

Acceptance of AI-enabled Augmented Reality Exhibition Guide Systems in Chinese Museums

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ABSTRACT

As museums globally accelerate digital transformation, AI-enabled Augmented Reality (AR) guide systems represent a critical innovation for enhancing visitor involvement; however, understanding the psychological drivers of their acceptance remains understudied despite significant implementation costs and visitor experience implications. This study thus examines: How do core attributes of AI-enabled Augmented Reality Exhibition Guide Systems (AAEGS)—informativeness, personalisation, and interactivity—influence visitor acceptance through cognitive and affective involvement pathways? Based on a survey of 417 visitors in a Chinese museum, this study examines acceptance of AI-enabled Augmented Reality Exhibition Guide Systems (AAEGS). Applying the Elaboration Likelihood Model (ELM), it proposes that AAEGS acceptance is influenced by the system's informativeness, personalisation, and interactivity. Using a quantitative methodology with a 7-point Likert scale questionnaire, the research empirically tests the model. Findings corroborate these three attributes significantly impact visitor acceptance. Furthermore, the study demonstrates that cognitive involvement and affective involvement act as significant mediators in this process; the system attributes influence visitors' cognitive and affective responses, thereby leading to their decision to accept AAEGS.

Keywords: AI-enabled AR guide systems, museum visit experience, visitor acceptance, elaboration likelihood model, informativeness, personalization, interactivity, cognitive involvement, affective involvement.

INTRODUCTION

Museums are treasure troves of knowledge and culture where visitors can access to fulfill their various needs, social, learning, entertainment, just to name a few (Izzo *et al.*, 2023). Contemporary museum exhibition curators increasingly use digital technologies to engage visitors (Chen *et al.*, 2021; Cheng *et al.*, 2023). However, creating a museum environment to continuously engages and interests visitors remains a challenge (Choi & Kim, 2017).

One of the promising technologies to engage visitors is Augmented Reality (AR) that helps enhance visitors' experience by applying digital content over real museum environments (Duguleană *et al.*, 2020) to integrate the digital world with the real world (Chung *et al.*, 2017). In combination with Artificial Intelligence (AI), such AI-enabled Augmented Reality (AR) technology can afford an even more enhanced visitor experience (Sadamali Jayawardena *et al.*, 2023).

AI-enabled AR for museum exhibitions can create a rich and personalised visitor experience. Through applications, visitors can engage with exhibits, for example by triggering animations, or playing audio or video. The AI-enabled Augmented Reality Exhibition Guide Systems (AAEGS) is a tour guide system designed to incorporate AI into an AR application. The AAEGS allows visitors to interact with a virtual environment that can be changed according to individual visitors' interests and behaviour (Jeong & Shin, 2019). It uses data extractions, natural language processing and knowledge fusion to provide interactive and personalised museum information to visitors (Jiang *et al.*, 2022; Kamariotou *et al.*, 2021) (Komarac & Ozretić Došen, 2021).

Chinese museums have been a pioneer in the adoption of emerging technology (Jeong & Shin, 2019). The adoption of such technologies, including AI and AR, has significantly changed the visitor's experience and expectations for what a museum can provide (Lin *et al.*, 2022; Park & Yoo, 2020; Sang *et al.*, 2023). Visitors are no longer satisfied with traditional exhibitions that lack interaction and personalised content (Guo *et al.*, 2021; Yang & Zhang, 2022). This study aims to address this gap by examining what attributes of the AAEGS and how such attributes can promote visitors' involvement with and acceptance of museum exhibit and the technology per se.

In this study, we focus on visitors' cognitive and affective involvement as dual pathways to influence their acceptance of the exhibit and technology. We adopt the Elaboration Likelihood Model (ELM) to propose that different attributes of the system can influence visitors' acceptance of the technology through distinct routes (Shahab *et al.*, 2021; Sung *et al.*, 2021). The three attributes of AAEGS that we examine are informativeness, personalisation, and interactivity. These three attributes have been identified as the core attributes of AAEGS. Informativeness provides rich contextual layers—like 3D artifact reconstructions or

animated historical scenes—that transform surface-level viewing into deep discovery; personalisation adapts content in real-time, offering tailored narratives (e.g., detailed artist insights for enthusiasts or interactive treasure hunts for families), ensuring every tour feels uniquely relevant; interactivity empowers hands-on engagement—visitors rotate virtual objects, solve AR-powered historical puzzles, turning visitors into active participants. These features shift museums from one-way information channels to personalized, multisensory dialogues with history, significantly boosting engagement and lasting memorability.

To test our research model, we collected data from a pool of museum visitors who has recently visited a museum using an AAEGS in China. 417 valid responses were collected. Our findings indicate that informativeness, personalisation, and interactivity significantly influenced AAEGS acceptance, mediated by both cognitive involvement (central route) and affective involvement (peripheral route).

This paper is structured as follow: Section 2 covers Literature Review and hypothesis development; Section 3 details methodology; Section 4 presents findings; Section 5 discusses; Section 6 concludes with limitations and future directions.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

AAEGS Acceptance

Visitors' or users' acceptance of a new technology determines whether such a technology will be adopted (Chen *et al.*, 2025; El Archi & Benbba, 2023; Kelly *et al.*, 2023). In the tourism literature, many studies have found that users' acceptance of new technology improve their traveling experience and interaction with such technology (Komarac & Ozretić Došen, 2021; Lee & Lim, 2010; Liu & Shrum, 2009; Siu *et al.*, 2022). Indeed, increased literature demonstrates that visitor needs have driven the adoption of new technologies in the industry, emphasizing the importance of technology in meeting users' expectations and needs (Engelbrecht *et al.*, 2019; Giotis & Papadionysiou, 2022; Han *et al.*, 2018; Vitali *et al.*, 2022).

AAEGS acceptance refers to visitors' willingness to adopt and utilize the AI-enabled Augmented Reality Exhibition Guide System within the museum environment and other tourist scenarios. It encompasses their positive behavioral intention to use the system, perception of its usefulness in enhancing learning and engagement, and favorable attitude towards its integration into their visit (Haugtvedt & Petty, 1992; Lin *et al.*, 2022; Zhuang *et al.*, 2020). AAEGS transforms traditional museum exhibitions through three core features: Informativeness delivers multi-dimensional content (e.g., 3D reconstructions, contextual animations) that replaces static labels with immersive, depth-adjustable knowledge, empowering visitors to explore exhibits at their preferred intellectual level. Personalisation leverages AI-driven real-time feedback—analyzing visitor behavior (dwell time, selected interests), demographics, and interaction patterns—to dynamically tailor content (e.g., offering ceramic-firing techniques to pottery enthusiasts while triggering AR treasure hunts for families). Interactivity enables tactile participation, allowing visitors to rotate holographic artifacts, solve historical puzzles via gesture/voice, converting passive observation into experiential storytelling. This acceptance signifies endorsement of AAEGS as a valuable tool, driven by its attributes—informativeness, personalisation, and interactivity—which operate through cognitive and affective involvement pathways to shape visitors' decision to adopt the technology for achieving their experiential goals.

Elaboration Likelihood Model

The Elaborate Likelihood Model (ELM) suggests two routes of persuasion to form and change an individual's attitudes (Petty *et al.*, 1986). The central route necessitates deep, effortful elaboration, where individuals rigorously evaluate the merits and logical arguments of a message or stimulus to form enduring, well-reasoned attitudes (Mardhatilah *et al.*, 2023; Petty *et al.*, 1986). The peripheral route relies on heuristic processing of superficial cues within the environmental context, enabling quicker, less cognitively demanding attitude formation that is often more affective driven but potentially less stable (Mardhatilah *et al.*, 2023).

For AAEGS acceptance in museums, these dual pathways can be distinctly activated by the system's core attributes, namely informativeness, personalisation, and interactivity. Informativeness serves as the primary catalyst for the central route (Ukpabi & Karjaluoto, 2017). By delivering high-quality, relevant, and substantive content about exhibits, AAEGS encourage visitors to engage in cognitive elaboration (Choi & Kim, 2017). Users systematically evaluate the information's accuracy, depth, and utility for understanding and learning, leading to acceptance decisions grounded in reasoned judgments about the system's perceived usefulness and value for achieving their cognitive goals (e.g., learning the history of an exhibited artefact) (Siu *et al.*, 2022). Personalisation is argued to influence acceptance through the central route by engaging users' cognitive evaluation of content relevance and tailoring (Lin *et al.*, 2022). When visitors consciously evaluate the system's tailoring precision—assessing whether AI-generated recommendations align with their personal interests, knowledge goals, or demographic profile—they engage in effortful cognitive elaboration (Reychav & Wu, 2015). Interactivity operates primarily via the peripheral route, leveraging low-effort heuristic cues, such as intuitive interface design, visual appeal, and immediate enjoyment (e.g., delight in manipulating AR objects)—to trigger positive affective responses (Hsiao *et al.*, 2022). This surface-level engagement reduces cognitive load, but fosters visitors' affective involvement (emotional arousal/curiosity) with the exhibit and technology and ultimately visitors' AAEGS acceptance (Sung *et al.*, 2021). Figure 1 represents our research model.

Involvement

Zaichkowsky (1986) pioneered its conceptualization in consumer behavior, framing involvement as "a person's perceived relevance of an object based on inherent needs, values, and interests." This intrinsic motivation determines cognitive allocation and emotional investment (Zaichkowsky, 1986). This study, involvement is delineated as the extent to which users perceive their interaction with content during an information-seeking endeavor as necessary and fitting. Involvement is defined as people's active and positive subjective engagement in completing something based on a cognitive need or a goal motivation. It is categorized into cognitive and affective involvement. Cognitive involvement refers to rational thinking and information processing, where visitors evaluate AAEGS' relevance and usefulness through logical assessment (Reychav & Wu, 2015; Soni, 2017; Steinhardt *et al.*, 2022; Wu *et al.*, 2024). Affective involvement, which is rooted in hedonism, derives from value expression or emotional motivation (Tung *et al.*, 2017).

Affective involvement is defined as the emotional experience of visitors during a tour, such as the experience of positive and negative emotions, and it refers to an important part of visitor involvement besides behavioral and cognitive involvement, which directly influences the user's behavioral involvement and plays a key role in AAEGS. (Faisal *et al.*, 2020; Putrevu & Lord, 1994). We argue that cognitive involvement enhances rational evaluation of AAEGS functionality because visitors adopt AAEGS not because of novelty, but because cognitive labor confirms its functional superiority over traditional guides (e.g., audio tours or placards). Hence, we hypothesize:

H1: Cognitive Involvement positively affects AAEGS acceptance.

Likewise, affective involvement boosts acceptance through hedonistic experiences (Akram & Kortam, 2020; Su *et al.*, 2019). For example, when an AAEGS surprises visitors by overlaying a playful AR dragon that "hatches" from a Ming Dynasty vase when viewed through their device, the spontaneous delight (affective involvement) transforms functional interaction into emotional storytelling. The study hypothesizes: Hence, we hypothesize:

H2: Affective Involvement positively affects AAEGS acceptance.

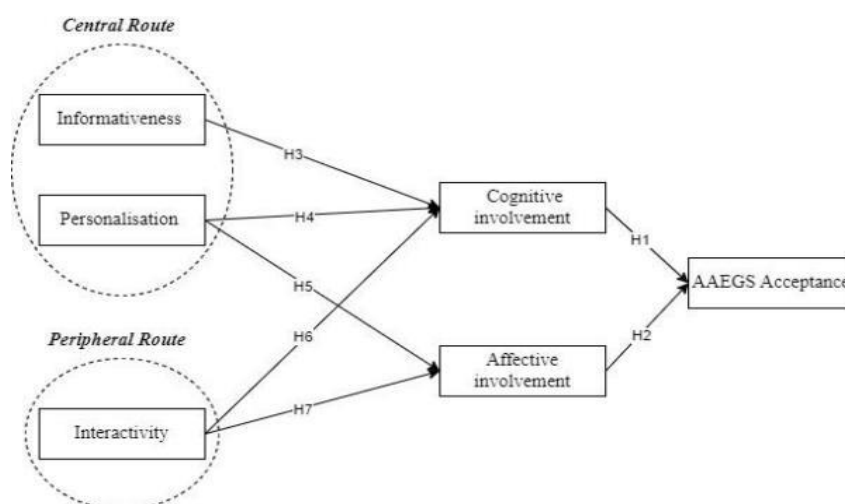


Figure 1: Research Model

Informativeness, Personalisation, and Interactivity

Informativeness refers to the ability of the AAEGS to provide a range of insightful content, varied and experiential interactions, broad knowledge, and comprehensive information about the museum exhibits (Kim & Hall, 2020; Sustacha *et al.*, 2023; Ukpabi & Karjaluo, 2017). AAEGS' informational output not only engages visitors' attention but also uses high-quality, intellectually stimulating information to keep them involved.

Informativeness meets visitors' needs for information quantity by giving details of the exhibits, their historical context and explanations, but also meets their needs to use their own intellect to analyse and judge the quality of this information as good or bad (Mo *et al.*, 2023). When visitors view AAEGS provided information as useful, precise, and suited to their interests, their cognitive involvement will increase significantly, which is positively affecting their acceptance and continued involvement (Craig & Choi, 2024). However, this information may not cause the visitors to become involved affective. The dissociation of cognitive and affective processing suggests that while AAEGS can information-saturate users, yet by it provides intellectual stimuli that are often different from affective involvement (Faisal *et al.*, 2020; Zaichkowsky, 1986). Hence, we hypothesize:

H3: Informativeness has a positive effect on visitors' cognitive involvement.

Personalisation is based on the user's settings. The system collects and organizes information to provide a user-tailored experience that keeps the customer engaged at all times to meet the customer's needs (Zanker *et al.*, 2019). The personalised attribute of the system allows the content provided by the system to be able to resonate with the visitor and lead the visitor to a more cognitive involvement (Ivanov & Velkova, 2025; Zanker *et al.*, 2019). Personalized push functions, which are based on deep analysis of user preferences are possible (Gao *et al.*, 2023; Jeong & Shin, 2019). Content that is tailored to an individual's preferences and understanding level can increase visitors' cognitive involvement (Ivanov & Velkova, 2025). Further, personalized systems have been found to increase visitors' satisfaction and acceptance, and also to encourage them to process content at a deeper cognitive level (Tung *et al.*, 2017). Hence, we hypothesize:

H4: Personalisation has a positive effect on cognitive involvement.

The theory of emotion suggests that personalisation can elicit significant emotional responses from visitors (Zanker *et al.*, 2019). Personalisation in AAEGS is a key factor in a visitor's decision to make an emotional investment in a museum (Jeon *et al.*, 2018). In summary, the literature confirms that personalisation works in developing emotional connections. Hence, we hypothesize:

H5: Personalisation has a positive effect on affective involvement.

Interactivity increases users' cognitive involvement by promoting an active learning experience for them (Ponsignon & Derbaix, 2020; Sternberg *et al.*, 2021). This interaction allows users to make decisions about the tour route during the visit, they need to solve and answer questions about history and heritage asked by the system and they need to reflect on the information received during the visit, which is a source of cognitive involvement for tourists (Cheng *et al.*, 2023; Duguleană *et al.*, 2020). Hence, we hypothesize:

H6: Interactivity has a positive effect on cognitive involvement.

The interactivity in AAEGS is a key element of peripheral cues from an ELM point of view, which makes the whole of the exhibition more playful and experiential, and serves as a channel for deeper affective involvement of the visitors (Craig & Choi, 2024). More importantly, it will emotionally connect with the visitor, developing a personal feeling of connection to the system and increasing customer satisfaction (Lee & Lim, 2010). Hence, we hypothesize:

H7: Interactivity has a positive effect on affective involvement.

METHODOLOGY

Research Paradigm and Method

This study adopts positivism as the study's worldview since it postulates that there are principles and laws that govern acceptance of technology and these laws are discoverable through systematic, quantitative research (Lin *et al.*, 2022; Park & Yoo, 2020). Following the positivism paradigm, which focuses on the physical and truth-dependent aspects of the art, researchers are able to systematize and conduct an empirical research on how these elements foster the acceptance of AAEGS in museums (Lu & Taghipour, 2025; Mustofa, 2023). Objectivism also facilitates this analysis because the advocated realities and opportunities of the AAEGS acceptance extend beyond individual perceptions and are governed by principles that are objectively rational and can be thoroughly investigated (Lu & Taghipour, 2025).

It is crucial to use a questionnaire as it contributes greatly to the research methodologies that guarantee standardized format of data collection thus ensuring that the information collected from the participants is well standardized for comparison (Sharma, 2022). For the data collection tool of this study, a self-administered close-ended questionnaire was employed which incorporated a 7-point Likert scale, a form of quantitative reasoning methodology that quantifies qualitative opinion into proportionate numbers (South *et al.*, 2022).

Variables and Measurement

As indicated in Table 1. AAEGS Acceptance (EA) was assessed through three reflective items designed to capture the depth of users' involvement and commitment to utilizing AI-enabled Augmented Reality Exhibition Guide Systems in museum settings. This scale was adopted from Lee & Lim, (2010) with certain modifications to the context of technology in a museum. Cognitive involvement (CI) as used in this study, thus captures the extent of which visitors interact and absorb when visiting the AAEGS Museum. To measure this concept, seven reflective items were adopted from Soni, (2017), Su *et al.*, (2019), Reychar & Wu, (2015) and Faisal *et al.*, (2020). Affective involvement (AI), this study quantifies affective involvement using four specific measures that reflect the emotional involvement of visitors with the AAEGS during their museum visits. The four measures were taken from Faisal *et al.*, (2020). The amount of information is defined by four indicators. All four measurements were taken from Kim & Hall, (2020). Personalisation within AAEGS greatly enhances the experience of museum visitors since it sets up a unique encounter for a given user (Jeong & Shin, 2019). The three measurements mentioned above are from Jeong & Shin (2019). Interactivity is determined as a key determinant in this research, and the scales for measuring it are well and systematically derived from the work of Sternberg *et al.*, (2021).

To minimize the effects of these confounding factors, it is methodologically appropriate to include individual-level control variables, including age, gender, education, income status, and annual frequency of museum visits, as performed by Liu & Shrum, (2002) . These demographic characteristics serve as control variables to account for extraneous variation that could influence the outcome of interest—in this case, individual visitors' acceptance of AAEGS (Liu & Shrum, 2002). Therefore, it is necessary to add these variables as control variables to the analysis to see the impact of demographic factors, while testing the hypothesis that the system attributes impacting on the usage of AAEGS is through the level of information, personalisation and interaction factors.

Table 1: Questionnaire scales and sources

Variable	Measurement Items	Supporting Studies
Informativeness (IF)	IF1. I appreciate various aspects of the museum exhibits through the AAEGS. IF2. I have a variety of experiences while exploring the museum exhibits with AAEGS. IF3. I get varied knowledge about the museum exhibits through using AAEGS. IF4. I collect diverse information about the museum exhibits from using AAEGS.	Kim & Hall, (2020)
Personalisation (PER)	PER1: AAEGS allowed me to receive tailored information. PER2: I could interact with AAEGS to get personalized information. PER3: The personalized information provided by AAEGS met my need.	(Jeong & Shin, 2019)
Interactivity (INT)	INT1: While exploring museum exhibits, I can access a variety of other visitors' questions and answers through the AAEGS platform. INT2: AAEGS are highly responsive during my museum visits. INT3: AAEGS is interactive when I am exploring museum exhibits INT4: It is easy to share information and content on AAEGS) during museum visits.	Sternberg et al., (2021)
Cognitive involvement (CI)	CI1: The information provided by AAEGS can draw my attention during museum visits. CI2: I process the content delivered by AAEGS with considerable attention while exploring exhibits. CI3: I am able to remember the information from AAEGS for a long time after my museum visit. CI4: My thoughts on the information provided by AAEGS can last for a long time following my visit." CI5: AAEGS is needed for my engagement with the exhibits. CI6: AAEGS is valuable to my experience of the museum. CI7: AAEGS offers features that are relevant to the exhibitions I am interested in.	(Su et al., 2019) (Soni, 2017) (Reychav & Wu, 2015) (Faisal et al., 2020)
Affective involvement (AI)	AI1: AAEGS is fascinating and captures my interest in the exhibits. AI2: AAEGS is interesting, making me want to learn more about the exhibits. AI3: AAEGS is appealing, enhancing the museum experience. AI4: AAEGS is involving, drawing me into a deeper engagement with the exhibit narratives.	
AAEGS Acceptance (EA)	EA1: I have the intention to use again the AAEGS. EA2: I have the intention to use the AAEGS as frequently as possible. EA3: I will persistently use the AAEGS in the future.	Lee & Lim, (2010)

Sample and Data Collection

To capture the diverse usage patterns of users of the AI-enabled AR Exhibition Guides systems (AAEGS) in Chinese museums, the study used a data collection method by employed random sampling to engage about 424 participants. As part of quantitative research, random sampling offers reliability in the results as each individual from the target population has equal risk of being chosen (Sousa *et al.*, 2007). In the context of current study, random sampling serves to obtain accurate and representative data for future use in fine-tuning and expanding the application of AAEGS methods in museums as well as the corresponding overall philosophy of research (Mehrad & Zangeneh, 2019). The utilization of “Questionnaire Star” , one of the leading online survey tools available in China, facilitates the smooth distribution and collection of questionnaires without complications. The survey began with questions about age, gender, education level, income level, and number of visits to

museums per year to build a basic background knowledge of the participant in order to understand their responses (Östlund *et al.*, 2011; Walker, 2005). The anonymity of the participants was very important because their responses could only be used for research and not any other purpose that may harm them in any way. Hence, the questioner was designed so that participants did not have to identify themselves to anyone. The information collected from the respondents is stored on private computers that only the study members have access to. In this way, we can also ensure that the security or data remains high and advances in technology are provided. These data will be deleted forever by me 6 months after the study is completed.

Data Analysis

The validity of the model for analysis of the data has been tested in Smart PLS 4, which is a Partial Least Squares Structural Equation Modeling software (Cheung *et al.*, 2024). The analytical journey of Smart PLS is divided into two distinct phases. Namely, the measurement model phase and the structural model phase (Memon *et al.*, 2021). During the measurement model phase, reliability coefficients such as the cronbach alpha coefficient are obtained to test reliability (Malkewitz *et al.*, 2023). Values of Composite Reliability (CR) provide an insight of internal consistency of the model, while factor load-ings and the Average Variance Extracted (AVE) make it possible to assess convergence validity (Cheung *et al.*, 2024). When transiting to the structural modeling stage, AMOS analysis was used to extract the standardized regression coefficients, the coefficients of determination (R²), as well as the overall measures of model fitness that provided a comprehensive view of the explanatory, influencing, and predictive power of the described structural model (Purwanto & Sudargini, 2021). This was because path analysis can also elucidates the connections and the moderation roles of different variables in the model.

To further support the results of the PLS-SEM analysis, the Statistical Package for the Social Sciences (SPSS) was also used for other statistical tests. This included descriptive statistics to describe data features and inferential statistics to make conclusions. The combination of Smart PLS 4 and SPSS provided an interactive approach to analyze the complexity of the relationships within AAEGS and their acceptance by users (Purwanto & Sudargini, 2021). Moreover, the study was cross-sectional, meaning that it does not allow for the establishment of cause-and-effect relationships or tracking development (Herber *et al.*, 2020).

ANALYSIS AND FINDINGS

Demographic Characteristics of the Sample

The sample consisted of 417 respondents, with a majority falling within the 26-30 age group, which accounted for approximately 40.29% of the total, suggesting a strong representation of young adults who are likely familiar with digital technologies. The percentage of the 31-40 age bracket is next with 34.5% of the population, which is in the mid-career section, may have moderate to high disposable income and education level. Concerning gender distribution in the sample, females were slightly more represented than males with 56%. Males constituted 43.65% of the respondents while females constituted only 35% of the respondents which gives a balanced gender distribution that would be useful in analyzing the technology acceptance from both perspectives. Educational levels among the participants are predominantly high, with 78.66% having an undergraduate degree, followed by 10.31% possessing postgraduate qualifications. The largest share of the respondents (53%) indicated that they earn between 5000 and 10000 RMB per month, which indicates that the respondents fall into middle to upper-middle income category, whereas 30%. In terms of how often respondents attend museums, the highest proportion (52.28%) said that they go to museums three to four times a year, which indicates a good level of cultural involvement. Those who visit museums more often, five and more times per year, represent only 11% of all respondents. 75% of the sample, which means although there is always a strong desire to visit museums, hardly anyone does this very often. This demographic profile is helpful in knowing the context in which the respondents navigate while engaging with and perceiving the value of AAEGS; factors such as technology adoption and the user experience (Ivanov & Velkova, 2025).

Cronbach's α Reliability Analysis

The data collected through the questionnaires will be analyzed using Cronbach's α technique to determine the reliability of the measurements. Cronbach's α is a measure of internal consistency that measures the reliability of a psychometric tool by assessing the degree of correlation between the items in the test (Vaske *et al.*, 2017). The alpha coefficient is a standardized measure and varies from 0 to 1; the closer to 1 the higher the reliability (Bujang *et al.*, 2018). Reliability analysis is used to assess the reliable accuracy of the responses that are given out in the quantitative data (Malkewitz *et al.*, 2023).

In this study, Cronbach's α for informativeness is 0.91, Cronbach's α for personalisation is 0.909, Cronbach's α for interactivity 0.909, Cronbach's α for cognitive involvement is 0.909, Cronbach's α for affective involvement is 0.907 and Cronbach's α for acceptance is 0.908, which is higher than 0.9, thereby showing that the reliability of the research data is of good quality. the research data reliability coefficient value is higher than 0.9, which comprehensively indicates that the data reliability is of high quality and can be used for further analysis (Bujang *et al.*, 2018). The Composite Reliability (CR) values (see Table 2) are as follows and all of them are above the acceptable limit of 0.7. Thus, it also proves the internal consistency reliability of the constructs which in turn supports the reliability coefficient of the study (Purwanto & Sudargini, 2021). CR for Informativeness (0.821), Personalisation (0.781), Interactivity (0.763), Cognitive Involvement (0.811), Affective Involvement (0.819), and AAEGS Acceptance (0.841) all indicate that the items under each construct are, in fact, reliable measures of the aforesaid constructs (Raubenheimer, 2004).

Results of Validity Analysis

The validity study is used to analyze whether the research items are reasonable and meaningful, the validity analysis uses factor analysis as a data analysis method to conduct the study, through the Kaiser-Meyer-Olkin (KMO), commonality, variance explained rate, factor loading coefficient value and other indicators to comprehensively analyze in order to verify the validity level of the data (Smith, 2005). In this study all the research items corresponding to the commonality value is higher than 0.5, which indicates that the information of the research items can be extracted effectively. The KMO value is 0.932 which is greater than 0.6 and the data can be extracted information effectively. The variance explained values of the six factors are 14.079%, 9.044%, 8.858%, 7.698%, 7.505%, 7.336%, and the cumulative variance explained is 64.52% > 50%. It means that the amount of information of the research item can be extracted effectively.

The Average Variance Extracted (AVE) values for each construct exceed the minimum threshold of 0.50, suggesting a satisfactory level of convergent validity. Convergent validity is established when a construct captures a high proportion of the variance in its items. For instance, AVEs for Informativeness (0.605), Personalisation (0.559), Interactivity (0.558), Cognitive Involvement (0.619), Affective Involvement (0.603), and AAEGS Acceptance (0.637) indicate that the majority of the variance in the observed variables is due to the hypothesized latent constructs, affirming the adequacy of the construct measurements (Smith, 2005). The results showed that the measures of informativeness, personalisation, interactivity, cognitive involvement, affective involvement, and AAEGS acceptance confirm both convergent and discriminant validity.

Table 2: Inter-Construct Correlations and AVE values

	Composite Reliability	Average Variance	IF	PER	INT	CI	AI	EA
Informativeness (IF)	0.821	0.605	0.778					
Personalisation(PER)	0.781	0.559	0.154	0.748				
Interactivity(INT)	0.763	0.558	0.191	0.507	0.747			
Cognitive Involvement(CI)	0.811	0.619	0.217	0.574	0.592	0.787		
Affective Involvement (AI)	0.819	0.603	0.727	0.419	0.017	0.304	0.777	
AAEGS Acceptance (EA)	0.841	0.637	0.732	0.231	0.105	0.321	0.751	0.798

Structural Equation Modeling Analysis

The measurement model and structural model were tested by using Partial Least Squares-Structural Equation Modeling (PLS-SEM) analysis with SmartPLS 4, as the results evident in Figure 2. The relationship between information volume and cognitive involvement (H3: IF → CI) was established with highly significant positive effects. The standardized path coefficient for this relationship is 0.276, which signifies a strong correlation, and which is further supported by the low p-value of < 0.01. The relationship between personalisation and cognitive involvement (H4: PER → CI) is defined by a clear and unambiguous division of the standardization coefficient 0.264, indicating a strong positive relationship that is statistically significant at p < 0.01 level. The influence of personalisation on affective involvement (H5: PER → AI) is evident in the standardized coefficient of 0.338, which highlights a significant and highly essential effect (p < 0.01). The path from interaction to cognitive involvement (H6: INT → CI) is positively influenced, as can be seen from the standardized coefficient of 0.379 and a highly significant p-value (p < 0.01). This effect underlines the importance of interactivity in increasing levels of cognitive presence in AAEGS. The relationship between interactivity and affective involvement (H7: INT → AI), as suggested by a standardized coefficient of 0.429 (p < 0.01). Interactive elements in AAEGS positively influence users' emotional involvement. The path from cognitive involvement to AAEGS acceptance (H1: The path from CI to EA) was significant, as indicated by a standardized coefficient of 0.378 and a highly significant p-value (p < 0.01), show that level of cognitive involvement has substantial effect on the level of user acceptance. The relationship between affective involvement and AAEGS acceptance (H2: The fact that AI → EA) is equal to 0.350 is supported by a standardized coefficient. 0.350 high level of statistical significance (p < 0.01). Thus, the correlation proves that the emotional response is critical in the acceptance of technology, which supports the peripheral route of the ELM where affective elements have a great impact on the decision-making.

In the context of structural modeling, R^2 value is the measure that is used to determine the goodness of a structural equation model, the value which may range between 0 and 1. The R^2 values obtained in the study are as follows 0.579 for the cognitive involvement, 0.463 for the affective involvement, 0.396 for AAEGS acceptance—offer clear and strong support for the model's good fit and significant predictive utility. The results support the hypothesized relationships stated in ELM, that the features of AAEGS are indeed affecting the level of interaction of visitors.

In the statistical analysis, particularly in the SEM, the effectiveness of the model is tested by using various fit indices that are particularly designed to assess various aspects of the model (Fan *et al.*, 2016; Mulaik *et al.*, 1989; Singh, 2009). See Table 3 the chi-square (X^2) value, standing at 544.801 with 265 degrees of freedom, yields a X^2/df ratio of 2.056. This ratio is

comfortably below the recommended threshold of 3, indicating a good fit of the model to the data (Mulaik *et al.*, 1989). This metric is important as it gives a simple measure of model discrepancy for each degree of freedom where lower is generally better. Adding to the reliability of the model is the Goodness of Fit Index (GFI) and the Comparative Fit Index (CFI), which are both more than 0.9 threshold (cite), recording values of 0.905 and 0.909 respectively. These indices are relative measures of how well the hypothesized model fits the data compared to a null model and are interpreted such that values closer to 1 represent a small difference between the hypothesized model and the observed data (Mulaik *et al.*, 1989). The Root Mean Square Error of Approximation (RMSEA) is 0.05, which is comparable to the ideal situation of being below 0.1. This implies that the model is a good fit for the population data. To this, we have the Root Mean Residual (RMR) at 0.046. In addition, the Normed Fit Index (NFI) and the Non-Normed Fit Index (NNFI), referred to as the Tucker-Lewis Index (TLI), are 0.939 and 0.97, respectively. Both indices measure the relative fit of the target model to the independence model, with higher values denoting better fit (Goretzko *et al.*, 2024).

In conclusion, the SEM analysis supports the model's structural validity in the extent to which it captures various factors relating to AAEGS acceptance among museum visitors, and at the same time, it highlights the need to interpret fit indices in a complex manner. These indices should therefore be taken as part of a more comprehensive set of criteria, where empirical and theoretical considerations regarding the model's validity are taken into account.

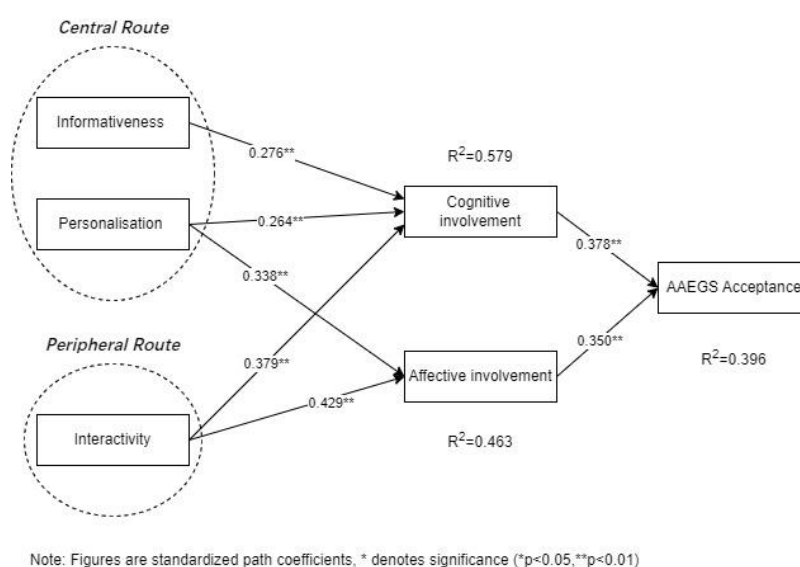


Figure 2: Structural regression model

Table 3: Fit indices results

Fit Indices	χ^2	df	p	χ^2/df	GFI	RMSEA	RMR	CFI	NFI	NNFI
Recommended Value	-	-	>0.05	<3	>0.9	<0.10	<0.05	>0.9	>0.9	>0.9
Structural Model	544.801	265	0	2.056	0.905	0.05	0.046	0.909	0.939	0.97

Default Model: $\chi^2(300)=3374.175$, $p=1.000$

Mediating Effect Test

Table 4 offers the mediation effect analysis from our study, where cognitive and affective involvement are considered as potential mediators. A total of 417 respondents were analyzed using percentile bootstrap method. Cognitive involvement as the mediator of the relationship between information content and AAEGS acceptance: Analysis of the mediating effects of Cognitive Involvement (CI) from Informativeness (IF) to AAEGS Acceptance (EA) suggests that cognitive processing plays a strong and significant role in mediating the information content to system acceptance. Total effect in this pathway is also very high with a total coefficient of 0.734, thus suggesting that while information has a significant effect on acceptance, its effect is moderated by cognitive factors. The regression coefficients show that the path between the two variables is indirect effect coefficient ($a*b$) of 0.373. This mediating effect emphasizes the importance of cognitive involvement in transforming information into higher levels of system acceptance through the process of involvement and cognition. The partial mediator from personalisation to cognitive involvement to AAEGS acceptance is 0.334, accounting for 61.05%. This mediating role shows that the content holds more cognitive appeal as it is specifically created to appeal to the users, making them accept the system because they regard it as important and useful information (Singh, 2009). Personalisation, on the other hand, affects the

consumer through affective involvement with the brand, and has a mediating effect (ab) of 0.305, which represents 55.82%. This pathway highlights how personalisation elicits strong emotional responses from users, since users feel more emotionally engaged and content with a system that adapts to their tastes (Zanker *et al.*, 2019).

Table 7: Mediating effect test (n=417)

Items	c	a	b	a*b	a*b (Boot SE)	a*b (z value)	a*b (p value)	a*b (95% BootCI)	c'	Results	a * b / c
IF=>CI=>EA	0.734**	0.697**	0.534**	0.373	0.04	9.387	0	0.198 ~ 0.354	0.361**	Partial mediation	50.80%
PER=>CI=>EA	0.547**	0.578**	0.578**	0.334	0.043	7.762	0	0.222 ~ 0.392	0.213**	Partial mediation	61.05%
PER=>AI=>EA	0.547**	0.608**	0.503**	0.305	0.036	8.495	0	0.210 ~ 0.352	0.242**	Partial mediation	55.82%
INT=>CI=>EA	0.549**	0.585**	0.543**	0.318	0.041	7.779	0	0.229 ~ 0.389	0.231**	Partial mediation	57.86%
INT=>AI=>EA	0.549**	0.609**	0.471**	0.287	0.039	7.354	0	0.202 ~ 0.358	0.263**	Partial mediation	52.17%

Note: $p < 0.05$ * $p < 0.01$, bootstrap type: Number of bootstrap samples for percentile bootstrap confidence intervals is 5000. a path = effect of the independent variable on the mediator; b = effect of the mediator on the dependent variable when controlling for the independent variable; c = total effect, including direct and indirect; c' = effect of the independent variable on dependent variable when controlling for the mediating variable.

The tests for the mediating roles of CI and AI in the relationship between INT and EA of AAEGS acceptance show that CI and AI mediate only a partial influence in both paths. Regarding the $INT \rightarrow CI \rightarrow EA$ pathway, the total impact of interaction on acceptance is positive and considerably high with a value of $c = 0.549$, which signifies a strong direct impact. When mediated by cognitive involvement, the path coefficient (a) from INT to CI is 0.585 and from CI to EA is 0.543, with the product of these coefficients ($ab = 0.318$) showing a significant mediating effect (z-value 7.779, $p=0.000$). This mediating effect accounts for 57.86% of the total effect, demonstrating that cognitive processes significantly enhance the acceptance of AAEGS when users interact with the system. Similarly, the $INT \rightarrow AI \rightarrow EA$ pathway illustrates interactivity effect on acceptance through affective involvement. Here, the direct path coefficient (c) is 0.549, with an indirect pathway mediated by affective involvement (AI) where INT to AI has a path coefficient (a) of 0.609 and AI to EA has a coefficient (b) of 0.471, resulting in an indirect effect ($ab = 0.287$). This mediation is significant (z-value 7.354, $p=0.000$) and represents 52.17% of the total influence, highlighting that interactivity not only enhances cognitive involvement but also significantly affects emotional responses which in turn influence acceptance.

Statistical significance is achieved across all tested paths ($p < 0.01$), which strongly supports the hypothesized mediation relationships within the model (Valente *et al.*, 2016). The Bootstrap Confidence Intervals (BootCI) which do not contain the value 0 further emphasizes the statistical significance of these effects and reiterates that the mediating variables transmit the effect of the independent variables to the dependent variable (Steffener, 2021)

DISCUSSION

The mediation analysis proportions of ($a*b/c$) provided in the analysis are ranging from 0.50 to 0.60, which implies that direct effects are still evident, but the most part of the impact of informativeness, personalisation and interactivity regarding the acceptance of AAEGS is mediated by cognitive and affective involvement. Based on the results of our study, we can state that informality increases cognitive demands, which fits this hypothesis. This relationship is important for AAEGS systems, as these systems are meant to enhance the visitor experience by offering the latter precise, interesting and relevant information about exhibition. Thus, Cognitive Mediation Model in that the depth and clarity of the content provided on AAEGS are critical determinants of the level of cognitive involvement (Eveland Jr, 2001). This is supported by the Elaboration Likelihood Model (ELM), which posits that people are more likely to take the central route when they encounter relevant, persuasive and high-quality information (Mardhatilah *et al.*, 2023). This type of processing not only leads to more lasting changes of attitude, but also increases the chances of receiving accurate information. When used in the present context, informality helps AAEGS prompt visitors to explore content in a deeper way and improve cognitive immersion as well as acceptance of the system (El Archi & Benbba, 2023; Ukpabi & Karjaluo, 2017). However, while the findings provide support for informativeness as a way of increasing cognitive involvement, it is also important to note that the findings call into question the effectiveness of information quality as a means of increasing system acceptance alone (Engelbrecht *et al.*, 2019). Therefore, our study implies that while informativeness is indeed a critical factor, it is not enough to ensure that visitors are informed and receive the information given to them; there are other factors, such as personalisation and interaction, that also come into play in influencing visitor experiences (Chen *et al.*, 2025). The value of this approach is that it helps to gain insight into how different factors of AAEGS are related, and how they affect the visitor acceptance.

We also found that personalisation has significant and positive impact on cognitive and emotional involvement, which means that users are more engaged when their experience is personalized, and therefore, personalisation strategies should be

encouraged. Findings from a sample of 417 museum visitors showed that personalisation enhanced the levels of cognitive processing ($\beta = 0.578^{**}$, $p < 0.01$), as a result of spending time closely to information that is relevant to one's personal experiences. This involvement is particularly useful in museums, which provide a great deal of information to the audience. As for the effect of personalisation on affective involvement, it was also significant ($\beta = 0.608^{**}$, $p < 0.01$). The positive experiences in the survey also provided support for the notion of increased pleasure and satisfaction through personalisation as perceived by the visitors to the museum (Zanker *et al.*, 2019). This emotional appeal is important because it takes the simplest experience, such as a visit and makes it more meaningful and even emotionally moving.

This study also points out that interaction has a powerful regulatory capacity to increase levels of cognitive and emotional involvement in a museum environment, as supported by the incorporation of interactive elements into AAEGS (Cheng *et al.*, 2023). This finding underscores that these technologies not only stimulate visitors' higher mental processes by encouraging the active utilization of information, but also by engaging visitors' emotions, thereby creating a better visitor experience through personalized and interactive way (Duguleană *et al.*, 2020). These two paths lead to the concept that interactivity can develop or enhance the value of access, as well as make it a more satisfying and fulfilling experience for users. The analysis of SEM showed that interactivity had a great impact on cognitive aspect regarding the standardized path coefficient of 0.379, significant at the 0.01 level. From the findings of this research, we conclude that organizational commitment is positively correlated with job engagement, and thus establishing itself is a considerable determinant factor. This implies that interactivity continues to form the core of how human engage and create meaning for information in the museum setting (Zanker *et al.*, 2019).

Interactive features are designed to capture the visitor's attention and maintain it, thereby increasing the time spent engaging with the content and enhancing the understanding and retention of information (Hsiao *et al.*, 2022; Sung *et al.*, 2021). The influence of interactivity on affective involvement was even higher, and amounted to 0.429. This finding further suggests that interaction not only captures the visitors' attention and keeps them actively involved on a cognitive level, but also engages them emotionally (Lin *et al.*, 2022). In museums, people can have certain types of emotional reactions that can enhance or diminish the overall visit, and interaction can be the determining factor between an ordinary visit and an extraordinary one.

Cognitive and emotional involvement, therefore, served as key mediators in the context of the present study in establishing how a number of features of AAEGS determine overall acceptance. Cognitive Involvement traditionally focused on the intellectual engagement that visitors experience when interacting with AAEGS (Putrevu & Lord, 1994). Cognitive factors revolve around the storage and interpretation of information presented by the system, focusing more on the amount of information and function to enhance the understanding of the exhibits (Faisal *et al.*, 2020; Tung *et al.*, 2017). Based on our results, it can be concluded that the path coefficient between cognitive involvement and acceptance is significant and quite strong, equal to 0.378 ($p < 0.01$), suggesting that with increased attention level of visitors, so does their willingness to accept and use the system. Perceived interactivity, and hence, a key antecedent of emotional involvement, exhibits a higher standardized path coefficient of 0.429 ($p < 0.01$) this indicates that emotional responses towards the system are key factors towards acceptance of the system.

The features of AAEGS had influence visitor receptivity through the medium of cognitive and affective involvement, which demonstrated the intricate relation of characteristic of an attraction. While cognitive involvement ensures that the content presented and experienced by the system is meaningful and interesting, affective involvement ensures that the emotional needs of the visitation experience are met (Craig & Choi, 2024).

CONCLUSION AND LIMITATIONS

This research seeks to examine how AAEGS affect visitor acceptance in Chinese museums with reference to informativeness, personalisation, and interaction. A key focus of this study is to explore how cognitive and affective involvement can moderate the experiences and acceptance of the visitors. Informativeness, which refers to the depth and relevance of information delivered by AAEGS, is another crucial factor that determines the level of cognitive involvement (Ukpabi & Karjaluo, 2017). When visitors find that the information they are seeking to be both well-organized and complete, and provides more than just the facts, they are more likely to interact with the content (Sang *et al.*, 2023). In the paper is the fact that the use of personalisation has an impact on both cognitive and affective dimensions of the visitors (Zanker *et al.*, 2019). It ensures that the information provided to visitors is narrowed down to information that is of great interest to them, and provides them with some form of interaction or recognition (Hsiao *et al.*, 2022). Meanwhile, the AAEGS platform, through technologies such as augmented reality and virtual guided tours, creates an interactive experience that effectively enhances the visitors' participation at both the cognitive and emotional levels, thereby improving learning outcomes and increasing the acceptance of the technology.

However, based on the current study, it can be argued that affective involvement might be more influential in the acceptance of AAEGS. It has been noted that people tend to be motivated by emotions rather than rational assessments, especially when the value of a service is defined by an individual's experiences and satisfaction (Su *et al.*, 2019). The short-term affective responses generated by personalisation and interaction can play a critical role in shaping the visitors' impressions and willingness to engage, erasing any other long-term rational evaluation (Lee & Lim, 2010). Based on the Elaboration

Likelihood Model (ELM), this paper argues that the interaction of cognitive and affective responses to technology in museums impacts the acceptance level of AAEGS. In addition to demonstrating that ELM can be effectively applied in this new context, the study also contributes to the development of additional theoretical models that embrace the technological acceptance in different cultural and cognitive perspectives that take affective factors into account (Kelly *et al.*, 2023). In a practical perspective, this study provides guidance for museum administrators and exhibition designers in planning future museum routes. Due to the clear separation of the aspects contributing to information, personalisation, and interactivity, the positive impact on visitors' involvement and acceptance, it would be crucial for museums to focus on these features in further development of digital components.

Despite the identified contributions this study has made, there are some limitations that show the scope for the future research and improvement. The first limitation relates to this research findings arising from the Chinese contexts only and this limits a broader understanding from different geographical locations like other countries' museums. While this approach helps to provide a clear picture of how AAEGS is disseminating in the context of a particular culture and technology, it may prevent the generalization of results accrued in the other parts of the world. It is crucial to consider the consistency of using technology in museums or visiting museums in different countries, as cultural factors may affect the way that people perceive and use AAEGS. Further research may generalize this study to a large geographical coverage in order to ascertain whether the results would hold true across different geographical locations (Han *et al.*, 2018).

Another factor of the fast pace of society caused by technology advancement is also a challenge to the long-term applicability of this study (Kim & Hall, 2020). Given the new technologies of these interactions, the functionalities and benefits reasons for using AAEGS may slightly change in the future thereby affecting the features of the above interactive gizmos along with their acceptance factors. Further research is required to monitor these advances and keep them updated constantly in order to understand as to how these departing technologies can be implemented effectively in museums. As for future studies, it may be important to continue the attempt to analyze the operational effectiveness of similar technological solutions in such environments as art museums, historical and scientific centers, and other objects of different types of tourism to compare informational, personalisation and interaction impact of such environments.

REFERENCES

- Akram, S., & Kortam, W. (2020). The impact of customer experience in online brand communities on customer engagement and purchase intentions among Arab internet users: Theoretical analysis, conceptual framework and research agenda. *Business and Management Studies*, 6(3), 26-54. <https://doi.org/doi:10.11114/bms.v6i3.5021>
- Bujang, M. A., Omar, E. D., & Baharum, N. A. (2018). A review on sample size determination for Cronbach's alpha test: A simple guide for researchers. *The Malaysian Journal of Medical Sciences: MJMS*, 25(6), 85-99 <https://doi.org/doi:10.21315/mjms2018.25.6.9>
- Chen, Q., Huang, D., & Miao, M. (2025). Service robot acceptance: Agenda for tourism and hospitality research. *Tourism Review*, 80(4), 871-893. <https://doi.org/https://doi.org/10.1108/TR-03-2024-0159>
- Chen, S., Tian, D., Law, R., & Zhang, M. (2021). Bibliometric and visualized review of smart tourism research. *International Journal of Tourism Research*, 24(2), 298-307. <https://doi.org/10.1002/jtr.2501>
- Cheng, A., Ma, D., Pan, Y., & Qian, H. (2023). Enhancing museum visiting experience: Investigating the relationships between augmented reality quality, immersion, and TAM using PLS-SEM. *International Journal of Human-Computer Interaction*, 40(17), 4521-4532. <https://doi.org/10.1080/10447318.2023.2227832>
- Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 41(2), 745-783. <https://doi.org/https://doi.org/10.1007/s10490-023-09871-y>
- Choi, H., & Kim, S. (2017). A content service deployment plan for metaverse museum exhibitions—Centering on the combination of beacons and HMDs. *International Journal of Information Management*, 37(1), 1519-1527. <https://doi.org/10.1016/j.ijinfomgt.2016.04.017>
- Chung, N., Lee, H., Kim, J. Y., & Koo, C. (2017). The role of augmented reality for experience-influenced environments: The case of cultural heritage tourism in Korea. *Journal of Travel Research*, 57(5), 627-643. <https://doi.org/10.1177/0047287517708255>
- Craig, M. J., & Choi, M. (2024). The role of affective and cognitive involvement in the mitigating effects of AI source cues on hostile media bias. *Telematics and Informatics*, 88(10), 102097. <https://doi.org/https://doi.org/10.1016/j.tele.2024.102097>
- Duguleană, M., Briciu, V. A., Duduman, I. A., & Machidon, O. M. (2020). A virtual assistant for natural interactions in museums. *Sustainability*, 12(17). <https://doi.org/10.3390/su12176958>
- El Archi, Y., & Benbba, B. (2023). The applications of technology acceptance models in tourism and hospitality research: A systematic literature review. *Journal of Environmental Management & Tourism*, 2(66), 379-391. [https://doi.org/https://doi.org/10.14505/jemt.v14.2\(66\).08](https://doi.org/https://doi.org/10.14505/jemt.v14.2(66).08)
- Engelbrecht, W. H., Sotiriadis, M. D., & Swart, M. P. (2019). Investigating the intentions of tourism providers and trade exhibition visitors to use technology: A technology acceptance model approach. *Acta Commercii*, 19(1), 1-11. <https://doi.org/https://doi.org/10.4102/ac.v19i1.693>

- Eveland Jr, W. P. (2001). The cognitive mediation model of learning from the news: Evidence from nonelection, off-year election, and presidential election contexts. *Communication Research*, 28(5), 571-601. <https://doi.org/https://doi.org/10.1177/009365001028005001>
- Faisal, C. M. N., Fernandez-Lanvin, D., De Andrés, J., & Gonzalez-Rodriguez, M. (2020). Design quality in building behavioral intention through affective and cognitive involvement for e-learning on smartphones. *Internet Research*, 30(6), 1631-1663. <https://doi.org/https://doi.org/10.1108/INTR-05-2019-0217>
- Fan, Y., Chen, J., Shirkey, G., John, R., Wu, S. R., Park, H., & Shao, C. (2016). Applications of structural equation modeling (SEM) in ecological studies: An updated review. *Ecological processes*, 5, 19. <https://doi.org/https://doi.org/10.1186/s13717-016-0063-3>
- Gao, B., Wang, Y., Xie, H., Hu, Y., & Hu, Y. (2023). Artificial intelligence in advertising: Advancements, challenges, and ethical considerations in targeting, personalization, content creation, and ad optimization. *Sage Open*, 13(4), 59. <https://doi.org/doi.org/10.1177/215824402312107>
- Giotis, G., & Papadionysiou, E. (2022). The role of managerial and technological innovations in the tourism industry: A review of the empirical literature. *Sustainability*, 14(9), 5182. <https://doi.org/https://doi.org/10.3390/su14095182>
- Goretzko, D., Siemund, K., & Sterner, P. (2024). Evaluating model fit of measurement models in confirmatory factor analysis. *Educational and Psychological Measurement*, 84(1), 123-144. <https://doi.org/https://doi.org/10.1177/00131644231163813>
- Guo, K., Fan, A., Lehto, X., & Day, J. (2021). Immersive digital tourism: The role of multisensory cues in digital museum experiences. *Journal of Hospitality & Tourism Research*, 47(6), 1017-1039. <https://doi.org/10.1177/10963480211030319>
- Han, H., Koo, C., & Chung, N. (2018). Exhibition guide system acceptance for smart MICE. *Asia Pacific Journal of Information Systems*, 28(1), 61-74. <https://doi.org/https://doi.org/10.14329/apjis.2018.28.1.61>
- Haugtvedt, C. P., & Petty, R. E. (1992). Personality and persuasion: Need for cognition moderates the persistence and resistance of attitude changes. *Journal of Personality and Social Psychology*, 63(2), 308-319. <https://doi.org/10.1037/0022-3514.63.2.308>
- Herber, R., Kaiser, A., Grählert, X., Range, U., Raiskup, F., Pillunat, L., et al (2020). Statistical analysis of correlated measurement data in ophthalmology: Tutorial for the application of the linear mixed model in SPSS and R using corneal biomechanical parameters. *Der Ophthalmologe*, 117(1), 27-35. <https://doi.org/https://doi.org/10.1007/s00347-019-0904-4>
- Hsiao, W. H., Lin, Y. H., & Wu, I. L. (2022). Advergame for purchase intention via game and brand attitudes from antecedents of system design, psychological state, and game content: Interactive role of brand familiarity. *Journal of Organizational Computing and Electronic Commerce*, 32(1), 45-68. <https://doi.org/https://doi.org/10.1080/10919392.2022.2038526>
- Ivanov, R., & Velkova, V. (2025). Analyzing visitor behavior to enhance personalized experiences in smart museums: A systematic literature review. *Computers*, 14(5), 191. <https://doi.org/https://doi.org/10.3390/computers14050191>
- Izzo, F., Camminatiello, I., Sasso, P., Solima, L., & Lombardo, R. (2023). Creating customer, museum and social value through digital technologies: Evidence from the MANN Assiri project. *Socio-Economic Planning Sciences*, 85, 101502. <https://doi.org/10.1016/j.seps.2022.101502>
- Jeon, H., Ok, C., & Choi, J. (2018). Destination marketing organization website visitors' flow experience: An application of Plog's model of personality. *Journal of Travel & Tourism Marketing*, 35(4), 397-409. <https://doi.org/10.1080/10548408.2017.1358234>
- Jeong, M., & Shin, H. H. (2019). Tourists' experiences with smart tourism technology at smart destinations and their behavior intentions. *Journal of Travel Research*, 59(8), 1464-1477. <https://doi.org/10.1177/0047287519883034>
- Jiang, Q., Chen, J., Wu, Y., Gu, C., & Sun, J. (2022). A study of factors influencing the continuance intention to the usage of augmented reality in museums. *Systems*, 10(3). <https://doi.org/10.3390/systems10030073>
- Kamariotou, V., Kamariotou, M., & Kitsios, F. (2021). Strategic planning for virtual exhibitions and visitors' experience: A multidisciplinary approach for museums in the digital age. *Digital Applications in Archaeology and Cultural Heritage*, 21. <https://doi.org/10.1016/j.daach.2021.e00183>
- Kelly, S., Kaye, S. A., & Oviedo Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, 77(2), 101925. <https://doi.org/https://doi.org/10.1016/j.tele.2022.101925>
- Kim, M. J., & Hall, C. M. (2020). What drives visitor economy crowdfunding? The effect of digital storytelling on unified theory of acceptance and use of technology. *Tourism Management Perspectives*, 34(1), 100638. <https://doi.org/https://doi.org/10.1016/j.tmp.2020.100638>
- Komarac, T., & Ozretić Došen, Đ. (2021). Discovering the determinants of museum visitors' immersion into experience: The impact of interactivity, expectations, and skepticism. *Current Issues in Tourism*, 25(22), 3675-3693. <https://doi.org/10.1080/13683500.2021.1952941>
- Lee, Y. H., & Lim, E. A. C. (2010). When good cheer goes unrequited: How emotional receptivity affects evaluation of expressed emotion. *Journal of Marketing Research*, 47(6), 1151-1161. <https://doi.org/https://doi.org/10.1509/jmkr.47.6.1>
- Lin, W., Lo, W. T., & Yueh, H. P. (2022). Effects of learner control design in an AR-based exhibit on visitors' museum learning. *PLoS One*, 17(10), e0274826. <https://doi.org/10.1371/journal.pone.0274826>

- Liu, Y., & Shrum, L. J. (2002). What is interactivity and is it always such a good thing? Implications of definition, person, and situation for the influence of interactivity on advertising effectiveness. *Journal of Advertising*, 31(4), 53-64. <https://doi.org/https://doi.org/10.1080/00913367.2002.10673685>
- Liu, Y., & Shrum, L. J. (2009). A dual-process model of interactivity effects. *Journal of Advertising*, 38(2), 53-68. <https://doi.org/10.2753/joa0091-3367380204>
- Lu, X., & Taghipour, A. (2025). A review of supply chain digitalization and emerging research paradigms. *Logistics*, 9(2), 47. <https://doi.org/https://doi.org/10.3390/logistics9020047>
- Malkewitz, C. P., Schwall, P., Meesters, C., & Hardt, J. (2023). Estimating reliability: A comparison of Cronbach's α , McDonald's ω and the greatest lower bound. *Social Sciences & Humanities Open*, 7(1), 100368. <https://doi.org/https://doi.org/10.1016/j.ssaho.2022.100368>
- Mardhatilah, D., Omar, A., & Septiari, E. D. (2023). A literature review on persuasive communication: Utilising elaboration likelihood model to understand consumer engagement on social media platforms. *Journal of Technology Management and Business*, 10(2), 87-100. <https://doi.org/https://doi.org/10.30880/jtmb.2023.10.02.008>
- Mehrad, A., & Zangeneh, M. H. T. (2019). Comparison between qualitative and quantitative research approaches: Social sciences. *International Journal for Research in Educational Studies*, 5(7), 1-7. <https://doi.org/https://orcid.org/0000-0003-4364-5709>
- Memon, M. A., Ramayah, T., Cheah, J. H., Ting, H., Chuah, F., & Cham, T. H. (2021). PLS-SEM statistical programs: A review. *Journal of Applied Structural Equation Modeling*, 5(1), 1-14. [https://doi.org/DOI:10.47263/JASEM.5\(1\)06](https://doi.org/DOI:10.47263/JASEM.5(1)06)
- Mo, L., Zhang, X., Lin, Y., Yuan, Z., & Peng, Z. (2023). Consumers' attitudes towards online advertising: A model of personalization, informativeness, privacy concern and flow experience. *Sustainability*, 15(5), 4090. <https://doi.org/https://doi.org/10.3390/su15054090>
- Mulaik, S. A., James, L. R., Van Alstine, J., Bennett, N., Lind, S., & Stilwell, C. D. (1989). Evaluation of goodness-of-fit indices for structural equation models. *Psychological Bulletin*, 105(3), 430. <https://doi.org/https://doi.org/10.1037/0033-2909.105.3.430>
- Mustofa, M. (2023). Epistemological paradigms in positivism, interpretivism, and action research in educational research: A literature review. *Journal of Office Administration: Education and Practice*, 3(3), 214-224. <https://doi.org/https://doi.org/10.26740/joaep.v3n3.p214-224>
- Östlund, U., Kidd, L., Wengström, Y., & Rowa-Dewar, N. (2011). Combining qualitative and quantitative research within mixed method research designs: A methodological review. *International Journal of Nursing Studies*, 48(3), 369-383. <https://doi.org/https://doi.org/10.1016/j.ijnurstu.2010.10.005>
- Park, M., & Yoo, J. (2020). Effects of perceived interactivity of augmented reality on consumer responses: A mental imagery perspective. *Journal of Retailing and Consumer Services*, 52. <https://doi.org/10.1016/j.jretconser.2019.101912>
- Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In L. Berkowitz (Ed.), *Advances in Experimental Social Psychology*, 19, 123-205. New York: Academic Press. [https://doi.org/10.1016/S0065-2601\(08\)60214-2](https://doi.org/10.1016/S0065-2601(08)60214-2)
- Ponsignon, F., & Derbaix, M. (2020). The impact of interactive technologies on the social experience: An empirical study in a cultural tourism context. *Tourism Management Perspectives*, 35, 100723. <https://doi.org/https://doi.org/10.1016/j.tmp.2020.100723>
- Purwanto, A., & Sudargini, Y. (2021). Partial least squares structural equation modeling (PLS-SEM) analysis for social and management research: A literature review. *Journal of Industrial Engineering & Management Research*, 2(4), 114-123. <https://doi.org/https://doi.org/10.7777/jiemar.v2i4.168>
- Putrevu, S., & Lord, K. R. (1994). Comparative and noncomparative advertising: Attitudinal effects under cognitive and affective involvement conditions. *Journal of Advertising*, 23(2), 77-91. <https://doi.org/https://doi.org/10.1080/00913367.1994.10673443>
- Reychav, I., & Wu, D. (2015). Are your users actively involved? A cognitive absorption perspective in mobile training. *Computers in Human Behavior*, 44, 335-346. <https://doi.org/https://doi.org/10.1016/j.chb.2014.09.021>
- Sadamali Jayawardena, N., Thaichon, P., Quach, S., Razzaq, A., & Behl, A. (2023). The persuasion effects of virtual reality (VR) and augmented reality (AR) video advertisements: A conceptual review. *Journal of Business Research*, 160, 113739. <https://doi.org/10.1016/j.jbusres.2023.113739>
- Sang, W., Ji, S., Pu, B., & Phau, I. (2023). The effect of tourism live streaming information quality and source credibility on users' continuous viewing intention: An application of elaboration likelihood model. *Asia Pacific Journal of Tourism Research*, 28(3), 177-190. <https://doi.org/10.1080/10941665.2023.2217954>
- Shahab, M. H., Ghazali, E., & Mohtar, M. (2021). The role of elaboration likelihood model in consumer behaviour research and its extension to new technologies: A review and future research agenda. *International Journal of Consumer Studies*, 45(4), 664-689. <https://doi.org/https://doi.org/10.1111/ijcs.12658>
- Sharma, H. (2022). How short or long should be a questionnaire for any research? Researchers dilemma in deciding the appropriate questionnaire length. *Saudi Journal of Anaesthesia*, 16(1), 65-68. https://doi.org/doi:10.4103/sja.sja_163_21
- Singh, R. (2009). Does my structural model represent the real phenomenon?: A review of the appropriate use of Structural Equation Modelling (SEM) model fit indices. *The Marketing Review*, 9(3), 199-212. <https://doi.org/https://doi.org/10.1362/146934709X467767>

- Siu, N. Y. M., Zhang, T. J., & Kwan, H. Y. (2022). Reference effects and customer engagement in a museum visit. *International Journal of Contemporary Hospitality Management*, 34(2), 482-508. <https://doi.org/10.1108/IJCHM-02-2021-0208>
- Smith, G. T. (2005). On construct validity: Issues of method and measurement. *Psychological Assessment*, 17(4), 396. <https://doi.org/https://doi.org/10.1037/1040-3590.17.4.396>
- Soni, M. J. (2017). Effects of varying involvement level within a television program on recall of cognitive versus affective advertisement. *Journal of Consumer Marketing*, 34(4), 338-348. <https://doi.org/https://doi.org/10.1108/JCM-09-2015-1532>
- Sousa, V. D., Driessnack, M., & Mendes, I. A. C. (2007). An overview of research designs relevant to nursing. Part 1: quantitative research designs. *Revista Latino-americana De Enfermagem*, 15, 502-507. <https://doi.org/https://doi.org/10.1590/S0104-11692007000300022>
- South, L., Saffo, D., Vitek, O., Dunne, C., & Borkin, M. A. (2022). Effective use of Likert scales in visualization evaluations: A systematic review. *Computer Graphics Forum*, 41, 43-55. <https://doi.org/10.1111/cgf.14521>
- Steffener, J. (2021). Power of mediation effects using bootstrap resampling. *arXiv preprint*, arXiv: 2106.02482. <https://doi.org/https://doi.org/10.48550/arXiv.2106.02482>
- Steinhardt, F., Dolva, A. S., Jahnsen, R., & Ullenhag, A. (2022). Exploring two subdimensions of participation, involvement and engagement: A scoping review. *Scandinavian Journal of Occupational Therapy*, 29(6), 441-463. <https://doi.org/https://doi.org/10.1080/11038128.2021.1950207>
- Sternberg, R. J., Glaveanu, V., Karami, S., Kaufman, J. C., Phillipson, S. N., & Preiss, D. D. (2021). Meta-intelligence: Understanding, control, and interactivity between creative, analytical, practical, and wisdom-based approaches in problem solving. *Journal of Intelligence*, 9(2), 19. <https://doi.org/https://doi.org/10.3390/jintelligence9020019>
- Su, N., Mariadoss, B. J., & Reynolds, D. (2019). Emotional and cognitive involvement of consumers with hotel brands on social networking sites. *Journal of Hospitality and Tourism Insights*, 2(4), 377-390. <https://doi.org/https://doi.org/10.1108/JHTI-10-2018-0064>
- Sung, E., Bae, S., Han, D. I. D., & Kwon, O. (2021). Consumer engagement via interactive artificial intelligence and mixed reality. *International Journal of Information Management*, 60, 102382. <https://doi.org/10.1016/j.ijinfomgt.2021.102382>
- Sustacha, I., Banos-Pino, J. F., & Del Valle, E. (2023). The role of technology in enhancing the tourism experience in smart destinations: A meta-analysis. *Journal of Destination Marketing & Management*, 30, 100817. <https://doi.org/https://doi.org/10.1016/j.jdmm.2023.100817>
- Tung, T., Koenig, H. F., & Chen, H. L. (2017). Effects of green self-identity and cognitive and affective involvement on patronage intention in eco-friendly apparel consumption: A gender comparison. *Sustainability*, 9(11), 1977. <https://doi.org/https://doi.org/10.3390/su9111977>
- Ukpabi, D. C., & Karjaluoto, H. (2017). Consumers' acceptance of information and communications technology in tourism: A review. *Telematics and Informatics*, 34(5), 618-644. <https://doi.org/https://doi.org/10.1016/j.tele.2016.12.002>
- Vaske, J. J., Beaman, J., & Sponarski, C. C. (2017). Rethinking internal consistency in Cronbach's alpha. *Leisure Sciences*, 39(2), 163-173. <https://doi.org/https://doi.org/10.1080/01490400.2015.1127189>
- Vitali, V., Bazzani, C., Gimigliano, A., Cristani, M., Begalli, D., & Menegaz, G. (2022). Trade show visitors and key technological trends: From a literature review to a conceptual framework. *Journal of Business & Industrial Marketing*, 37(13), 142-166. <https://doi.org/10.1108/JBIM-10-2021-0461>
- Walker, W. (2005). The strengths and weaknesses of research designs involving quantitative measures. *Journal of Research in Nursing*, 10(5), 571-582. <https://doi.org/https://doi.org/10.1177/136140960501000505>
- Wu, T., Jiang, N., Kumar, T. B. J., & Chen, M. (2024). The role of cognitive factors in consumers' perceived value and subscription intention of video streaming platforms: A systematic literature review. *Cogent Business & Management*, 11(1), 2329247. <https://doi.org/https://doi.org/10.1080/23311975.2024.2329247>
- Yang, X., & Zhang, L. (2022). Smart tourism technologies towards memorable experiences for museum visitors. *Tourism Review*, 77(4), 1009-1023. <https://doi.org/10.1108/tr-02-2022-0060>
- Zaichkowsky, J. L. (1986). Conceptualizing involvement. *Journal of Advertising*, 15(2), 4-34. <https://doi.org/https://doi.org/10.1080/00913367.1986.10672999>
- Zanker, M., Rook, L., & Jannach, D. (2019). Measuring the impact of online personalisation: Past, present and future. *International Journal of Human-Computer Studies*, 131(1), 160-168. <https://doi.org/https://doi.org/10.1016/j.ijhcs.2019.06.006>
- Zhuang, X., Hou, X., Feng, Z., Lin, Z., & Li, J. (2020). Subjective norms, attitudes, and intentions of AR technology use in tourism experience: The moderating effect of millennials. *Leisure Studies*, 40(3), 392-406. <https://doi.org/10.1080/02614367.2020.1843692>