JOURNAL OF INTERDISCIPLINARY RESEARCH IN ARTIFICIAL INTELLIGENCE AND SOCIETY

Journal of Interdisciplinary Research in Artificial Intelligence and Society,
2026, 2(1), Article 4
eISSN: 3117-793X

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Review paper

Culturally Responsive Tourism Intelligence: Integrating Cross-Cultural Encounters, Machine Learning and Big Data Forecasting in Tourism and Hospitality

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Citation: Jahid, M. A., Rahman, M. B., & Morsalin, M. (2026). Culturally responsive tourism intelligence: integrating cross-cultural encounters, machine learning and big data forecasting in tourism and hospitality. *Journal of Interdisciplinary Research in Artificial Intelligence and Society, 2*(1), Article xx. https://doi.org/10.20897/jirais/18992

Published: July 22, 2026

ABSTRACT

Tourism and hospitality research increasingly uses machine learning, platform traces and big-data forecasting, yet many analytics studies still treat culture as background context rather than as a source of meaning, behavior and model validity. This conceptual article develops a Culturally Responsive Tourism Intelligence framework by integrating recent peer-reviewed work on cross-cultural tourism encounters, smart tourism technologies, machine learning and big-data forecasting. Using a structured integrative documentary synthesis, the article identifies how cultural encounters generate digital traces, how numerical, textual, visual and behavioral data can be connected without reducing culture to a technical feature, and how predictive models can be assessed through technical, cultural and ethical validity. The synthesis shows that tourism analytics becomes more useful when digital traces are interpreted through cultural meanings, language practices, visitor expectations, stakeholder relations and governance conditions. The proposed framework links cultural encounter, data trace, feature construction, model layer, validation and governance, and decision outcome. The contribution is a theory-building model that moves tourism analytics beyond technical prediction toward culturally valid, explainable and stakeholder-sensitive decision support.

Keywords: cross-cultural tourism, hospitality analytics, machine learning, big-data forecasting, cultural intelligence, multimodal data

Tourism and hospitality are cultural industries before they are data industries. Visitors do not simply move through destinations, purchase services and leave digital traces. They interpret places, negotiate service encounters, evaluate authenticity, communicate experience and perform identity through language, image, rating, search and behavior (Chaimongkol & Rattanakantadilok, 2026). The growth of digital platforms has made these traces increasingly measurable, but measurability does not remove the cultural meanings that produced them.

Recent tourism research confirms that digitalization has transformed visitor planning, service delivery and destination governance. Smart tourism technologies influence exploration, exploitation and travel satisfaction (Huang et al., 2017), while real-time service interactions allow tourism firms to co-create value with guests during the experience rather than only after it (Buhalis & Sinarta, 2019; Latif & Yasin, 2025). Big data analytics also helps tourism organizations detect demand signals, review patterns, mobility flows and sustainability challenges (Li et al., 2018; Mariani et al., 2018; Agrawal et al., 2022). However, the same literature warns that analytics can become overly technical when it prioritizes prediction accuracy without explaining why digital traces carry particular meanings.

Culture is central to this problem. Cross-cultural encounters shape how tourists judge politeness, waiting time, privacy, authenticity, safety, crowding, food, heritage and service recovery (Bakir et al., 2017; Mattila, 2019; Gjini & Hernandez-Gantes, 2025). A negative online review may reflect poor service, but it may also reflect translation difficulties, unfamiliar service scripts or culturally specific complaint norms. A destination image may appear attractive in a visual dataset while carrying sacred, political or identity meanings for local communities. A search spike may indicate travel intention, but it may also reflect anxiety, media exposure, visa uncertainty or festival planning. These examples show that tourism data are not culturally neutral. This concern is consistent with evidence that digital connectivity can support cultural awareness and cross-cultural communication while remaining shaped by local context (Sultan et al., 2025; Akinwande & Egbetola, 2026; Latif et al., 2026).

The rapid expansion of artificial intelligence, robotics and machine learning in tourism further increases the need for cultural interpretation. Automated systems can forecast demand, classify reviews, analyze images, personalize recommendations and support service recovery (Koo et al., 2021; Tussyadiah, 2020; Sarkar, 2025; Lee et al., 2025; Dalgalıdere, 2025; Ismayil et al., 2026). Yet models trained on uneven languages, markets or platforms may underperform for minority groups and less visible destinations. Smart governance research also indicates that technological optimization should be connected with stakeholder inclusion, citizen-centered services and destination-specific context (Mandić & Kennell, 2021; Katz, 2026). Therefore, tourism intelligence must combine predictive capacity with interpretive and ethical safeguards.

The research gap is that cross-cultural tourism theory, machine learning research and big data forecasting are often discussed separately. Cross-cultural studies explain meaning but rarely specify how cultural constructs can guide algorithmic feature construction. Machine learning studies classify numerical, textual and visual data but often understate cultural bias, language variation and contextual validity. Forecasting studies demonstrate the value of web traces, social media and unstructured data but often lack a strong theory explaining why these signals represent demand in different cultural markets (Wu et al., 2025; Kowsar et al., 2025). This article addresses that gap by proposing an integrated framework for culturally responsive tourism intelligence.

The study is guided by four research questions: RQ1. How do cross-cultural encounters shape the generation, and interpretation of tourism data used in machine learning and forecasting? RQ2. How can numerical, textual, visual and behavioral tourism data be integrated without reducing culture to a purely technical feature? RQ3. What validation and governance safeguards are required for culturally valid tourism intelligence? RQ4. What implications does a culturally responsive analytics framework offer for researchers, destination managers and hospitality organizations?

LITERATURE REVIEW

Cross-cultural encounters and tourism meaning

Cross-cultural tourism research begins from the recognition that tourism is built through encounters among hosts, guests, employees, communities, destinations and platforms. Bakir et al. (2017) emphasize that tourism and hospitality are shaped by interactions among stakeholders who bring different cultural expectations to service and destination settings. Mattila (2019) similarly argues that hospitality and tourism inquiry must examine cultural dimensions because service encounters and global business practices are interpreted through culturally grounded assumptions.

Culture should therefore not be treated as a simple demographic label. Following interpretive cultural theory, culture can be understood as a system of meaning through which people interpret experience (Geertz, 1973). In tourism and hospitality, this means that service quality, satisfaction, authenticity, destination image and behavioral intention are mediated by shared and contested meanings. A guest's evaluation of warmth, privacy, food authenticity or complaint handling may depend on learned expectations. A host community may interpret tourism development as opportunity, intrusion, commodification or empowerment depending on local history and social context.

This cultural logic has direct implications for analytics. Reviews contain idioms, humour, sarcasm, politeness conventions and indirect criticism. Images encode aesthetics, social distance, dress norms, sacred space and heritage value. Search behavior reflects language, calendars, media narratives, visa rules, family structures and uncertainty. A data-driven model that ignores culture may still obtain acceptable aggregate accuracy while producing biased or misleading insights for specific visitor groups, destinations or service contexts.

Machine learning, smart tourism technologies and big data forecasting

Machine learning has become a major analytical approach in tourism and hospitality. Li et al. (2025) reviewed 406 peer-reviewed articles from 2007 to 2023 and showed that the field has expanded across numerical, textual and image data. Numerical data are often used for tourism demand, accommodation demand and revenue forecasting. Textual data are used for sentiment analysis, customer experience, review helpfulness and electronic word-of-mouth. Visual data are used to analyze destination image, social media engagement, aesthetic preference and tourist perception. Multimodal language scholarship likewise emphasizes coordinated multimodal input, human mediation and equitable access when technology is used across linguistic contexts (Martin, 2026; Latif et al., 2026).

Earlier work also shows why this expansion requires theoretical grounding. Li et al. (2018) found that big data research in tourism uses online textual data, social media data, search engine data, user-generated content and device-based traces to understand tourist behavior. Mariani et al. (2018) similarly showed that hospitality and tourism organizations use business intelligence and big data for operational and strategic decision-making, but the literature requires stronger attention to value creation, managerial use and methodological quality. These findings support the present article's claim that tourism analytics should not only ask whether a model predicts well, but also whether it explains culturally meaningful behavior.

Smart tourism technologies add another layer. Huang et al. (2017) demonstrated that smart tourism technologies support both exploratory and exploitative uses in travel planning, influencing travel experience satisfaction. Pai et al. (2020) found that perceived smart tourism technology experience is related to tourist satisfaction, happiness and revisit intention. Zhang et al. (2022) further showed that smart technology attributes influence tourist experience, satisfaction and behavioral intentions in visitor attractions. These studies support the importance of digital systems, but they also imply that technological usefulness depends on how tourists interpret information, accessibility, interactivity, personalization and security within specific contexts.

Forecasting research extends this conversation by showing that search queries, website traffic, online reviews, social media statistics, photos and videos can improve demand prediction. Wu et al. (2025) identify these data types but also note persistent gaps, including weak theoretical foundations, incomplete use of high-frequency data, limited integration of unstructured data, insufficient dynamic analysis and the need for cloud-based demand information systems. These gaps are not merely technical. They are cultural when models fail to account for source-market language, festival calendars, crisis narratives, heritage meaning or platform participation inequality.

Toward culturally responsive tourism intelligence

Culturally responsive tourism intelligence refers to the design, validation and use of analytics systems that treat culture as part of the data-generation process. The concept connects three ideas. First, cross-cultural encounters produce the meanings that tourists later express through reviews, searches, bookings and images. Second, machine learning and big data forecasting transform those traces into predictions or classifications. Third, governance determines whether the resulting intelligence is transparent, fair and useful for tourists, employees, communities and managers.

This approach responds to the call for transformative and reflexive e-tourism research (Gretzel et al., 2020). It also aligns with AI and robotics scholarship that frames tourism technology as a force affecting customers, businesses and communities rather than merely an efficiency tool (Koo et al., 2021; Tussyadiah, 2020; Latif et al., 2026). The purpose is not to reject machine learning or big data forecasting, but to specify how these methods should be culturally interpreted, validated and governed in tourism and hospitality contexts. Interdisciplinary AI scholarship similarly argues that analytics should balance computational power with interpretive judgment and social legitimacy (Islam, 2026).

METHODOLOGY

This article uses a structured integrative literature synthesis. The approach is appropriate because the research problem crosses three bodies of literature that are often examined separately: cross-cultural tourism and hospitality, machine learning applications, and big data forecasting. The purpose is not to estimate a new empirical model, but to construct a conceptual framework that integrates these streams into a theory-building architecture.

The documentary evidence base consisted of three primary source streams and supporting peer-reviewed literature. The primary streams were cross-cultural tourism and hospitality, machine learning in tourism and hospitality, and tourism forecasting with big data. To address recency and academic currency, the synthesis prioritized peer-reviewed journal articles published between 2017 and 2025, while retaining foundational works where necessary and including the latest review papers used to frame the manuscript. Key recent sources included work on smart tourism technologies, big data analytics, AI and robotics, e-tourism transformation, cross-cultural research, smart governance and sustainable tourism analytics. A recent bibliometric study of AI research also warns that uneven national participation can shape the visibility and transferability of emerging knowledge (Almarashdi et al., 2026; Latif et al., 2026).

The inclusion criteria were: (a) clear relevance to tourism or hospitality; (b) peer-reviewed publication status, except for foundational books used for theory; (c) explicit connection to culture, smart tourism, machine learning, big data, forecasting, governance or sustainability; and (d) conceptual usefulness for explaining how tourism data become meaningful and actionable. Excluded sources were non-academic commentaries, purely technical studies with no tourism or hospitality relevance, industry reports without peer review and publications that did not address data, culture, forecasting or governance.

The synthesis proceeded in four stages. Stage 1 extracted constructs from each stream, including service encounter, cultural interpretation, data modality, feature construction, model validation, forecasting signal, unstructured data and governance. Stage 2 mapped these constructs across levels of analysis: tourist, employee, organization, destination, platform and governance system. Stage 3 identified gaps where the three streams did not yet fully connect. Stage 4 developed the Culturally Responsive Tourism Intelligence framework, research propositions and practical implications. Analytical reliability was supported by documenting the inclusion logic, comparing multiple research streams and aligning propositions with the reviewed literature (**Table 1**).

Table 1

Source streams, recent citations and synthesis gaps

Source stream	Key recent evidence	Main insight	Gap addressed in this article
Cross-cultural tourism and hospitality	Bakir et al. (2017); Mattila (2019)	Tourism encounters are interpreted through cultural expectations, service scripts, stakeholder relations and meanings.	Analytics often under-specifies how culture affects data generation and interpretation.
Smart tourism technologies and AI	Huang et al. (2017); Tussyadiah (2020); Koo et al. (2021); Zhang et al. (2022)	Smart technologies and AI shape experience, satisfaction, automation and service decision-making.	Technology studies require stronger attention to cultural validity, multilingual contexts and governance.
Big data and forecasting	Li et al. (2018); Mariani et al. (2018); Agrawal et al. (2022); Wu et al. (2025)	Digital traces improve prediction and decision support through search, review, social media and visual data.	Forecasting needs cultural theory to explain why signals predict demand differently across markets.

Note. The table summarizes the revised evidence base used to integrate cross-cultural tourism, machine learning and big data forecasting.

RESULTS AND CONCEPTUAL SYNTHESIS

The synthesis produced five findings (**Table 2**). First, culture generates tourism data rather than merely contextualizing it. Tourists search, book, complain, praise, photograph and recommend within socially learned systems of meaning. Consequently, platform traces record cultural behavior mediated by technology. A low rating may indicate service failure, but it may also reveal expectation gaps, language barriers or culturally specific complaint behavior. A high image frequency may indicate destination appeal, but it may also reflect social media performance or iconic visual norms.

Second, multimodal data require cultural alignment. Numerical booking records, review text, search indices, geo-tagged photos and social media engagement capture different aspects of the same tourism experience. Text may communicate explicit evaluation, images may communicate aspiration or identity, and search data may represent planning uncertainty. When these modalities are fused without interpretation, a model may become statistically powerful but less explainable. Culturally aligned modeling requires attention to language, calendars, events, platform norms, rating styles and source-market differences.

Third, forecasting needs a theory of cultural information flow. A tourist may search for a destination because of a festival, family obligation, influencer content, safety concern, visa policy, price change or crisis narrative. Each pathway has a different temporal structure and predictive meaning. Dynamic keyword selection, rolling validation and time-varying models are therefore necessary when cultural events or media narratives alter the meaning of digital traces.

Fourth, model validity must include cultural validity. Conventional metrics such as accuracy, precision, recall, error rate and forecasting loss are necessary but insufficient. A model can perform well in aggregate while underperforming for minority languages, rural destinations, small hotels, low-volume events or culturally distinctive service scripts. Cultural validity requires representation validity, semantic validity, interpretive validity and consequence validity. An intersectional perspective is also necessary because digital systems can reproduce algorithmic bias and digital exclusion when representation is uneven (Işıklı & Fazlıoğlu, 2026).

Fifth, tourism intelligence is a governance issue. Models influence pricing, targeting, staffing, crowd management, destination marketing, service recovery and crisis response. These decisions affect tourists, employees, host communities, small firms and public agencies. Analytics therefore requires privacy protection, responsible data use, stakeholder review and transparent model interpretation.

Table 2

Culturally responsive tourism intelligence framework

Framework layer	Core question	Indicative operationalization
Cultural encounter	What cultural interaction generates the behavior?	Host-guest service script, authenticity judgment, heritage encounter, language community, local event.
Data trace	What observable data record the behavior?	Search volume, review text, rating, booking record, photo, video, mobile trace or website traffic.
Feature construction	How is the trace made meaningful?	Dynamic keywords, sentiment index, topic model, cultural lexicon, market calendar, image labels.
Model layer	Which analytical method fits the task?	Regression, ARIMAX, MIDAS, LSTM, random forest, support vector machine, ensemble model or multimodal fusion.
Validation and governance	Is the result technically accurate and culturally valid?	Cross-validation, subgroup testing, explainability, privacy control, human review and stakeholder interpretation.
Decision outcome	How will the insight be used responsibly?	Demand planning, staffing, pricing, service recovery, destination marketing, crowd management and sustainability planning.

Note. The framework presents a six-layer pathway from culturally embedded encounters to responsible decision support.

Framework propositions

The Culturally Responsive Tourism Intelligence framework leads to five propositions that can guide future empirical studies. These propositions translate the conceptual synthesis into testable research directions for destinations, hotels, restaurants, platforms and public tourism organizations (**Table 3**).

Table 3

Research propositions for culturally responsive tourism intelligence

Proposition	Statement	Suggested empirical test
P1: Cultural feature construction	Models will produce stronger tourism insights when culturally specific variables are incorporated into feature construction.	Compare models with and without cultural calendars, language-specific features and market-specific search terms.
P2: Multimodal alignment	Multimodal models will perform best when textual, visual and numerical features are linked to the same cultural encounter.	Test textual, visual and numerical fusion against single-modality baselines in destination image or demand studies.
P3: Cultural validity	Models validated across languages, source markets and destination types will show stronger external validity.	Report model performance by language, nationality, destination type, platform and visitor segment.
P4: Dynamic cultural signals	Adaptive models will be stronger when cultural events, crises or media narratives shift search and social media traces.	Use rolling windows, dynamic keyword selection, MIDAS or time-varying parameter models.
P5: Governance	Stakeholder review will improve the legitimacy and usefulness of tourism intelligence systems.	Evaluate model outputs through managers, employees, local stakeholders and human raters.

Note. The propositions are intended for future empirical validation rather than as statistically tested findings in this conceptual article.

DISCUSSION

The aim of this article was to integrate cross-cultural tourism theory, machine learning applications and big data forecasting into a culturally responsive framework for tourism intelligence. The findings address this aim by showing that tourism data are culturally generated, multimodal data require cultural alignment, forecasting needs theory of cultural information flow, model validity must include cultural validity and analytics requires governance. These findings directly answer the research questions by explaining how cultural encounters shape data, how data modalities can be integrated responsibly and how validation and governance can improve decision support.

The study extends cross-cultural tourism research by translating cultural encounter theory into analytics design. Bakir et al. (2017) and Mattila (2019) highlight the centrality of culture in tourism and hospitality interactions; the present framework adds that these interactions later appear as digital traces that models classify or forecast. This is an important extension because it links culture not only to service interpretation but also to the production of tourism data. It therefore moves cross-cultural inquiry closer to computational tourism research.

The findings also complement smart tourism technology studies. Huang et al. (2017), Pai et al. (2020) and Zhang et al. (2022) show that smart technology attributes can influence tourist experience, satisfaction and behavioral intentions. The present framework agrees with these findings but adds that information, accessibility, interactivity, personalization and security should be interpreted through cultural context. A feature that appears accessible to one visitor group may be confusing to another because of language, interface convention or risk perception. Thus, technology effectiveness depends not only on system design but also on cultural fit.

The framework further advances big data and forecasting literature. Li et al. (2018), Mariani et al. (2018) and Agrawal et al. (2022) show that tourism and hospitality analytics can improve decision-making, sustainability and market insight. Wu et al. (2025) argue that forecasting studies still need stronger theory, high-frequency integration and unstructured-data use. The current article responds by explaining digital traces as culturally mediated signals. For example, search data, review sentiment and photo sharing should be connected to festivals, risk narratives, platform participation, visual norms and source-market behavior before they are used as forecasting inputs.

The study also contributes to AI and automation debates in tourism. Tussyadiah (2020) argues that the automated future of tourism must be shaped as both a social and economic issue, while Koo et al. (2021) emphasize that AI and robotics will influence customers, businesses and communities. The present framework supports this view by positioning validation and governance as central layers. AI does not become responsible because it is accurate; it becomes responsible when the model is interpretable, culturally valid, privacy-sensitive and useful for stakeholders.

Implications of the study

The revised framework offers several implications for researchers, managers and policy-makers:

- Researchers should define the cultural encounter that produces the data before selecting variables, algorithms or forecasting models.
- Tourism and hospitality organizations should validate model outputs across languages, source markets, visitor segments and destination types rather than relying only on aggregate accuracy.
- Managers should combine automated analytics with human review from front-line employees, local communities and destination stakeholders.
- Destination marketing organizations should interpret search and social media signals alongside festivals, heritage meanings, crisis narratives and market-specific calendars.
- Platform owners should document training data, model limitations, privacy safeguards and potential biases when analytics influence pricing, visibility, service recovery or destination policy.
- Future empirical studies should compare culturally enriched models against conventional models to test whether cultural feature construction improves both predictive accuracy and decision relevance.

Limitations and future research

This manuscript has limitations. It is a conceptual synthesis rather than a new empirical test, and it does not claim to exhaust all tourism analytics, cross-cultural tourism or forecasting research. Although the revision added recent peer-reviewed literature from 2017 to 2025 and retained the latest review papers, the synthesis remains selective. Future researchers should conduct systematic reviews or bibliometric analyzes with explicit database search protocols and quality appraisal.

A second limitation concerns operationalization. Culture is dynamic, relational and context-dependent, so researchers must avoid reducing it to fixed national stereotypes. Future studies should combine quantitative modeling with qualitative interviews, field observation, expert panels and stakeholder workshops to validate how cultural meanings are represented in data. Longitudinal studies should also test whether culturally enriched forecasting models remain valid during crises, festivals, policy changes or sudden media events.

A third limitation relates to implementation. Many small tourism and hospitality firms lack advanced data science capacity. Future research should therefore develop scalable tools that allow smaller firms to apply culturally aware review analysis, multilingual validation and stakeholder interpretation without requiring complex infrastructure. Larger platforms and destinations can test more advanced multimodal and cloud-based systems.

CONCLUSION

This article developed a Culturally Responsive Tourism Intelligence framework by integrating cross-cultural tourism, machine learning and big data forecasting. The core argument is that tourism and hospitality analytics must move beyond technically accurate prediction toward culturally valid, explainable and accountable decision support. Culture is not an external background variable. It generates the meanings, behaviors and digital traces that machine learning and forecasting models analyze.

The synthesis showed that cross-cultural tourism research provides the interpretive foundation for understanding service encounters, authenticity, stakeholder relations and destination meanings. Machine learning research provides methods for analyzing numerical, textual and visual data, but it requires stronger attention to data quality, validation, explainability, multilingual complexity and ethics. Big data forecasting provides methods for using search, social media, text, photo and video traces, but it requires stronger theoretical grounding and more dynamic interpretation.

The proposed framework links cultural encounter, data trace, feature construction, model layer, validation and governance, and decision outcome. It also offers propositions for future empirical work. In practical terms, tourism and hospitality organizations should not ask only whether a model predicts. They should ask whose culture produced the data, which meanings the model preserves or loses, who benefits from the decision and how errors are detected and corrected. In a sector built on human encounter, responsible intelligence must be culturally responsive.

Acknowledgement

The authors thank their institutions for providing an academic environment in which this conceptual work could be developed. No external individual or organization influenced the analysis or interpretation.

Funding

The authors received no specific grant from any funding agency in the public, commercial or not-for-profit sectors for this study.

Ethical statement

Not applicable. This conceptual literature-based synthesis involved no human participants, animals, surveys, interviews, interventions or identifiable personal data; formal institutional ethical approval was therefore not required.

Competing interests

The authors declare that they have no competing interests.

Author contributions

M.A.J., M.B.R. and M.M. conceived and designed the study; all authors performed the literature search and evidence collection; all authors analyzed and interpreted the literature; M.A.J. drafted the manuscript; and M.B.R. and M.M. critically reviewed and revised the manuscript. All authors have read and agreed to the published version of the manuscript.

Data availability

No new empirical dataset was generated or analyzed for this manuscript. The arguments are based on the published literature cited in the reference list.

AI disclosure

OpenAI ChatGPT was used during manuscript preparation to support language editing, structural organization, citation cross-checking and document formatting. The authors verified the cited sources, reviewed all substantive content and remain responsible for the accuracy, integrity and originality of the manuscript. No AI system is listed as an author.

Biographical sketch

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