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Mobile Augmented Reality in Architectural Heritage Environments: Associations of Heritage–MAR Fit with Learning Interest and Continuance Usage Intention

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Abstract

Mobile augmented reality (MAR) embeds digital information into real or simulated built-heritage environments, offering a novel means of connecting architectural spaces, cultural content, and user experiences. However, existing research has focused primarily on immersion, interactivity, and technology acceptance, with limited attention to how users evaluate the fit between heritage content and digital media or how these evaluations relate to learning interest and continuance usage intention. This study therefore proposes the Heritage–MAR Fit model. Drawing on the Stimulus–Organism–Response (S–O–R) framework and Cue Consistency Theory, the model examines how MAR design and information cues are associated with learning interest and continuance usage intention through fit evaluations. A sequential explanatory mixed-methods design was adopted. Study 1 analyzed 330 valid questionnaires collected through non-probability voluntary response sampling after participants experienced COSMOTE CHRONOS on mobile devices for 3–5 min (92.73% aged 18–34), using Partial Least Squares Structural Equation Modeling (PLS-SEM), Artificial Neural Networks (ANNs), and Necessary Condition Analysis (NCA). Study 2 comprised semi-structured interviews with 30 participants to contextualize and elaborate on the quantitative findings. Design aesthetics ($\beta = 0.158$) and information quality/perceived authenticity ($\beta = 0.531$) were significantly associated with Heritage–MAR Fit, whereas human–information interaction and human–system interaction were not. In the H–M FIT1-only sensitivity analysis, the design-aesthetics path became nonsignificant ($\beta = 0.045$, $p = 0.542$), indicating measurement sensitivity. Heritage–MAR Fit was significantly and positively associated with both learning interest and continuance usage intention and was indirectly associated with continuance usage intention through learning interest. However, elevated HTMT values indicate substantial empirical overlap among these constructs, so the relationships require cautious interpretation. ANNs identified information quality/perceived authenticity as the strongest predictor of fit, while NCA showed the largest necessity effect for design aesthetics and identified fit as necessary for high learning interest and continuance usage intention. The qualitative findings indicate that users formed fit judgments based on the authenticity of cultural information, its visual presentation, and its congruence with the architectural context. These judgments were also associated with continuance usage intention. These findings highlight the importance of aligning digital presentations with architectural heritage content and prioritizing credible information while treating design-aesthetics implications as provisional pending further measurement validation when developing MAR applications for heritage learning.

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Keywords: architectural heritage; mobile augmented reality; Heritage–MAR Fit; learning interest; continuance usage intention; Cue Consistency Theory; mixed methods

1. Introduction

Architectural heritage encompasses both physical space and repositories of historical memory, social memory, and cultural values [1]. Its conservation and communication concern not only the preservation of buildings but also the public's ability to understand their architectural forms, spatial relationships, and historical and cultural significance [2,3]. In recent years, augmented reality (AR) has been widely applied to three-dimensional reconstruction, education, tourism, and digital exhibitions in the cultural heritage field [4,5]. Nevertheless, presenting digital information alone cannot ensure that the public develops an in-depth understanding of heritage content. Although interactive media can capture learners' immediate attention, whether this initial sense of novelty can develop into learning interest and continuance usage intention remains unclear [6,7]. Heritage digitization must therefore preserve cultural assets while helping users connect digitally mediated knowledge with specific architectural forms, spatial locations, and historical contexts.

Mobile augmented reality (MAR) offers a new technological means of addressing this challenge. By overlaying digital information onto real-world environments through mobile devices, MAR enables the contextualized presentation of heritage content and supports heritage education. However, technological stimulation alone cannot explain how learners develop an interest in architectural heritage or why they intend to continue using MAR systems. Previous studies have shown that immersion and interactivity can enhance engagement and motivation, but a more intensive technological experience does not necessarily produce greater cognitive gains or better learning outcomes [8,9]. Research on interest development further suggests that situational interest triggered by external stimuli can develop into relatively stable individual interest only through continued cognitive engagement [10]. Research on MAR-based architectural heritage learning must therefore examine not only whether a system is engaging but also which features of digital presentation align with heritage content and how this congruence is associated with learning interest and continuance usage intention.

Existing research has approached this issue from two main perspectives. First, immersive learning studies have focused largely on technological attributes such as system functionality, immersion, interactivity, and usability. However, insufficient attention has been paid to how heterogeneous cues jointly shape learners' judgments and evaluations. Technological design and user experience have received considerably more attention than the theoretical mechanisms underlying learning [8]. Learners can develop a stable situational understanding and sustain their willingness to engage only when relevant information is organized into a coherent whole [11–13]. Conversely, when visual presentation, information communication, and interaction design are not effectively integrated, meaning construction may be disrupted, thereby weakening sustained engagement in the learning process. Second, immersion and interactivity are commonly regarded as direct antecedents of learning outcomes, although technological attributes are neither sufficient nor necessary conditions for such outcomes [9]. This issue is particularly important in architectural heritage learning, where text, visual reconstructions, interactive feedback, and cultural information can form an engaging learning experience only when they are congruent with the specific heritage context [14]. Current research therefore lacks an intermediate mechanism that explains how MAR cues converge to generate learning interest and continuance usage intention. This gap reflects a disconnect between research on technological elements and research on

users' cognitive responses. The former explains how digital content represents architecture, whereas the latter has yet to adequately explain how users determine whether such representations fit the architectural content and spatial context.

To address this issue, the present study draws on task–technology fit (TTF) research in information systems [15] and proposes the Heritage–MAR Fit model, which describes users' perceived congruence between heritage content and its MAR-mediated digital representation. Unlike conventional system-fit analyses that focus on software and hardware configurations, this study examines whether MAR representations appropriately convey the historical and cultural significance and spatial characteristics of architectural heritage. The Stimulus–Organism–Response (S–O–R) framework is used to organize the relationships between the study variables, while Cue Consistency Theory (CCT) informs the development and empirical testing of the research model. A sequential explanatory mixed-methods design was adopted. Study 1 used Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships. Artificial Neural Network (ANN) analysis complemented the PLS-SEM results by assessing the relative predictive importance of selected variables, while Necessary Condition Analysis (NCA) examined statistical necessity patterns associated with high levels of learning interest and continuance usage intention. Study 2 used grounded-theory-informed coding of qualitative interviews to examine how participants formed Heritage–MAR Fit judgments and to provide contextual explanations for the quantitative findings. Comparable SEM/PLS-SEM–ANN–NCA combinations have already been used in digital cultural heritage and serious-game research [16–18]. Accordingly, the methodological contribution claimed here is not the first use of these tools but their integration within a sequential explanatory design to examine a context-specific Heritage–MAR Fit model. Together, the methods provide complementary evidence on structural relationships, predictor importance, necessity patterns, and participants' experiences [19,20].

This study makes three bounded contributions. First, it examines Heritage–MAR Fit as a context-specific adaptation of perceived fit while recognizing its measurement boundaries. Second, it combines quantitative analyses with qualitative contextualization to examine associations between MAR-related perceptions, learning interest, and continuance usage intention. Third, it offers evidence-informed design considerations while acknowledging measurement sensitivity.

2. Theoretical Review

2.1. MAR in Architectural Heritage

Augmented reality (AR) overlays virtual information onto real-world environments, enabling the integration and spatial registration of virtual and physical elements [21,22]. Mobile augmented reality (MAR) extends this capability to portable devices such as smartphones and tablets, providing users with information related to their location and surroundings while they move. Unlike fixed displays, MAR embeds digital information directly within the physical space occupied by users, allowing information acquisition and on-site observation to occur simultaneously. This capability is particularly suitable for the digital reconstruction and spatial interpretation of historic buildings. Panou et al. [23] demonstrated its potential by superimposing three-dimensional reconstructions of the historical states of buildings onto physical heritage sites, enabling visitors to access relevant historical information while moving around and observing the buildings in situ.

Learning about architectural heritage is highly context-dependent. Architectural entities possess not only physical forms but also values derived from their historical, artistic, and scientific significance [24]. The International Council on Monuments and Sites (ICOMOS) [25] has emphasized that architectural heritage must be understood and conserved

within its historical context. Accordingly, learning about architectural heritage involves more than memorizing information; it requires the integration of architectural forms, spatial relationships, and historical and cultural knowledge. MAR provides the technological means to support this integration. By overlaying text, images, three-dimensional reconstructions, and location-related information onto physical architectural environments, MAR enables learners to establish direct connections between digital information and physical heritage as they observe and move through a site.

Previous studies have applied MAR in architectural heritage and related cultural-heritage settings to support contextual information presentation and learning experiences [12,13,23,26,27]. Through virtual reconstructions, three-dimensional models, and representations of historical transformations, MAR can support the contextualized exploration of architectural heritage. As summarized in Table 1, previous studies have found that MAR can increase learning engagement, support the comprehension and retention of complex cultural information, and, to some extent, encourage exploration and revisiting of heritage sites [28]. Furthermore, MAR applications organized across multiple cultural-heritage locations illustrate how mobile interaction can support spatially connected heritage exploration [26]. Nevertheless, although existing studies have shown that MAR can enhance user engagement and experiential perception, they have focused primarily on technological functionality, immersive experiences, and user acceptance. They have not adequately explained the conditions and mechanisms through which MAR experiences develop into sustained learning interest and continuance usage intention.

Table 1. Overview of AR/MAR-Related Research in Architectural Heritage Contexts.

Sources	Research Method	Application Area	Research Focus	Relevant Research Gap
Haugstvedt and Krogstie [29]	Design science + extended TAM survey	MAR; historic districts/cultural heritage	Perceived usefulness and enjoyment significantly enhance users' intention to adopt MAR.	Focuses primarily on technology acceptance, with limited attention to the mechanisms underlying content–technology integration.
Angelopoulou et al. [30]	System development + case application	Mobile AR; archaeological sites/museums	MAR facilitates heritage information presentation and enhances on-site learning experiences.	Emphasizes system design and implementation, with limited empirical validation of learning mechanisms.
Sylaiou et al. [31]	Case study + AR game evaluation	AR games for cultural heritage	Examines how AR games foster interest and engagement in cultural heritage learning.	Focuses on AR-based engagement and learning interest, with limited examination of the mechanisms underlying perceived usefulness and learning outcomes.
Panou et al. [23]	System development + application evaluation	Outdoor MAR; historic architecture/urban heritage	MAR supports the reconstruction of historic architecture and the contextualized presentation of heritage information.	Focuses primarily on technological implementation, with limited attention to the mechanisms underlying learning outcomes.

Table 1. *Cont.*

Sources	Research Method	Application Area	Research Focus	Relevant Research Gap
Chang et al. [32]	Quasi-experiment + behavioral pattern analysis	Mobile AR; art museums	AR-based guidance enhances learning performance and the overall learning experience.	Focuses primarily on navigation effects, with limited explanation of how multiple cues are integrated.
Boboc et al. [26]	Prototype development + user evaluation	MAR; cultural heritage sites	MAR facilitates on-site cultural heritage experiences and information acquisition.	Focuses primarily on usability and experiential evaluation, with limited explanation of the underlying mechanisms.
Chin and Wang [27]	Randomized controlled experiment	Mobile AR; cultural heritage learning	MAR enhances learning performance and stimulates learning interest.	Focuses primarily on learning outcomes, with limited explanation of the mechanisms underlying the formation of learning interest.
De Paolis et al. [12]	User experiment + quantitative analysis	Mobile AR; digital storytelling for cultural heritage	Usability and cognitive load influence users' experiences with MAR.	Focuses primarily on user experience, with limited explanation of content–technology fit.
Zhao et al. [33]	Controlled experiment	AR; historic architectural districts	Evaluates the effects of narrative AR exploration on cultural cognition, immersion, and dissemination intention.	Focuses on intervention outcomes rather than perceived Heritage–MAR Fit and its relationships with learning interest and continuance usage intention.
Galani and Vosinakis [13]	System development + user evaluation	MAR; architectural heritage and scale models	Examines how AR representations of historical practices support visitor experience and learning.	Focuses on AR presentation and learning outcomes rather than the structural relationships between perceived fit and subsequent intentions.

2.2. Cue Consistency Theory (CCT)

Cue consistency theory explains how individuals form holistic judgments from multiple informational cues. Anderson [34] explained how individuals integrate multiple information cues to form overall judgments. Cue consistency can influence individuals' perceptions of an object's credibility, their attitudes toward it, and their overall evaluations [35]. The central concern of Cue Consistency Theory (CCT) is therefore not the independent effect of a single cue but how consistency or conflict among multiple cues shapes individuals' overall judgments [36].

In MAR-based architectural heritage contexts, learners must simultaneously process heritage texts, historical images, three-dimensional reconstructions, spatial information,

and interactive feedback. Their overall evaluations depend not only on the individual cues but also on how these cues relate to the heritage content and the digitally represented architectural context. For example, historically accurate information may not facilitate coherent understanding if the digital reconstruction is inconsistent with the represented architectural form or spatial logic. Conversely, coordinated content, visual representation, and simulated spatial context may help learners connect digital information with architectural heritage. Cue Consistency Theory provides a theoretical explanation for this judgment process, although no single cue can independently represent the overall experience [36–38].

As shown in Table 2, previous studies have examined the relationships between informational cues, destination images, and digital representations in virtual tourism, user-generated content, and digital heritage experiences. Although these studies differ in context, conceptualization, and analytical approach, some have applied similar principles of fit or coordination without explicitly proposing or testing CCT. Further research is therefore needed to examine how learners form overall fit evaluations from different types of MAR cues in architectural heritage learning contexts and how these evaluations relate to learning interest and continuance usage intention [37,38].

Table 2. Applications of CCT and Implicit CCT Logic in the Cultural Heritage Domain.

Sources	Research Method	Application Area	Research Focus
Bassols-Gardella and Coromina [37]	UGC content analysis	Multi-heritage cities and destinations	Examines the consistency of destination images conveyed through different types of user-generated content (UGC).
Luo et al. [38]	Mixed-methods research + PLS-SEM	Cultural heritage tourism/digital humans	Applies CCT to examine how internal and external cues shape DHA–destination fit and its subsequent behavioral outcomes.

The present study applies the cue consistency perspective to explain the development of the Heritage–MAR Fit model. Heritage–MAR Fit refers to learners' overall perception of the congruence between architectural heritage content and its MAR-mediated presentation, together with the extent to which the MAR experience supports their heritage-related learning needs. Although this construct is related to cue consistency, it is not equivalent to consistency among individual cues. This study examines how human–information interaction, Human–System Interaction, design aesthetics, and the combined construct of information quality and perceived authenticity relate to Heritage–MAR Fit. It further investigates the mediating role of fit in the relationships between these cues and learning interest and continuance usage intention. Accordingly, the study focuses on how different cue types contribute to learners' overall fit judgments rather than directly measuring consistency or conflict between pairs of cues.

2.3. Stimulus–Organism–Response (S–O–R) Model

The Stimulus–Organism–Response (S–O–R) model explains how environmental stimuli influence behavioral responses through individuals' internal affective and cognitive states [39,40]. Within this model, stimuli represent environmental or system characteristics, the organism represents users' affective and cognitive states, and responses are expressed as attitudes or behavioral intentions [39,41].

In digital cultural heritage and serious-game research, the S–O–R model has been applied to examine how experience-related stimuli are associated with users' psychological

responses and behavioral intentions [18,42,43]. This framework emphasizes the role of internal psychological states in linking external stimuli to behavioral intentions.

However, existing studies have focused largely on general digital learning environments and have not systematically examined how MAR relates to learning interest and continuance usage intention in architectural heritage contexts. To address this gap, the present study adopts the S–O–R model as its theoretical foundation and integrates Cue Consistency Theory (CCT) to examine how MAR system characteristics relate to learning interest and continuance usage intention through users' affective and cognitive responses. This integration establishes a pathway of experience formation based on a stimulus–organism–response mechanism. Table 3 summarizes representative applications of the S–O–R framework in digital learning and cultural heritage contexts.

Table 3. Applications of the S–O–R Model in Digital Learning and Cultural Heritage Research.

Sources	Research Method	Application Area	Research Focus
Bao, Q., Wang, S., Nah, K., & Guo, W [18]	Questionnaire survey + PLS-SEM + Artificial Neural Networks (ANNs) + Necessary Condition Analysis (NCA)	Architectural heritage + serious games + digital cultural heritage communication	Examines how enhanced realism, instructional design, and knowledge acquisition influence user enjoyment and continuance usage intention through the S–O–R mechanism, integrating SEM, ANNs, and NCA.
Zhang, R., Huang, Q., Luo, J., Xu, J., & Pan, Y [42]	Questionnaire survey (n = 302) + PLS-SEM	Serious games + cultural heritage communication	Applies the S–O–R framework to examine the factors influencing user participation and affective identification in serious games and cultural heritage communication.
Wang, G., & Men, D [43]	Questionnaire survey + structural equation modeling	Digital serious games + cultural heritage experiences	Examines how external stimuli influence psychological responses and sustained engagement through an S–O–R-based mechanism.
Jiang, S., Zhang, Z., Xu, H., & Pan, Y [44]	Questionnaire survey + PLS-SEM	Cultural heritage virtual tourism	Applies the S–O–R framework to examine how environmental stimuli, cultural value, and immersion influence continuance usage intention.
Bai, Y., Wu, S., Liu, R., & Zheng, F [45]	Experiment + questionnaire survey + structural equation modeling	Intangible cultural heritage serious games	Applies the S–O–R model to examine how game-related stimuli shape psychological experiences and affective responses, which subsequently influence non-learning-related intentions.

2.4. Hypothesis Development and Conceptual Model

2.4.1. Human–Information Interaction

In MAR-based architectural heritage learning, human–information interaction concerns not only the efficiency of information acquisition but also learners' ability to establish meaningful connections between digital information and physical heritage. The structural clarity, semantic consistency, and comprehensibility of information presentation affect learners' understanding of task content and their subsequent perceptions of fit between the content and the technology [15]. High-quality information cues can also strengthen contextual authenticity, cognitive integration, perceived control over the learning context, and certainty of understanding, thereby facilitating meaning construction [38]. Accordingly, this study proposes the following hypothesis:

H1. *The quality of human–information interaction positively influences Heritage–MAR Fit.*

2.4.2. Human–System Interaction

In MAR-based architectural heritage learning, system responsiveness, stability, and interaction fluency provide essential technological support for task completion. From a task–technology fit (TTF) perspective, a system's ability to provide timely, stable, and predictable support during task execution is an important basis on which learners evaluate its fit with the learning task [15]. Previous studies have shown that a favorable system interaction experience can reduce barriers to use, strengthen learners' sense of control and expectations regarding successful task completion, and improve their overall assessment of a system's ability to support a task [15,43,46]. Sylaiou et al. examined the relationship between presence and enjoyment in a virtual museum [47]. Accordingly, this study proposes the following hypothesis:

H2. *The quality of Human–System Interaction positively influences Heritage–MAR Fit.*

2.4.3. Design Aesthetics

In MAR interaction design, design aesthetics encompass not only visual appeal but also the coordination and consistency of interface elements, modes of information presentation, and virtual architectural spaces. According to Cue Consistency Theory (CCT), when visual and interactive cues are consistent in form and meaning, users are more likely to form an overall perception of fit and regard the system as usable [38]. Previous studies have further shown that interface aesthetics and usability are interrelated. When aesthetic presentation aligns with operational logic, users are more likely to perceive a system as clear, comprehensible, comfortable, and easy to use [48]. Accordingly, this study proposes the following hypothesis:

H3. *Design aesthetics positively influences Heritage–MAR Fit.*

2.4.4. Information Quality/Perceived Authenticity

In MAR-based virtual reconstructions of cultural heritage, learners' comprehension and assimilation of information depend substantially on the accuracy, clarity, and credibility of the content presented by the system. Information quality and perceived authenticity are fundamental to effective cognition and can shape learners' evaluations of cultural content and their willingness to engage [49]. Previous studies have shown that when a system presents clear and reliable information that aligns with the learning objectives, users are more likely to perceive the system as authentic and trustworthy, thereby strengthening immersion and cognitive integration within the learning context [46]. When information

presented through an MAR system is accurate, clear, and credible, learners are more likely to regard it as effective support for architectural heritage learning and to perceive greater congruence between the heritage content and its MAR representation.

Although information quality and perceived authenticity are conceptually distinct, they are closely related in the present measurement context. The three IQA items assess users' overall evaluations of the authenticity, accuracy, reliability, and credibility of architectural heritage information presented through MAR. Rather than treating information quality and perceived authenticity as independently measured dimensions, this study integrates these related attributes into a single construct reflecting users' perceived quality and trustworthiness of heritage information. Accordingly, IQA is interpreted as a combined evaluation of heritage information, and its statistical effects cannot be attributed separately to information quality or perceived authenticity. Accordingly, this study proposes the following hypothesis:

H4. *The combined construct of information quality and perceived authenticity (IQA) positively influences Heritage–MAR Fit.*

2.4.5. Heritage–MAR Fit

The concept of fit describes the degree of congruence among individuals, tasks, and technologies. Previous studies have shown that when technological characteristics closely correspond to task requirements or user goals, users are more likely to form positive evaluations and continue using the technology [15,50]. However, traditional fit theory focuses primarily on the correspondence between technological functionality and task requirements and has limited explanatory power regarding the relationship between the meaning of heritage content and its digital representation. Building on existing fit theory, this study defines Heritage–MAR Fit as learners' overall perception of how well the MAR experience aligns with architectural heritage content and supports their heritage-related learning needs. It encompasses two related aspects: the perceived congruence between heritage content and its digital presentation, and the perceived suitability of MAR functions for supporting learning activities.

Recent research confirms that fit is already established in digital heritage and extended-reality research. Experience–Technology Fit explains whether XR attributes support the intended visitor experience [51]. Task–Technology Fit has been applied to digital-museum continuance intention [52] and to immersion and engagement in intangible-cultural-heritage VR [50]. Unlike the task–capability relationship examined in the digital-museum study [52], the present study focuses on users' integrated perception of content–representation congruence and support for heritage-related learning needs. Digital Human Avatar–Destination Fit instead concerns the congruence between a digital representative and a heritage destination [38]. The present study therefore does not claim the first application of fit theory to digital heritage. Its narrower contribution is to examine users' perceived congruence between architectural heritage content and its MAR-mediated presentation, together with the extent to which the MAR experience supports heritage-related learning needs, and to assess how this perception is associated with learning interest and continuance usage intention. Heritage–MAR Fit is thus treated as a context-specific adaptation rather than an entirely new or independently validated construct. Table 4 compares the fit constructs discussed above.

A higher level of Heritage–MAR Fit may reduce cognitive uncertainty during learning, strengthen learners' perceptions of the value of the MAR system, and promote learning interest and continuance usage intention [50–52]. Accordingly, this study proposes the following hypotheses:

H5. *Heritage–MAR Fit positively influences learning interest.*

H6. *Heritage–MAR Fit positively influences continuance usage intention.*

Table 4. Comparison of Fit Constructs Relevant to Digital Heritage and Architectural Heritage Learning.

Construct	Primary Fit Relationship	Core Focus	Representative Reference
Task–Technology Fit (TTF)	Task requirements ↔ Technological capabilities	Whether technological functions adequately support task performance	Goodhue & Thompson [15]
Experience–Technology Fit (ETF)	Experience goals ↔ Technology attributes	XR visitor-experience support	Jung et al. [51]
Task–Technology Fit in digital museums	Museum tasks ↔ Digital-museum capabilities	Continuance in digital-museum use	Zheng et al. [52]
Task–Technology Fit in heritage VR	Heritage tasks ↔ VR capabilities	Immersion and engagement in heritage VR	Ren et al. [50]
Digital Human Avatar–Destination Fit	Digital avatar ↔ Heritage destination	Avatar–destination congruence	Luo et al. [38]
Heritage–MAR Fit	Heritage content and MAR presentation ↔ Learners' heritage-related learning needs	Perceived congruence between heritage content and MAR presentation, together with the suitability of MAR functions for supporting heritage-related learning needs.	This study

Note: The comparison is conceptual and does not establish empirical discriminant validity among the listed constructs. The symbol ↔ indicates the fit between the two elements listed in the "Primary Fit Relationship" column.

2.4.6. Learning Interest

Learning interest refers to the positive cognitive engagement and sustained inclination to explore that learners develop during the learning process [10]. In MAR-based architectural heritage learning, it encompasses both learners' affective responses during the immediate experience and their willingness to remain attentive to and explore heritage content in greater depth. Learners with a strong interest in the learning process are more likely to remain actively engaged and to perceive greater value and future benefits from using the MAR system [10,53,54]. Learning interest may therefore serve as an important psychological mechanism linking the learning experience with continuance usage intention. Accordingly, this study proposes the following hypothesis:

H7. *Learning interest positively influences continuance usage intention.*

2.4.7. Continuance Usage Intention

In MAR-based cultural heritage learning environments, continuance usage intention refers to an overall behavioral tendency formed through learners' cumulative experiences and affective responses [10]. Previous studies have shown that learning interest can strengthen learning engagement and, through repeated interactions, gradually develop into intentions to continue using and recommending a system [10,43].

Accordingly, continuance usage intention is treated as a key outcome variable in this study, reflecting learners' overall acceptance of the MAR-based heritage learning system and their willingness to use it in the future.

2.4.8. Conceptual Model

Based on the preceding analysis, this study develops a conceptual framework that integrates the Stimulus–Organism–Response (S–O–R) model with Cue Consistency Theory (CCT). The framework explains how mobile augmented reality (MAR) relates to users' psychological responses and behavioral intentions in architectural heritage learning contexts (Figure 1).

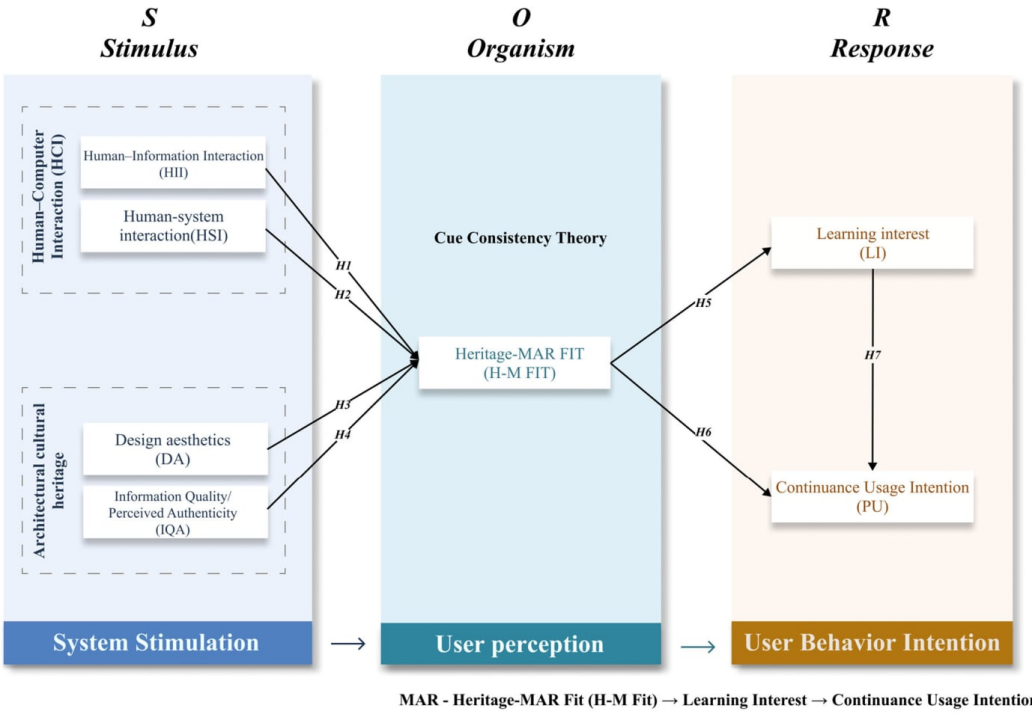

Figure 1. Conceptual Model of MAR-Based Architectural Heritage Learning Based on the S–O–R Framework. Source: Authors' own illustration. Note: MAR = Mobile Augmented Reality. H–M FIT = Heritage–MAR Fit.

The model treats human–information interaction (HII), Human–System Interaction (HSI), design aesthetics (DA), and information quality/perceived authenticity (IQA) as external stimuli (S). These system characteristics elicit psychological responses at the organism level (O) by shaping users' perceptions of Heritage–MAR Fit (H–M FIT). This construct reflects learners' overall perception of how well the MAR presentation aligns with architectural heritage content and how effectively the MAR experience supports their heritage-related learning needs. Stronger perceptions of fit are expected to enhance learning interest (LI), which is treated as a psychological response and an intermediate outcome that may further relate to continuance usage intention (PU). Overall, the model presents a stimulus–organism–response pathway in which technological cues contribute to learning motivation and continued use through cultural cognition and perceived fit. The proposed conceptual model therefore explains the psychological and behavioral mechanisms underlying MAR-based architectural heritage learning and provides a systematic theoretical framework for subsequent empirical investigation.

3. Methodology

3.1. Research Design

To systematically investigate how mobile augmented reality (MAR) relates to learning interest and continuance usage intention in architectural heritage contexts, this study adopted a sequential explanatory mixed-methods design [55,56]. This approach involves

collecting and analyzing quantitative data first and then using qualitative data to explain and extend the quantitative findings.

The study comprised two stages. In Study 1, 330 valid questionnaire responses were analyzed sequentially using Partial Least Squares Structural Equation Modeling (PLS-SEM), Artificial Neural Network (ANN) analysis, and Necessary Condition Analysis (NCA). PLS-SEM was used to evaluate the measurement model, structural relationships, and mediating effects [57–59]. ANN analysis examined the relative predictive importance of selected MAR-related variables, while NCA assessed whether selected factors exhibited patterns of necessity for high levels of learning interest and continuance usage intention. In Study 2, semi-structured interviews were conducted with 30 participants from Study 1. Using a grounded-theory-informed approach, the interview data were analyzed through open, axial, and selective coding [60] to further explain the quantitative findings. Building on previous research on digital cultural heritage experiences [61,62], the qualitative stage further examined how users form judgments of Heritage–MAR Fit and how cultural cognition, engagement motivation, and contextual factors relate to learning interest and continuance usage intention. Figure 2 illustrates the sequential mixed-methods design employed in this study.

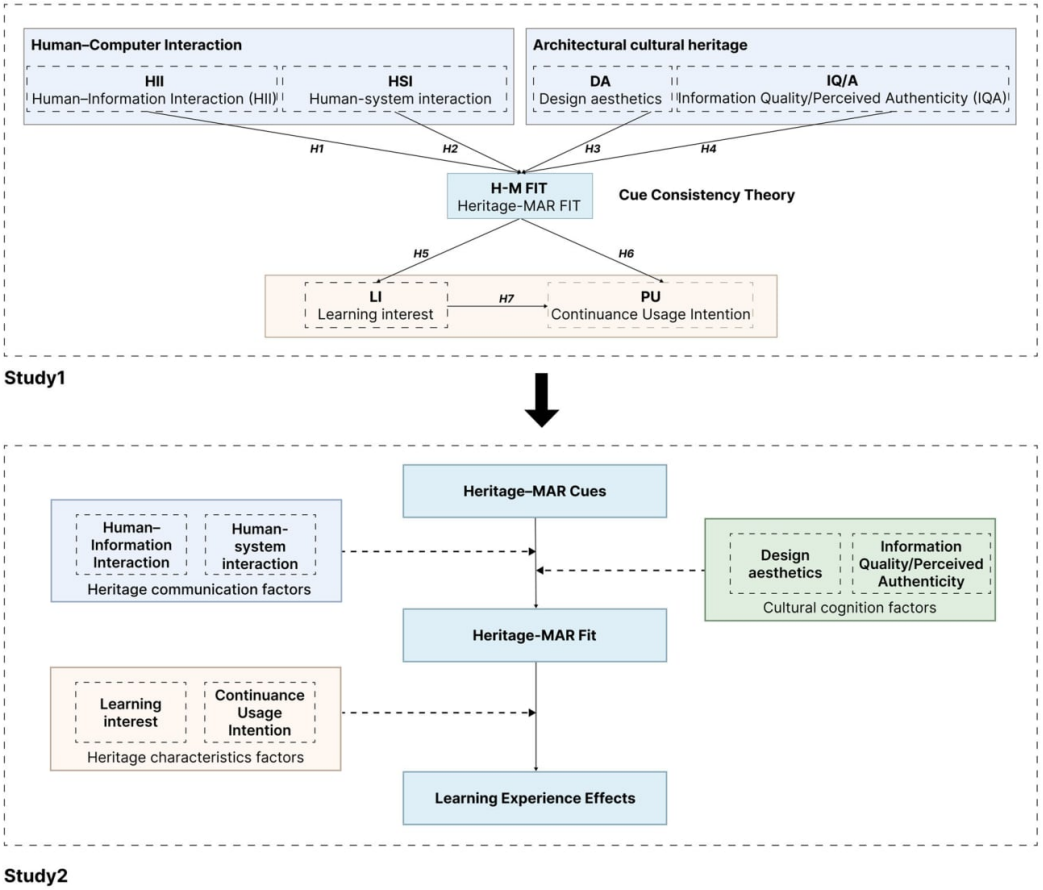

Figure 2. Research model with explanatory sequential mixed-methods design.

3.2. Study 1: Quantitative Phase

3.2.1. Case Selection

COSMOTE CHRONOS, currently distributed as Telekom Chronos, was selected as the MAR platform for this study. Developed by COSMOTE Telecommunications S.A., the application presents three-dimensional digital reconstructions of monuments of the Acropolis of Athens and related cultural-heritage content. It supports both location-based

use at the Acropolis and remote AR use on a mobile device. In the remote mode employed in this study, users can place the reconstructed content on a detected horizontal surface and explore it by browsing, rotating the device, changing viewpoints, and moving around the model. Participants were therefore not required to visit the Acropolis or another physical heritage site. At the time of the study, participants were instructed to download the publicly available application from the App Store and use it on their own compatible mobile devices. Figure 3 shows the setup, tutorial, and interaction screens of the COSMOTE CHRONOS app. It was selected for the following four reasons:

1. **Interaction Support.** The platform supports human–system and human–information interaction through functions such as browsing, clicking, rotating, and exploring. These functions provide the interactive MAR cues required for the study.
2. **Cultural Representation.** Architectural heritage information is presented through multiple cues, including text, images, and three-dimensional models. This multimodal presentation supports content authenticity and interpretive depth, helping users form informed cognitive judgments.
3. **Design Aesthetics.** The interface and three-dimensional environment maintain visual consistency in color, composition, and detailed presentation. This consistency reduces interference from background information and facilitates the assessment of design aesthetics.
4. **Accessibility and Standardized Participation.** The application could be accessed on participants' own mobile devices and used in its remote, surface-based AR mode. All participants received the same basic instructions and an approximate exploration period. This provided a common participation procedure, although individual device conditions and actual exposure duration were not fully controlled.

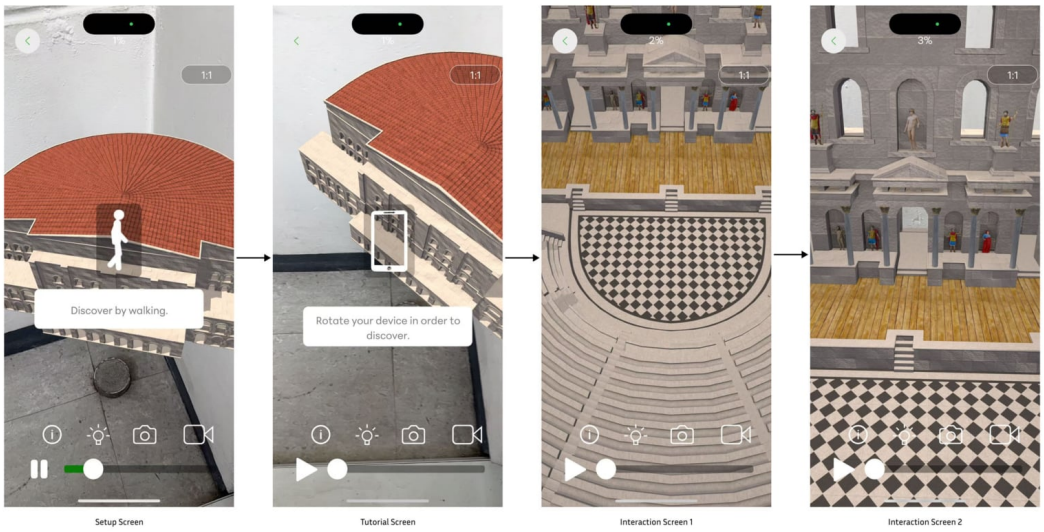

Figure 3. User experience and usage scenarios of COSMOTE CHRONOS in architectural heritage learning.

3.2.2. Instrumentation and Procedure

The questionnaire was developed from the theoretical model and its constructs. All items were adapted from validated scales used in previous studies and contextualized for MAR-based architectural heritage learning. Appendix A presents the construct definitions, measurement items, and corresponding sources. All items were assessed using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Participants

used the English-language version of COSMOTE CHRONOS. The questionnaire and study instructions were administered in Chinese.

Previous experience with MAR was not an inclusion criterion. Before completing the questionnaire, participants were instructed to explore COSMOTE CHRONOS on their own mobile devices for approximately 3–5 min. Participants were not assigned a specific monument. During the 3–5-min period, they were instructed to explore the Acropolis content available in the remote mode and to examine the interface, navigation, three-dimensional representations, and heritage information. Their individual content selections were not recorded. Participants then completed the questionnaire based on their experience with the application. Previous MAR experience was recorded separately as a background characteristic.

Completion of the MAR experience was based on participants' self-report rather than independently verified through platform logs. Because the questionnaire referred directly to the interface, navigation, information presentation, and heritage-learning content encountered during the experience, prior engagement with the application was necessary for meaningful completion.

3.2.3. Data Collection and Analysis

A questionnaire survey was conducted to evaluate the proposed Heritage–MAR Fit model. The questionnaire measured users' multidimensional perceptions of the digital heritage experience, including HII, HSI, DA, and IQA, as well as the core psychological constructs of H–M FIT, LI, and PU. Existing scales were adapted and localized to the study context [63]. An initial reliability assessment was conducted using the first 80 responses received during the formal survey. These responses did not constitute a separate pilot sample. No questionnaire items, response options, or measurement scales were modified following this assessment, and the 80 responses were retained as part of the final dataset. Reliability and validity were subsequently evaluated using the complete sample of 330 valid responses.

Formal data collection was conducted from April to May 2026. The questionnaire was administered through the online survey platform Wenjuanxing using a non-probability voluntary response sampling approach. Participation was voluntary, and respondents decided whether to complete the questionnaire. Therefore, the sample was self-selected rather than randomly drawn from a defined population. A total of 341 questionnaire responses were collected. Eleven responses were excluded because they failed the attention-check item, leaving 330 valid responses for the final analysis. No responses were excluded on the basis of prior AR experience. The earlier Figure 4 incorrectly retained a preliminary classification developed during the questionnaire-design stage, in which five responses were labelled as screening exclusions and six as invalid responses. This classification was not applied in the formal survey. A recheck of the final response records confirmed that all 11 excluded responses failed the attention-check item. Figure 4 and the corresponding description have therefore been corrected.

Before beginning the questionnaire, all respondents reviewed the study information and provided electronic informed consent. Participation was voluntary, respondents could discontinue before submitting the questionnaire, and no sensitive personal information was requested.

3.2.4. Respondent Profile

Women comprised 78.18% of the sample. Most participants were aged 18–34 years (92.73%), and 96.06% held a bachelor's degree or higher. Participants represented diverse

occupational backgrounds and differed in their prior experience with AR/MAR applications. Detailed demographic characteristics are presented in Appendix B.

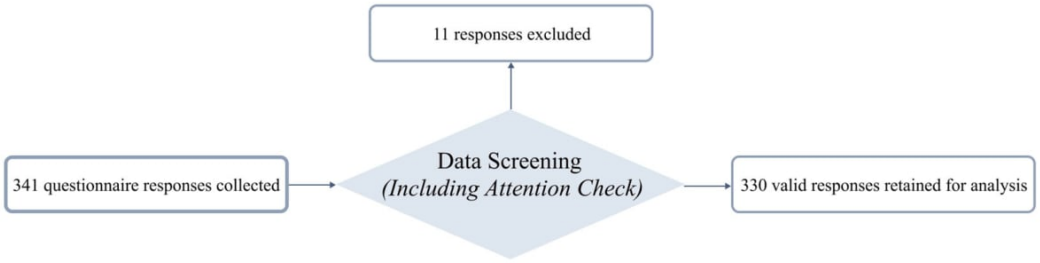

Figure 4. Data collection procedure.

3.2.5. Data Analysis Tools

To systematically evaluate the proposed mechanisms underlying MAR-based architectural heritage learning and examine the relationships between stimulus cues, perceived fit, and learning motivation, this study employed PLS-SEM, ANNs, and NCA as complementary analytical methods.

PLS-SEM: Partial Least Squares Structural Equation Modeling was the primary method used to evaluate the proposed structural model. PLS-SEM can accommodate multivariable, multipath, and non-normally distributed data and is well suited to examining relationships between latent variables [57,64]. Following the two-stage modeling procedure proposed by Anderson and Gerbing [65], SmartPLS 4.1 was used to evaluate the measurement and structural models separately. The reliability and validity of the measurement model were assessed using Cronbach's α, composite reliability (CR), Average Variance Extracted (AVE), and the Heterotrait–Monotrait Ratio (HTMT). The structural model was evaluated using path coefficients, their significance levels, and coefficients of determination (R^2). The significance of the path coefficients was tested through bootstrapping with 5000 resamples. PLS-SEM was used to examine how MAR stimulus cues, including HII, HSI, DA, and IQA, relate to Heritage–MAR Fit and subsequently predict learning interest (LI) and continuance usage intention (PU).

ANNs: Structural equation modeling is based primarily on linear relationships and may not fully capture potential nonlinear associations between MAR stimulus cues and users' psychological responses. Artificial Neural Network (ANN) analysis was therefore employed as a complementary method. ANNs can model complex nonlinear data structures and use predictors identified through SEM to train multilayer perceptron models, potentially improving the prediction of outcomes such as H–M FIT and learning interest [66]. The models were trained using a multilayer perceptron (MLP) architecture and evaluated through ten repeated random training–testing splits (90%/10%). Sensitivity analysis was subsequently conducted to rank the relative importance of the input variables in predicting the model outputs. Previous studies of cultural heritage and immersive technologies have demonstrated the utility of hybrid SEM–ANN models for behavioral prediction and variable-importance assessment [18]. ANN analysis therefore complements linear path analysis by identifying influential predictors and providing practical evidence for optimizing the digital representation of architectural heritage. The ANN procedure followed established hybrid SEM–ANN and variable-importance guidance [67,68].

NCA: Necessary Condition Analysis (NCA) examines whether the observed data exhibit patterns consistent with hypothesized necessary conditions for reaching specified outcome levels. In this study, NCA was used to determine whether bottleneck conditions exist for H–M FIT, learning interest, and continuance usage intention. NCA calculates effect sizes (d) and constructs necessity plots to identify minimum thresholds, thereby

revealing noncompensatory constraints that may be difficult to detect using SEM and ANNs [69]. Subsequent methodological developments introduced statistical significance testing for NCA, supporting its more robust application in behavioral science and technology-enhanced learning [70]. Dul et al. [46] also systematically reviewed the methodological principles and practical guidelines for NCA, further demonstrating its applicability to behavioral and management research. Accordingly, NCA was used to examine potential necessity relationships between MAR-related factors, Heritage–MAR Fit, learning interest, and continuance usage intention, complementing the relationships examined using PLS-SEM and ANNs.

3.3. Study 2: Qualitative Phase

To further explore the quantitative findings from Study 1, Study 2 employed a qualitative approach informed by grounded theory coding techniques. Semi-structured interviews were conducted with 30 participants from Study 1 [71,72]. The interview questions were developed around the research model and the findings of the quantitative phase. The analysis therefore aimed to provide contextual explanations for the observed relationships rather than to generate a new theory. Interview transcripts were examined using open, axial, and selective coding techniques [60], allowing participants' descriptions of their experiences to be organized and compared with the proposed constructs. The coding procedure was informed by established grounded-theory guidance [73,74].

3.3.1. Procedure

The Study 1 questionnaire was hosted on Wenjuanxing, while its link and QR code were distributed through WeChat, Weibo, Xiaohongshu, official university groups, and the researcher's personal networks. Participation followed a non-probability voluntary response sampling procedure. At the end of the questionnaire, respondents could voluntarily provide contact information if they were willing to participate in a follow-up interview. This information was used only for interview recruitment and was excluded from the quantitative dataset. Thirty respondents who had completed Study 1 were subsequently recruited for follow-up interviews within one week. The researcher confirmed their participation in Study 1 and asked whether they could clearly recall the MAR experience. Only those who confirmed their recollection were included. After providing informed consent, participants completed online interviews via Zoom or Tencent Meeting. Each interview lasted approximately 30–40 min and was audio-recorded with participants' consent.

All interviews were transcribed verbatim and analyzed using open, axial, and selective coding techniques informed by grounded theory. These techniques were used to organize and interpret participants' experiences rather than to develop a new theory. Figure 5 illustrates the coding process.

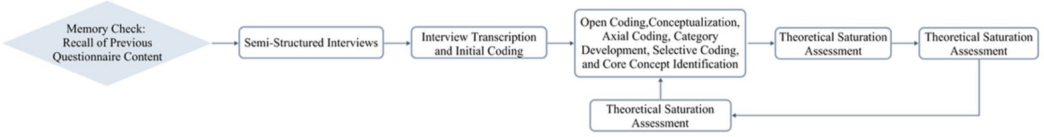

Figure 5. Qualitative coding procedure informed by grounded theory.

3.3.2. Sample

A multiphase sampling strategy combining a questionnaire survey with qualitative interviews was adopted. During the quantitative phase, 330 valid questionnaire responses were collected for statistical analysis. During the qualitative phase, purposive sampling was used to select 30 questionnaire respondents for semi-structured interviews. They

represented a range of professional backgrounds and levels of prior experience, providing some diversity within the sample. Detailed participant characteristics are presented in Appendix F.

3.3.3. Semi-Structured Interview Questions

The semi-structured interview questions were organized around four core themes: MAR-based architectural heritage, cultural understanding, learning interest, and continuance usage intention. The questions were designed to further explain the relationships between the key variables in the structural equation model and their underlying mechanisms. During the interview-design stage, the research team searched the Web of Science database using terms such as "Mobile Augmented Reality," "Architectural heritage," "Learning Interest," and "User Experience." Relevant studies were selected based on citation frequency and disciplinary relevance. The core questions were subsequently developed around the principal model variables, including H–M FIT, information quality, interactive experience, learning interest, and continuance usage intention. Open-ended questions were also included to explore cultural information comprehension, interactive experiences, fit judgments, and learning motivation. To minimize interviewer-induced bias, the questions were phrased neutrally and openly, allowing participants to describe their perceptions, affective responses, pathways of understanding, and sources of motivation during the MAR cultural heritage experience. The final interview guide addressed participants' perceptions of MAR presentation methods, their understanding of and judgments about the credibility of cultural information, the role of interaction methods in learning interest, their perceptions of fit between cultural content and its presentation, and the relationship between learning interest and continuance usage intention. The complete interview guide is provided in Appendix G.

4. Study 1: Quantitative Study Results

4.1. PLS-SEM Results

4.1.1. Assessment of Measurement Model

As shown in Table 5, Cronbach's α and composite reliability (CR) values for all latent variables exceeded 0.70, indicating good internal consistency [75]. The variance inflation factor (VIF) values for all observed indicators were below 5, indicating no problematic multicollinearity [58]. The standardized factor loadings of all measurement items exceeded 0.70, and the Average Variance Extracted (AVE) values were above 0.50, supporting adequate convergent validity [76].

Discriminant validity was assessed using the Fornell–Larcker criterion, the Heterotrait–Monotrait Ratio (HTMT), and indicator cross-loadings. As shown in Table 6, the Fornell–Larcker criterion was satisfied, with the square root of the Average Variance Extracted (AVE) for each construct exceeding its correlations with other constructs. However, the HTMT results in Table 7 revealed that eight construct pairs exceeded the recommended threshold of 0.90: HSI–DA (0.926), HSI–HII (0.914), IQA–H–M FIT (0.934), IQA–HSI (0.905), LI–H–M FIT (0.913), LI–IQA (0.915), PU–H–M FIT (0.947), and PU–LI (0.946). Although the corresponding bootstrap confidence intervals did not include 1.00 (Table 8), this does not resolve the concern created by the elevated HTMT values. Indicator cross-loadings were highest on their assigned constructs, but this evidence does not establish adequate discriminant validity for all construct pairs. Accordingly, adequate discriminant validity among H–M FIT, LI, and PU is not established, and their relationships are interpreted cautiously as associations between overlapping self-reported perceptions. Their structural relationships and indirect effects are interpreted as associations between theoretically distinguishable but empirically overlapping self-reported perceptions, rather than as evidence of separate psy-

chological mechanisms. The HTMT assessment followed established discriminant-validity guidance [77].

Table 5. Cronbach's α, Composite Reliability and Average Variance Extracted.

Variables	Cronbach's Alpha	Composite Reliability	AVE	Items	VIF	Factor Loading
HII	0.892	0.925	0.756	HII1	2.175	0.839
				HII2	3.083	0.904
				HII3	2.658	0.886
				HII4	2.185	0.846
HSI	0.859	0.914	0.780	HSI1	2.091	0.870
				HSI2	2.320	0.896
				HSI3	2.110	0.882
DA	0.877	0.924	0.802	DA1	2.756	0.908
				DA2	2.141	0.883
				DA3	2.470	0.896
IQA	0.839	0.903	0.756	IQA1	1.946	0.864
				IQA2	1.994	0.879
				IQA3	1.969	0.865
LI	0.891	0.920	0.696	LI1	2.049	0.809
				LI2	2.487	0.831
				LI3	2.178	0.823
				LI4	2.607	0.850
				LI5	2.432	0.859
PU	0.867	0.910	0.716	PU1	1.923	0.833
				PU2	2.271	0.859
				PU3	2.142	0.852
				PU4	2.027	0.839
H–M FIT	0.858	0.914	0.779	H–M FIT1	2.398	0.891
				H–M FIT2	1.846	0.851
				H–M FIT3	2.540	0.904

An exploratory full-collinearity assessment based on the latent-variable correlation matrix yielded approximate VIF values of 3.45–4.68, exceeding the suggested threshold of 3.3. Because the key constructs were collected from the same respondents at the same time, common method bias cannot be ruled out. The elevated values may also partly reflect substantive overlap among the constructs, but they reinforce the need for caution when interpreting the strong relationships between H–M FIT, LI, and PU.

Table 6. Fornell–Larcker criterion.

	DA	H–M FIT	HII	HSI	IQA	LI	PU
DA	0.896						
H–M FIT	0.703	0.883					
HII	0.782	0.678	0.869				
HSI	0.803	0.714	0.800	0.883			
IQA	0.740	0.793	0.734	0.768	0.869		
LI	0.767	0.799	0.700	0.720	0.791	0.835	
PU	0.745	0.818	0.683	0.714	0.767	0.834	0.846

4.1.2. Structural Model

The structural model was evaluated using SmartPLS 4 to examine the hypothesized associations between the latent variables and the model's explanatory power. As shown in Table 9, most hypotheses were supported in the original three-item specification. Human–information interaction (HII) was not significantly associated with Heritage–MAR Fit

(β = 0.059, t = 0.855, p = 0.393), and H1 was not supported. The positive association between Human–System Interaction (HSI) and Heritage–MAR Fit was also nonsignificant (β = 0.132, t = 1.723, p = 0.085), and H2 was not supported. Design aesthetics (DA) was positively associated with Heritage–MAR Fit in the original model (β = 0.158, t = 2.471, p = 0.013), supporting H3 in that specification. Information quality/perceived authenticity (IQA) was also positively associated with Heritage–MAR Fit (β = 0.531, t = 8.964, $p <$ 0.001), supporting H4. Heritage–MAR Fit was positively associated with learning interest (LI; β = 0.799, t = 35.199, $p < 0.001$) and continuance usage intention (PU; β = 0.420, t = 7.374, $p < 0.001$), while LI was positively associated with PU (β = 0.498, t = 9.099, $p <$ 0.001). These results support H5–H7 within the original specification, but the elevated HTMT values prevent interpreting the paths as relationships between fully distinct empirical constructs. The stability of the H3 result is examined in the sensitivity analysis below.

Table 7. Heterotrait–Monotrait (HTMT) Ratio Values.

	DA	H–M FIT	HII	HSI	IQA	LI	PU
DA							
H–M FIT	0.810						
HII	0.884	0.776					
HSI	0.926	0.832	0.914				
IQA	0.863	0.934	0.848	0.905			
LI	0.868	0.913	0.785	0.824	0.915		
PU	0.835	0.947	0.770	0.815	0.867	0.946	

Table 8. HTMT Inference Results for Construct Pairs Exceeding 0.90.

Construct Pair	HTMT	2.5%	97.5%
HSI–DA	0.926	0.876	0.969
HSI–HII	0.914	0.863	0.957
IQA–H–M FIT	0.934	0.870	0.991
IQA–HSI	0.905	0.841	0.966
LI–H–M FIT	0.913	0.866	0.957
LI–IQA	0.915	0.854	0.970
PU–H–M FIT	0.947	0.896	0.994
PU–LI	0.946	0.901	0.989

Note: The 2.5% and 97.5% columns represent the lower and upper bounds of the 95% bootstrap confidence intervals based on 5000 subsamples.

The structural-model results include the R^2 values for the three endogenous variables. The R^2 value for Heritage–MAR Fit was 0.667, indicating that its antecedent variables explained 66.7% of its variance. The R^2 value for learning interest was 0.638, indicating that the model explained 63.8% of its variance. The R^2 value for continuance usage intention was 0.759, indicating that the model explained 75.9% of the variance in this outcome. Collectively, these results demonstrate that the structural model accounted for substantial variance in Heritage–MAR Fit, learning interest, and continuance usage intention.

The inner VIF values ranged from 1.000 to 3.988, remaining below the commonly used threshold of 5. Effect sizes (f^2) ranged from 0.003 to 1.760, with information quality/perceived authenticity showing a moderate effect on Heritage–MAR Fit (f^2 = 0.296) and Heritage–MAR Fit showing a large effect on learning interest (f^2 = 1.760). PLSpredict further showed positive Q^2 predict values for all 12 endogenous indicators (0.396–0.530), with lower prediction errors than the linear model benchmark for 10 indicators based on RMSE and five based on MAE.

Table 9. A summary of the results of hypotheses testing.

	Original Sample (O)	Mean (M)	STDEV	T Statistics	*p* Values	Result
DA → H–M FIT	0.158	0.161	0.064	2.471	0.013	Supported
H–M FIT → LI	0.799	0.799	0.023	35.199	0.000	Supported
H–M FIT → PU	0.420	0.418	0.057	7.374	0.000	Supported
HII → H–M FIT	0.059	0.059	0.069	0.855	0.393	Unsupported
HSI → H–M FIT	0.132	0.134	0.077	1.723	0.085	Unsupported
IQA → H–M FIT	0.531	0.527	0.059	8.964	0.000	Supported
LI → PU	0.498	0.501	0.055	9.099	0.000	Supported

Note: DA = Design Aesthetics; IQA = Information Quality/Perceived Authenticity; H–M FIT = Heritage–MAR Fit; LI = Learning Interest; PU = Continuance usage intention.

4.1.3. Exploratory Sensitivity Analysis of Heritage–MAR Fit Measurement

To examine whether the structural findings were sensitive to the operationalization of Heritage–MAR Fit, an exploratory analysis replaced the original three-item measure with H–M FIT1, the item that directly assesses congruence between heritage content and its MAR presentation. All other structural paths and measurement specifications were retained. This single-item specification is a sensitivity check rather than a validated competing measurement model. The results of this exploratory comparison are summarized in Table 10.

Table 10. Exploratory sensitivity analysis of Heritage–MAR Fit measurement.

Structural Path	Original Model β	Original *p*	H–M FIT1-Only β	H–M FIT1-Only *p*
DA → H–M FIT	0.158	0.013	0.045	0.542
HII → H–M FIT	0.059	0.393	0.057	0.447
HSI → H–M FIT	0.132	0.085	0.041	0.632
IQA → H–M FIT	0.531	<0.001	0.634	<0.001
H–M FIT → LI	0.799	<0.001	0.695	<0.001
H–M FIT → PU	0.420	<0.001	0.241	<0.001
LI → PU	0.498	<0.001	0.666	<0.001
Explained variance	Original R^2	Original *p*	H–M FIT1-only β	H–M FIT1-only *p*
H–M FIT	0.667		H–M FIT1-only R^2	
LI	0.638		0.554	
DA → H–M FIT	0.158		0.483	

Note: The H–M FIT1-only specification is an exploratory sensitivity analysis and does not constitute a validated competing measurement model. All structural paths and other measurement specifications were retained.

The IQA, H–M FIT, LI, and PU paths remained statistically significant in the H–M FIT1-only specification. However, DA → H–M FIT became nonsignificant (β = 0.045, $p = 0.542$), H–M FIT → PU decreased from 0.420 to 0.241, and the R^2 of H–M FIT decreased from 0.667 to 0.554. H3 is supported in the original three-item specification but not in the H–M FIT1-only sensitivity analysis; its support is therefore measurement-dependent and should not be treated as a stable finding. The original model is retained because it reflects the intended broader perception of content–representation congruence and learning support, but the sensitivity results limit the stability and generalizability of the design-aesthetics conclusion.

4.1.4. Indirect Effects of Structural Model

To further examine the indirect associations within the original structural specification, the study estimated the indirect and serial indirect paths shown in Table 11. DA and IQA

had statistically significant indirect associations with PU through H–M FIT (DA → H–M FIT → PU: β = 0.066, $p < 0.05$; IQA → H–M FIT → PU: β = 0.223, $p < 0.001$) and with LI through H–M FIT (DA → H–M FIT → LI: β = 0.126, $p < 0.05$; IQA → H–M FIT → LI: β = 0.424, $p < 0.001$). Because H–M FIT, LI, and PU show substantial empirical overlap, these estimates are treated as associations within the specified model and not as evidence of distinct causal or psychological mediation mechanisms. The DA-related indirect paths should also be interpreted in light of the H–M FIT1 sensitivity result.

Table 11. Indirect effects.

Indirect Path	Path Coefficient	*p*-Value	t-Values	Confidence Interval		Significance
				2.5%	97.5%	
DA → H–M FIT → LI	0.126	0.015	2.443	0.030	0.232	Significant
DA → H–M FIT → PU	0.066	0.024	2.257	0.015	0.130	Significant
IQA → H–M FIT → LI	0.424	<0.001	8.433	0.319	0.518	Significant
IQA → H–M FIT → PU	0.223	<0.001	6.400	0.155	0.292	Significant
H–M FIT → LI → PU	0.398	<0.001	8.598	0.312	0.492	Significant
IQA → H–M FIT → LI → PU	0.211	<0.001	5.632	0.143	0.289	Significant
HII → H–M FIT → LI	0.047	0.393	0.854	−0.060	0.158	Not Significant
HSI → H–M FIT → LI	0.106	0.084	1.726	−0.014	0.226	Not Significant
HII → H–M FIT → LI → PU	0.024	0.395	0.850	−0.030	0.079	Not Significant
HSI → H–M FIT → LI → PU	0.053	0.094	1.674	−0.007	0.117	Not Significant
HII → H–M FIT → PU	0.025	0.404	0.835	−0.032	0.087	Not Significant
HSI → H–M FIT → PU	0.056	0.097	1.658	−0.007	0.126	Not Significant
DA → H–M FIT → LI → PU	0.063	0.017	2.381	0.015	0.119	Significant

Note: Path coefficients represent specific indirect effects. Confidence intervals are the 95% bootstrap percentile intervals. Statistical significance was assessed at $p < 0.05$.

The original specification also yielded a statistically significant serial indirect association of IQA with PU through H–M FIT and LI (IQA → H–M FIT → LI → PU: β = 0.211, $p < 0.001$). The indirect paths involving HSI and HII were not statistically significant. Given the elevated HTMT values and possible common method bias, these results describe the covariance pattern estimated by the model and should not be interpreted as establishing a sequence of empirically independent mechanisms.

4.2. ANN Results

4.2.1. Model Building

To complement the PLS-SEM results and examine the relative predictive importance of selected variables, this study employed Artificial Neural Network (ANN) analysis using the multilayer perceptron (MLP) procedure in IBM SPSS Statistics (version 27). SPSS. Two ANN models were constructed based on the significant relationships identified through PLS-SEM. Model A used design aesthetics (DA) and information quality/perceived authenticity (IQA) as input variables to predict Heritage–MAR Fit (H–M FIT), whereas Model B used H–M FIT and learning interest (LI) to predict continuance usage intention (PU).

Both models were specified with one hidden layer (see Figure A1 in Appendix C). SPSS automatically selected two hidden neurons in each of the ten runs for both Model A and Model B. The hidden layer used the hyperbolic tangent (Tanh) activation function, while the output layer used the identity activation function. Input and output variables were standardized, and model training employed batch optimization using the scaled conjugate gradient algorithm.

Each ANN model was run ten times, with approximately 90% of observations allocated to training and 10% to testing in each run. No fixed random seed was specified. This procedure constituted repeated train–test evaluations rather than tenfold cross-validation.

4.2.2. Validation of ANNs

The predictive performance of the ANN models was evaluated using root mean square error (RMSE) across ten repeated train–test evaluations. RMSE was calculated from the sum-of-squares error reported by SPSS and the corresponding sample size, accounting for the scaling factor in the error function. Because the dependent variables were standardized before model estimation, all RMSE values are reported on the standardized scale.

For Model A, the mean training RMSE was 0.583 (SD = 0.011), whereas the mean testing RMSE was 0.620 (SD = 0.116). The testing RMSE ranged from 0.388 to 0.814. For Model B, the mean training RMSE was 0.445 (SD = 0.013), and the mean testing RMSE was 0.457 (SD = 0.100), with testing values ranging from 0.308 to 0.639.

Although the mean testing errors were relatively close to the corresponding training errors, the variation across repeated runs indicates sensitivity to the training–testing partitions, particularly for Model A. Therefore, the ANN results are interpreted as complementary predictive evidence rather than definitive confirmation of model robustness. Detailed results are presented in Appendix D.

4.2.3. Sensitivity Analysis

The relative predictive importance of the input variables was examined using the independent variable importance analysis provided by SPSS. Relative importance (RI) values were obtained from ten ANN runs and averaged for each predictor. The mean importance values were then normalized by setting the highest mean importance within each model to 100%. The results are presented in Table 12.

Table 12. Relative and Normalized Importance of ANN Predictors Across Ten Runs.

	Model A (Output: H–M FIT)		**Model B (Output: PU)**	
Neural Network	**DA**	**IQA**	**H–M FIT**	**LI**
ANN1	0.377	0.623	0.552	0.448
ANN2	0.342	0.658	0.590	0.410
ANN3	0.290	0.710	0.550	0.450
ANN4	0.337	0.663	0.551	0.449
ANN5	0.346	0.654	0.524	0.476
ANN6	0.343	0.657	0.571	0.429
ANN7	0.343	0.657	0.551	0.449
ANN8	0.456	0.544	0.581	0.419
ANN9	0.369	0.631	0.485	0.515
ANN10	0.315	0.685	0.487	0.513
RI	0.352	0.648	0.544	0.456
NI (%)	54.273	100.000	100.000	83.756

For Model A, information quality/perceived authenticity (IQA) had the highest normalized importance (100%) in predicting H–M FIT, followed by design aesthetics (DA; 54.273%). For Model B, H–M FIT had the highest mean normalized importance (100%) in predicting continuance usage intention (PU), followed by learning interest (LI; 83.756%). Although H–M FIT ranked first on average, LI showed slightly higher importance in two of the ten runs. These findings indicate that the relative importance rankings were consistent with the PLS-SEM results for Model A but differed for Model B. The ANN results

therefore provide a complementary perspective on predictor importance rather than direct confirmation of the PLS-SEM coefficients.

4.3. NCA Results

NCA was used to examine whether the observed data supported necessity relationships between the selected variables. The analysis focused on the five relationships with significant positive PLS-SEM coefficients and was not intended as an exhaustive assessment of all potential necessary conditions. Unlike methods that estimate average associations, NCA examines constraints on attainable outcome levels. NCA was conducted in R using construct scores calculated as the arithmetic means of their corresponding questionnaire items. The ceiling envelopment–free disposal hull (CE-FDH) method was applied to estimate necessity patterns, with statistical significance assessed through 10,000 permutation tests [69] (Figure 6).

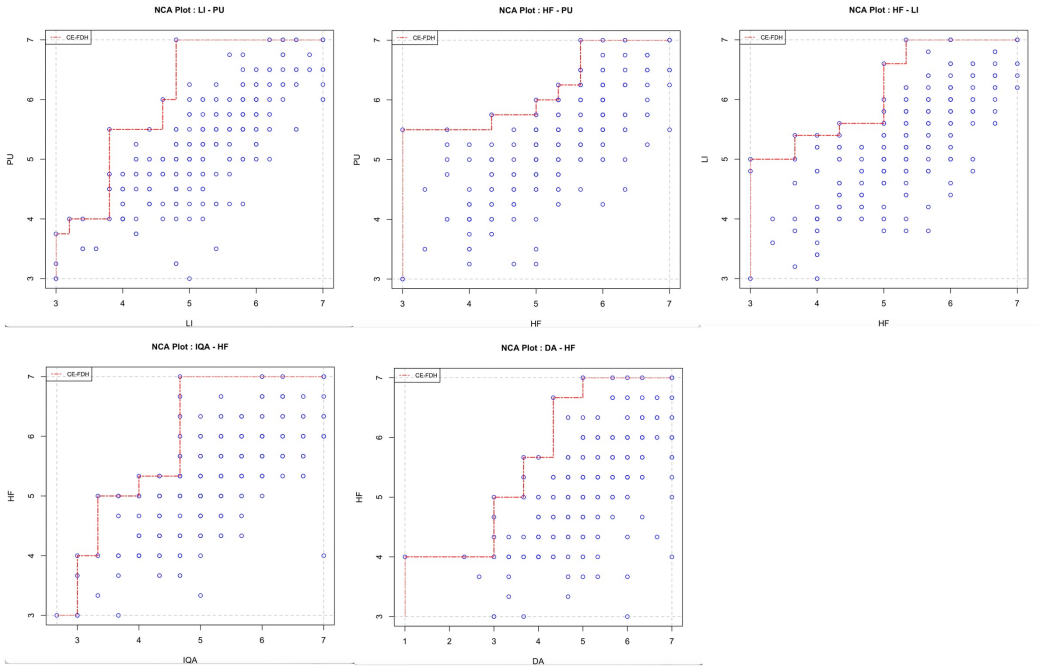

Figure 6. NCA scatter plots and CE-FDH ceiling lines for the five examined relationships. Each blue circle represents one respondent's scores on the two constructs shown in that panel.

4.3.1. Effect Size and Significance Testing

A permutation test was conducted to assess the statistical reliability of the necessity effect sizes. According to the NCA criteria, a predictor may be considered a statistically significant necessary condition for an outcome when its effect size is $d \geq 0.10$ and $p < 0.05$ [19,69]. The effect size indicates the extent to which an insufficient level of a condition constrains the attainment of an outcome, whereas the permutation test determines whether the observed boundary pattern could have arisen from a random distribution of the data [19]. Table 13 presents the results of the necessity significance tests. All five relationships examined using NCA had effect sizes greater than 0.10 and were statistically significant in the permutation tests ($p < 0.05$). According to Dul [69], DA showed a large necessity effect ($d = 0.352$), while the other four relationships showed medium effects ($d = 0.214$–0.276). These results provide evidence of necessity patterns within the observed sample. They do not, however, establish that the predictors are causal prerequisites for the corresponding outcomes.

Table 13. NCA effect sizes (Method: CE-FDH).

Parameters	Ceiling Zone	Scope	Effect Size	*p*-Value
DA → H–M FIT	8.444	24.000	0.352	<0.001
IQA → H–M FIT	4.778	17.333	0.276	<0.001
H–M FIT → PU	3.417	16.000	0.214	<0.001
LI → PU	3.850	16.000	0.241	<0.001
H–M FIT → LI	3.467	16.000	0.217	<0.001

4.3.2. Bottleneck Analysis

Bottleneck analysis was used to estimate the minimum predictor levels associated with specified outcome levels in the observed data. Within the NCA framework, these thresholds indicate constraints on attainable outcome levels based on the estimated ceiling lines [69]. However, they should not be interpreted as universal thresholds or as evidence that changing a predictor will necessarily change the outcome. The estimated bottleneck levels are reported in Appendix E. For example, achieving 80% of the observed PU range required H–M FIT and LI to reach at least 75% and 45% of their respective observed ranges, respectively.

The PLS-SEM and NCA findings were compared to examine how the selected relationships were supported by the two approaches (Figure 7). PLS-SEM provided evidence of statistical associations, whereas NCA identified patterns consistent with necessary conditions within the observed data [19]. All five relationships examined by NCA—DA–H–M FIT, IQA–H–M FIT, H–M FIT–LI, H–M FIT–PU, and LI–PU—were statistically significant in both the PLS-SEM and NCA analyses. These findings suggest that the corresponding factors may play important roles in the observed outcomes, although neither analysis establishes causal effects. Together, the results provide complementary evidence for interpreting the proposed relationships and informing MAR design.

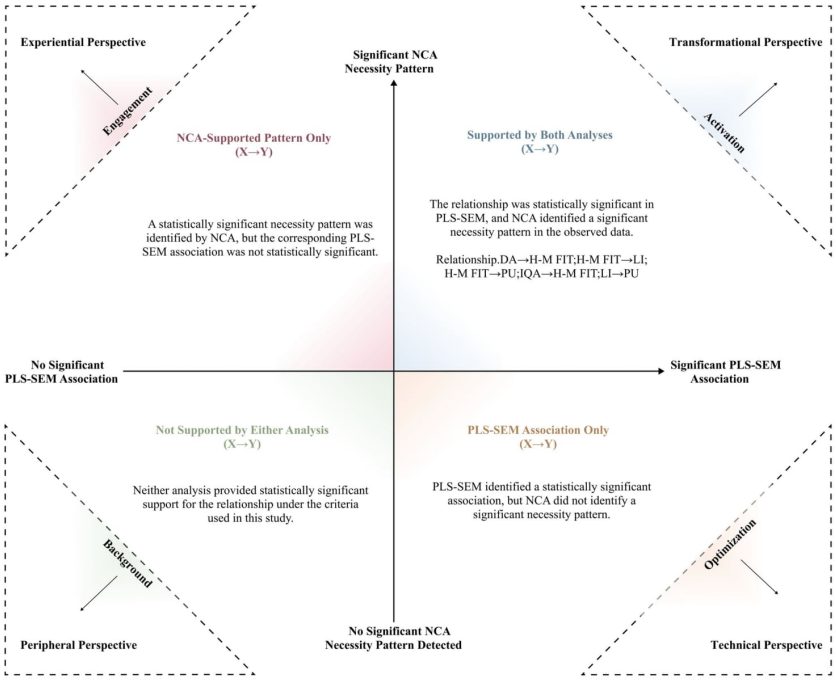

Figure 7. Comparison of PLS-SEM associations and NCA necessity patterns. Note: The quadrants classify relationships according to their statistical significance in PLS-SEM and NCA. This classification does not establish causal sufficiency or necessity.

5. Study 2: Qualitative Study Results

5.1. Grounded Theory-Informed Coding

All 30 interviews were transcribed verbatim and analyzed using coding techniques informed by grounded theory. All interview transcripts were manually coded by a single researcher using Microsoft Word, without specialized qualitative analysis software. The transcripts were reviewed systematically, and relevant statements were assigned initial codes. Related codes were then grouped into broader categories, which were compared with the constructs developed in Section 2. The analysis identified seven main themes, which are presented alongside their associated categories and researcher-synthesized thematic summaries in Table 14. Rather than developing a new theory, this process was used to identify recurring patterns in participants' experiences and to provide contextual explanations for the quantitative findings. The analysis focused on coded meaning units and researcher-synthesized thematic statements. These statements are not presented as verbatim participant quotations.

Table 14. Themes derived from grounded theory-informed coding.

No.	Researcher-Synthesized Thematic Summaries	Category	Main Theme
1.	Participants' willingness to continue using MAR depended on whether the system preserved the spatial experience of the architecture itself. (R1)	Authenticity and effectiveness of architectural and cultural information	Information authenticity
	MAR supported architectural-cultural understanding by making building methods and the reasons behind construction decisions more visible. (R3)		
	MAR was perceived as valuable when it improved learning efficiency while providing reliable information. (R30)		
2.	MAR translated abstract structural concepts, relationships between components, and construction sequences into intuitive visual information. (R3)	Consistency between information presentation and architectural cognitive logic	Structural consistency
	Consistency between the MAR presentation and participants' prior understanding of space reinforced confidence in their interpretations. (R4, R7)		
	MAR's nonlinear presentation was perceived as compatible with the multidimensional ways in which architectural culture is understood. (R17)		
	Verification of the historical sites referenced in the application strengthened confidence in the accuracy of the information. (R8)		
3.	Continued-use willingness increased when the interface was visually appealing, the experience was comfortable, and the application required limited effort. (R19)	Aesthetic experience and usage intention shaped by multisensory design coordination	Design aesthetics

Table 14. *Cont.*

No.	Researcher-Synthesized Thematic Summaries	Category	Main Theme
3.	Coordinated visual presentation, lighting, shadows, and sound encouraged participants to remain engaged for longer periods. (R11, R20)	Aesthetic experience and usage intention shaped by multisensory design coordination	Design aesthetics
	An unattractive interface or awkward interaction reduced participants' interest in continuing the experience. (R13, R19)		
4.	Participants' emotional engagement was strongly influenced by the perceived interactivity and immersion of the experience. (R14)	Influence of interaction flow and system feedback on user comfort	Human–System Interaction
	Smooth interaction and rapid system feedback improved participants' comfort during use. (R22, R30)		
	A clear system structure, explicit navigation paths, and appropriate feedback supported continued-use willingness. (R23)		
	Interest was stronger when the interaction was appropriate, the information was clearly structured, and the overall experience was smooth. (R21)		
5.	Participants understood architectural culture through spatial logic and functional relationships rather than through information acquisition alone. (R4)	Immersive spatial presence and embodied experience	Spatial perception
	Compared with viewing images or reading textual descriptions, MAR strengthened participants' perceived spatial presence in the represented environment. (R19, R24)		
	The combination of visual imagery, sound, and spatial overlays created a stronger sense of presence in the represented place. (R11, R20)		
6.	MAR externalized processes that would otherwise require mental construction, making them directly observable and perceptible. (R1)	Visualization of multidimensional architectural information	Visualization
	MAR related digital content directly to architectural and spatial representations. (R2, R9)		
	MAR helped reconstruct traces of historical modifications and clarify decisions that were no longer physically visible. (R4)		
	MAR was valued for presenting, in an intuitive form, content that would otherwise require substantial experience or expertise to understand. (R7)		

Table 14. *Cont.*

No.	Researcher-Synthesized Thematic Summaries	Category	Main Theme
7.	Participants were more willing to explore abstract or professionally complex information when it was directly connected to the represented place. (R10, R12) MAR reduced the need to switch repeatedly between pages or manually organize fragmented information by presenting the content more intuitively. (R22, R24)	Concise information provision and contextual relevance	Information conciseness and contextual relevance

Source: Authors' own compilation. Note: The table presents researcher-synthesized thematic summaries rather than verbatim participant quotations. Participant identifiers indicate the interview records contributing to each theme.

The consistency of the category system was examined by comparing the coding results across interviews. The first 25 transcripts were used to develop the initial categories, and the remaining five were reviewed to assess whether additional categories emerged. These five interviews provided further contextual detail but did not result in new major categories. This finding suggests that the main categories were reasonably stable within the present dataset. However, it should not be interpreted as evidence of theoretical saturation in the strict grounded-theory sense, as the interviews were designed primarily to explain the quantitative findings rather than to develop a new theory.

5.2. Research Findings

Analysis of the 30 interviews identified seven main themes: information authenticity, structural consistency, design aesthetics, Human–System Interaction, spatial perception, visualization, and information conciseness and contextual relevance. These themes correspond to the categories presented in Table 14 and provide a basis for interpreting participants' experiences with MAR in architectural heritage settings.

First, participants emphasized the reliability of heritage information and the consistency of its digital representation with the represented architectural forms and spatial relationships. The coded accounts associated MAR with more efficient access to heritage information when the content was perceived as reliable. Participants also described three-dimensional representations of architectural structures and component relationships as helpful for understanding spatial logic. These findings indicate that information credibility and representational consistency contributed to participants' evaluations of the MAR experience.

Second, design aesthetics and Human–System Interaction featured prominently in participants' descriptions of the user experience. Visually appealing interfaces, comfortable experiences, and lower operational effort were associated with greater willingness to continue using MAR, whereas unattractive presentation and difficult controls were associated with reduced interest. Participants also linked smooth interaction, rapid system feedback, clear navigation, and appropriate system structure with greater comfort during use.

Third, the coded accounts highlighted the roles of human–information interaction and information visualization. Participants preferred information that was directly related to the architectural content represented in the application and described the presentation as more intuitive than abstract or highly technical explanations. They also reported that visualizing architectural components and historical transformations reduced the need to construct these relationships mentally or consult multiple information sources.

Finally, spatial perception emerged as a supplementary theme. Compared with viewing static images or reading text alone, participants associated the combination of three-dimensional representations, sound, and spatial presentation with a stronger sense of presence in the represented environment. Because the application was used remotely, this finding concerns perceived presence within the digitally represented environment rather than experience of the physical heritage site.

Overall, the qualitative findings were conceptually consistent with the Study 1 constructs of information quality and authenticity, structural congruence, design aesthetics, Human–System Interaction, and human–information interaction. Spatial perception and information visualization further contextualized participants' experiences. These findings help interpret the quantitative variables but do not independently confirm the structural pathways or causal mechanisms.

6. Discussion

Most core relationships yielded complementary findings across the SEM–ANN–NCA analyses, although the methods did not produce identical rankings of predictor importance. As shown in Table 15, when H–M FIT was the outcome, both SEM and ANN analysis indicated that IQA had a stronger relative association or predictive importance than DA, whereas NCA showed that DA had a larger necessity effect size. When PU was the outcome, SEM and NCA indicated that LI had a stronger relative association or necessity effect than H–M FIT, whereas ANN analysis identified H–M FIT as the more important predictor. These differences reflect the distinct analytical purposes of the three methods. PLS-SEM estimates structural associations, ANN analysis assesses relative predictive importance, and NCA examines necessity patterns at specified outcome levels. The results should therefore be interpreted as complementary evidence rather than expected to produce identical rankings.

Table 15. Comparison of PLS-SEM, ANN, and NCA results for ANN predictors.

	PLS-SEM	ANN	NCA	Ranking	Ranking	Ranking
	Path Coefficient	Normalized Relative Importance (%)	Effect Size	(PLS-SEM)	(ANN)	(NCA)
DA → H–M FIT	0.158	54.273	0.352	2	2	1
IQA → H–M FIT	0.531	100.000	0.276	1	1	2
H–M FIT → PU	0.420	100.000	0.214	2	1	2
LI → PU	0.498	83.756	0.241	1	2	1

This study also developed an integrated mechanism model linking design and information cues, structural congruence (H–M FIT), learning interest, and continuance usage intention. The model summarizes how MAR-related cues are associated with perceived Heritage–MAR Fit, learning interest, and continuance usage intention in architectural heritage learning. It summarizes the roles of DA, IQA, and interaction cues in shaping H–M FIT; the pathways from H–M FIT to LI and PU; and the support provided for these mechanisms by the multimethod and qualitative evidence (Table 16).

Grounded in the Stimulus–Organism–Response (S–O–R) framework and Cue Consistency Theory (CCT), this study systematically investigated how different system cues relate to learning interest (LI) and continuance usage intention (PU) through judgments of structural congruence (H–M FIT) in MAR-based architectural heritage learning contexts. Whereas previous studies have largely examined whether MAR enhances immersion or engagement, the present study focused on how learners evaluate the congruence between heritage content and its MAR representation and how this evaluation relates to learning motivation and continuance usage intention. By combining PLS-SEM, ANNs, and NCA

with grounded-theory-informed interviews, the study identified several associations within the specified model and differences in predictor importance and necessity patterns. These findings provide a bounded multimethod account of perceived fit in MAR-based heritage learning. From an architectural perspective, the value of MAR arises not only from technological novelty but also from the consistent alignment of digital information with the physical environment, spatial cues, and cultural context.

Table 16. Research findings and insights.

Research Dimension	Key Findings	Theoretical Implications	Managerial Implications
Formation of Heritage–MAR Fit through design and information cues (S → O)	In the original model, DA and IQA were positively associated with H–M FIT. In the H–M FIT1-only sensitivity analysis, IQA remained significant, but DA became nonsignificant. The DA finding is therefore measurement-sensitive.	H–M FIT is treated as a context-specific adaptation whose measurement and empirical distinctiveness require further validation. IQA was the more stable antecedent across the examined specifications.	Prioritize credible heritage information. Treat aesthetic recommendations as provisional and test them across alternative fit measures and application settings.
Mechanism through which H–M FIT drives learning interest and continuance usage intention	The original model estimated strong associations between H–M FIT, LI, and PU, including an indirect association through LI. Elevated HTMT values indicate substantial empirical overlap among these constructs.	The estimated paths describe associations within the specified model and do not establish fully distinct psychological mechanisms or causal mediation.	Use perceived fit and learning interest as related design indicators while avoiding claims that improving one will necessarily cause sustained use.
Quantitative Analysis (PLS-SEM, ANN, and NCA)	PLS-SEM, ANN analysis, and NCA provide complementary evidence for the core relationships, although the relative importance of the predictors varies across methods.	The three methods examine the model from complementary perspectives: PLS-SEM estimates net effects, ANN analysis captures nonlinear predictive importance, and NCA identifies necessary-condition constraints, thereby providing a multidimensional understanding of the underlying mechanisms.	Integrating PLS-SEM, ANN analysis, and NCA provides a multi-method framework for identifying structural relationships, predictive importance, and necessary conditions, thereby informing intervention priorities and design decisions.
Qualitative Research (Grounded Theory-Informed Analysis)	The qualitative findings show that information authenticity, structural consistency, aesthetic presentation, and interaction clarity repeatedly emerged in participants' descriptions of H–M FIT formation and subsequent evaluations of usage value.	From the participants' perspective, the qualitative findings clarify the experiential meaning of H–M FIT and provide contextual explanations for the quantitative relationships identified in the cultural heritage setting.	MAR design should emphasize credible cultural content, coherent presentation, clear interaction, and trust-related cues to strengthen experiential continuity and support long-term use and sustained engagement.

Source: Authors' own compilation.

The structural equation modeling results showed that information quality/perceived authenticity (IQA) was significantly and positively associated with Heritage–MAR Fit, whereas the direct relationships of human–information interaction (HII) and human–system interaction (HSI) with Heritage–MAR Fit were not statistically significant in the specified model. The HII and HSI items assessed the perceived clarity of information interaction, ease of obtaining information, navigational clarity, system responsiveness, and ease of system operation; they did not measure interaction intensity or operational complexity. Accordingly, the nonsignificant paths should not be interpreted as indicating that interaction is unimportant or that users prefer more complex forms of interaction. Previous research has identified system usability and interaction-related characteristics as important factors in MAR learning motivation [78]. Heritage-AR research has also shown that technical, individual, and situational factors can influence post-experience intentions through satisfaction [79], while serious-game research has identified authenticity and design aesthetics as relevant to cultural engagement [16]. The present findings do not contradict these broader conclusions. Rather, within the present model and sample, perceived interaction clarity and ease of system use did not show statistically significant direct associations with Heritage–MAR Fit after the other predictors were considered. Information quality/perceived authenticity showed the more stable association with Heritage–MAR Fit, whereas the design-aesthetics result was sensitive to the operationalization of Heritage–MAR Fit. This interpretation is limited to the dimensions measured in this study and does not exclude possible indirect, conditional, or context-dependent roles of interaction quality.

Building on the structural path analysis, the combined ANN and NCA analyses revealed nonlinear predictive patterns and boundary conditions that are difficult to capture using SEM alone. The ANN results showed that both Heritage–MAR Fit and learning interest had high predictive importance for continuance usage intention, with the normalized importance of H–M FIT exceeding that of learning interest. This finding demonstrates that the magnitude of PLS-SEM path coefficients does not necessarily correspond to the nonlinear predictive importance identified through ANNs. The NCA results indicated a necessity pattern involving H–M FIT and continuance usage intention within the observed sample. The estimated ceiling line suggested that higher levels of continuance usage intention were observed only above certain levels of H–M FIT. This pattern complements the positive association identified by PLS-SEM, although it does not establish that increasing H–M FIT would necessarily lead to greater continuance usage intention. Accordingly, the design of MAR systems for architectural heritage should not focus exclusively on increasingly complex forms of interaction. Greater priority should be given to aligning content presentation with the represented architectural context and supporting coherent and credible user experiences. These priorities may inform the design of MAR experiences for sustained engagement and cultural communication.

The qualitative findings help explain the nonsignificant direct relationships between HII, HSI, and H–M FIT. Although these paths were not statistically significant, interviewees emphasized the importance of clear navigation, smooth interaction, and appropriate system feedback. These findings suggest that interaction quality remains relevant to users' experiences. One possible explanation is that its contribution depends on the quality of the information and visual presentation: when information is unreliable or the interface is poorly designed, improvements in interaction alone may have limited value. Conversely, interaction quality may become more meaningful when these basic expectations are met. This conditional interpretation is consistent with the qualitative accounts but was not directly tested by the structural model. The nonsignificant paths may also partly reflect shared variance among the antecedents, given their relatively high correlations. Future research

could examine whether DA and IQA moderate the relationships between interaction quality and H–M FIT.

6.1. Theoretical Contributions

This study makes three bounded theoretical contributions. First, it examines Heritage–MAR Fit as a context-specific adaptation of perceived fit that combines content–representation congruence with support for heritage-related learning needs. The study does not present the current scale as an independently validated construct. The original model associated DA and IQA with Heritage–MAR Fit, but the H–M FIT1-only sensitivity analysis retained the IQA association while the DA association became nonsignificant. The theoretical contribution therefore lies in examining a context-specific fit perspective and identifying its measurement boundaries, rather than in establishing a fully distinct construct or a stable set of antecedents. Second, the study applies the S–O–R framework to associations between MAR-related perceptions, Heritage–MAR Fit, learning interest, and continuance usage intention. Because elevated HTMT values indicate substantial empirical overlap among H–M FIT, LI, and PU, these relationships are not interpreted as evidence of separate psychological mechanisms. Third, the study contributes to MAR-based heritage-learning research by showing how participants connected cultural information, digital representation, and learning support in their evaluations. This interpretation remains bounded to immediate self-reported perceptions and intentions following a single MAR experience. Figure 8 summarizes the key findings of this study.

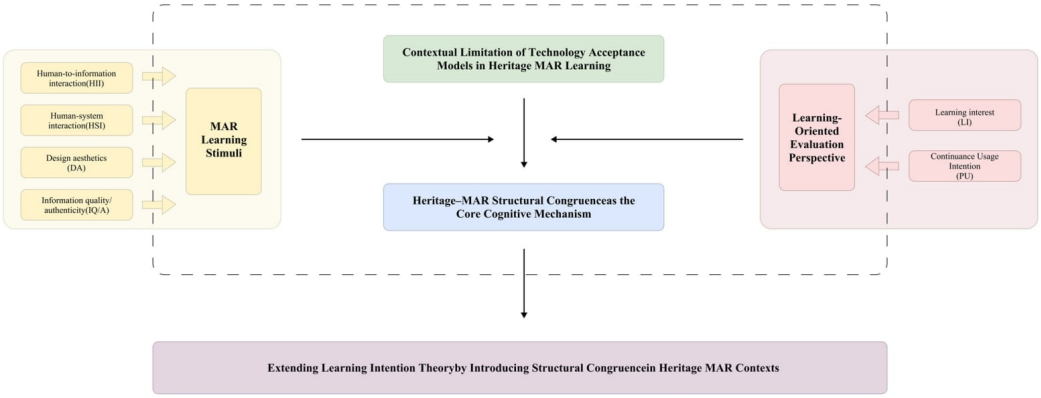

Figure 8. Summary of key findings.

6.2. Practical Contributions

This study offers practical guidance for the design, development, and implementation of mobile augmented reality (MAR) systems for architectural heritage. First, it examines Heritage–MAR Fit as a focal evaluative construct linking heritage content, its digital representation, and users' learning-related perceptions. The findings suggest that learning interest and continuance usage intention are not determined solely by technological novelty but develop partly through users' perceptions of fit. This result is consistent with previous research showing that experiential consistency facilitates cognitive fluency and positive responses [12,13]. MAR design should emphasize credible heritage information, coherent content presentation, and clear interface operation. Visual aesthetics should be considered as part of the overall experience rather than as an independently established design priority. Such design considerations may help create a more coherent MAR experience and encourage users' interest in exploring architectural heritage. Whether these improvements also lead to measurable gains in heritage knowledge or understanding remains to be tested. Second, the findings suggest a possible pathway linking perceived fit, learning interest, and

continuance usage intention within the present model. In the original model, perceived fit was indirectly associated with continuance usage intention through learning interest. Given the empirical overlap among these constructs, this finding is interpreted as an indirect association within the specified model rather than evidence of a distinct mediation mechanism. This finding is consistent with research on interest-driven engagement in digital cultural heritage experiences [10,62]. Institutions should therefore regard MAR as a long-term tool for promoting cultural understanding and cultivating interest rather than merely as a temporary display or promotional technology. MAR applications should extend beyond isolated experiences to support sustained educational and communicative outcomes. Before introducing additional immersive effects or interactive functions, architectural heritage teams should verify the correspondence among digitally overlaid content, architectural elements, spatial locations, historical conditions, and supporting evidence.

6.3. Methodological Contributions

This study integrates PLS-SEM, ANNs, and NCA within a complementary multi-method analytical framework. PLS-SEM was used to examine structural relationships and mediating effects among variables, ensuring the structural interpretability of the theoretical model. ANNs complemented the PLS-SEM results by providing an additional assessment of the relative predictive importance of selected variables, allowing the findings to be examined from both structural and prediction-oriented perspectives. NCA identified patterns consistent with necessary conditions for learning interest and continuance usage intention within the observed sample, complementing the associations estimated using PLS-SEM [19]. The quantitative findings were further examined through qualitative interviews and grounded-theory-informed coding, providing contextual explanations for the statistical results and highlighting aspects of participants' experiences that were not fully captured by the quantitative analyses. Together, these methods provide complementary perspectives on the relationships examined in this study. Their integration offers a structured approach to interpreting users' experiences with MAR in architectural heritage settings, while recognizing the limitations of each method.

6.4. Limitations and Future Research

Several limitations should be considered. The study used non-probability voluntary response sampling, with predominantly female and younger participants, and examined a single MAR application without a documented a priori power analysis. Participants completed a brief, remote surface-based experience, and their completion and exposure duration were not verified through application logs. The qualitative analysis was conducted by a single researcher without an intercoder check, formal audit trail, category-frequency analysis, or verbatim excerpts. In addition, cue consistency was not directly measured or manipulated. Elevated HTMT and full-collinearity VIF values also indicate concerns about discriminant validity and potential common method bias. These limitations restrict the generalizability and interpretation of the structural and indirect associations.

Future research should use more diverse samples, multiple MAR applications, objective learning measures, and longitudinal or experimental designs. Independent scale development and validation are also needed to clarify the boundaries of Heritage–MAR Fit, distinguish content–representation congruence from learning-related support, and examine the stability of the proposed relationships.

7. Conclusions

This study investigated how users evaluate mobile augmented reality experiences in architectural heritage learning and how these evaluations are associated with learning interest

and continuance usage intention. Based on 330 questionnaire responses and 30 follow-up interviews, the study examined a context-specific Heritage–MAR Fit model through a sequential explanatory mixed-methods approach. In the original three-item specification, IQA and DA were positively associated with Heritage–MAR Fit, while the interaction-related constructs were not. The exploratory H–M FIT1-only analysis retained the IQA association but rendered the DA path nonsignificant, demonstrating that the design-aesthetics result is sensitive to measurement. H–M FIT, LI, and PU were strongly associated in the original model, but their elevated HTMT values and the possibility of common method bias mean that these paths should not be interpreted as evidence of fully distinct psychological mechanisms. ANNs and NCA provide complementary exploratory perspectives within the observed sample rather than confirmation of robustness or causality. The interviews contextualized how participants described cultural information, visual presentation, and fit. Overall, the study offers a bounded account of perceived fit in architectural heritage MAR and identifies further measurement validation as necessary before stronger theoretical or design claims are made.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: The anonymized data supporting the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available because they contain information collected from human participants and are subject to privacy and ethical restrictions.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MAR	Mobile Augmented Reality
TTF	Task–Technology Fit
CCT	Cue Consistency Theory
HII	Human–Information Interaction
HSI	Human–System Interaction
DA	Design Aesthetics
IQA	Information Quality/Perceived Authenticity
H–M FIT	Heritage–MAR Fit
LI	Learning Interest
PU	Continuance usage intention
PLS-SEM	Partial Least Squares Structural Equation Modeling
ANN	Artificial Neural Network
NCA	Necessary Condition Analysis

HTMT	Heterotrait–Monotrait Ratio
AVE	Average Variance Extracted

Appendix A

Table A1. Questionnaire scales and references.

	Item	Measurement Item	Source(s)
Human–Information Interaction (HII)	HII1	The information presented by the system is clear and easy to understand.	Lewis [80]
	HII2	I can easily find the cultural or learning content I need.	
	HII3	The organization and presentation of information in the system help me better understand the cultural content.	
	HII4	The information provided by the system is well organized and facilitates the learning process.	
Human–System Interaction (HSI)	HSI1	The system is convenient to use.	Davis, F. D [81]
	HSI2	I find it easy to interact with the system.	Chin, J. P., Diehl, V. A., & Norman, K. L [82]
	HSI3	The interaction with the system is clear and easy to understand.	Lewis, J. R [80]
Design Aesthetics (DA)	DA1	The visual design of the system is attractive.	Cyr, D., Head, M., & Larios, H [83]
	DA2	The interface colors and layout are visually pleasing.	Lavie, T., & Tractinsky, N [48]
	DA3	The interface layout and visual style of the system help me engage more deeply with the architectural heritage content.	Zhou, C., & Li, J [84]
Information Quality/Perceived Authenticity (IQA)	IQA1	I believe that the architectural heritage content presented by the system is authentic and reliable and helps me understand its cultural context.	Kolar & Zabkar [63]
	IQA2	The information provided by the system is accurate and reliable.	DeLone, W. H., & McLean, E. R [85]
	IQA3	The information provided by the system is credible and trustworthy.	Yoo, B., & Donthu, N [86]
Learning Interest (LI)	LI1	The architectural cultural content presented by this MAR system attracts my attention.	Keller, J. M [87]
	LI2	The learning approach provided by this system stimulates my interest in architectural culture.	
	LI3	The way the system presents the content helps me remain focused during the learning process.	

Table A1. *Cont.*

	Item	Measurement Item	Source(s)
Learning Interest (LI)	LI4	When using this system, I would like to continue learning more about architectural culture.	Di Serio, Á., Ibáñez, M.-B., & Delgado-Kloos, C [54]
	LI5	Learning about architectural culture through this system is interesting and engaging.	
Continuance usage intention (PU)	PU1	I intend to continue using this MAR system to learn about architectural culture.	Han, D. I., tom Dieck, M. C., & Jung, T [88]
	PU2	I plan to continue using similar MAR technologies for future learning or research.	
	PU3	If similar MAR learning systems become available in the future, I intend to use them.	Rauschnabel, P. A., Felix, R., & Hinsch, C [89]
	PU4	I am willing to continue using this system because it helps me understand and appreciate architectural culture.	
Heritage–MAR Fit (H–M FIT)	H–M FIT1	The MAR-based presentation is consistent with the architectural heritage content being learned.	Adapted from Goodhue, D. L., & Thompson, R. L [15]
	H–M FIT2	The system's functions and presentation methods match my needs for understanding architectural heritage.	
	H–M FIT3	MAR technology effectively supports my learning needs related to architectural heritage.	

Appendix B

Table A2. Demographic characteristics of valid respondents (n = 330).

Variable	Options	Frequency	Percentage
Gender	Male	62	18.79
	Female	258	78.18
	Prefer not to answer	10	3.03
Age	<18	7	2.12
	18–24	250	75.76
	25-34	56	16.97
	35-44	12	3.64
	≥45	5	1.52
Degree	College Degree and below	13	3.94
	Bachelor's Degree	238	72.12
	Master's Degree	68	20.61
	Doctoral Degree	11	3.33

Table A2. *Cont.*

Variable	Options	Frequency	Percentage
Familiarity	General familiarity	134	40.61
	Relatively familiar	112	33.94
	Slightly familiar	52	15.76
	Very familiar	20	6.06
	Not familiar at all	12	3.64
Heritage Exposure	1–2 times per year	164	49.7
	Once every few months	90	27.27
	Almost never	53	16.06
	Monthly	20	6.06
	Weekly or more	3	0.91
AR/MAR Usage	Never used	138	41.82
	1–2 times use	137	41.52
	Occasionally used	50	15.15
	Frequently used	5	1.52

Appendix C

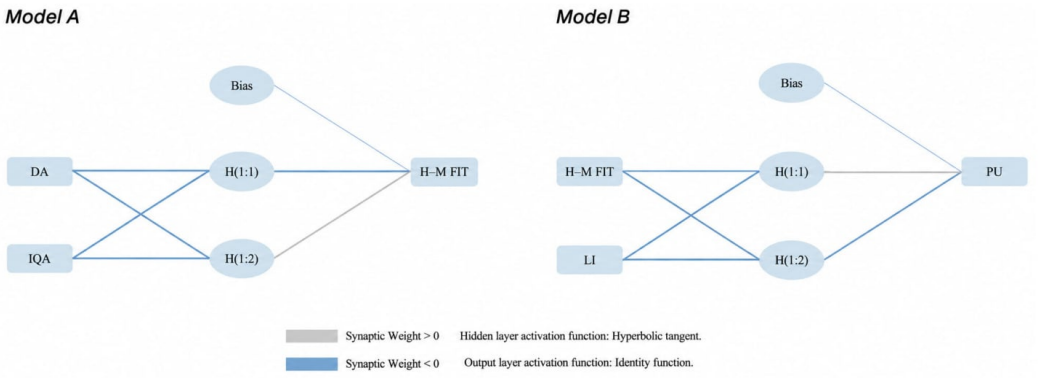

Figure A1. ANN model.

Appendix D

Table A3. RMSE values for models.

ANN	Model A		Model B	
	Input: DA, IQA; Output: H–M FIT		Input: LI, H–M FIT; Output: PU	
	Training (90)	Testing (10)	Training (90)	Testing (10)
ANN1	0.582	0.636	0.454	0.473
ANN2	0.577	0.665	0.451	0.413
ANN3	0.595	0.530	0.429	0.639
ANN4	0.593	0.589	0.439	0.534
ANN5	0.581	0.688	0.446	0.386
ANN6	0.584	0.576	0.449	0.530
ANN7	0.572	0.726	0.472	0.308
ANN8	0.563	0.814	0.442	0.341
ANN9	0.581	0.584	0.430	0.438

Table A3. *Cont.*

ANN	Model A		Model B	
	Input: DA, IQA; Output: H–M FIT		Input: LI, H–M FIT; Output: PU	
	Training (90)	Testing (10)	Training (90)	Testing (10)
ANN10	0.602	0.388	0.436	0.508
Mean	0.583	0.620	0.445	0.457
SD	0.011	0.116	0.013	0.100

Note: RMSE = root mean square error; SD = standard deviation. RMSE was calculated as the square root of twice the SPSS sum-of-squares error divided by the corresponding sample size. All values are reported on the standardized dependent-variable scale. Mean and SD were calculated across ten repeated ANN runs; SD denotes the sample standard deviation.

Appendix E

Table A4. Bottleneck table (in percentage).

Predictors	H–M FIT		PU		LI
	DA	IQA	H–M FIT	LI	H–M FIT
0	NN	NN	NN	NN	NN
10	NN	7.7	NN	NN	NN
20	NN	7.7	NN	5.0	NN
30	33.3	15.4	NN	20.0	NN
40	33.3	15.4	NN	20.0	NN
50	33.3	15.4	NN	20.0	NN
60	44.4	46.2	25.0	20.0	16.7
70	55.6	46.2	25.0	40.0	50.0
80	55.6	46.2	75.0	45.0	50.0
90	55.6	46.2	75.0	45.0	50.0
100	66.7	46.2	75.0	45.5	58.3

Appendix F

ID	Gender	Age	Education	Occupation	Recruitment Source
R1	Female	24	Master's	Architecture Student	Official University Group
R2	Male	23	Master's	Architecture Student	Official University Group
R3	Male	45	Bachelor's	Construction Supervisor	WeChat
R4	Male	42	Bachelor's	Interior Designer	WeChat
R5	Female	24	Master's	Design Student	Official University Group
R6	Male	21	Master's	Fine Arts Student	Official University Group
R7	Female	44	Bachelor's	Interior Designer	Weibo
R8	Female	44	Master's	Interior Design Lecturer	Xiaohongshu
R9	Female	27	Master's	Programmer	Weibo
R10	Female	50	Bachelor's	Teacher	Weibo
R11	Female	23	Master's	Non-design Student	Xiaohongshu
R12	Male	49	Master's	Civil Servant	WeChat
R13	Female	38	Bachelor's	Non-design Professional	Xiaohongshu
R14	Female	24	Bachelor's	Non-design Job Seeker	Xiaohongshu
R15	Female	24	Master's	Design Student	Official University Group
R16	Female	24	Bachelor's	Non-design Job Seeker	Weibo
R17	Female	24	Bachelor's	Non-design Job Seeker	Weibo
R18	Female	24	Master's	Design Student	Official University Group
R19	Male	26	Master's	Design Student	Official University Group

ID	Gender	Age	Education	Occupation	Recruitment Source
R20	Female	25	Master's	Non-design Student	Weibo
R21	Female	23	Bachelor's	Non-design Job Seeker	Weibo
R22	Male	22	Bachelor's	Design Student	Official University Group
R23	Male	25	Bachelor's	Non-design Professional	Xiaohongshu
R24	Female	25	Master's	Design Student	Official University Group
R25	Male	23	Bachelor's	Architecture Job Seeker	Xiaohongshu
R26	Female	25	Bachelor's	Non-design Professional	WeChat
R27	Female	21	Bachelor's	Design Student	Xiaohongshu
R28	Male	24	Bachelor's	Non-design Job Seeker	WeChat
R29	Female	21	Bachelor's	Non-design Student	Weibo
R30	Female	27	Bachelor's	Non-design Professional	Weibo

Appendix G

Table A5. Semi-Structured Interview Guide.

Q1	Thinking back to your experience with the MAR-based architectural heritage learning questionnaire, what aspect left the strongest impression on you, and why?
Q2	How did MAR help you understand architectural culture, and how was this experience different from your previous ways of learning about it?
Q3	How well do you think MAR fits with the presentation of architectural heritage? Which aspects made you feel that they fit well or did not fit well, and why?
Q4	When using MAR to explore architectural culture, what types of presentation, content, or experiences made you want to explore further? What contributed to this interest—for example, visual presentation, interaction, cultural narratives, or other factors?
Q5	How did you feel while using MAR—for example, curious, engaged, surprised, or something else? What aspects of the experience contributed to these feelings?
Q6	What did this way of learning about architecture mean to you, and what impact, if any, did it have on you? Did it change the way you perceive architectural culture?
Q7	If you encountered similar MAR applications for architectural heritage in the future, would you continue to use them? Why or why not?

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