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REVIEW

Does artificial intelligence improve accessibility in cultural and heritage tourism? Evidence from a design-led review and the Inclusive Human–AI Mediation (IHAM) framework

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Abstract

Accessibility and inclusion remain persistent challenges in cultural and heritage tourism, particularly as artificial intelligence (AI) increasingly mediates visitor experience and destination management. While prior research has examined AI-enabled personalisation and smart tourism development, less attention has been paid to how accessibility is shaped through the collaborative relationship between human users and AI systems in public cultural environments. This paper presents a design-led review of 66 peer-reviewed journal articles published between 2022 and 2026, identified through a PRISMA-guided search of Web of Science, Scopus, and the ACM Digital Library. Drawing on perspectives from human–AI collaboration, inclusive design, and human–data interaction, the review synthesises how AI-enabled systems interpret user data, mediate cultural experiences, and distribute agency across tourism service ecosystems. Building on this synthesis, the paper proposes the Inclusive Human–AI Mediation (IHAM) model, a theoretical framework that conceptualises accessibility as an emergent outcome of data interpretation, AI mediation, human agency, and governance. The model advances tourism technology research by reframing accessibility as a systemic and design-mediated challenge, and provides guidance for designing inclusive, ethical, and sustainable AI-enabled cultural and heritage tourism systems.

Keywords Cultural heritage tourism · Sustainable urban tourism · Human–AI collaboration · Inclusive design · Human–data interaction · Accessibility · Disabled users

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1 Introduction

The rapid integration of artificial intelligence (AI) into contemporary socio-technical systems has fundamentally reshaped how services, decision-making, and user interaction are organised (Herrmann and Pfeiffer 2023). Increasingly, AI technologies are not deployed as isolated tools that support discrete human tasks, but are embedded within collaborative arrangements in which humans and AI systems jointly contribute to sense-making, coordination, and action (Daly et al. 2025; Liu et al. 2025). This shift has given rise to the concept of human–AI (H-AI) teams, in which agency, authority, and responsibility are distributed across human and artificial actors rather than residing exclusively with either party (O'neill et al. 2022; Sharma 2025). As AI systems become more autonomous, adaptive, and data-driven, questions concerning how collaboration is designed, how interaction is structured, and how decision-making is negotiated are becoming central concerns (Tummala et al. 2025).

To date, research on H-AI teams has primarily focused on organisational and workplace settings, emphasising task allocation, trust calibration, explainability, and performance optimisation (Wang et al. 2025; Jiang et al. 2025). While this work provides important insights, it often evaluates collaboration through efficiency-oriented metrics and pays limited attention to how H-AI interaction is experienced by diverse users in public-facing environments (Doncieux et al. 2025; Hopko et al. 2022). In particular, disability and accessibility are rarely positioned as foundational considerations in H-AI team design (Zallio and Clarkson 2021; Doussard et al. 2024).

Cultural and heritage tourism is especially relevant because AI systems in these settings influence not only functional access but also public meaning-making and cultural representation. As publicly accessible environments with diverse visitor populations, these contexts provide a critical testbed for examining inclusive human–AI collaboration beyond organisational settings.

The design of H-AI teams becomes especially consequential when considered in relation to disabled users. Cultural and heritage tourism plays a crucial role in fostering social participation and equitable access to shared histories. Yet accessibility barriers extend beyond infrastructure (Duignan et al. 2023; Lu et al. 2025) to include sensory, cognitive, informational, and emotional dimensions of engagement. AI-enabled technologies hold the potential to support inclusion through adaptive interaction (Woolley et al. 2023), multimodal communication, and personalized guidance. At the same time, they introduce new challenges. Behavioural inference may misinterpret constrained interaction as disengagement; opaque system adaptation may reduce user agency; and data-driven optimisation may prioritise efficiency over dignity and autonomy. Recent research has also examined how emerging AI technologies embedded in everyday devices reshape tourism experiences and interactions with smart destinations. In particular, AI-powered smartphones enable new forms of "phygital" tourism experiences that seamlessly integrate physical and digital environments and support hyper-customised tourist interactions (Stankov et al. 2025).

Disability is foregrounded in this review because accessibility challenges reveal underlying assumptions embedded within data practices, interaction design, and institutional governance. When applied to H-AI teams, inclusive design raises funda-

mental questions about how data is interpreted, how roles are distributed, and whose needs shape systems behaviour (Sarkar 2025; Leena and Maheswari 2024).

These concerns intersect closely with scholarship on human–data interaction (HDI), which highlights issues of legibility, agency, and negotiability in algorithmic systems (Sailaja et al. 2021). AI-enabled systems increasingly act on inferred or probabilistic representations of users derived from behavioural and contextual data (Wang et al. 2024). Within H-AI teams, data does not merely inform computation; it structures collaboration and shapes how access and participation are mediated. For disabled users, such interpretations can profoundly influence autonomy and self-representation.

Despite rapid growth in research on AI-enabled tourism and human–AI collaboration, existing studies remain conceptually fragmented. Prior reviews primarily focus on organisational settings, performance optimisation, and trust in AI-assisted decision-making, with limited attention to public cultural environments. Accessibility and disability are also rarely positioned as central analytical concerns. As a result, current literature provides only a partial understanding of how AI-enabled systems mediate inclusive visitor experiences in cultural and heritage tourism contexts.

To address this gap, this study conducts a design-led review of peer-reviewed literature on AI-enabled systems in cultural and heritage tourism. In this context, a design-led review refers to a synthesis approach that foregrounds interaction roles, mediation processes, and experiential implications of AI systems, rather than focusing primarily on technical performance metrics. This perspective is particularly appropriate because accessibility in cultural tourism emerges through interaction design and service orchestration across socio-technical systems. Guided by this approach, the review addresses the following research questions:

RQ1 What types of user data are utilised by AI-enabled systems to support accessibility in cultural and heritage tourism contexts?

RQ2 How do AI-enabled systems mediate interaction and decision-making within tourism service ecosystems?

RQ3 What design strategies are employed to translate AI capabilities into inclusive visitor experiences?

RQ4 What ethical and governance challenges shape inclusive human–AI collaboration in cultural and heritage tourism context?

By synthesising 66 peer-reviewed journal articles, this review advances understanding of AI-enabled cultural and heritage tourism in three ways. First, it reframes AI systems as active mediators within tourism service ecosystems rather than as neutral tools. Second, it positions accessibility as a systemic, design-mediated outcome shaped by data interpretation, interaction design, and governance structures. Third, it proposes the Inclusive Human–AI Mediation (IHAM) model as a theoretical framework for analysing inclusive human–AI collaboration in public cultural environments.

2 Review scope and methodology

2.1 Scope and conceptual boundaries

This approach is grounded in design research traditions, particularly Research through Design (RtD) and human–computer interaction (HCI), which conceptualise design practice as a mode of inquiry capable of generating knowledge about interaction, experience, and socio-technical systems (Gaver 2012; Zimmerman et al. 2007, 2010). Within HCI and service design research, design-led approaches are particularly valuable for examining how interaction roles, mediation processes, and experiential conditions emerge across complex socio-technical environments, rather than focusing solely on technical performance metrics. Rather than aiming for exhaustive coverage, the review focuses on design-relevant studies of AI-enabled interaction, collaboration, and experience in cultural and heritage contexts.

The scope of the review is defined by three conceptual boundaries. First, it includes AI-enabled systems involved in interaction, decision-making, or experience mediation (e.g., adaptive guides, recommendation systems, conversational agents), while excluding purely technical studies that lacked explicit user interaction or design implications. Second, it centres on accessibility and inclusion for disabled users, broadly defined across physical, sensory, cognitive, and situational conditions, excluding studies that address general usability without explicit consideration of inclusion. Third, it is limited to cultural and heritage tourism settings, such as museums and heritage sites, excluding broader tourism contexts without a clear cultural dimension.

The review does not evaluate technical performance or predictive accuracy; instead, it foregrounds design strategies, interaction roles, and experiential implications, consistent with research on human–AI collaboration, human–data interaction, and inclusive service design.

2.2 Search strategy and data sources

A systematic search was conducted across three major academic databases that collectively cover tourism studies, human–computer interaction, design research, and AI-enabled systems: Web of Science (Core Collection), Scopus, and ACM Digital Library. These databases were selected because they provide broad interdisciplinary coverage across tourism and hospitality research, design and HCI scholarship, and human–AI interaction literature, thereby ensuring both domain relevance and methodological diversity. The database search was conducted in January 2026.

The search strategy was developed iteratively, combining keywords related to: (1) AI-enabled or intelligent systems; (2) disability, accessibility, or inclusive design; (3) design, interaction, or experience; and (4) cultural, heritage, or tourism contexts (Table 1). This four-part structure was chosen to ensure that included studies simultaneously addressed technological mediation, accessibility concerns, design processes, and tourism settings. The search strings were adapted to the syntax requirements of each database while maintaining the same four conceptual groups.

Table 1 Search keyword groups used in the literature search

Concept group	Keywords
AI-enabled systems	"artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR "intelligent system*" OR "recommendation system*" OR chatbot* OR "conversational agent*" OR "generative AI"
Accessibility and inclusion	accessib* OR disab* OR inclus* OR "inclusive design" OR "universal design" OR "assistive technolog*" OR impairment* OR "special need*"
Design and interaction	design OR "experience design" OR interaction OR "human-computer interaction" OR HCI OR "human-AI interaction" OR "human-AI collaboration" OR "user experience"
Cultural/heritage tourism	tourism OR tourist* OR visitor* OR museum* OR heritage OR "cultural heritage" OR "cultural tourism" OR "heritage tourism" OR exhibition*

The initial search included peer-reviewed journal articles and conference papers published in English. However, during the screening stage, conference papers and other non-article formats were excluded to ensure consistency and quality, resulting in a final corpus of peer-reviewed journal articles only.

The review followed a PRISMA-guided process to improve transparency in study identification, screening, eligibility assessment, and inclusion (Page et al. 2021; Moher et al. 2009). Records retrieved from the three databases were exported and merged into a single dataset before duplicate removal, title and abstract screening, and full-text assessment. The PRISMA-style flow diagram presented in Fig. 1 summarises the review process and exclusion stages.

2.3 Screening and inclusion criteria

The initial search across Web of Science, Scopus, and the ACM Digital Library identified 166 records, which were merged into a single dataset. After removing 22 duplicates through title, DOI matching, and manual checks, 144 unique records remained. Screening by document type excluded conference papers, book chapters, and other non-article formats, resulting in 92 peer-reviewed journal articles for title and abstract review. Three criteria guided the screening process: (1) studies involving AI-enabled systems that incorporated data interpretation and user interaction; (2) cultural or heritage tourism settings, such as museums, exhibitions, or heritage sites; and (3) explicit consideration of accessibility or inclusive design, including physical, sensory, cognitive, emotional, or situational conditions. Studies were excluded if they focused solely on technical optimisation without user interaction, addressed general tourism contexts without a clear cultural or heritage dimension, or discussed accessibility only indirectly without explicit consideration of inclusion or disabled users. Eligible studies were subjected to full-text review, followed by a second round of deduplication to remove overlapping records. This process resulted in a final corpus of 66 peer-reviewed journal articles included in the thematic synthesis (Fig. 1).

2.4 Analytical approach

Given the interdisciplinary scope and diversity of the 66 reviewed studies, this review adopts a theory-informed, design-led thematic synthesis, suitable for analysing com-

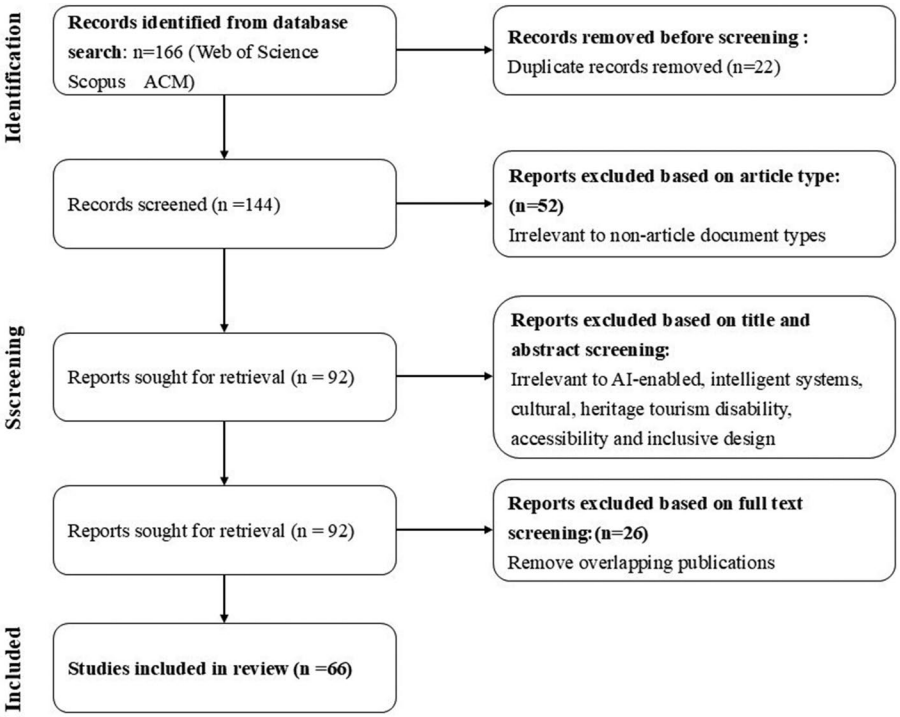

Fig. 1 PRISMA-style flow diagram of the literature selection process, showing study identification, deduplication, screening, and inclusion across Web of Science, Scopus, and the ACM Digital Library (Page et al. 2021)

plex socio-technical phenomena where quantitative aggregation is neither feasible nor meaningful. The analysis proceeded in three stages. First, descriptive coding captured key characteristics, including publication year, disciplinary orientation, study context, AI system type, and target users. Second, inductive thematic analysis identified recurring patterns in how AI-enabled systems support accessibility, focusing on data practices, AI mediation roles, inclusive interaction strategies, and experiential outcomes. Emerging categories were iteratively refined through constant comparison across the reviewed studies. Third, interpretive synthesis connected these themes to broader perspectives from inclusive design, human–AI collaboration, human–data interaction, and service design, informing the development of the Inclusive Human–AI Mediation (IHAM) framework.

Coding was conducted iteratively across the dataset using constant comparison and thematic interpretation (Table 2). Initial descriptive codes were progressively grouped into higher-level analytical categories through repeated comparison between studies. To improve consistency and transparency, coding categories were continuously refined and reapplied across the corpus during the review process. Analytical notes were used to document coding decisions, emerging thematic relationships, and the development of the IHAM framework.

Table 2 Coding framework and thematic synthesis structure

Analytical dimension	Representative codes/themes	Related Research Questions
User data practices	Behavioural data; contextual data; emotional data; sensor data; implicit accessibility indicators	RQ1
AI mediation roles	Adaptive mediator; assistive collaborator; decision-support actor	RQ2
Inclusive design strategies	Multimodal interaction; co-creation; participatory design; experience-oriented mediation	RQ3
Ethical and governance issues	Opacity; surveillance; accessibility marginalisation; accountability	RQ4
IHAM synthesis dimensions	Data interpretation; AI mediation; human agency; governance	Section 4 (Framework synthesis)

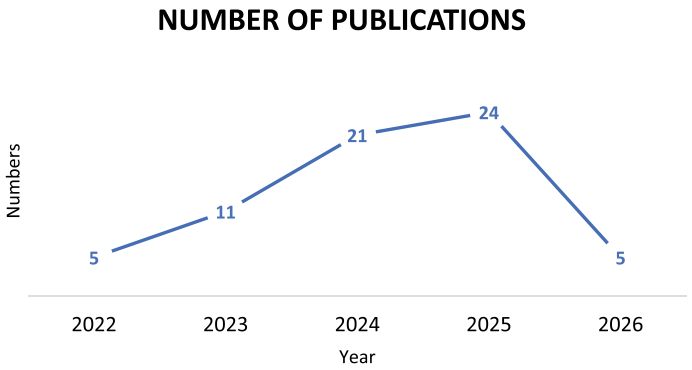

Fig. 2 Number of included peer-reviewed journal articles by publication year (2022–2026)

The thematic categories identified through the analytical process directly informed the organisation of the Results section (RQ1–RQ4) and the subsequent development of the IHAM framework presented in Sect. 4. Appendices A–C provide additional examples of how user data practices, AI mediation roles, and inclusive design strategies were categorised across the reviewed studies, thereby improving transparency between the coding process, thematic findings, and conceptual synthesis.

3 Results

This section presents the findings of the thematic synthesis of 66 studies, organised around the four research questions. The analysis focuses on how AI-enabled systems are designed and applied to support disabled users in cultural and heritage tourism, foregrounding design strategies, interaction roles, and experiential implications. The final corpus comprises 66 peer-reviewed journal articles published between 2022 and 2026 (Fig. 2). Publication trends indicate a rapidly emerging field, with outputs

increasing from 5 studies in 2022 to 24 in 2025, alongside 5 early-access articles in 2026. This growth reflects rising scholarly attention to AI-mediated tourism experiences, particularly in relation to recent developments in generative and data-driven technologies, and underscores the timeliness of a design-led synthesis.

3.1 Types of user data utilised in AI-enabled systems (RQ1)

Analysis of the 66 reviewed studies shows that AI-enabled systems in cultural and heritage tourism rely on diverse user data to support accessibility, personalisation, and engagement (Appendix A). However, this distribution is uneven: behavioural and contextual data dominate, while emotional, affective, and disability-specific data remain marginal. As a result, accessibility is often treated as a by-product of personalisation rather than a foundational design concern. Most studies are situated in museum and heritage contexts in Europe and East Asia, with accessibility primarily framed around visual, cognitive, and mobility-related barriers. Engagement with neurodiversity, psychosocial disability, and culturally specific access needs remains limited.

3.1.1 Behavioural data as the primary driver of adaptation

Behavioural data is the most prevalent form of user data, typically derived from interaction histories, navigation patterns, and content selection. It is often treated as a proxy for visitor engagement, enabling real-time personalisation without explicit user input. However, this assumption risks misinterpreting constrained behaviours of disabled users as disengagement, highlighting a critical limitation in current data practices.For instance, destination-level profiling systems employ machine-learning techniques to cluster tourists based on observed behaviour and to personalise recommendations accordingly (Schrader et al. 2025). Similarly, conversational agents deployed in religious and cultural tourism contexts adapt dialogue structure and response depth based on ongoing interaction patterns (Alharbi et al. 2025). In both cases, behavioural data underpins real-time adaptation and is framed as a low-friction mechanism for personalisation. From an inclusive design perspective, this reliance on behavioural data reflects an implicit assumption that observable behaviour adequately represents user needs. However, such assumptions risk obscuring accessibility-related constraints experienced by disabled users, whose interaction patterns may reflect fatigue, sensory overload, or navigational barriers rather than preference or disengagement. The reviewed studies rarely interrogate these interpretive risks, suggesting a need for more critical engagement with how behavioural data is read and acted upon.

3.1.2 Contextual and sensor-based mediation

Contextual data, including spatial location, temporal conditions, and environmental context, is also widely used, particularly in smart tourism and digital heritage systems. Location-aware guides and adaptive exhibition platforms frequently rely on

contextual triggers to activate content, recommend routes, or adjust narrative pacing as visitors move through physical space.

Data-driven modelling approaches in cultural heritage demonstrate how contextual information enables adaptive mediation across physical–digital environments (Alharbi et al. 2025). Likewise, smart cultural tourism platforms integrating AI and IoT technologies use contextual data to align information delivery with situational constraints (Suanpang and Pothipassa 2024). These systems indirectly support accessibility by reducing cognitive load and supporting wayfinding, particularly in complex heritage environments. Nevertheless, few studies critically examine how contextual inference may disadvantage users whose movement patterns or temporal rhythms diverge from normative expectations. For disabled users, contextual data can both enable and constrain access, depending on how inclusively it is interpreted within algorithmic logic.

In addition to spatial context, a small number of studies explore physiological or sensor-based data—such as motion tracking, audio input, or multimodal sensory signals,to support adaptive interaction in immersive or mixed-reality heritage experiences. These data are typically collected via wearable devices, XR systems, or environmental sensors and are used to infer user presence, orientation, or interaction intent rather than explicit emotional states. Examples include audio-first mixed-reality frameworks designed for non-visual interaction (Cagiltay et al. 2025) and AI-enabled approaches combining VR/AR with intelligent systems to enhance accessibility in built and cultural environments (Arranz-Paraíso and Arranz-Paraíso 2024). While sensor data enables alternative interaction modalities that may benefit users with visual or mobility impairments, such approaches remain largely exploratory and raise ethical concerns regarding privacy, consent, and data governance. Few studies provide detailed discussion of how sensor data is communicated to users, how consent is negotiated in public cultural spaces, or how risks of profiling and surveillance are mitigated (Zhao et al. 2022; Arranz-Paraíso and Arranz-Paraíso 2024).

3.1.3 User profiling and implicit accessibility assumptions

A smaller subset of studies incorporates user profile data, often collected during onboarding or inferred from prior interactions. Profiles typically include language preferences, content interests, or interface settings. In some cases, accessibility is explicitly foregrounded. For example, AI-assisted virtual reality systems designed to improve access to cultural heritage explicitly frame user profiles in relation to sensory and cognitive needs (Ballı et al. 2025). Similarly, generative-AI-based digital mediation stations in museums employ adaptive profiling to support alternative modes of interpretation (Schauer et al. 2024). However, across the broader corpus, profiling approaches remain largely generic rather than disability-aware. Accessibility is often treated as a configurable layer of personalisation rather than as a foundational design parameter shaping data collection and inference. This reflects a persistent gap between inclusive design principles and the structuring of AI-driven data practices in cultural and heritage tourism.

3.1.4 Emotional and affective data: experiential outcomes rather than inputs

Explicit use of emotional or affective data is comparatively rare across the reviewed literature. In many studies, "emotion" is discussed primarily as an experiential outcome, for example, emotional engagement, cultural immersion, or sense of place, rather than as a measured data input driving AI adaptation. Interactive cultural experiences often foreground emotion as part of meaning-making and narrative resonance but typically operationalise it through indirect indicators rather than direct affect sensing. For instance, interactive installations linking place identity and engagement treat emotional experience as a design goal and interpretive effect (Guo et al. 2025). Related work on emotional interaction in public art similarly conceptualises emotion as emerging through human–technology interaction and sociocultural context, rather than as a stable internal state that can be straightforwardly detected and acted upon (Qi and Feng 2025). Studies examining AI-driven digital heritage platforms also connect user engagement to downstream cultural participation intentions, again relying on perceptual and behavioural proxies more than affective measurement (Lai et al. 2025). This pattern likely reflects both methodological caution and ethical sensitivity: affective computing in public cultural settings raises concerns about consent, misinterpretation, and surveillance. However, the practical consequence is that few systems meaningfully support emotion-aware accessibility, for example, adapting interactions when a visitor experiences anxiety, fatigue, or sensory overload. From a human–data interaction perspective, this highlights a key gap: emotional states may be central to visitor experience and disability-related access needs, yet they remain difficult to represent and govern within current AI-enabled tourism systems.

3.1.5 Implicit accessibility indicators and algorithmic inference

Several studies rely on implicit accessibility indicators, where AI systems infer access needs based on observed interaction patterns rather than explicit disclosure. Adaptive pacing, modality switching, or content simplification may be triggered when users exhibit prolonged dwell time, repeated help requests, or reduced interaction frequency (Materazzini et al. 2024; Chiurco et al. 2025). While such inference-based adaptation can enable situational accessibility and reduce the burden of self-identification, it also introduces risks of misclassification, paternalism, and reduced user agency, particularly when system logic is opaque and users are unable to contest, or override inferred "needs". The reviewed literature rarely addresses feedback loops, transparency mechanisms, or user control features that would allow disabled users to negotiate these inferences.

3.2 Roles of AI systems within human–AI teams (RQ2)

In cultural and heritage tourism, AI-enabled systems increasingly shape how visitors navigate spaces, access interpretation, and engage with cultural narratives. Across the reviewed studies, these systems do not merely support isolated tasks but participate in broader socio-technical arrangements involving visitors, staff, curators, and institutional infrastructures (Appendix B). While the language of H-AI teams or human–

AI collaboration is rarely used explicitly, collaboration is nevertheless embedded in system design through the distribution of agency, decision-making, and responsibility between human and artificial actors. Synthesising these design configurations reveals three recurring ways in which AI systems operate within such arrangements: as adaptive mediators, assistive collaborators, and decision-support actors.

3.2.1 AI as adaptive mediator of cultural experiences

The most prevalent role identified across the corpus is that of adaptive mediator, in which AI systems shape how cultural and heritage experiences are organised, interpreted, and encountered over time. Rather than simply delivering personalised content, AI systems in this role actively structure the flow of interaction by sequencing narratives, coordinating modalities, and aligning interpretive elements with situational conditions. In doing so, AI mediates between cultural content, spatial environments, and visitors' unfolding experiences. This mediating function is particularly evident in AI-enabled museum and heritage platforms that emphasise experience orchestration and narrative mediation across physical and digital settings. Research on multisensory and hybrid museum environments highlights how AI-supported systems coordinate narration, interaction modalities, and spatial cues to guide visitor engagement (Pietroni 2025). Similarly, studies of interactive and cyber-physical heritage environments describe AI as a mechanism for managing reciprocal communication between visitors and exhibitions, dynamically shaping interpretation rather than merely responding to user input (Aliyev et al. 2025; Nisiotis et al. 2025).

Beyond museums, work on digital and metaverse-oriented tourism platforms further illustrates how AI operates as a mediator across interconnected systems, coordinating content delivery, interaction timing, and experiential continuity (Chen and Chen 2025; Tran 2025). In these contexts, AI systems help align diverse experiential components rather than acting as isolated personalisation engines. From a human–AI team perspective, this mediating role positions AI systems as semi-autonomous collaborators that shape how cultural experiences are structured and encountered. However, most studies provide limited discussion of how these adaptive mediations are made visible to users, or how visitors, particularly disabled users, can influence, negotiate, or override system behaviour. As a result, mediation often occurs without explicit negotiation of agency, raising concerns about transparency and user control when AI interpretations misalign with individual access needs or experiential preferences.

3.2.2 AI as assistive collaborator supporting accessibility and engagement

A second prominent role evident in the reviewed literature is that of assistive collaborator, in which AI systems support users by augmenting navigation, interpretation, communication, and access to cultural knowledge. In this configuration, AI systems do not primarily act by autonomously shaping experience flow, but by working alongside users to reduce barriers and support participation within cultural and heritage tourism contexts. A number of studies focus on assistive technologies designed to facilitate inclusive engagement in museum and heritage environments. Inclusive

audio-visual systems developed for visitors with learning disorders illustrate how AI can support comprehension and sustained engagement through guided narration and multimodal interaction (Materazzini et al. 2024). Similarly, AI-assisted virtual reality applications aim to improve access to cultural heritage by offering guided exploration and alternative interaction modalities for users with diverse sensory or cognitive needs (Ballı et al. 2025). Beyond disability-specific interventions, several studies describe AI systems that assist visitors more broadly by supporting access to cultural information and interpretation. Research on AI-enabled personal assistants and digital mediation stations demonstrates how conversational and generative AI can help users navigate complex heritage content, retrieve contextual information, and engage with cultural narratives at their own pace (Chiurco et al. 2025; Schauer et al. 2024). In tourism service contexts, human-centred AI approaches are also applied to support inclusive travel planning and decision-making, particularly for neurodiverse users who may experience cognitive overload in conventional tourism systems (Mauro et al. 2025).

Additional work in digital and smart tourism highlights how assistive AI systems contribute to engagement by supporting communication and service interaction rather than by automating decisions. Studies examining conversational agents in religious and cultural tourism contexts emphasise the role of AI in sustaining dialogue and facilitating user–system interaction across service encounters (Alharbi et al. 2025). Similarly, research on digital heritage platforms suggests that AI-supported assistance can influence visitors' engagement and willingness to participate in cultural activities beyond the digital environment (Lai et al. 2025). In this configuration, AI systems operate as collaborative partners that support interaction, sense-making, and access, working alongside users rather than directing experience. However, across the reviewed studies, assistive collaboration is most often evaluated through usability, task success, or accessibility outcomes. There is limited discussion of how such collaboration affects users' sense of autonomy, competence, or dignity, or how levels of assistance might be negotiated dynamically. As a result, assistive AI is rarely conceptualised as a team member with adjustable or contestable roles, but rather as a supportive extension of the interface.

3.2.3 AI as decision-support actor within tourism service ecosystems

A smaller but conceptually significant subset of the reviewed literature positions AI systems as decision-support actors embedded within broader tourism service ecosystems. In these configurations, AI systems extend beyond individual interaction support to influence higher-level decisions related to experience sequencing, visitor flow management, service planning, and destination governance. Rather than mediating or assisting individual users, AI operates as an analytical and coordinative resource for multiple human stakeholders.

Research on AI agents and agentic systems in tourism and hospitality explicitly highlights the growing role of AI in distributed decision-making across organisational and human actors, framing AI as an integral component of complex service systems (Dwivedi et al. 2025). Complementary work on smart tourism destinations further demonstrates how AI-driven analytics inform strategic decisions concerning

infrastructure, accessibility, and service design (Sharma and Sharma 2025; Zhang and Cheng 2024).

Several studies extend this perspective by examining AI-supported planning and optimisation processes. Data-driven approaches to tourism path planning and product design illustrate how AI supports decision-making related to visitor routing, service configuration, and experience management (Lu and Zhu 2024). At a governance level, research on structural power in local tourism systems highlights how algorithmic decision-support intersects with institutional priorities and cultural values (Yamin et al. 2025). In cultural and heritage tourism contexts, these roles embed AI within broader socio-technical systems involving multiple stakeholders, including visitors, staff, and planners. AI contributes to collective sense-making and strategic coordination across service ecosystems rather than operating solely at the interface level. However, few studies explicitly examine how disabled users are represented within such decision-making processes, or how accessibility considerations are embedded within algorithmic governance and planning frameworks. This gap suggests that while AI increasingly shapes collective and institutional decisions, its role within inclusive human–AI teams remains under-theorised, particularly with respect to equity, representation, and participatory design.

Across these roles, collaboration remains largely implicit rather than intentionally designed. Key aspects such as role clarity, transparency, and accountability are rarely articulated, limiting understanding of how AI-mediated interaction shapes accessibility and user agency. The reviewed studies predominantly emphasise system functionality, technical capability, or experiential outcomes, while providing limited articulation of how agency, authority, and responsibility are distributed between human and artificial actors. As a result, concepts central to H-AI team research including trust calibration, explainability, role clarity, and shared situational awareness, are rarely examined in depth within cultural and heritage tourism contexts.

This conceptual gap is particularly evident in studies that engage with ethical or governance issues. While several works acknowledge concerns related to bias, fairness, and accountability in AI-enabled cultural heritage systems, these discussions are often decoupled from questions of collaboration and interaction design (Foka et al. 2025; Pansoni et al. 2023). Similarly, research addressing ethical challenges in immersive and metaverse-based cultural environments highlights risks associated with opacity and power asymmetries, yet seldom situates these risks within explicit H-AI team configurations (Al-Kfairy et al. 2025).

The absence of explicit collaboration framing is especially consequential in public-facing cultural and heritage tourism environments, where AI systems increasingly mediate access, interpretation, and communication. Studies of museum experience and curated interaction emphasise the importance of reciprocal communication, inclusion, and participatory meaning-making, but rarely connect these insights to the design of AI-mediated decision-making or support structures (Aliyev et al. 2025; Huang and Liem 2022). Without explicit H-AI team framing, AI systems risk functioning as opaque intermediaries rather than accountable collaborators, potentially undermining accessibility, autonomy, and inclusion for disabled users. At an ecosystem level, this implicitness also intersects with broader issues of governance and power. Research on tourism governance and co-creation highlights how decisions

about cultural representation, resource allocation, and experience design are shaped by institutional priorities and structural dynamics (Yamin et al. 2025). When AI systems are embedded within these contexts without explicit consideration of collaborative roles and responsibilities, their influence on inclusion and participation may remain unexamined and unaccountable.

3.3 Inclusive design approaches and strategies for accessible and meaningful experiences (RQ3)

While the previous sections examined the types of user data utilised and the roles assumed by AI systems within human–AI teams, this section focuses on how AI-enabled systems are designed to translate technological capability into accessible, meaningful, and socially situated cultural and heritage tourism experiences. Across the reviewed literature, inclusive outcomes are less strongly associated with specific AI techniques than with design strategies that shape interaction, participation, and experience over time. Analysis of the corpus reveals four recurring design approaches that support inclusion: multimodal and flexible interaction design, participatory and co-creative design, experience-oriented mediation within service ecosystems, and ethically grounded and culturally situated AI design (Appendix C).

3.3.1 Multimodal and flexible interaction design

A prominent design strategy involves the use of multimodal and flexible interaction frameworks that accommodate diverse sensory, cognitive, and situational needs. Rather than privileging a single mode of engagement, these approaches emphasise the availability of multiple representational and interaction pathways, enabling users to engage with cultural content according to their abilities, preferences, and changing conditions.

Design-oriented studies of museum and exhibition environments highlight how multimodal systems can support inclusion by combining visual, auditory, spatial, and narrative elements. Work on meta-exhibition design foregrounds flexibility and reconfigurability as core principles for inclusive engagement, allowing visitors to construct personalised pathways through complex cultural content (Caradonna 2024). Similarly, research on extended reality in industrial heritage interpretation demonstrates how narrative design and immersive media can offer alternative modes of engagement that go beyond conventional text-based interpretation (Shawash et al. 2025).

AI-enhanced mixed reality frameworks further illustrate how prioritising non-visual or audio-first interaction can support accessibility in environments where visual dominance may exclude some users (Cagiltay et al. 2025). Broader studies examining the integration of AI with virtual and augmented reality in the built environment emphasise that accessibility gains emerge not from technological sophistication alone, but from deliberate design choices that allow users to shift between modalities as needed (Arranz-Paraíso and Arranz-Paraíso 2024).

3.3.2 Participatory and co-creative design approaches

A second key strategy centres on participatory and co-creative design approaches, in which diverse stakeholders, including visitors, local communities, and marginalised groups, are actively involved in shaping how AI-enabled systems represent, interpret, and mediate cultural heritage. These approaches move beyond conventional user-centred design paradigms toward models of shared authorship and collective meaning-making, in which interpretive authority is distributed rather than institutionally centralised. Several studies emphasise the role of participatory digital methods in democratising heritage interpretation. Collaborative frameworks that enable community input into heritage narratives demonstrate how participatory design can redistribute interpretive power, challenge institutional dominance, and foreground plural perspectives within digital heritage systems. In a related vein, research on community archives positions digital platforms as tools for place-based decision-making, allowing local actors to influence how cultural heritage is documented, curated, and accessed (La Rocca et al. 2023). These approaches highlight the potential of participatory design to reconfigure not only interfaces, but also the governance structures that shape heritage representation.

Participatory design is also foregrounded in work addressing cultural validity, inclusion, and ethical responsibility in AI-enabled heritage systems. Studies exploring responsible AI frameworks in indigenous heritage contexts illustrate how co-design processes can embed culturally situated values, ethical considerations, and long-term sustainability into AI-driven heritage futures. By engaging communities as co-designers rather than as data sources or end users, these approaches foreground relational accountability and cultural stewardship as core design concerns. Taken together, these studies demonstrate that inclusive design in cultural and heritage tourism is not solely a matter of accommodating individual access needs. Rather, it involves a broader reconfiguration of relationships between technology, institutions, and communities, repositioning AI-enabled systems as participatory infrastructures that support shared ownership, cultural plurality, and socially grounded forms of human–AI collaboration.

3.3.3 Experience-oriented mediation within service ecosystems

A third design approach conceptualises accessibility as an experiential and relational quality that emerges across the tourism service ecosystem, rather than as a property of individual interfaces or technologies. Drawing on experience design and service design perspectives, these studies emphasise that meaningful engagement is co-produced through coordinated interactions among visitors, AI-enabled technologies, spatial environments, and organisational practices. From this viewpoint, accessibility is not delivered by discrete technological features, but unfolds through the alignment of multiple actors and touchpoints over time. Research on co-creation in tourism and hospitality underscores how tourism experiences are jointly produced through interactions between heterogeneous actors, including service providers, technological systems, and visitors themselves, rather than being passively consumed (Borges-Tiago and Avelar 2025). This perspective is particularly salient for AI-enabled cultural and

heritage tourism, where systems mediate not only access to information, but also social interaction, temporal sequencing, and emotional engagement throughout the visitor journey. AI-enabled mediation therefore plays a formative role in shaping how experiences are structured, paced, and interpreted across physical and digital contexts.

Empirical studies of interactive art installations and place-based digital experiences further illustrate how AI-supported systems can foster emotional connection and a sense of place by sustaining experiential continuity across hybrid environments (Guo et al. 2025). From an inclusive design standpoint, experience-oriented mediation shifts attention away from isolated accessibility features toward the overall coherence and inclusivity of the visitor journey. However, despite these conceptual advances, the reviewed literature rarely examines how experience-oriented mediation accommodates fluctuating access needs over time, or how disabled users can actively influence the shaping of their experiences rather than adapting to pre-configured pathways. This gap highlights the need for design approaches that treat accessibility as an ongoing, negotiable process within AI-mediated service ecosystems, rather than as a fixed outcome embedded in predetermined experiential scripts.

3.4 Challenges, ethical concerns, and research gaps in AI-enabled systems for disabled users (RQ4)

Despite the growing deployment of AI-enabled systems in cultural and heritage tourism, the reviewed literature reveals a series of persistent challenges, ethical concerns, and research gaps that constrain their inclusive potential. These limitations are not confined to technical performance, but emerge from how AI systems are conceptualised, governed, and embedded within public-facing tourism service ecosystems. For disabled users in particular, these issues raise questions about agency, representation, and accountability in AI-mediated environments.

3.4.1 Opacity, explainability, and limited user understanding

A recurring challenge identified across the reviewed literature concerns the limited transparency and explainability of AI-enabled systems deployed in tourism and cultural settings. While many studies describe increasingly sophisticated AI-driven platforms for travel planning, recommendation, and experience enhancement, they offer little insight into how system logic, data use, or adaptive decisions are communicated to users. As a result, AI-mediated processes often remain opaque, positioning users as recipients of algorithmic outputs rather than as informed participants capable of understanding or influencing system behaviour. For instance, research on AI-mediated travel planning and recommendation systems predominantly evaluates decision outcomes and behavioural effects, with minimal attention to how users interpret, question, or contest algorithmic suggestions (Rashidin and Javed 2025). Similarly, studies examining the application of AI and data-driven optimisation in smart tourism destinations emphasise efficiency, scalability, and performance gains, while leaving issues of transparency, explainability, and user comprehension largely unaddressed (Zhang and Cheng 2024). This outcome-oriented focus risks obscuring the

experiential and ethical implications of opaque AI mediation in public-facing tourism environments. In cultural and heritage contexts, where engagement is closely tied to meaning-making, trust, and interpretation, such opacity can have particularly significant consequences. Limited explainability undermines users' ability to form accurate mental models of AI systems, constraining informed participation and reducing opportunities for agency and negotiation. For disabled users, who may depend more heavily on AI-mediated guidance for navigation, interpretation, or access, opaque system behaviour can exacerbate existing power asymmetries, erode trust, and limit autonomy. These findings highlight the need to treat explainability not merely as a technical feature, but as a core design and governance concern within inclusive AI-enabled tourism systems.

3.4.2 Surveillance, profiling, and consent in public cultural spaces

A further ethical concern identified in the reviewed literature relates to the implicit surveillance and profiling practices enabled by AI-driven systems in cultural and heritage tourism. Many AI-enabled applications rely extensively on large-scale behavioural, spatial, and usage data to support visitor analysis, profiling, and system optimisation. However, relatively few studies critically examine how consent is obtained, how data collection practices are communicated to visitors, or how continuous monitoring is experienced and interpreted within public cultural environments. As a result, surveillance often becomes normalised as an infrastructural condition of participation rather than an explicit design and governance choice. For example, studies that analyse visitor behaviour, movement patterns, or site utilisation through data-driven methods tend to prioritise analytical efficiency and decision support, while offering limited reflection on the experiential, ethical, or social implications of sustained data collection (Schrader et al. 2025; Yu et al. 2025). In such cases, visitors are frequently abstracted into aggregated data points, obscuring the situated, contextual, and embodied nature of their interactions with cultural spaces. Issues of agency, transparency, informed consent, and meaningful opt-out mechanisms are rarely addressed in depth, despite their central relevance to public-facing AI systems. In cultural and heritage tourism settings, where participation is voluntary, publicly situated, and often emotionally or culturally meaningful, the absence of explicit engagement with surveillance, profiling, and consent is particularly consequential. Data-driven inference risks reshaping how visitors are categorised, guided, or prioritised without their awareness or involvement. For disabled users, whose interaction patterns may diverge from normative expectations due to access constraints, fatigue, or alternative modes of engagement, such profiling practices increase the risk of misinterpretation, inappropriate adaptation, and diminished autonomy.

3.4.3 Accessibility marginalised in strategic and institutional decision-making

At the institutional level, the review reveals a persistent disconnect between the growing use of AI-enabled decision-support systems and the integration of inclusive governance principles. Although AI is increasingly deployed to inform destination management, service planning, visitor flow optimisation, and infrastructure develop-

ment, accessibility is rarely treated as a strategic priority within these decision-making processes. Instead, accessibility considerations are often subsumed under broader objectives related to operational efficiency, economic growth, or destination competitiveness, rather than being foregrounded as a core dimension of system performance. Research on tourism governance and structural power highlights how technological innovation in tourism systems tends to align with dominant institutional logics that privilege efficiency, scalability, and economic return, frequently at the expense of social inclusion and equity (Yamin et al. 2025). Within such governance structures, AI-enabled analytics and optimisation tools risk reinforcing existing power asymmetries by encoding prevailing priorities into algorithmic decision-making processes. As a result, accessibility-related needs, particularly those of disabled users, remain weakly represented or entirely absent in strategic system models, performance indicators, and planning assumptions. Future-oriented analyses of tourism innovation further suggest that technological development often outpaces the evolution of governance mechanisms capable of ensuring inclusive participation, transparency, and accountability (Dar and Dar 2025). This temporal misalignment means that AI systems may become embedded in institutional decision-making before inclusive safeguards, participatory structures, or evaluation criteria are established. Consequently, disabled users are seldom positioned as legitimate stakeholders in AI-informed strategic decisions, but are instead framed as downstream recipients of accommodation measures. This systemic exclusion reinforces marginalisation at the ecosystem level, limiting the capacity of AI-enabled tourism systems to support equitable access and meaningful participation over time.

3.4.4 Ethical and cultural implications: from aspiration to operationalisation

Although ethical considerations are increasingly recognised across the reviewed literature, they are most often articulated as high-level normative commitments rather than being embedded within concrete design, implementation, and evaluation practices. Many studies invoke principles such as responsible innovation, sustainability, inclusivity, or cultural preservation in discussions of AI-enabled tourism and heritage systems, yet provide limited specification of how these ethical commitments are operationalised within system architectures, interaction design decisions, or service workflows. As a result, ethics frequently functions as an overarching rationale or evaluative lens, rather than as a set of actionable design constraints shaping system behaviour. Research on responsible and sustainable AI in cultural contexts underscores the importance of aligning technological innovation with long-term cultural values, social responsibility, and stewardship (Afaq et al. 2025; Lau 2025). However, these contributions often remain at the level of frameworks or guiding principles, offering insufficient guidance on how ethical values can be translated into everyday system use. Key questions, such as how ethical priorities are encoded in algorithmic logic, how value conflicts are negotiated during system adaptation, or how ethical performance is assessed over time, are rarely addressed. Similarly, studies concerned with cultural preservation through digital technologies emphasise inclusivity and equity as desired outcomes, but seldom articulate how AI-enabled systems can meaningfully support user agency, contestability, or informed participation in

practice (Kaluvilla 2024). Ethical concepts such as transparency, accountability, and fairness are typically discussed abstractly, without corresponding interaction mechanisms, governance processes, or evaluative metrics that would enable users to understand, influence, or challenge system decisions. This gap between ethical aspiration and operational design suggests that ethics remains conceptually acknowledged yet insufficiently institutionalised within AI-enabled cultural and heritage tourism systems, limiting its capacity to shape inclusive and responsible human–AI collaboration in practice.

Beyond the challenge of operationalising ethical principles in AI system design, the reviewed literature also raises broader concerns regarding how AI systems shape cultural representation and interpretive authority in heritage contexts. Rather than treating ethics as an external constraint or post-hoc evaluative lens, these studies conceptualise ethical considerations as integral to design practice, shaping how AI systems represent cultural knowledge, allocate interpretive authority, and structure participation. From this perspective, ethics is not separate from technical or interaction design, but actively informs system architecture, data practices, and modes of mediation. Research on ethical frameworks for AI in cultural heritage explicitly foregrounds issues of accountability, cultural sustainability, and long-term stewardship, emphasising the responsibility of AI-enabled systems to respect cultural values and support responsible heritage futures (Pansoni et al. 2023). Complementary studies in algorithmic art and museum practice further demonstrate how AI systems can either reinforce dominant cultural narratives or create space for plural, marginalised, or contested perspectives, underscoring the importance of reflexive and culturally sensitive design in sustaining cultural diversity (Taurino 2023). Broader critical scholarship on AI and cultural production highlights the risks of digital colonialism, cultural homogenisation, and exclusion when cultural specificity, local knowledge, and community governance are not embedded within AI design processes (Yamaguchi 2025). These critiques draw attention to power asymmetries inherent in data-driven cultural systems and the potential for AI to reproduce structural inequities under the guise of technological neutrality. Despite the growing articulation of ethical principles across this literature, relatively few studies translate these concerns into concrete interaction or service design mechanisms that support user agency, contestability, or informed participation. Ethical commitments are often expressed at the level of values or intentions, without corresponding design strategies that enable users to understand, influence, or challenge AI-mediated representations and decisions. This gap underscores the need for design frameworks that integrate ethics, inclusion, and human–AI collaboration at both interactional and institutional levels, ensuring that ethical considerations meaningfully shape how AI-enabled cultural and heritage tourism systems are designed, governed, and experienced in practice.

3.4.5 Research gaps and directions for future work

The challenges identified across the reviewed literature point to several interrelated research gaps that constrain the inclusive potential of AI-enabled cultural and heritage tourism systems. To provide a clearer synthesis, Table 3 summarises the key

Table 3 Key research gaps and directions for future research in AI-Enabled cultural and heritage tourism

Research gap	Current limitation in the literature	Directions for future research
Lack of longitudinal and experiential studies	Most existing studies evaluate accessibility, usability, or engagement at a single interaction point, providing limited insight into how user experiences evolve over time.	Conduct longitudinal studies examining how trust, autonomy, dignity, and perceived agency develop through repeated interaction with AI-enabled tourism systems.
Limited human–AI teaming perspective	AI systems are often treated as tools or interfaces rather than collaborative actors within socio-technical tourism ecosystems. As a result, issues such as role distribution, explainability, and shared decision-making remain underexplored.	Apply human–AI teaming frameworks to analyse how responsibility, authority, and decision-making are distributed between human and artificial actors in tourism contexts.
Accessibility weakly embedded in governance and planning	AI-enabled analytics and decision-support systems in tourism often prioritise efficiency and optimisation, while accessibility considerations remain marginal in institutional decision-making processes.	Investigate governance models and policy frameworks that integrate accessibility as a strategic criterion within AI-supported tourism planning and destination management.
Limited attention to emotional and affective accessibility	Emotional experience is frequently treated as an outcome of tourism interaction rather than as a data input that informs system adaptation.	Explore emotion-aware interaction design and affect-sensitive AI systems that can respond to visitor stress, fatigue, or sensory overload in public cultural environments.
Insufficient participatory and co-design approaches	Many AI-enabled tourism systems are designed without sustained involvement of disabled users or community stakeholders.	Adopt participatory and co-design approaches that position disabled users and local communities as active contributors to the design, governance, and evaluation of AI-enabled tourism systems.

research gaps identified in the reviewed studies together with corresponding directions for future research.

First, many reviewed studies report accessibility or usability outcomes based on short-term evaluations or single interaction episodes. As a result, there is limited insight into how disabled users' experiences with AI-enabled tourism systems evolve over time, including how trust, autonomy and perceived agency develop through repeated or sustained interaction. Future research could therefore examine user engagement across longer timeframes to better understand how inclusive AI-enabled tourism experiences unfold in practice. Existing studies tend to evaluate accessibility or usability at discrete moments, offering limited insight into how trust, autonomy, dignity, and perceived agency evolve through repeated or sustained interaction. Without such longitudinal perspectives, it remains difficult to assess whether AI-enabled adaptations genuinely support inclusive participation or merely provide short-term functional accommodation.

Second, relatively few studies explicitly conceptualise AI-enabled tourism technologies as human–AI teams. As a result, critical questions concerning how responsibility, authority, and decision-making are distributed between human and artificial actors remain underexplored, particularly in public-facing service contexts. The absence of an explicit teaming perspective limits understanding of how collaboration is negotiated in practice, how users interpret AI roles, and how accountability is maintained when AI systems influence access, interpretation, or service delivery in cultural environments.

Third, accessibility continues to be weakly embedded within AI-supported governance, planning, and evaluation at institutional and ecosystem levels. While AI is increasingly used to inform strategic decisions related to destination management and service optimisation, disabled users are rarely positioned as stakeholders within these processes. Consequently, accessibility considerations are often reactive, addressed through downstream adaptation rather than being embedded as a structural criterion shaping system design, governance, and performance assessment. Addressing these gaps requires research approaches that move beyond narrow evaluations of system performance and optimisation toward design-led, participatory, and ethically grounded inquiry. Future work should foreground disabled users as active contributors in the co-design, governance, and evaluation of AI-enabled tourism systems, recognising them as knowledgeable actors rather than passive beneficiaries of technological adaptation. Without such a shift, AI risks reinforcing existing inequalities and exclusions at both interactional and systemic levels, even as it continues to promise innovation, efficiency, and enhanced experience delivery.

4 The Inclusive Human–AI Mediation (IHAM) model

Building on the thematic synthesis, this section presents the Inclusive Human–AI Mediation model (Fig. 3) as an analytical framework for understanding accessibility in AI-enabled cultural and heritage tourism. The model integrates the four main areas identified in the review: user data practices, AI mediation roles, inclusive design strategies, and ethical governance challenges. It explains accessibility as an emergent outcome shaped by how user data is interpreted, how AI systems mediate experience and decision-making, how human agency is supported, and how governance structures enable accountability and co-creation.

4.1 Model structure and linkage to review themes

The Inclusive Human–AI Mediation (IHAM) Model synthesises the main themes identified across the review and explains how accessibility is produced, constrained, or negotiated in AI-enabled cultural and heritage tourism. Rather than presenting AI as a neutral technical layer, the model positions AI systems as mediators that interpret user data, shape cultural experiences, distribute agency, and operate within institutional governance structures.

The model is structured around three interrelated layers: data interpretation, AI mediation, and human agency, situated within a broader governance context. These layers correspond directly to the four areas of analysis developed in the Results section. First, the data interpretation layer reflects the finding that AI-enabled tourism systems rely heavily on behavioural, contextual, profile-based, sensor-based, and implicit accessibility data. These data practices shape how users are represented before interaction takes place. Second, the AI mediation layer reflects the three roles identified in the review: adaptive mediator, assistive collaborator, and decision-support actor. These roles show that AI systems do not simply support access but actively organise how cultural content, navigation, assistance, and institutional deci-

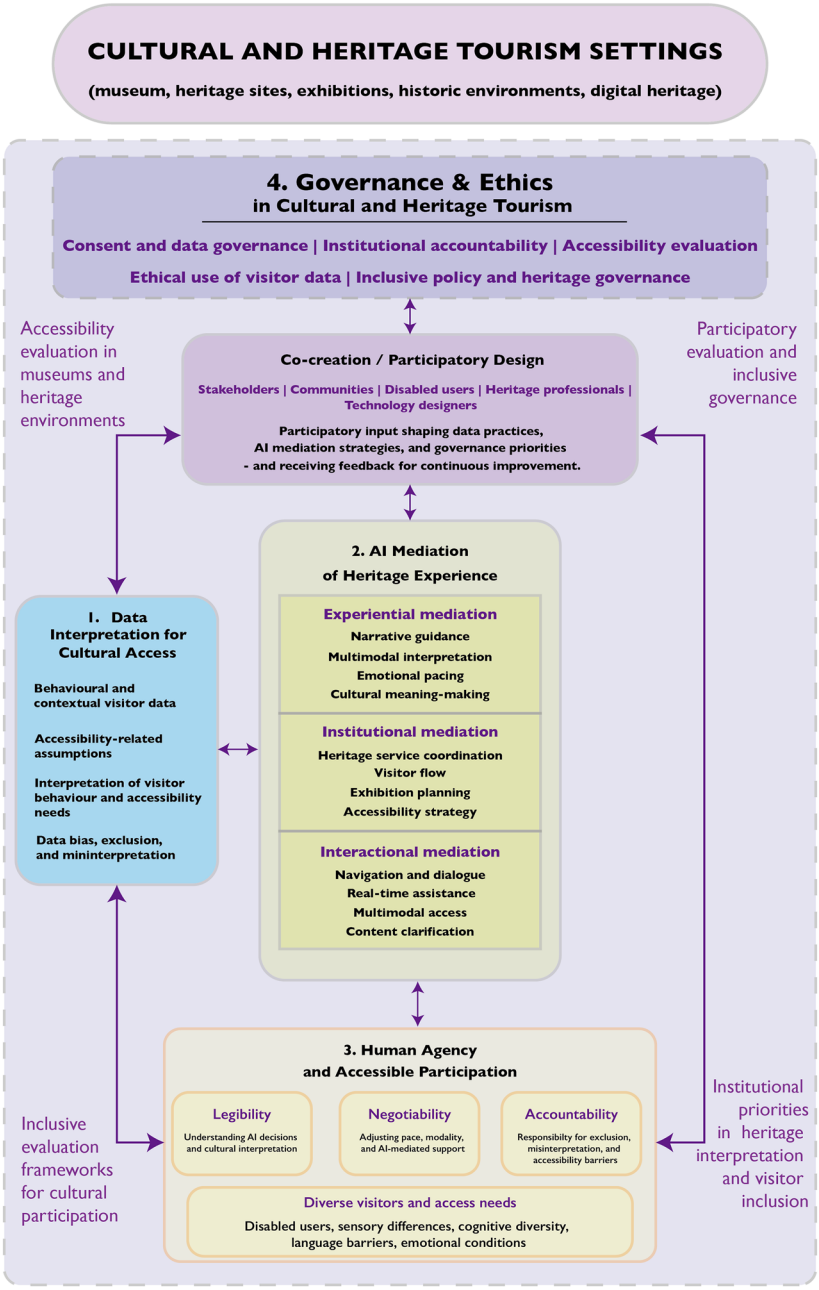

Fig. 3 The Inclusive Human–AI Mediation (IHAM) framework for accessible cultural and heritage tourism. The framework explains how accessibility emerges through the interaction of data interpretation, AI mediation, human agency, governance, and co-creation within AI-enabled tourism ecosystems

sions are mediated. Third, the human agency layer responds to the inclusive design strategies identified in the review, particularly multimodal interaction, user control, participatory design, and co-creative approaches. This layer highlights that inclusive AI systems should allow users and communities to understand, negotiate, and influence AI-mediated experiences. Finally, governance operates across all three layers, reflecting the ethical and institutional challenges identified in the review, including opacity, surveillance, weak accessibility representation in strategic planning, and the limited operationalisation of ethical principles.

In this sense, the IHAM model is representative of the core themes of the review rather than a separate conceptual addition. It brings together the empirical patterns identified across user data, AI roles, inclusive design strategies, and governance challenges to explain how accessibility emerges through the relationships between data practices, AI mediation, human participation, and institutional accountability.

4.2 The three layers of inclusive human-AI mediation

The first layer, data interpretation, foregrounds how accessibility is shaped through the ways AI systems collect, classify, and interpret user data. The review showed that behavioural and contextual data dominate current AI-enabled cultural and heritage tourism systems, while emotional, disability-specific, and affective data remain less developed. Within the IHAM model, data interpretation is therefore treated as an accessibility-critical layer. If movement patterns, dwell time, or interaction frequency are interpreted through normative assumptions, disabled users' behaviours may be misread as disengagement, inefficiency, or lack of interest. Inclusive mediation therefore requires data practices that make assumptions visible, allow uncertainty, and avoid treating behavioural proxies as direct evidence of user needs.

The second layer, AI mediation, explains how AI systems shape access and participation through different forms of mediation. The review identified three main roles: adaptive mediator, assistive collaborator, and decision-support actor. As adaptive mediators, AI systems structure the pacing, sequencing, and modality of cultural experiences. As assistive collaborators, they support navigation, interpretation, dialogue, and access to cultural knowledge. As decision-support actors, they influence broader service and institutional decisions, including visitor flow, route planning, and destination management. These roles show that AI mediation operates not only at the interface level, but also across service ecosystems and institutional contexts. For accessibility, this means that inclusion depends not only on whether AI tools are available, but also on how their mediating roles are communicated, controlled, and evaluated.

The third layer, human agency, addresses whether users are positioned as passive recipients of AI outputs or as active participants in AI-mediated cultural experiences. The review showed that inclusive design strategies are most effective when they enable multimodal flexibility, user control, participation, and co-creation. In the IHAM model, human agency is therefore understood through three design conditions: legibility, negotiability, and accountability. Legibility refers to whether users can understand how AI systems interpret data and adapt experiences. Negotiability refers to whether users can adjust, refuse, or override AI-mediated decisions.

Accountability refers to whether responsibility for AI-mediated outcomes is clear when systems produce exclusion, misinterpretation, or harm. These conditions are particularly important for disabled users, whose access needs may fluctuate across time, context, and cultural setting.

4.3 Governance, co-creation, and inclusive implementation

Governance is the cross-cutting condition that determines whether the three layers of IHAM can operate inclusively. The review showed that ethical principles such as transparency, consent, accountability, and cultural representation are frequently acknowledged in AI-enabled tourism research, but are less often translated into concrete design mechanisms, service procedures, or institutional evaluation criteria. Within the IHAM model, governance therefore refers not only to regulation or data protection, but also to the organisational decisions that shape what forms of accessibility are prioritised, how users are represented in data, and who is able to influence AI-mediated cultural experiences.

Co-creation plays an important role within this governance layer because accessibility cannot be fully defined by technical systems or institutional actors alone. As shown in the review, participatory and co-creative design approaches can redistribute interpretive authority, embed lived experience into system design, and support culturally situated forms of inclusion. For this reason, the revised IHAM model positions co-creation as a mechanism linking human agency and governance. This means that disabled users, visitors, cultural communities, staff, and technology providers should not only be consulted after AI systems are implemented, but should contribute to how data categories, mediation strategies, accessibility indicators, and accountability mechanisms are defined from the beginning.

The model therefore suggests that inclusive AI design in cultural and heritage tourism requires more than accessible interfaces. It requires a governance structure in which data interpretation is scrutinised, AI mediation is made legible and negotiable, and co-creative participation informs institutional decision-making. In practical terms, this may include accessibility audits of training data and visitor analytics, clear explanations of AI-mediated adaptations, user controls for personalisation and opt-out, participatory testing with disabled visitors, and procurement requirements that treat accessibility as a core performance criterion.

5 Discussion

Existing review studies on artificial intelligence in tourism have primarily examined technological adoption, smart tourism infrastructures, and data-driven service optimisation. These reviews have generated valuable insights into recommendation systems, visitor profiling, destination management, and service innovation, often emphasising efficiency, scalability, and technological transformation within tourism ecosystems (Dwivedi et al. 2025, Sharma and; Sharma 2025). However, accessibility and disability are rarely treated as central analytical dimensions in these reviews. In particular, limited attention has been paid to how AI-enabled systems mediate cul-

tural interpretation, interaction, and participation for disabled users in cultural and heritage tourism contexts. The present review extends this literature by foregrounding inclusive design, accessibility, and human–AI collaboration as central concerns. A central pattern identified in this review is the tendency to conceptualise accessibility as an outcome of system performance rather than as an organising principle of system design and governance. Many studies report improvements in usability, navigation, or visitor engagement through AI-enabled adaptation (Kaur et al. 2025), yet offer limited reflection on how these adaptations are produced, interpreted, or governed over time. This output-oriented framing obscures the relational nature of accessibility, particularly in cultural and heritage tourism, where access is inseparable from processes of interpretation, meaning-making, and emotional engagement (Pietroni 2025). From the perspective of the IHAM model, this reflects a narrow understanding of accessibility that prioritises measurable outputs over the mediating processes through which access is produced. As a result, many interventions achieve localised gains while leaving systemic forms of exclusion unaddressed.

The dominance of behavioural and contextual data further reinforces these limitations. Data-driven approaches enable profiling, segmentation, and optimisation across diverse visitor populations (Yu et al. 2025; Zhang and Cheng 2024), but they also rely on normative assumptions about movement, attention, and interaction that are rarely examined critically. For disabled users, observed behaviours may reflect fatigue, sensory overload, mobility constraints, or other access barriers rather than preference or disengagement. When such behaviours are treated as neutral indicators of intent, AI systems risk reproducing exclusionary interpretations at the level of data inference. These findings suggest that accessibility challenges in AI-enabled tourism are often embedded upstream within data interpretation practices, rather than emerging solely at the interface level.

A related limitation concerns the weak integration of emotional and affective dimensions within AI-enabled tourism systems. Although emotional engagement and experiential quality are widely recognised as central to cultural and heritage tourism (Guo et al. 2025; Aliyev et al. 2025), emotional states are usually treated as outcomes of experience rather than as inputs shaping real-time adaptation. This is particularly significant in immersive, narrative-driven, and multimodal cultural environments, where anxiety, fatigue, cognitive overload, or sensory stress may directly influence accessibility and participation (Caradonna 2024; Shawash et al. 2025). As a result, current AI-enabled systems remain limited in their ability to support emotionally responsive and sustainable forms of cultural participation.

The review also shows that more inclusive alternatives already exist, but remain marginal within dominant research and practice. Participatory and co-creative approaches offer ways of redistributing interpretive authority and embedding lived experience into digital heritage systems (Wehmeier and Artopoulos 2023; La Rocca et al. 2023), while inclusive museum technologies and AI-supported access solutions demonstrate how design can foreground diversity, plurality, and situated engagement (Materazzini et al. 2024; Ballı et al. 2025). Yet these approaches are typically presented as isolated case-specific interventions rather than as systemic challenges to prevailing AI-enabled tourism logics. This suggests that inclusive design is still too

often treated as supplementary rather than foundational in the development of AI-mediated cultural tourism systems.

From a practical perspective, the reviewed literature also reflects uneven attention to different accessibility needs and cultural contexts. Most reviewed applications are situated in museum and heritage contexts in Europe and East Asia, where accessibility discussions predominantly focus on visual, mobility, and cognitive barriers. Other forms of disability, including neurodivergence, psychosocial conditions, and culturally specific accessibility requirements, receive comparatively limited attention. For practitioners designing AI-enabled tourism systems, this suggests the importance of expanding inclusive design practices beyond commonly addressed impairments and considering how accessibility expectations may vary across cultural and institutional contexts. Future implementations should therefore move beyond standard accessibility categories and support more adaptive, culturally situated, and neurodiversity-aware forms of participation.

Ethical considerations further expose the limits of current research. Although a growing body of work acknowledges risks related to bias, cultural misrepresentation, and accountability in AI-enabled heritage systems (Foka et al. 2025; Taurino 2023), and some studies propose ethical or responsible AI frameworks tailored to cultural heritage contexts (Pansoni et al. 2023; Lau 2025), these contributions frequently remain abstract. Questions of consent, transparency, responsibility, and cultural representation are rarely translated into concrete interaction mechanisms, governance structures, or evaluative practices. The IHAM model helps clarify this gap by showing that ethical principles such as transparency, accountability, and consent must be embedded structurally across data practices, mediation strategies, and institutional governance, rather than appended post hoc.

The significance of this review lies in the convergence of three developments across the literature: the rapid institutionalisation of AI-enabled tourism systems, the growing policy emphasis on accessibility and inclusive tourism, and increasing concern regarding AI ethics and governance. Together, these developments suggest that accessibility in AI-enabled cultural and heritage tourism should be understood as a systemic and design-mediated challenge rather than a technical add-on.

The main contribution of this review is therefore theoretical as well as practical. By integrating insights across data interpretation, mediation roles, inclusive design, and governance, the IHAM model moves the field from descriptive critique toward a more explanatory account of how accessibility is produced or constrained in AI-enabled tourism systems. In doing so, it provides a reusable analytical framework through which future research and design practice can analyse, evaluate, and redesign AI-enabled cultural and heritage tourism systems in more inclusive and sustainable ways.

6 Conclusion

This review examined how AI-enabled systems are being designed, deployed, and discussed in relation to accessibility for disabled users in cultural and heritage tourism, based on a synthesis of 66 peer-reviewed journal articles across tourism studies,

cultural heritage research, HCI, and AI-enabled design. The review shows that AI is becoming increasingly embedded in museums, heritage sites, historic cities, and tourism destinations, yet accessibility is still addressed unevenly and is often under-theorised, especially when questions of governance, sustainability and ecosystem-level decision-making are involved.

Across the reviewed literature, AI is commonly framed as a solution for flow management, personalisation, experience enhancement, and operational efficiency. Reflecting broader smart tourism and smart city priorities, many AI-enabled systems prioritise optimisation-oriented approaches that rely heavily on behavioural and contextual data. Such approaches support scalable adaptation but often sideline emotional, experiential, and disability-specific dimensions of access. In practice, this means accessibility is often treated as a downstream benefit of personalisation rather than a core design and governance requirement. To address this limitation, we proposed the IHAM model, which reframes accessibility in AI-enabled cultural and heritage tourism as a systemic, relational, and design-mediated outcome. Rather than viewing AI as a neutral tool layered onto existing tourism experiences, the IHAM conceptualises AI-enabled systems as active mediators of access, interpretation, and participation, where accessibility emerges through the interaction of data interpretation practices, AI-mediated processes, the distribution of human agency and governance structures across tourism service ecosystems. The review makes three main contributions to research on AI-enabled cultural and heritage tourism. First, it reconceptualises accessibility as a mediated and systemic outcome rather than a property of individual technologies. Second, it introduces the Inclusive Human–AI Mediation (IHAM) model, which extends human–AI collaboration research by integrating data practices, mediation processes, and governance structures within public cultural environments. Third, it contributes to human–data interaction scholarship by demonstrating how interpretive assumptions embedded in AI systems shape inclusion, agency, and participation for disabled users.

Ethical considerations further underscore the need for this systemic perspective. While transparency, consent, accountability, and cultural representation are increasingly discussed in AI-enabled heritage and tourism research, these principles are often expressed at the level of general principles rather than built into concrete interaction mechanisms, decision rights and governance processes. By positioning governance as a cross-cutting condition of human–AI mediation, the IHAM model helps translate ethical concerns into designable and governable system properties, rather than treating ethics as a post hoc evaluation step.

The review yields actionable implications for museums, heritage organisations, destination managers and technology providers designing AI-enabled cultural tourism systems. First, treat data interpretation as an accessibility-critical design layer, not a back-end technical choice: organisations should audit what data types are prioritized, document the assumptions used to infer "engagement", and introduce safeguards against misclassifying constrained participation as disinterest. Second, make AI mediation legible and negotiable at the point of use: systems should clearly communicate what is being adapted, why it is happening, and how users can override or personalize this decision without penalty. Third, design agency distribution intentionally: staff roles, user control options and AI autonomy levels should be specified

as part of service design, so disabled visitors are not forced into opaque, paternalistic assistance patterns. Fourth, embed accessibility into governance and procurement: institutions should require accessibility targets and accountability mechanisms in vendor contracts, and integrate accessibility indicators into destination-level AI planning and performance assessment rather than treating them as add-ons. Finally, because cultural tourism is experience-driven, evaluate inclusion through experiential continuity, not only usability: organisations should test whether AI mediation supports dignity, autonomy and meaningful participation across the full visitor journey, not only at isolated touchpoints.

This review has several limitations that should be considered when interpreting the findings. *First,* the evidence base is drawn from peer-reviewed English-language articles indexed in Web of Science, Scopus, and the ACM Digital Library, which may under-represent practitioner reports, policy documents, industry evaluations, and accessibility standards that often shape real-world deployment. *Second,* the included studies are heterogeneous in system type, disability framing, and evaluation approach, which supports conceptual synthesis but limits the ability to make strong comparative claims about effectiveness across technologies or contexts. *Third,* much of the reviewed literature reports short-term or prototype-focused evaluations, meaning the synthesis can identify recurring design patterns and risks, but cannot fully resolve how trust, autonomy, dignity, and sustained participation develop over time in live service ecosystems. *Finally,* because many studies do not explicitly adopt a human–AI teaming lens, some constructs central to IHAM must be inferred from system descriptions rather than directly tested as theoretical variables. These limitations reinforce the need for the longitudinal, experiential, and governance-oriented research agenda identified in the review.

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Declarations

Competing interests The authors declare no competing interests.

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