation framework: prediction accuracy and decision quality.

Proposed artefact architecture and workflow

The proposed DSS architecture comprises three layers: (i) data acquisition and governance, (ii) predictive modelling, and (iii) decision support. The data layer ingests government-internal systems and open-data sources, applies quality checks, and harmonizes indicators across agencies. The model layer supports time-aware learning on panel or time-series data and can leverage tree-based ensembles (e.g., Random Forests and gradient boosting) to handle nonlinearities and heterogeneous signals. The decision layer converts predicted risk into ranked priorities and generates an audit report that includes feature-attribution explanations (XAI) and recommended intervention categories [8], [9], [10], [19], [20], [21], [24], [25], [26], [27], [28], [29], [30]. The end-to-end architecture and workflow are illustrated in Figure 6. The corresponding RQ-to-data/method/metric/output mapping is summarized in Table 2. In accountable public administration, predictive accuracy is necessary but insufficient; therefore, our architecture integrates an XAI layer leveraging SHAP or LIME to generate a transparent audit trail. This ensures that every risk score is logically defensible during budgeting and official audit processes by linking scores to their dominant drivers.

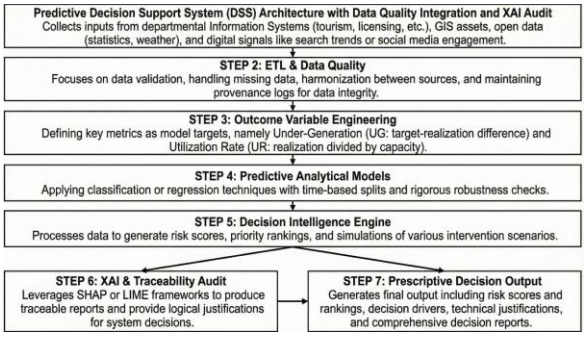


Figure 6. Proposed predictive DSS architecture with explicit data-quality and XAI audit layers.

To clarify how the proposed architecture is operationalized, Table 2 maps each research question to its corresponding data inputs, analytical methods, evaluation metrics, and expected outputs. This mapping demonstrates that the proposed DSS is not limited to predictive modelling alone, but is structured as an end-to-end decision-support pipeline that links underutilization measurement, multidimensional risk analysis, predictive performance, and policy-oriented prioritization with auditable outputs.

Table 2. Research question (RQ) to data-method-metric-output mapping.

RQ	Data & methods	Metrics	Outputs
RQ 1	Tourism visits and potential baseline; UG/UR labelling	Expert validation; statistical consistency checks	Risk label (H/M/L) or continuous UG/UR
RQ 2	Multi-dimensional feature engineering; robustness checks	Stability of feature importance; sensitivity analysis	Risk drivers map; controllable levers
RQ 3	Panel data (2021–2026) with time-based split; classification/regression	AUC/F1 or MAE/RMSE; robustness over seasons	Risk score; predicted UG/UR

RQ 4	Decision engine + expert input; ranking and allocation simulation	Spearman/Kendall rank agreement; rank overlap; budget efficiency	Prioritization ranking; audit trail report

The RQ-to-data-method-metric-output mapping in Table 2 provides the analytical bridge between the conceptual architecture and its intended policy function. By explicitly linking each research question to measurable inputs, evaluation criteria, and decision-support outputs, the table reinforces that the proposed DSS is designed not merely as a predictive model, but as a governance-oriented artefact capable of supporting transparent prioritization, interpretable intervention design, and accountable public-sector decision making.

Taken together, these results show that the current evidence base is still dominated by model-centric and demand-oriented approaches, with limited attention to underutilization as a policy risk, decision-oriented outputs, and auditable evaluation procedures. These empirical patterns not only confirm the existence of a governance gap in the literature, but also provide the foundation for discussing why a policy-ready, transparent, and accountable DSS architecture is needed in the public-sector tourism context.

Discussion

Research gaps and novelty

The evidence mapping conducted in this study identifies four interconnected gaps that current tourism analytics research has yet to bridge: (i) Formalization of Underutilization as a Policy Risk: While tourism demand forecasting is ubiquitous, the evidence mapping reveals a critical governance blind spot: none of the 117 analyzed studies (0%) explicitly formalize "underutilization" as a policy outcome in their titles [1], [5], [6]. Most research remains demand-centric, focusing on visit volume or competitiveness indicators rather than operationalizing the risk of stranded publicly funded assets which implies inefficient capital spending and foregone socio economic returns [1]. (ii) Integration and Quality Control of Data Pipelines: Data sources used in current studies are heavily skewed toward GIS (34.2%) and surveys (31.6%), while local government internal statistics are utilized in only 11.1% of cases. Furthermore, multi-source integration remains rare (7.7%), and existing pipelines seldom incorporate explicit quality controls, such as data provenance logs or FAIR aligned standards, which are mandatory for maintaining data integrity in public sector settings [25], [26], [27]. (iii) Alignment with Bureaucratic Decision Workflows: There is a significant disconnect between research outputs and operational needs. While most studies (60.7%) provide general policy or scenario insights, only 6% deliver explicit operational DSS artefacts. Consequently, few studies align their outputs with the specific ranking and allocation requirements of bureaucratic budgeting workflows, where officials must prioritize limited resources across competing destinations and intervention options [5], [6]. (iv) Evaluation of Decision Quality Beyond Technical Accuracy: Perhaps the most concerning gap is the "evaluation vacuum." Evaluation procedures were not clearly described in 79.5% of the studies mapped. Research typically stops at predictive performance (E1), such as AUC or F1-scores, while neglecting downstream decision-quality metrics (E2) such as rank agreement with experts or simulated allocation efficiency that are required to prove a system's practical utility [11].

Collectively, these gaps motivate the development of a predictive DSS that is uniquely "policy-ready" [1], [24]. By shifting the focus from mere demand forecasting to an auditable architectural framework, this study introduces a conceptual artefact that ensures transparency and accountability through XAI-enabled traceability [8], [9], [10], [11]. This ensures that every risk score is not only technically accurate but also logically defensible and traceable to its dominant drivers during official audit processes [8], [9], [10].

Practical implications for local governments

For local governments, the proposed DSS establishes a framework for anticipatory governance by shifting from reactive performance monitoring to proactive underutilization risk management. The system supports early warning and prioritization by translating heterogeneous indicators ranging from government-internal systems to external socio economic data into standardized risk scores, specifically the Underutilization Gap (UG) and Utilization Ratio (UR). These scores generate prioritized rankings that provide a robust evidence base to inform annual planning, infrastructure program design, and strategic resource allocation.

A critical implication for public administration lies in the system's accountability and transparency. The integration of an XAI audit layer, leveraging SHAP or LIME frameworks, generates transparent audit trails that are essential for bureaucratic defensibility. These

auditable explanations facilitate cross-agency coordination by visualizing which multidimensional drivers dominate risk for each destination and identifying which levers such as accessibility or management capacity are plausibly controllable through policy interventions. This ensures that officials can justify their decisions during official audit and budgeting processes by linking every risk score to its underlying data drivers.

Furthermore, the DSS's decision engine enables officials to conduct allocation simulations to compare various budget scenarios and quantify the marginal utility of intervention bundles. By coupling predictive performance with decision-quality metrics (such as rank agreement and simulated allocation efficiency), the system ensures that tourism investments maximize local socio economic returns and reduce the likelihood of publicly funded assets becoming stranded. Ultimately, this provides local governments with a theoretically grounded instrument to optimize the utilization of public assets and ensure efficient capital spending in an increasingly volatile tourism landscape.

Theoretical implications

The study reframes destination analytics from demand-centric forecasting to a policy-risk framing of underutilization and translates evidence gaps into an artefact development roadmap grounded in design science. By formalizing the underutilization risk through a conceptual artefact, this study bridges the gap between theoretical risk framing and practical system architecture, offering a rigorous blueprint for future public-sector implementations. By integrating prediction, prioritization, and auditability, the proposed work aims to deliver actionable contributions for both tourism analytics and public-sector decision support [1], [11], [12], [13], [14], [15].

This study significantly reframes tourism destination analytics by shifting the paradigm from traditional demand-centric forecasting to a strategic policy risk framing of underutilization [1]. By translating identified evidence gaps into a structured development roadmap grounded in Design Science Research Methodology (DSRM), the research provides a robust conceptual artefact [12], that addresses the systemic lack of auditable decision support in current literature [1], [11].

Crucially, by formalizing underutilization risk through mathematically measurable targets specifically the Underutilization Gap (UG) and Utilization Ratio (UR) this study bridges the longstanding disconnect between theoretical risk framing and the practical system architecture required for public sector implementations [1]. This formalization moves beyond simple performance indicators to establish a theoretically grounded basis for anticipatory governance, allowing officials to treat underutilization as a predictable and manageable risk [1], [11].

Furthermore, the integration of predictive modeling with an XAI-enabled audit layer establishes a new theoretical standard for transparency and accountability in algorithmic decision making [11], [15]. By explicitly coupling prediction accuracy with decision-utility metrics, such as rank agreement and allocation efficiency, the proposed framework offers a more holistic evaluation paradigm than traditional model-centric approaches [14]. Ultimately, this work provides a rigorous blueprint that delivers actionable contributions for both tourism analytics and public-sector decision support [1], [11], [12], [13], [14], [15].

Overall, the discussion confirms that the main contribution of this study lies not in proposing another demand-centric analytical model, but in articulating a governance-oriented DSS roadmap that directly addresses the underexplored problem of underutilization risk in public-sector tourism. By linking evidence gaps to design requirements for prediction, prioritization, explainability, and auditability, the proposed artefact establishes a stronger foundation for comparison with existing state of the art approaches

Comparison

Compared with the state-of-the-art in tourism analytics and decision support, the proposed framework offers a more policy-ready and auditable contribution. Existing studies predominantly focus on demand forecasting, destination competitiveness, or descriptive spatial analysis, whereas our framework explicitly formalizes underutilization as a public-sector policy risk through the operationalization of Underutilization Gap (UG) and Utilization Ratio (UR). This distinction is important because, based on the evidence mapping, none of the 117 reviewed studies explicitly positioned underutilization as a policy outcome, multi-source integration remained limited (7.7%), explicit DSS artefacts were rare (6.0%), and most studies did not clearly report evaluation procedures (79.5%). In contrast, the proposed artefact extends beyond model-centric prediction by integrating heterogeneous government-relevant data, embedding an XAI-based audit trail for transparency, and introducing a two-

layer evaluation framework that combines predictive performance (E1) with decision utility (E2), including rank agreement and simulated allocation efficiency. Therefore, unlike prior approaches that mainly produce analytical insights, this study contributes a governance-oriented DSS roadmap that is not only technically defensible but also operationally aligned with public budgeting, prioritization, and accountability requirements.

Taken together, the comparison shows that the proposed framework extends beyond the dominant state-of-the-art by integrating underutilization risk formalization, multi-source government-relevant data, XAI-enabled auditability, and two-layer evaluation into a single policy-ready DSS roadmap. These comparative advantages provide the basis for concluding that the proposed artefact offers both conceptual novelty and practical relevance for accountable public-sector tourism decision making.

5. Conclusions

This study shows that tourism decision-support research remains largely demand-centric, with evidence mapping of 117 studies revealing limited multi-source integration (7.7%), weak reporting of decision-quality impacts, and a major evaluation gap, as 79.5% of studies do not clearly specify evaluation procedures; most importantly, none explicitly formalize underutilization as a policy outcome. To address this gap, the study proposes a design-science roadmap for a predictive DSS that operationalizes underutilization through the Underutilization Gap (UG) and Utilization Ratio (UR), integrates government-internal and open-data sources, and generates auditable risk scores and intervention rankings. By embedding an Explainable AI layer, the framework links each risk score to its dominant drivers to support transparent and defensible budgeting and audit processes, while its two-layer evaluation combines predictive performance with decision utility, such as rank agreement and allocation efficiency. Although the study remains at the conceptual-artefact stage, it provides a necessary foundation for future implementation, with subsequent research needed to validate the UG/UR measures through expert elicitation and to test the framework longitudinally across regions to assess its generalizability and socio-economic impact.

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