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

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Abstract

This study focuses on a survey of visitors' acceptance of AI-enabled Augmented Reality (AR) Exhibition Guide Systems (AAEGS) in a Chinese museum environment. I have studied how visitor acceptance of a museum guide system can be improved by improving the informativeness, personalisation and interactivity of the system. In this paper, I developed a model through my understanding of the Elaboration Likelihood Model (ELM) theory to show that visitors' acceptance of AAEGS is impacted by these three attributes. The mediating effects of cognitive and affective involvement in this process are also tested.

In this study, a quantitative research methodology was used, I used a 7-point Likert scale questionnaire and collected visit data from 417 museum visitors to empirically validate the model developed in the thesis. My findings suggest that the informative, personalised and interactive features of AAEGS can impact on visitors' acceptance of AAEGS. Cognitive and affective involvement worked in the modelling of this study. I tested the mediating impact of cognitive involvement and affective involvement and found that these attributes influenced visitors' cognitive involvement and affective involvement, leading to their decide to accept AAEGS.

The utilization of AI-enabled Augmented Reality (AR) Exhibition Guide Systems aids museum personnel, in comprehending how to improve visitors' immersive experience and satisfaction. This study provides a basis for future research on AI guided tours.

Keywords: AI-enabled AR Guide Systems, museum visit experience; visitor acceptance; Elaboration Likelihood Model; informativeness; personalization, interactivity; cognitive involvement; affective involvement.

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In the process of data collection, I am very thankful to the management and staff of the museum for their help that provided the necessary conditions for data collection in this study. I would also like to thank the staff of the Questionnaire Star software for their guidance and patience in distribution and collection of the questionnaires. I would also like to thank my family, who gave me a lot of understanding and support during the whole process. This thesis not only shows my hard work, but also proves that technology can change the tourism environment and the cultural experience of tourists.

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

1. Introduction

1.1 Research Background

Museums are a treasure trove of knowledge and language, and they need to be developed to meet social needs (Izzo et al., 2023). In the 21st century, science and technology are driving changes in every industry in the world. Over the past few decades, museums around the world have embarked on a journey of transformation, integrating various technologies to meet the changing expectations of visitors (Khalil et al., 2023). Many museums have introduced digital technologies such as artificial intelligence (AI), augmented reality (AR), big data, etc. Museum exhibition designers use digital technologies in exhibitions in order to complement the weaknesses of traditional exhibitions, such as traditional exhibitions where visitors are unable to interact with the exhibits (Battour et al., 2023). The staff wanted to create immersive experiences for visitors (Choi & Kim, 2017). However, creating an interactive visitor environment that engages and interests users, is acceptable and continues to be visited is still a challenge (Guo et al., 2021). In particular, museum visitors have a variety of motivations and needs, including learning about history, gathering information, being entertained, learning about the latest exhibition techniques, etc (Gregg et al., 2001).

The museum visiting experience can be improved by applying digital content to real museum environments (He et al., 2018). In particular, the AI-enabled Augmented Reality potential to improve the museum visiting environment and visitor experience has been discussed in various studies (Huang et al., 2010). This potential can be seen in different areas such as retail, education, healthcare, entertainment and navigation (Chen et al., 2021; He et al., 2018; Ramkumar et al., 2022). Augmented Reality (AR) technology is a technology that cleverly integrates digital information with the real world (Khalil et al., 2023). Technicians use computer tools to produce virtual information including text, images, 3D models, music and video. This simulated information is then applied to the real world to enhance experiences

across different domains (Azuma, 1997; Huang et al., 2010). Miah (2017) asserts that virtual reality creates 'simulated experiences of the physical world', while augmented reality adds 'layers of digital content to a physical-world camera perspective'. The use of Artificial Intelligence (AI) technology will give the development of Virtual Reality (VR) and Augmented Reality (AR) technology a push further (Miah, 2017). AI is a new technological science. This technology is used to develop theories, methods, technologies and application systems that simulate human intelligence (Kokash et al., 2024). Its research areas include machine learning, language identification, image identification, natural language processing, computer vision, and so on (Mogaji et al., 2024).

Corrêa and Gosling (2021) argue that AI and AR technologies for museum exhibitions are the future. It provides a rich and varied visitor experience. Through applications, visitors can engage with exhibits, for example by triggering animations, playing audio or video, and so on. In the last few years, AR guided tours have become popular in museums (Corrêa & Gosling, 2021). An AR tour system is an app that uses AR technology to provide users with tour guides and exhibition services. It provides users with a more informative guided tour by displaying virtual objects, images, text, or other interactive components (Yang & Zhang, 2022). Visitors can use digital tools (e.g., smartphones, tablets, AR glasses, or other devices) to view and interact with virtual content. AI's virtual assistant functions can understand and respond to a user's natural language, offering visitors an intuitive and tailored experience (Zhang et al., 2022). AI-enabled Augmented Reality Exhibition Guide Systems (AAEGS) is the newest application of AI, which debuted in 2022. This is a new tour guide system that designers have designed to incorporate AI into an AR application. It allows the user to interact with a virtual environment that can be changed according to the visitor's interests and behaviour (Battour et al., 2023).

It uses functions such as data extractions, natural language processing and knowledge fusion across multiple disciplines to provide museum information to visitors (Lee & Lim, 2010; Yawised et al., 2023). AAEGS researches users' historical behavioural habits and their social connections, their previous knowledge base, to provide visitors with content that is tailored to

their needs. This content can resonate with visitors' personal preferences (Borràs et al., 2014). It learns and analyses the visitor's past interaction behaviors and visit experiences, thus improving the reliability of the guided tour recommendations for this visit. Visitors use AR glasses or other AR devices to interact with virtual content, and receive personalized content from artificially intelligent virtual people (Lin et al., 2022). AAEGS aims to control and manage the use of smart technologies in museum exhibitions, discovering valuable suggestions for exhibitions and services to improve the visitor experience (Chaturvedi et al., 2023). The AAEGS has been used in museums to make up for the gaps in traditional exhibitions (Chaturvedi et al., 2023; Duguleană et al., 2020).

1.2 Research Motivation

My anchor of this study in Chinese museums was motivated by a range of reasons. The most important reason is that Chinese museums are leaders in the technology of AR and AI integration, especially as they have integrated AI by using AR-guided tour devices, such as AR glasses (Jeong & Shin, 2019). In 2022, AAEGS showed up and took the center of attention at the 9th China Museums and Related Products and Technologies Expo. The AAEGS represented a great leap forward in enhancing the traditional museums into digital museums (Gong et al., 2022). Several famous museums around China, such as the National Museum of China and the Guangdong Provincial Museum, are already using AAEGS. This situation ensures the scope of sample collection for my study. In July 2022, the AI virtual human "AI Wenwen" made its first appearance (see Figure 1). It became the newest member of the National Museum of China.

On the other hand, the growing use of AAEGS has increased visitor expectations and concerns, requiring immediate and focused research efforts by those involved (Yang & Zhang, 2022). The integration of AI and AR in museum travel has significantly changed the visitor experience. It has become an area of research of interest to academic and museum practitioners (Dwivedi et al., 2023). Therefore, consumer expectations and concerns about

AAEGS emphasize the urgent need for such exploration (Alam & Mohanty, 2023; Mogaji et al., 2024; Yan et al., 2023). The AAEGS' deep influence on visitor acceptance has clearly raised interest and need. This has urged studies to conduct in-depth research on its effectiveness and impact (Chaturvedi et al., 2023).

Figure 1 Virtual Homo sapiens of the National Museum of China:AI Wenwen.

Tourist acceptance of technologies and services in the travel and tourism industry is indeed influenced by their level of involvement (Pantano & Corvello, 2014). Involvement is defined by the level of visitors' interest in services, places, or technologies and their emotional connection to those services, places, or technologies (Jiang et al., 2022; Turan et al., 2015;

Wu et al., 2021). Visitors are more likely to accept technologies or services that match their interests, needs, and preferences (Buhalis & Amaranggana, 2015). They find the service or technology worthwhile, then they develop a high level of engagement. This increases the probability that this technology or service will be accepted by visitors (Park et al., 2020). On the one hand, cognitively involved tourists engage in more extensive information search and processing about a service or technology (Ho et al., 2012). Involvement can improve acceptance by allowing tourists to understand the benefits and functions of the technology (Craig & Choi, 2024). Visitors can promote acceptance of the technology by creating positive attitudes towards it. This is the main form of affective involvement of visitors. Visitors who develop an emotional connection to a service or technology are more likely to make them accept and promote it.

Cognitive involvement is defined as the depth of users' cognitive and intellectual engagement when they use a system (Kim & Hall, 2020). It plays a driving role in the process of developing the user's behavioral intentions. On the other hand, affective involvement is the user's emotional experience of whether or not something meets their needs. This experience makes them have an emotional connection to an item (Putrevu & Lord, 1994). Cognitive and affective involvement both impact users' attitudes and behaviours on AAEGS. I analyse them separately to understand the different influences they create (Faisal et al., 2020; Perse, 1998; Putrevu & Lord, 1994; Tung et al., 2017). In this study, cognitive and affective involvement were chosen as mediating variables to resolve the gap between system attributes and user acceptance (Zhang et al., 2022). While research on the role of these functional factors in influencing user acceptance is well established, there is still very little research available on AAEGS. Researchers have tended to lose sight of the functional attributes of the systems and their impact on cognitive and affective involvement (Bronzin et al., 2021).

1.3 Research Question

In this study, I will explore how the attributes of AAEGS promote visitor acceptance through

cognitive and affective engagement. This investigation was driven by this key research question:

RQ: What factors do drive museum visitors' acceptance of AI-enabled augmented reality exhibition guide systems?

1.4 Research Aim and Objectives

In this study, I endeavor to decipher the complex dynamics of how the features of AAEGS influence museum visitors' acceptance of such systems, with a particular focus on cognitive and affective involvement acting as crucial mediators. This paper uses the Elaboration Likelihood Model (ELM) as a grounded theoretical framework. It hypothesizes that different attributes of the system influence tourists' acceptance of the technology through central or peripheral routes, depending on the individual's level of involvement (Kizito & Sun, 2018). I will shed light on the processes by which the attributes of AAEGS influence museum visitor adoption through the prismatic analysis of ELM theory. I will provide a complete review and analysis of available theories and models to develop a research model that can be used to more fully study how the attributes of AAEGS contribute to technology acceptance. The ELM serves as a theoretical lens for understanding how users engage with particular technology features of AAEGS (Petty et al., 1986), ultimately influencing their acceptance of the AAEGS.

Petty and Cacioppo developed the Elaboration Likelihood Model (ELM) in the 1980s. The model describes when a person is contacted a message, and how the features of that message influence the development of their attitudes, and then how that influences their behaviours (Petty et al., 1986). There are two routes in this model, a central route and a peripheral route (Haugtvedt & Petty, 1992). The central route means that when people are highly motivated and competent, they will use more attention in processing relevant information (Li & See-To, 2024). They will carefully and deeply think about considering to assess and understand the exhibition, and if the message is relevant, it will lead to a better experience, and a positive

attitude. The peripheral route means that when people's motivation and ability are relatively weak, their attitudes are primarily defined by affective cues in the environment, rather than by thinking about the message argument (Haugtvedt & Petty, 1992). ELM explains that the system's functions can influence user attitudes and acceptance directly by deep cognitive processing or indirectly by surface cues (Bhattacherjee & Sanford, 2006; Petty et al., 1986; Schumann et al., 2012). This model can explain how AAEGS functions affect the attitudes and behaviours of museum visitors.

In this paper, I focus on three defining functional properties of AAEGS: informativeness, personalization, and interactivity. The Informativeness of AAEGS means that the system has the function of providing tourists with rich and extensive information content, diversified experience interaction, extensive knowledge and comprehensive information of museum exhibits, which enhances the experience of tourists (Kim & Hall, 2020; Liew & Tan, 2021; Mo et al., 2023). Personalisation offers important updates regarding AAEGS adoption and can offer tourists relevant and appropriate AAEGS personalised information. Personalised user updates employ data based on consumers' past behaviours (Salvadori et al., 2023). Interactivity is human-computer interaction, which means that the user can respond to the system through the human-computer interaction device's when using the system, which is a two-way communication that allows the visitor to interact with the exhibition (Park et al., 2020). These attributes make AAEGS different from traditional museum guide systems. Traditional museum guide systems normally provide a single piece of information to visitors by using sound, images, etc., and visitors can only accept it reactively (Alam & Mohanty, 2023). It compares with AAEGS, it does not have the wealth of information, it cannot be customized according to the interests of visitors, and it cannot be interactive in the exhibition.

Informativeness, personalisation and interactivity have been identified as the core attributes of AAEGS. I study the impact of these attributes in museum exhibitions because they together solve the most key problems that tourists have in their visit experience. Informative, it makes the museum's exhibition content easily accessed, rich and reliably (Mo et al., 2023). It meets visitors' knowledge needs. Personalisation, this attribute meets the visitor's individual

interests and likes in the exhibition (Buhalis & Amaranggana, 2015). It gives visitors a fresh feeling every time when they visit the museum. Interactivity, it allows visitors to engage with the exhibition proactively and not just receive information passively(Liu & Shrum, 2002). It allows visitors to engage more deeply with the exhibition (He et al.)

1.5 Research approach

Considering the purpose of this study, the empirical research method emerges as the optimal approach (Flynn et al., 1990). This approach has been widely accepted and applied in past studies (Bhattacherjee & Sanford, 2006; Eweoya et al., 2016; Liang et al., 2017; Ponsignon & Derbaix, 2020), and is the basis of our findings. Herein, I focus on examining the impact of AAEGS attributes on visitor acceptance, analyzing this effect through the dual perspectives of cognitive and affective involvement. To ensure a broad representation, participants will be randomly chosen from a pool of museum visitors with personal experience with AAEGS in China. I excluded participants who had not used AAEGS from our study. This process reflects users' real interactions with and opinions of AAEGS and improves the general validity and reliability of the findings (Noble & Smith, 2015). I used the Chinese language survey software "Questionnaire Star". It helps me to distribute and collect questionnaires.

Once the questionnaires have been collected, I will clean the data, which focuses on identifying mistakes in the questionnaires to ensure the data is correct and complete (Mayfield et al., 2009). These steps include checking the measurement items for completeness and identifying outliers as well as incorrect answers (Morgan et al., 2004). I will also check for duplicate entries to ensure that each participant's response is counted only once. Then the data were analyzed by using the statistical software SPSS and SmartPLS.

1.6 Structure of the Paper

The structure of this dissertation is organized as follows: In section 2, I will describe the basic

AAEGS concepts. This includes the three key attributes of AAEGS, cognitive and affective involvement, AAEGS acceptance, and the theoretical model, and hypotheses of this study. In section 3, I outline the research methodology. The data collection procedures are described, as well as the statistical analysis of the data. In section 4, I describe the findings that came out of the analysis process, providing an overview of the data through the theoretical lens of the study. In section 5, I discuss the findings of the study. In section 6, I summary the conclusions. I discuss the limitations of the research process and suggest directions for future research.

2. Literature Review and hypothesis development

2.1 AAEGS acceptance

The tourism literature has always emphasized acceptance is an element of the tourism industry's measurement of whether or not to adopt a technology. Many studies have viewed acceptance as an inducer for improving user experience and the practice of technology integrations (Carayannis & Turner, 2006; Davis, 1985; Hasija & Esper, 2022). In the same way, the acceptance is necessary to study for using AI-enabled AR technologies to be effectively deployed in the tourism industry. There are two main reasons: First, acceptance could solve user concerns (Rekimoto & Nagao, 1995). For example, the personalized needs of visitors. Second, acceptance can promote visitor interaction and engagement, and encourage museum staff to improve the visitor experience by integrating exhibition design concepts.

Literature shows that visitor needs have made the travel industry accept new exhibition technologies, and emphasizes the importance of matching technology with users' expectations and the visiting experience (Cimbaljević et al., 2023; Pantano & Corvello, 2014; Ukpabi & Karjaluoto, 2017). Cimbaljević et al. (2023) suggest that museums showing visitors the usefulness of AAEGS functions, this will make visitors understand that these technologies give them a good visiting experience, and this experience will increase the acceptance of AAEGS. Kim and Hall (2020) also advised that museums are able to increase the

functionality of the guided tour system to meet the individual needs of visitors, thus increasing visitor acceptance of the system. According to Leventhal and Scherer (1987), increasing the system's functionality can increase users' cognitive and emotional involvement. This is a good strategy for improving visitor acceptance and increasing visitor involvement (Leventhal & Scherer, 1987).

Acceptance as a dependent variable appears in this study. It refers to the degree to which museum visitors accept and use AAEGS during their visit. It may be influenced by the cognitive and affective involvement of the visitor, which finally leads to a good or bad experience of visiting this museum. This concept includes not only a visitor's willingness to use AAEGS in the first place, but also the willingness to continue to use it and recommend it to others. Acceptance is informed by the interplay between informativeness, personalization, and interactivity (Venkatesh & Morris, 2000). These three factors all contribute to cognitive and affective involvement (Mo et al., 2023). AAEGS acceptance in a museum environment is the visitors' willingness to use this advanced system as part of their discovery of the museum's exhibits. Visitors' reasoned assessment of AAEGS functionality is reflected in cognitive involvement. The user develops an emotional connection with the system creating the affective involvement of the tourists. Cognitive and affective involvement are influenced by three key attributes of the system that determine the acceptance of AAEGS.

2.2 Elaboration Likelihood Model

The Elaborate Likelihood Model (ELM) was developed by psychologists Richard E. Petty and John T. Cacioppo (Kizito & Sun, 2018). It is one of the most influential theoretical models of consumer information processing. According to this model, it is known that the basic outline of information processing and attitude change is the depth and amount of information processing (Cook et al., 2004; Kizito & Sun, 2018; Petty et al., 1986). People will deal with information in different ways depending on their motivations and abilities. It affects how people recognize and think about things and the attitude with which they make

decisions. It also affects the extent to which people collect information and assess their sources. The model suggests that two paths of thinking can lead to the formation and change of an individual's attitudes (O’ Keefe, 2013). One is the central route, in which people think about a concept in a deeper way based on causal logic; another is the peripheral route, in which people consider an issue with more focus on several environmental factors and surface cues (Petty et al., 1986; Schumann et al., 2012).

The center route involves receivers changing their attitudes by carefully thinking about and evaluating the quality of the information and its relevance (Kizito & Sun, 2018). This requires a higher degree of finishing. It's a cognitive process where attitudes change mostly because of message logic arguments and content (Alharahsheh & Pius, 2020). The central route involves a high degree of detail processing, i.e., careful review, reflecting, and thinking about the message (Li & See-To, 2024). Users have the motivation, needs, and ability to process information completely. It is very important when people make decisions, especially in situations with major implications and high relevance. When users have high motivation and needs, they can consider the advantages and benefits of a technology completely, they will use the center route to decide whether or not the technology is acceptable to them (Cook et al., 2004; Li & See-To, 2024).

The peripheral route refers to the fact that information receivers change their attitudes by processing some peripheral cues, such as the credibility of the information the way it is presented, and so on (Li & See-To, 2024; Siu et al., 2022). They are not changing attitudes through the substance of the message, which requires a lower degree of refining. This route deals with less cognition and depends more on surface cues of information (Petty et al., 1986; Sang et al., 2023). It deals with information that is processed to a lesser degree, and people are influenced by factors other than the argument or point of view. For example, cues like music, visuals, or emotion. Influence through peripheral routes can lead to more unstable attitudinal changes. Peripheral routes play an important role in the general environment when people don't have the time, energy, or motivation to think deeply about the information they encounter (Angst & Agarwal, 2009; Bhattacherjee & Sanford, 2006).

Informativeness and personalization influence the acceptance of AAEGS through the central route of the ELM primarily due to their deep engagement with the cognitive processes of users (Cook et al., 2004; Kizito & Sun, 2018). The central route is activated when the message content requires and receives careful, thoughtful evaluation by individuals who are both motivated to process the information and able to do so (Li & See-To, 2024; Sang et al., 2023). This route leads to more durable attitude changes because it involves high levels of cognitive engagement (Craig & Choi, 2024).

Informativeness provides complete, accurate, and relevant content by visitors who find this content material credible, thus improving their center route processing (Mo et al., 2023). As applied to the context of AAEGS in museum settings, refers to the system's ability to enrich visitors' experiences by providing a wide range of insightful content, diverse experiential interactions, extensive knowledge, and comprehensive information about museum exhibits (Choi & Kim, 2017; Chung et al., 2017; Kim & Hall, 2020). Petty and Cacioppo (1986) argued that when visitors find information to exhibit high quality and direct relevance to their interests, they will become more deeply involved and invest a great deal of cognitive effort in understanding and valuing the information. This deep cognitive processing helps in forming strong, well-grounded attitudes towards the technology. Kim et al. 's (2020) study also proved that detailed and informative content improves visitors' understanding of the technology interfaces and their degree of satisfaction, thus increasing the chances of visitors accepting the technology.

Personalization 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 (Morosan & DeFranco, 2016; Roussou & Katifori, 2018). When the system provides personalised services or information, these services and information are linked to the user's interests and past experiences, which increases the motivation of visitors to process the information through the center route (Ricotta & Costabile, 2007; Roussou & Katifori, 2018). 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 (Mo

et al., 2023). Visitors are encouraged to think critically about this information and how it applies to the current visiting environment and knowledge systems.

Both informativeness and personalization demand and drive the cognitive resources of visitors to engage with the content deeply, promoting a thorough evaluation and integration of the information presented by the AAEGS (Ho & Bodoff, 2014; Kim & Gambino, 2016). The visitors processed the information with great attention and noted the details of the information. This state of their focus influences their acceptance of the system in a more stable and long-standing way. Visitor acceptance is based on their clear understanding of the technology (Mo et al., 2023). The impact of technology on the user's museum experience is that the technology meets the needs of the visitors (Khalil et al., 2023). This is a feature of the ELM's central route. These attributes impact visitors' acceptance of AAEGS. They use cognitive and affective involvement to promote purposeful visitor interaction with the technology.

Interactive influences the AAEGS acceptance through the peripheral route of ELM (Komarac & Ozretić Došen, 2021; Ponsignon & Derbaix, 2020). It attracts users with less cognitive effort and users do not process the content in-depth, relying on superficial cues that influence attitudes (Kizito & Sun, 2018; Lin et al., 2022). AAEGS interactivity is that visitors need to interact with the AI or digital exhibits for pleasure and enjoyment. When visitors do not have the motivation or ability to process information in depth, and yet are still influenced by the direct and visible features of the communication (Pallud, 2017). They will use peripheral routes to process information (MacKenzie & Spreng, 1992), such as attraction, newness, or any other surface cues related to the technology.

AAEGS interactive functions include user interface design, user experience design, function enablement and feedback mechanisms (Kokash et al., 2024). Interactive functions need to suit the user's habits, language and culture. Those can make the software easier for users to understand and use. These features can enhance the user's visit experience without the user needing in-depth knowledge of the content (Park et al., 2020). These interactive functions

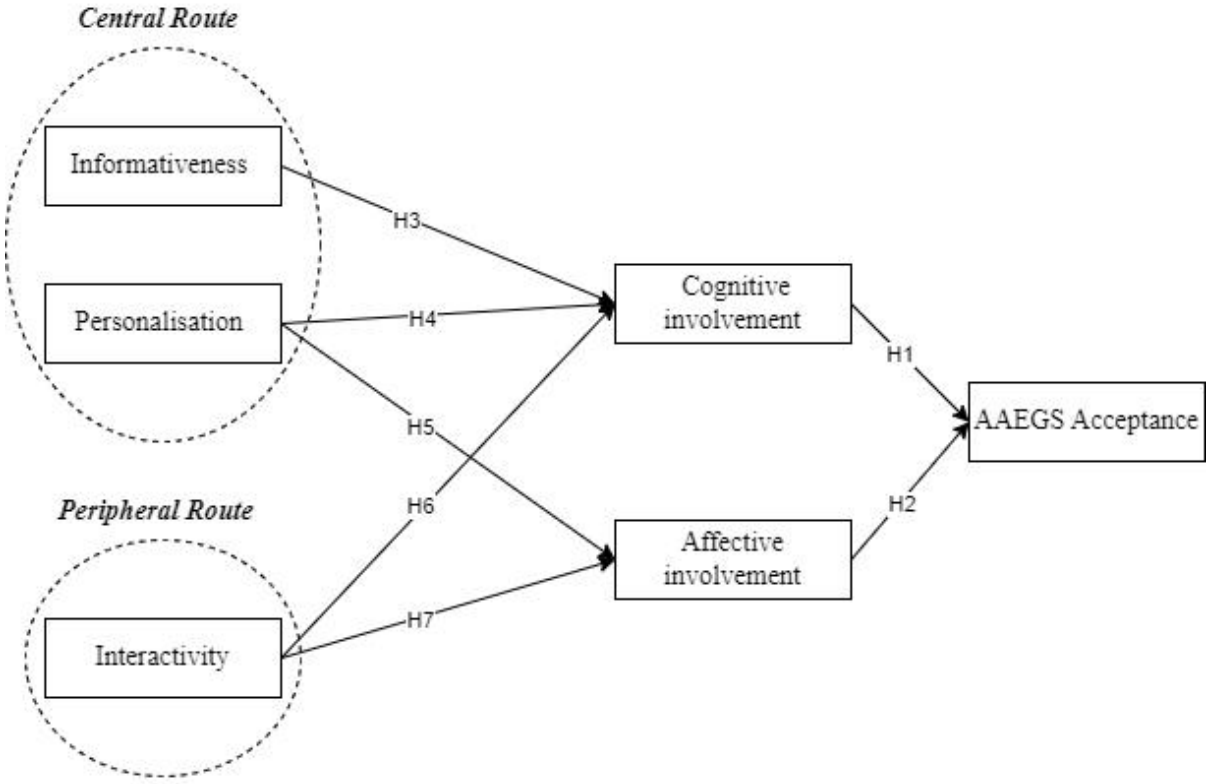
allow visitors to feel involved and interested in the exhibition, and create a positive emotional experience for them (Lin et al., 2022). Park and Yoo's (2020) study showed that interactive functions induced visitors' sense stimuli and emotional waves, which can effectively impact users' attitudes and behaviours. The system's interactive elements provide a strong feeling of involvement to the visitor. The feeling of involvement reflects that AAEGS is friendly and fun, although the user is not involved in in-depth content processing (Turan et al., 2015). In a museum environment, visitors tend to enjoy the process and experience interacting with the exhibition instead of analysing and processing the information in depth (Wu et al., 2021). Therefore, interactivity promotes acceptance through peripheral routes. Its aspects of immediacy, pleasure, and low cognitive demand make users more likely to employ and enjoy the system without having to engage deeply in the content of the information (Huang et al., 2010; Perse, 1998). It is experience and emotional engagement-led, allowing AAEGS to attract more museum visitors.

Research focussing on ELM has used attitudes as a key dependent variable affecting a multifaceted review (Bhattacherjee & Sanford, 2006; Cook et al., 2004; Petty et al., 1986). However, research in information and communication has already looked at cognitive and affective engagement as influencing factors (Angst & Agarwal, 2009), to build researchers' knowledge of the relationship between technology acceptance and user experience (Jiang et al., 2022; Kokash et al., 2024; Lowry et al., 2012; Novak et al., 2016). It is interesting to note that Novak et al. (2016) discussed the influence of technology and system attributes - i.e. informativeness, personalization, interactivity, and responsiveness - on customer engagement, reactivity, and emotional state during use. Ethier et al. (2008) also highlighted the influence of technological attributes in the cognitive process of causing an emotional response in users, the wealth and intelligence of the system's attributes cause a good emotional reaction in customers, keeping them interested in and using the technology on a continued level. Similarly, research on AR technology acceptance has shown that both cognitive (e.g. perceived information quality and tailoring) and affective (e.g. enjoyment and curiosity) motivations contribute significantly to acceptance and engagement intent ((Éthier et al., 2008; Oyman et al., 2022). This range of studies has highlighted the complexity of technology

acceptance. In particular, the influential relationship between user acceptance and the relationship with new technologies underlines the need for research on cognitive involvement and emotional engagement (Sang et al., 2023).

Based on previous studies, I propose a model as shown in Figure 2. The aim is to investigate the influential role of AAEGS attributes including informativeness, personalization and interactivity (Faisal et al., 2020). The goal is to evaluate the role of AAEGS multidimensional features and attributes and to determine which attributes improve cognitive and emotional involvement and better experiences, ultimately leading to AAEGS acceptance and continued use by users in Chinese museums.

Figure 2 Research Model and hypotheses



2.3 Involvement

Zajcikowski (1986) explains that involvement comes from one's internal needs, values, and interests that push a person toward an object, concept, or event. The literature has discussed this concept in several ways, including engagement, gameplay, satisfaction, attitudes, loyalty, intention, and perceived availability, all of which are based on a positive experience (Craig & Choi, 2024; Oyman et al., 2022; Wünderlich et al., 2013; Zhuang et al., 2020). The literature is clear on the common understanding. Positive experiences can amplify engagement, which increases users' intention to use the system (Morosan & DeFranco, 2016). Researchers have found a positive relationship between hedonic components in modeling users' positive attitudes toward technology (Lim et al., 2012). The hedonic pleasure felt in user experiences increases their involvement and continued use (Lim et al., 2012; Reychav & Wu, 2015; Wu et al., 2021; Zhang et al., 2015). Hedonic factors are defined as pleasures in the user experience that move past the utilitarian (Wu & Kuo, 2008). The hedonic elements of the system's design extended the definition of involvement from the purely functional to all areas of user emotion and satisfaction (Lim et al., 2012).

The level of a user's involvement with stimuli—whether objects, situations, or activities—is measured by the user's perception of the stimulus's appropriateness and relevance (Kim & Hall, 2020). Within 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 (Craig & Choi, 2024). It is powered by cognitive and affective factors (Morosan & DeFranco, 2016). The definition of involvement is basic to understanding and interpreting user attitudes and behaviours (Enopadria & Putri, 2022). Visitors' greater involvement in an exhibition creates a stronger motivation to study the content in depth (Perse, 1998). This study process can motivate the users, which leads to visitors' clear behaviours (Kim & Hall, 2020). Visitors' level of involvement influences the way they process information and also reflects their emotional state during a visit. A digital exhibition in the museum can create an engaging environment

for visiting. This will provide a positive motivation for users to engage with the exhibition. (Guo et al., 2021). Kim et al. (2007) argued that the level of involvement is key in showing user behavioural intentions. Involvement should be separated into two parts: cognitive involvement and affective involvement. Each part has a different impact on user behaviour. This highlights the complexity and importance of involvement in the digital field (Celuch & Slama, 1998; Faisal et al., 2020; Perse, 1998; Reychav & Wu, 2015).

Cognitively involved is the rational thinking that comes from utilitarian, pragmatic, and cognitive motives (Siu et al., 2022). It is a state of mind in which the learner stays positive and is willing to try to understand something and put it into practice. It also extends to how learners attempt to go beyond what is required and accept challenges. It begins with emotional engagement, behavioral engagement, and social engagement and ends with cognitive investment (Caputo & Evangelista, 2019; Reychav & Wu, 2015). In the AAEGS environment, it is expressed through the visitor's key mental processes of recognition, articulation, and attention (Balakrishnan & Dwivedi, 2021; Perse, 1998). A definition of recognition is when people save received messages in their memory and compare this messages with their previous knowledge acquisition in order to know whether or not these messages are new knowledge (Newen et al., 2015). Attention is defined as people's intentional focusing and distribution of knowledge that has been gained (Hartono & Raharjo, 2015). Cognitive involvement makes visitors highly efficient in content and information processing (Marangunić & Granić, 2015). In this study, the visitors engage with the exhibition through AAEGS and their cognitive involvement will be strongly related to the content of the exhibition.

Literature suggests that visitors' cognitive involvement can influence their willingness to accept AAEGS (Morewedge & Kahneman, 2010; Worth & Mackie, 1987). This literature highlights that psychological engagement plays an imperative role in technology adoption (Craig & Choi, 2024; Su et al., 2019; Zhang et al., 2006). When visitors use AAEGS, they are engaged in the process of getting to know the exhibition and understanding the information and knowledge that the exhibition provides. They will evaluate the system's provision of

contents in relation to the exhibition's relevance, usefulness and helpfulness (Celuch & Slama, 1998; Faisal et al., 2020). Cognitive involvement explains the visitors' process of getting knowledge or information and also how they process the information, which is the most basic psychological process of human beings (Morewedge & Kahneman, 2010; Oliver, 1993). Greater depth of cognitive involvement can result in a change in users' attitudes and continued use of the technology (San Martín & Del Bosque, 2008; Tung et al., 2017). Research has shown that when visitors use AAEGS in a museum environment, they are able to deeply cognitively engage with the content of the exhibition. They are more able to experience the benefits of AAEGS and recognise its benefits as a tool for learning and exploring the exhibition (Bhattacherjee & Sanford, 2006). When visitors believe that AAEGS is able to meet their needs effectively, they develop cognitive trust in the system, which directly affects their willingness to accept and use the system (Morosan & DeFranco, 2016). Therefore, the AAEGS functions and attributes influence the cognitive engagement of the visitors, and the depth of the visitors' cognitive involvement leads to their acceptance of the system in a rational way. Hence, I hypothesize:

H1: Cognitive Involvement has a positive effect on AAEGS acceptance.

Affective engagement, which is rooted in hedonism, derives from value expression or emotional motivation (Celuch & Slama, 1998; Enopadria & Putri, 2022; Hartono & Raharjo, 2015). 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). The main form of affective involvement is the affective investment that users make in the environment (Tung et al., 2017). It is shown in the emotional response that users show to the system, for example, whether the user's internal feelings or reaction to the content provided is positive or negative (Lee & Lim, 2010). In this study, affective involvement is explained as the user's affective connection with the exhibition, and emotional dependence on the exhibition (Alnawas & Hemsley-Brown, 2018). Affective involvement is the visitor's emotional response to using AAEGS, an expression of the visitor's self-created emotions as

they engage with the system. It shows the way in which users connect with the content and design of the system on an emotional level.

The AAEGS' affective involvement is an important catalyst for tourists' acceptance of the technology. It develops an emotional connection between visitors and AAEGS (Enopadria & Putri, 2022; Hartono & Raharjo, 2015). This dimension discusses the emotional element of the user experience that is the driving factor in visitors' acceptance and continued AAEGS adoption. The body of literature underscores this dynamic, illustrating how emotional investment—manifested as pleasure, satisfaction, and emotional gratification from interactions with AAEGS—crucially molds users' attitudes toward the technology (Celuch & Slama, 1998; Kim & Sung, 2009; Verkijika, 2020). An emotionally engaging experience elevates the perceived value of AAEGS, thereby increasing the likelihood that users will harbor a favorable attitude toward the system and influencing their acceptance decisively (Mogaji et al., 2024). Findings from human-computer interaction research suggest that technology can cause emotional resonance with visitors to an exhibition, making it more possible for the technology to be accepted and incorporated into everyday use (Surendran, 2012). AAEGS creates an emotional connection with visitors that increases visitor satisfaction and loyalty at exhibitions. If visitors develop positive affective engagement, they will take it upon themselves to promote the exhibition and recommend it to their friends, leading to a wider adoption of AAEGS.

ELM suggests that users' affective involvement greatly impacts technology acceptance when their motivation or ability to process detailed information is low (Haugtvedt & Petty, 1992; Petty et al., 1986). Visitors' affective responses to AAEGS may result in their acceptance of the system using less cognitive effort but positive experience of human-computer interaction (Steel & Lloyd, 1988; Zhang et al., 2006). This highlights that affective factors are one of the key factors in changing users' attitudes and their acceptance of technology. The affective factor creates an affective engagement connection for visitors in the museum environment (Faisal et al., 2020). When visitors use AAEGS, they may have a positive or negative affective experience. When this affective connection is positive and happy, it will improve

their acceptance of the system (Soni, 2017). Technicians designing AAEGS with an emotional elements can make the visitor's journey through the museum environment more satisfying and make the visitors more accepting of the technology. Hence, I hypothesize:
H2: Affective Involvement has a positive effect on AAEGS acceptance.

In the field of information and communication, cognitive and affective involvement are two factors in the development of a user's psychological structure (Faisal et al., 2020; Putrevu & Lord, 1994). Based on earlier studies(Celuch & Slama, 1998; Perse, 1998; Su et al., 2019), involvement is believed to be the key point that shapes users' behaviors and attitudes. Users' cognitive involvement affects their process of the information they receive, which leads them to make a decision to use or not to use the system (Tung et al., 2017). Emotional engagement is an emotional connection between the visitor and the human-computer in the process of using the system (Lee & Lim, 2010). Visitors will have emotional expressions of joy, anger, sadness, and happiness in the process of using the product, which will lead to them liking or disliking the exhibition (Lee & Lim, 2010; Schachter & Singer, 1962). In AAEGS, cognitive engagement is enabled through interactive functions that require the user to be involved and process the information intentionally. Affective involvement is made possible by the quality and engaging nature of immersion, which fosters an emotional connection between the user and the system (Jeong & Shin, 2019; Novak et al., 2016). Ethier et al. (2008) highlight that cognitive processes are not only cognitively rational but also emotionally engaging. The design components in AAEGS, such as AR visual design, interface design, and content relevance, develop users' interest and develop their rich affective states, which support the system's validity and users' continued willingness to use it (Éthier et al., 2008).

2.4 Informativeness, Personalization, and Interactivity

The informativeness of AAEGS applied to museum environments refers to the ability of the system to enable the visitor experience to be rich through the provision of a range of insightful content, varied and experiential interactions, broad knowledge, and comprehensive

information about the museum exhibits (Chung et al., 2017; Han et al., 2018). AAEGS' informatisation function can provide visitors basic information about the exhibition, such as visiting routes, names of exhibits, and so on. It also provides information that involves deeper processing, for example, information about 3D models of exhibits, details of artefacts, and so on, providing visitors with a multi-dimensional experience of exploring the exhibits (Han et al., 2018). It helps visitors to better understand the historical meaning of the exhibits and to appreciate the beauty of the exhibition (Kamariotou et al., 2021). Therefore, informativeness highlights the depth, breadth and exhibition relevance of the information provided by the system (Salvadori et al., 2023). The visitors get information of value on this museum trip which helps them to develop their knowledge of the history and heritage. When the visitors get very rich information about the exhibition, which meets their knowledge needs about this exhibition, they will engage in active learning and cognition.

Visitors' cognitive involvement needs the visitors engage deeply with the AAEGS while visiting the museum (Craig & Choi, 2024). When they interpret, analyze, and relate new information to their current knowledge, a deeper level of engagement is created (Haugtvedt & Petty, 1992; Kim & Sung, 2009; Su et al., 2019). Cognitive involvement at a high level is a key profile of self-learning for visitors (Perse, 1998). Visitors who tend to get more knowledge about the exhibition and take on cognitive challenges, the more they will use the AAEGS functions to get information. ELM's central route explains that when information is relevant and material, it is likely that individuals will process the information at a high level of cognitive detail, which influences their understanding and retaining of the information (Kizito & Sun, 2018; Petty et al., 1986).

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). This met their desire for knowledge, improved their ability to enjoy and understand the exhibits, and promoted their interaction with the system (Liang et al., 2017). 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 (Forgas‐Coll et al., 2017; Morosan & DeFranco, 2016). However, this information may not cause the visitors to become involved affectively. The dissociation of cognitive and affective processing (Soni, 2017) 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). A well-designed exhibit content's can change the visitors' knowledge environment and promote their cognitive activity and engagement without impacting their emotional engagement (Park et al., 2007; Tung et al., 2017).

Therefore, informativeness plays an important role in modeling cognitive involvement in museum environments. AAEGS' informational output not only engages visitors' attention but also uses high-quality, intellectually stimulating information to keep them involved. Hence, I hypothesize:
H3: Informativeness has a positive effect on cognitive involvement.

The impact of personalization on emotional engagement was also personalisation in AAEGS can amplify cognitive involvement and produce acceptance as the visitor's process meets their needs for the exhibition (Kim & Gambino, 2016; Morosan & DeFranco, 2016). It allows users to exchange information with each other and with the system that can be used to meet their personal preferences and needs, leading to links and senses that go above and beyond the interaction (Roussou & Katifori, 2018). This kind of tailored approach allows AAEGS to provide information and also create compelling and immersive experiences that connect with each user. It allows users to enjoy their learning styles and preferences and to develop a deeper cognitive knowledge of the content that is presented in AAEGS (Mo et al., 2023). AAEGS provides dynamic interactivity that pushes users to move from becoming passive viewers to active players in the learning experience (Pallud, 2017). Active learning and acceptance are important factors in visitors' cognitive engagement, which is perfectly in line with their internal motivation to learn, thus promoting deeper cognitive involvement (Su et al., 2019). There is a relevance between personalized content with cognitive involvement, and

when visitors find information directly applying to their interests, they naturally tend to look deeper and engage more completely (Lin et al., 2022).

According to Kokash et al. (2024), it is highlighted that AR can increase user engagement by providing personalized and immersive content. Therefore, AI-enabled AR in AAEGS shows an upgrade in personalization by collecting and analyzing visitors' past information through AI and giving them accurate information about this exhibition, which is catered to their needs (Kokash et al., 2024). When AAEGS publishes information that is resonant with visitors' interests, preferences, and needs, it draws visitors into an involved cognitive process across the exhibition. During the cognitive involvement process, AAEGS keeps updating and providing information on different contents to make sure that visitors have the sense of curiosity to continue exploring, which in turn leads to deeper cognitive processes (Jeong & Shin, 2019). This deep level of interaction makes the exhibition experience more rewarding, prompting a long-lasting, positive attitude towards AAEGS. It ensures that the information provided goes beyond simple viewing by centering on the detailed drawing of the content and the cognitive engagement of the visitor. Making it both intellectual and affective for visitors to appreciate (Faisal et al., 2020).

Research in education and digital technology has shown that personalized push functions, which are based on deep analysis of user preferences, are possible (Tarhini et al., 2016; Valente et al., 2016). Depending on the environment, time of day, and other factors, the recommended content is adjusted to provide a more personalized experience for the user in a more dynamic way (Bronzin et al., 2021). Content that is tailored to an individual's preferences and understanding level can increase visitors' cognitive engagement (Putrevu & Lord, 1994; Teltzrow & Kobsa, 2004). In the field of interaction, personalized systems have been found to increase visitors' satisfaction and acceptance, and also to encourage them to process content at a deeper cognitive level (Faisal et al., 2020). Kim et al. (2009) provide proof showing that having a personalized environment can bring visitors a better visiting experience and higher levels of engagement. Hence, I hypothesize:
H4: Personalization has a positive effect on cognitive involvement.

The connection between the personalization features of AAEGS and users' affective involvement is reflected in the content presentation, which shows the importance of tailored user experiences for customers' affective involvement(Kim & Gambino, 2016; Morosan & DeFranco, 2016; Ricotta & Costabile, 2007). The personalization function in AAEGS changes the traditional content output and provides the user with content that has the customer's personal favorites, past behaviors, and emotional experiences (Craig & Choi, 2024). During the visit, each customer's experience is created uniquely, making the visitor feel as respected and treated as possible. Evidence-based research has shown that personalized content is one of the key factors in visitors' positive involvement in the interaction and in developing an affective reaction, which develops an emotional connection between the customer and the system (Enopadria & Putri, 2022; Wu et al., 2021). Research in human-computer interaction confirms this point of view, arguing that personalization can significantly magnify the emotional experience by inculcating a feeling of attention and care, which enhances affective involvement (Craig & Choi, 2024; Ricotta & Costabile, 2007).

The impact of personalization on emotional engagement was also confirmed in the background of the technology acceptance model (Kim & Gambino, 2016). The agreement reached between the personalized service and the user's needs influences the customer's cognitive and affective view of the system, as well as the user's enjoyment and satisfaction with the interaction (Craig & Choi, 2024; Ho & Bodoff, 2014). AAEGS reaches users on an effective level by meeting visitors' personalized needs and building a personalized recommender system through complete data collection under conditions that protect visitors' privacy. The theory of emotion suggests that personalized interactions (Teltzrow & Kobsa, 2004) can elicit significant emotional responses from visitors (Morosan & DeFranco, 2016; Perse, 1998). Personalization in AAEGS is a key factor in a visitor's decision to make an emotional investment in a museum. In summary, the literature confirms that personalization works in developing emotional connections. Hence, I hypothesize:
H5: Personalization has a positive effect on affective involvement.

The interactivity of AAEGS is a new way of displaying information, instead of the traditional

exhibition in which the user's input is required to display the results. It reflects the system's automatic response in combination with AI and is an example of the rapid and dynamic exchange of information between the user and the system (Burgoon et al., 2000; Ricotta & Costabile, 2007). AAEGS provides users with immediate and relevant information when they use interactive functions to users to quickly respond and match their needs (Liu & Shrum, 2009). This fast response-ability is a basic function of current digitization systems and one of the main factors affecting the visitor's experience (Gong et al., 2022). It meets the expectations of modern society for fast and seamless communication with digital platforms (Zhang et al., 2006). Interactive information is communicated through AR to represent rich media content that interacts with the user through AI. It forms an output that creates a lively exhibition environment (Sung et al., 2021). Dynamic information and media content respond to users' active engagement and curiosity (Novak et al., 2016). An insight from tourism research highlights the important role of interactivity in enhancing the visitor experience (Lin et al., 2022). Evidence suggests that interactive technologies, including AR guides for historical sites or museums, increase visitor satisfaction significantly by providing tailored and engaging means of discovering and understanding exhibitions (Chen et al., 2020). These technologies move the visitor experience from passive information reception to active and engaged exploration and significantly impact memory retention and overall satisfaction.

However, some studies have confirmed technical accessibility, users' digital literacy, and the risks of information overload as current challenges for AI technologies combined with AR technologies (Dwivedi et al., 2023). The achievement of the best interactivity requires a fine balance that not only engages the user but does not mask other physical elements (Yawised et al., 2023). For example, the historical meaning of what the actual exhibits' patterns represent. In ELM's theoretical model, the delicate role of interaction is through peripheral routes that show its ability to model attitudes and behaviors (Kizito & Sun, 2018). In cases where deep engagement with content may not be the main motivation, the AAEGS technology's newness, the simple nature of the interface, the good system feedback mechanisms, and the interactive experience with gameplay are the best motivations for users to accept and use AAGES, even users who are less likely to deeply cognitively engage with the content (Sung et al., 2021).

This peripheral influence highlights that AAEGS must be designed with engaging content, simple and easy-to-use interfaces, sufficient gameplay, good interactive feedback mechanisms, and other elements that can have a positive impact on the user.

AAEGS interactions encourage visitors to take an active role in learning and exploring during their visit. This exploring allows users to both actively get information and add to the visitor's fun and risk-taking experience, and it creates a strong connection between the user and the content (Chung et al., 2017; Han et al., 2018; Pallud, 2017). Interactivity increases users' cognitive involvement by promoting an active learning experience for them (Ponsignon & Derbaix, 2020). When visitors interact with the exhibition through the AR interface, they are not only information discoverers but also active players in the learning process (Zhang et al., 2006). 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 engagement for tourists (Lin et al., 2022). For example, when users control digitized 3D models of cultural artifacts, they can think spatially as they view them from different angles and bring together information from the visual space and hearing information to enhance their understanding and memory retention (Wu et al., 2023). Hence, I hypothesize:
H6: Interactivity has a positive effect on cognitive involvement.

Interactivity in AAEGS is the basis for enhancing the museum visitor experience, it creates a dialogue and reaction between the user and the system(Liu & Shrum, 2009). This kind of combined AI interactivity is more than simply reactive, it allows visitors to have an adventurous experience that has tailored information about the user's current and past as well as producing shares with other users (Burgoon et al., 2000). This interactivity allows AAEGS users to become active players in the dialogue instead of passive receivers of information. In comparison to these two situations, the active engagement is the visitor's recognition and interest in the exhibit (Ponsignon & Derbaix, 2020). Passive acceptance of information is something that causes visitors to quickly forget the information acquired and lose their sense of interest. Active interactive engagement improves their affective involvement with the

content. This study has highlighted the basic role of real-time responses and appealing interactive elements in developing user satisfaction and enhancing emotional connection through a digital interface (Ricotta & Costabile, 2007; Wünderlich et al., 2013)

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). The interactive element of AAEGS creates a feeling of newness and engages the user through continuous updates and content customization. More importantly, it will emotionally connect with the visitor, developing a personal feeling of connection to the system and increasing customer satisfaction (Enopadria & Putri, 2022). Hence, I hypothesize:
H7: Interactivity has a positive effect on affective involvement.

3. Methodology

3.1 Research Paradigm and method

To analyse the research model, this study embraces an epistemological perspective that is positivism and objectivism. Positivism, an epistemological stance, asserts that knowledge can be derived from observable phenomena and must be empirically verified (Comte & Bridges, 2015; Park & Yoo, 2020). The view is that there is indeed an external reality that is in principle knowable by man and which can be investigated through scientific means (Clark, 1998). Objectivism substantiates this perspective by claiming that facts are real and exist, and that whole some other kind of existents are potentially created by the perceiver, and therefore, facts can be sought by procedures that minimize the subjectivity of the perceiver; thus, the researchers are capable of finding facts about the world as they exist (Jonassen, 1991).

When it comes to designing the framework intended to conduct and empirical investigation of acceptance in relation to the proposed AAEGS, exactly for this reason, it is deemed better to adhere to the principles of positivism. Positivism can be aligned to the belief that reality

exists, and it can be examined and interpreted in an objective way without influencing external events being considered (Comte & Bridges, 2015). Following the basic tenets of positivism, it assumes that the social world is as amenable to observation and logical analysis as the natural world (Alharahsheh & Pius, 2020). 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 (Park & Yoo, 2020; Sadamali Jayawardena et al., 2023).

For the understanding of acceptance with its multiple aspects related to informality, personalization, and interactivity, the concept fits perfectly (Liu & Shrum, 2009). It further supports the concept from the theoretical framework that acceptance cannot be viewed as an isolated event or a single behaviour, but rather as a complex construct that incorporate many dimensions and variables. 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 (Alharahsheh & Pius, 2020; Clark, 1998). This is cansistent with the notion that acceptance is a function of certain common characteristics as well as the impact they create on the users (Alharahsheh and Pius, 2020).

Objectivism also facilitates this analysis because the advocated realities and opportunities of the AAEGS acceptance extent beyond individual perceptions and are governed by principles that are objectively rational and can be thoroughly investigated (Peikoff, 1993; Pendlebury, 2011). When used in this context of opinion and feedback, survey data is treated as measured data regarding the existence of the system and its characteristics and efficiency (Leary et al., 1986). Thus, by generalizing and looking at these tendencies and relations of these individual experiences, this study introduces some general tendencies which may occur to be valid for the related segments of users whether they have a prejudice or have observed something with the given pattern (Pendlebury, 2011). This allows researchers to introduce and manipulate features such as information, personalization and interactivity incrementally in the framework and find out their impact on acceptance, as highlighted by Ning in 2017. For example, if a

large number of respondents said that the content made available to them by the AAEGS makes their museum experience more enjoyable, the statement could be taken as an objective evidence of the functionality of the system in this regard. Likewise, if the feedback indicates a problem of poor interactivity, then it would mean that there are areas that need enhancement, which are most probably relevant to all users including those who answered the feedback (Ning, 2017). In this way, by exploring those basic psychological factors, the study avoids dependency on personal perceptions and gives the valid results relevant to the general population of museum visitors (Tarhini et al., 2016). Applying this approach helps to avoid drawing conclusions that are not supported by empirical evidence and leads to better decisions regarding the improvement of AAEGS to meet the needs of the users.

Positivism supports the use of quantitative methods to test pre-specified concepts, structures, and hypotheses that are derived from the existing theory (Alharahsheh & Pius, 2020; Gregg et al., 2001; Kaplan & Duchon, 1988). It argues that social occurrences are quantifiable and that it is possible to arrive at generalizable causal determinations, which makes it a useful approach to study the drivers of acceptance of AAEGS. As this research adopted the positivist paradigm, the study sought to measure the level of information, personalization, and interactivity that influences the acceptance of AAEGS among the museum visitors, which aligns with the research's objective of quantifying the impact of the chosen attributes in the context of the overall user acceptance, while embracing a highly scientific approach to analyzing the researched phenomenon (Lu et al., 2019).

It is therefore important that any researcher has adequate knowledge of the philosophical framework within which any research method develops in order to properly position the investigational stance of any research work. In the realm of social sciences, two primary research paradigms dominate: research methods and techniques for conducting both quantitative and qualitative research. Quantitative research is more structured, as it uses surveys, questionnaires, and statistical data to quantify issues and analyze trends. Their goal is to generalize the results from a sample population to the total target population with certain margins of errors to give a general and wide-ranging conclusion (Smith, 2020). On the other

hand, there are qualitative research approaches, which focus on the perceptions of people. They use qualitative data collection methods which include interviews, observations and content analysis, which are either unstructured or semi-structured. This approach is usually oriented towards the identification of the reasons, attitudes, and motivations, which makes this approach more in-depth and multilayered in terms of research topics (Kaplan & Duchon, 1988).

Therefore, the type of research chosen is consistent with this paper, as adhering to the positivist paradigm where quantitative research is organized into a clear approach towards analyzing, testing, and measuring quantitative information in terms of hypotheses and variables. A quantitative approach is less flexible because it entails researching phenomena and the data collected in some form with the use of quantifiable measures of selected instruments (Bloomfield & Fisher, 2019; Goertzen, 2017; Sukamolson, 2007). This methodological choice is also connected with the chosen overall research paradigm of the study that implied objective approach and conduct of the research aimed at providing accurate and applicable results that could be used by the implied subject as basis for recommendations.

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 (Krosnick, 2018). For the data collection tool of this study, a self-administered close-ended close questionnaire was employed which incorporated a 7-point Likert scale, a form of quantitative reasoning methodology that quantifies qualitative opinion into proportionate numbers (Joshi et al., 2015; Tarka, 2017). This scale enables the respondents to capture their perceptions of the actions that the AAEGS has taken to provide informative, personalised and interactive content aligned to what Jebb et al. (2021) suggests could enable organisational adoption. Focusing on the methodology specifically chosen, the structured questionnaires and Likert scales keep positivism rules in data collection, which can minimize the effect of subjective attitudes of a researcher and focus on the objective characteristics (Jebb et al., 2021). This format helps one

analyze the relationships between distinct parameters, for example, the extent of user acceptance as influenced by the characteristics of AAEGS, which can be further analyzed empirically to verify the hypotheses formulated in the research study to either be true or false. This quantitative setting supports the necessary empirical research validity of positivist research and strengthens the reliability and generalizability of research findings in academic and professional fields that focus on concerned with AAEGS in museums.

3.2 Variables and measurement

Many of the measures were directly borrowed from other scales and modified to suit our purposes. As indicated in Table 1. AAEGS Acceptance (EA) was assessed through three reflective items designed to capture the depth of users' engagement and commitment to utilizing AI-enabled Augmented Reality Exhibition Guide Systems in museum settings. This scale was adopted from Han et al, (2018) and Lee et al, (2011) with certain modifications to the context of technology in a museum. The scale items are tailored to capture the behavioural intentions of the museum visitors with regards to AAEGS, which is a key attribute that determines the sustainability of the system and its institutionalisation into the visitors' experience. For instance, questions like “questions the user's willingness to come back and engage with the AAEGS regularly”, “probes the user's frequency of usage”, and “determines the user's loyalty to engage with the AAEGS frequently” were used (Han et al., 2018). Every item of these is assessed with a seven-point Likert scale which includes “strongly disagree” to “strongly agree”, which helps to capture the complexities of user acceptance. This way of operationalizing acceptance not only corresponds to the common practices in the context of technology adoption research but also incorporates the specific measurements of user behavior that could be pertinent to the museum context. The study seeks to quantify acceptance of AAEGS through a systematic way in order to determine the level of acceptance of the advanced systems in the society and hence help in future development and implementation of similar technologies in cultural institutions.

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 et al., 2020)
Personalization (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)	INT 1: 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.	(Lee et al., 2018)
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)
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.	(Faisal et al., 2020)
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.	(Han et al., 2018) (Lee et al., 2011)

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 Su et al. , (2019) , Soni, (2017), Reychav & Wu, (2015) and Faisal et al. , (2020). , each design aims to capture different facets of how visitors process, store and utilize the information provided by AAEGS. Example items include “assesses

whether AAEGS captures and retains visitors' attention, signifying initial engagement," "evaluates how thoroughly visitors engage with the content, suggesting deeper cognitive involvement," "the visitors' ability to recall information after their visit, indicating the system's impact on memory," "how long information stays in the visitor's mind, a sign of sustained engagement," "visitors perceive AAEGS as essential for interacting with exhibits, reflecting its perceived importance," "the overall enhancement of the museum experience attributed to AAEGS by the visitors," "how pertinent the AAEGS features are to the exhibits of interest, crucial for providing tailored content". These measures, rated on a 7-point Likert scale, provide a comprehensive understanding of how AAEGS fosters cognitive engagement, which is vital for its successful implementation and acceptance in the museum context.

Affective involvement, this study quantifies affective involvement using four specific measures that reflect the emotional engagement of visitors with the AAEGS during their museum visits. The four measures were taken from Faisal et al., (2020). Example items include "Assesses whether AAEGS has successfully captured visitor's interest in the exhibition," which is crucial for initial emotional engagement. "Seeks to measure the extent to which the system influences the curiosity of the visitors in order to make them learn more," "looks at how the system adds value to the experience of visiting the museum through adding an aesthetic value in the process," and "assesses how the system elicits an emotional response from the visitors in order to connect them to the stories and histories that are portrayed in the exhibits. These indicators are meant to capture a variety of feelings from first impression to long-term interest, allowing for an overall appreciation of the impact of the AAEGS on the visitor's emotional engagement within the museum (Su et al., 2019). By measuring these aspects of affective involvement, the study seeks to show how, through the design of AAEGS, an otherwise ordinary visit to a museum can be turned into an emotionally engaged experience. The items used were on a 7-point scale that included options such as strongly disagree, disagree, slightly disagree, neutral, slightly agree, agree and strongly agree."

The amount of information is defined by four indicators. All four measurements were taken

from Kim et al. (2020). Example items include: First, how the proposed system increases knowledge and interest in exhibitions; this section shows how the system improves the quality of educational experience of visitors. Second, experience diversity indicates that the system can accommodate different learning styles and therefore should be popular among learners. Third, knowledge acquisition reflects the extent of information that visitors obtain when visiting an attraction, thus transforming their visit into an informative experience. Lastly, information collection determines how complete the content presented by AAEGS is, so that visitors can have a balanced view of the exhibits (Zhang et al., 2006). Taken together, these measures capture the various ways in which information contributes to the success of AAEGS in museum contexts. Thus, having offered diverse, complex, and relevant content that can effectively increase the cognitive engagement, thereby increasing visitor satisfaction and system adoption. Questions were answered using a 7-point Likert scale, with 1 being the option “strongly disagree” and 7 representing the option “strongly agree”.

Personalization within AAEGS greatly enhances the experience of museum visitors since it sets up a unique encounter for a given user (Jeong & Shin, 2019). The effectiveness of personalization is measured through a meticulously designed scale: PER1 determines the effectiveness of the system to deliver personalized content and guarantee that it meets the interests of the end-users. PER2 measures the level of control the system offers to users and their ability to change the type of information they receive; it increases user engagement and satisfaction. In the case of PER3, it validates if the information being delivered to the user is relevant to the user's needs. The three measurements mentioned above are from Jeong & Shin (2019), but are customized for each learner. In this way, not only does the amount of information that the visitor receives becomes more relevant, but his/her interaction with the exhibits in the museum also becomes more diverse. By allowing visitors to change and adjust to their own liking, AAEGS enhances the visitor experience by engaging with the museum in a very memorable and meaningful way. Thus, each component of the personalization scale is designed to guarantee the perfect congruency of the system with the expected perception of the user, thus improving overall satisfaction and promoting more thorough interaction and multiple sessions. This is especially important to make the experience a one-of-a-kind and to

ensure that it is memorable every time the visitors engage with the organization and its exhibits. All items were on a 7-point Likert scale, the options of which were “strongly disagree,” “disagree,” “neutral,” “agree,” “slightly agree,” “mostly agree,” and “strongly agree.”

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 Lee et al. (2018). The interactivity scale measures several dimensions: INT 1 measures the extent to which AAEGS is able to provide access to a range of visitor interactions, including questions and answers, which enhance the user experience and engagement with the exhibition. INT 2 focuses on the ability of the system to respond to user queries and interaction effectively, so that users are not discouraged by lack of response, keeping the users active in the process. INT 3 assesses the total level of interactivity of the users as they visiting the museum and shows how AAEGS engages users and enables interaction through the process of the exhibition. Finally, INT 4 explores the ease with which users can share information and content, enhancing the social and collaborative aspects of the museum experience. These aspects of interactivity contribute to a satisfying and valuable visit and encourage a more profound engagement with content as well as a better grasp of the exhibition. Through encouraging active participation, AAEGS not only changes the basic structure of a museum visit, but also increases the enjoyment of visitors and the possibility of revisiting.

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 et al. (2015) . 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. Age also plays a key role in technology usage because people of different age groups may have different levels of comfort and usage of new technologies (Morris & Venkatesh, 2000). It is also clear that gender influences acceptance of technology, as men and women may have different reasons and perceptions of new systems (Morris & Venkatesh,

2000). Education and income levels: Those with high education and income levels will be accessible to the technology and may result in them having higher acceptance towards it (Tarhini et al., 2016). Last, the overall frequency of museum visits can also serve as a representative measure of cultural attendance, since those who frequently visit the museum may have different expectations and perceptions towards AAEGS (Brida et al., 2016).

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, personalization and interaction factors. The practical consequences of this finding is that the examination results will enhance internal credibility, as the effect of determinative attributes of AAEGS will become less qualified by the external noise, thus accepting the measure. The analysis that incorporates the different statistical models gives the increased chances of understanding the factors defining the acceptance of AAEGS and carry the implication of enhance the generality of the result to other visitors.

3.3 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 (Bloomfield & Fisher, 2019). Concretely, the present method helps lessen selection bias of museum participants and enhance the external validity of the results, which is valuable for how to generalize the accepted results of AI-based AR systems. To enhance generalizability of the findings in regards to the acceptance of AAEGS, the study adopts an intentional random sampling technique in administering the survey questionnaires to 424 Chinese museum visitors. It also lends itself well to what one might consider an objectivist ontology, by searching for truths rather than constructing realities

about the nature of human behaviors when it comes to technology adoption and buttress the research's epistemological position on positivism, an ontology that embraces methodological empirical research based on data and phenomena (Clark, 1998; Goertzen, 2017). Therefore, 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 (Lin et al., 2022).

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 (Lin et al., 2022; Remenyi & Williams, 1996).

The survey was designed in such a way that only those respondents who have used AAEGS before were allowed to respond to the survey, which would ensure that the findings obtained were from real users and not from assumptions. It was crucial for ensuring the validity of the data regarding the system's information, personalization, and interactivity. This was done to facilitate the formulation of clear and detailed questions, thus enabling the measurement of each variable in a way that would provide good insight into the issue. The final part of the survey was about the acceptance of AAEGS, which were developed based on user acceptance of the attributes of information technology systems and user perception of emotional and cognitive responses. Based on the critical analysis of the existing literature and the guidelines available in the literature on the survey design, the developed questionnaire was intended to capture the nuanced details of acceptance of AAEGS among the museum visitors.

Therefore, the sampling and data collection in this study were designed not only to promote the theoretical understanding of the acceptance of emerging technologies in a cultural context, but also to provide useful implications for any organization or institution seeking to improve visitor experiences through the use of technological solutions (Kim, 2019). The approach of

using surveys in the current study can be seen to be anchored in the positivist tradition of research since it seeks to measure variables in the population to reach an objective conclusion that is representative of the whole population. This is because questionnaire is suitable for collecting a vast amount of information in the different population group, which is relevant to studying the acceptance of the AI-enabled AR Exhibition Guide Systems among the visitors of museums, which is the subject of attitudes and behaviors among a massive number of people.

It is most relevant, especially in this study, that the impact of factors such as information, personalization, and interactivity on the acceptance of AAEGS can be established. It is feasible to collect data in these variables, and can be measured systematically using surveys, thus provide a data set which can be analyzed quantitatively for the purpose of testing hypothetically posed influences (Bloomfield & Fisher, 2019). Surveys also have an organized structure, even more, so when conducted using a proper online platform such as "Questionnaire Star", which makes real bias and inaccuracies hard to come by, rather than methods such interviews or focus group discussions. The inclusion of demographic questions in the survey also improves the research design because, in addition to having more in-depth information about how the population may have different perceptions about AAEGS, the research can easily identify common demographic characteristics among the population. This not only contributes in understanding the theories of global technology adoption postulated by positivism, but also creates inputs about technology deployment that may offer regards to the various cultural users (Clark, 1998; Lin et al., 2022).

The questionnaire used in this study for AAEGS is ethical in content and design as it has been through a peer reviewed low-risk ethical assessment by Massey University. This compliance ensures that research follows stringent ethical considerations, including informed consent, anonymity, data protection, transparency, potential bias, respect for participants, and cultural sensitivity. Prior to the survey, all participants were given an information sheet detailing the aims and objectives of the study, their roles in the study and how the collected data would be utilized. It was explained to them that they could choose to participate in the study and that

they could withdraw from the study at any time without any repercussions. This paper was written with the intention of the participants to easily understand it, and thereby, no technical terms were used to let participants aware of what they should be involved in. Participants musy agree to participate in the survey electronically, which was the next step. In the "Questionnaire Star" survey system, obtaining consent electronically, with the participant's consent, is considered a condition that he or she understands the study and agrees to it. 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. To ensure that the participants were anonymous, the details such as names and any other information that could lead to their identification was removed when data was collected to reduce the possibility of revealing the identities of the participants from the responses given. This was important in developing a basis of trust on which participants could offer their opinions, knowing that they would not be forwarded to someone with malicious intent like an identity thief. 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.

3.4 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 as recommended by Hair et al. (2019). Other strengths PLS-SEM as highlighted by Hair and other authors in 2019 includes; PLS-SEM is capable of predicting all forms of models with several structures, indicator variables as well as pathways, without the needs of normality of distributions (Hair et al., 2019). This flexibility is particularly desirable because, PLS-SEM does not limit the normality of the data and can be used effectively with small samples (Memon et al., 2021; Russo & Stol, 2021). Moreover, it gives the features of the resampling techniques that help in

the comparison of indirect effects compared to the Sobel test highlighted by Memon and his colleagues (2021). The analytical journey of Smart PLS is divided into two distinct phases: Namely, the measurement model phase and the structural model phase as described by Russo & Stol, 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 loadlings and the Average Variance Extracted (AVE) make it possible to assess convergence validity.

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. 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 integration of SPSS analysis added a wider perspective in the statistical analysis, which enriched the research results and made them more credible and comprehensive (Leyland, 2004). 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. This specific focus does not capture other, more diverse global audience involved in AI assisted AR systems in different cultures. However, both of the SPSS and PLS-SEM analysis enable detailed examination of the data, but the results strongly rely on the accuracy assumptions in the initial model and the interpretation of the complex statistical data, which can lead to errors if approached with negligence (Hair et al., 2019). Moreover, the study was cross-sectional, meaning that it does not allow for the establishment of cause-and-effect relationships or tracking development (Leyland, 2004). Future work could further remedy these limitations by

including longitudinal studies, recruiting a diverse subject pool from different countries, and employing quantitative and qualitative analysis to gain further insights into the user experience and acceptance of AAEGS.

4. Analysis and Findings

Before analyzing the data, the first thing that needs to be done is to look at the data, including whether there are any outliers, invalid samples, etc. Invalid samples can interfere with the analysis of the study, distort the conclusions of the data, etc., and thus it is especially necessary to mark the invalid samples to show before the analysis (Morgan et al., 2004). In this study, a total of 424 questionnaires were collected, and for the five data processing of data labeling, data coding, generating variables, outliers, and invalid samples, we used SPSSAU software to screen for invalid samples (McCormick & Salcedo, 2017). In general, if the number of identical numbers is too much, or the number of missing samples is too much, the sample should be set as invalid samples, invalid samples are generally set if the number of identical numbers is greater than 70%, or the percentage of missing samples is higher than 70%, the sample should be set as invalid samples. After screening we have a total of 417 valid questionnaires. A two-step approach will be used to analyze the data (Leyland, 2004; Morgan et al., 2004). First we test the reliability and validity of the items using SPSSAU before assessing the structural relationships. Then we analyze the data using SmartPLS 4 (Cheng et al., 2023; Memon et al., 2021).

4.1 Demographic characteristics of the sample

The demographic composition of the study sample provides crucial insights into the characteristics of individuals who participated in the survey on the acceptance of AAEGS in museums (Bloomfield & Fisher, 2019). As shown in Table 2, 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.This high educational attainment portrays a well informed sample that would be in a position to understand and effectively relate to the AAEGS. Regarding the income level, 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. Above 94% of the workers earn 10000 RMB and above, which indicates that they belong to the higher income group. These income levels are critical as they might influence the accessibility and frequency of museum visits, thus affecting the acceptance and usage of AAEGS. 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 engagement. Those who visit museums more often – five and more times per year – represent only 11 percent of all respondents. 75 percent 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 (Cheng et al. , 2023). According to the collected data, museum visitors are a young, educated, and financially stable audience who would probably respond positively to the adoption of new technologies in museums (Khalil et al. , 2023).

Table 2 Demographic characteristics of sample.

Variables	Characteristics	Frequency	Percentage
Age	18~25	83	19.9
	26~30	168	40.29
	31~40	142	34.05
	41~50	19	4.56
	51~60	5	1.2
Gender	Male	182	43.65
	Female	235	56.35
Education background	High school/technical secondary school	4	0.96
	Junior college	42	10.07
	Undergraduate	328	78.66
	Postgraduate and above	43	10.31
Current monthly income	Less than 2，500 RMB	21	5.04
	2500-5000 RMB	46	11.03
	5000-10000 RMB	221	53
	More than 10000 RMB	129	30.94
How often do you visit a museum in a year	None	1	0.24
	Once or twice	149	35.73
	Three or four times	218	52.28
	Five or more times	49	11.75
Total		**417**	**100**

4.2 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). It offers an approximation of the whole test reliability through the process of calculating correlations between items. 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). Usually, Cronbach's α value is greater than 0. Most psychological tests have indicated that a minimum of 7 is acceptable, but in specific areas of tests, the cutoff may be higher (Malkewitz et al., 2023). Thus, using a scale to measure the

level of knowledge is appropriate when applying Cronbach's α as statistical means to estimate the reliability of the scale. Cronbach's α is useful when one wishes to confirm that a number of items in a questionnaire or test are indeed measuring the same concepts consistently (Bujang et al., 2018). This method assists in confirming that scale items are measuring a single construct and are homogeneous in their measurements, which is vital for proper conclusions from the data gathered in the research.

Reliability analysis is used to assess the reliable accuracy of the responses that are given out in the quantitative data (Malkewitz et al., 2023). First of all, there is the assessment of the alpha coefficient; if this value is greater than 0.8, it shows higher reliability. If it is between 0.7 and 0.8, it means that there is no risk of failure when using the strategy as all the factors of the business can be optimized to work for it and the extent of reliability is satisfying. If this value is between 0 and 1 then the dependency graph is likely to have a high density and connectedness, which implies that it has moderate reliability of 0.7. If this value is below 0.6, it can be said that the reliability is very low (conduct). Secondly, the value of CITC should be less than 0.3, it signifies that the item can be deleted (Vaske et al., 2017). Corrected Item Total Correlation (CITC) is an option to examine the correlation between a single item in a scale or a test and the total sum of the remaining items (Zijlmans et al., 2019). It is a handy method that is utilized usually for determining the level of confidence of an assessment tool such as a questionnaire or a test and it generally hand-in-hand with other reliability co-efficients like Alpha. Third, if the value of 'Alpha if Item Deleted' is larger than alpha coefficient, one can examine the characteristics of the item after its removal (Vaske et al., 2017). Alpha if Item Deleted is a statistical measure used in scale reliability analysis and this is used when the item in concern is deleted. It can be described as a Cronbach's α coefficient that is determined when one item is removed from the scale. This measure is used to establish the the total score of the scale that would be accounted for by a specific item (Bujang et al., 2018).

As can be seen from Table 3, cronbach’s α for informativeness is 0.91, cronbach’s α for personalization 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. For the "Alpha if Item Deleted", the reliability coefficient does not increase significantly when any item is deleted, thus indicating that the item should not be deleted. Regarding the "CITC", the CITC values of the analyzed items are all greater than 0.4, which indicates that there is a good correlation between the analyzed items, and at the same time, it also indicates that the reliability level is good. In summary, 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 5) 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, 2021). CR for Informativeness (0.821), Personalization (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).

4.3 Results of validity analysis

All of the structures and measures had to be valid prior to hypothesis testing. Multiple items measured each variable (Clark, 1998). To analyze the validity of the data, here we use factor analysis to access their unit dimensions (Ford et al., 1986). 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). KMO is used to determine the suitability level of information extraction, the common degree value is used to exclude unreasonable research items, the

variance explained rate value is used to illustrate the level of information extraction, and the factor loading coefficient is used to measure the corresponding relationship between factors (dimensions) and question items (Mikkelsen, 2019). And it can be seen from Table 4, 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. In addition, the KMO value is 0.932 which is greater than 0.6 and the data can be extracted information effectively. In addition, 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.

Finally, we combine the factor loading coefficients to confirm that the factors (dimensions) correspond to the study items as expected. If the absolute value of the factor loading coefficient is greater than 0.5, it means that there is a correspondence between the option and the factor (Siu et al., 2022). Some items (factor loadings below 0.50) were removed during the factor analysis. Factor loadings greater than 0.50 were considered highly significant after Hair et al. In fact, all items in the research model had factor loadings greater than 0.60, and some of them had factor loadings greater than 0.70. The factor loadings are statistically significant, we can consider the validity as significant (Ford et al., 1986).

Furthermore,based on the Table 5 provided and following the guidelines for convergent and discriminant validity as per Fornell and Rudd (2009), a detailed data analysis can be conducted as follows:

The Average Variance Extracted (AVE) values for each construct exceed the minimum threshold of 0.50, suggesting a satisfactory level of convergent validity (Farrell & Rudd, 2009). Convergent validity is established when a construct captures a high proportion of the variance in its items. For instance, AVEs for Informativeness (0.605), Personalization (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 (Farrell & Rudd, 2009).

Table 3 Cronbach reliability analysis

Scale items	CITC	Alpha if Item Deleted	Cronbach α
Informativeness			
IF1.I appreciate various aspects of this museum exhibitthrough the AAEGS.	0.455	0.91	
IF2.I have a variety of experiences while exploring this museum exhibit with AAEGS.	0.45	0.91	0.91
IF3.I get varied knowledge about this museum exhibit through using AAEGS.	0.413	0.911	
IF4.I collect diverse information about this museum exhibit from using AAEGS.	0.487	0.91	
Personalization			
PER1. AAEGS allowed me to receive tailored information about this museum exhibit.	0.477	0.91	0.909
PER2. I could interact with AAEGS to get personalized information about this museum exhibit.	0.519	0.909	
PER3. The personalized information about this museum exhibitprovided by AAEGS met my need.	0.502	0.909	
Interactivity			
INT1.While exploring this museum exhibit, I can access a variety of other visitors' questions and answers through the AAEGS platform.	0.433	0.911	
INT2. AAEGS are highly responsive during this museum exhibit.	0.584	0.908	0.909
INT3. AAEGS is interactive when I am exploring this museum exhibit.	0.471	0.91	
INT4. It is easy to share information and content on AAEGS during this museum exhibit.	0.501	0.909	
Cognitive involvement			
CI1. The information provided by AAEGS can draw my attention during this museum exhibit.	0.487	0.91	
CI2. I process the content delivered by AAEGS with considerable attention while exploring this museum exhibit.	0.499	0.909	
CI3. I am able to remember the information from AAEGS for a long time after this museum exhibit.	0.494	0.91	0.909
CI4. My thoughts on the information provided by AAEGS can last for a long time following this museum exhibit.	0.577	0.908	
CI5. AAEGS is needed for my engagement with this museum exhibit.	0.54	0.909	
CI6. AAEGS is valuable to my experience of this museum exhibit.	0.572	0.908	
CI7. AAEGS offers features that are relevant to this museum exhibit I am interested in.	0.493	0.91	
Affective involvement			
AI1. AAEGS is fascinating and captures my interest in this museum exhibit.	0.557	0.908	
AI2. AAEGS is interesting， making me want to learn more about this museum exhibit.	0.617	0.907	0.907
AI3. AAEGS is appealing， enhancing this museum exhibit experience.	0.528	0.909	
AI4. AAEGS is involving， drawing me into a deeper engagement with this museum exhibit narratives.	0.615	0.907	
AAEGS Acceptance			
EA1. I have the intention to use again the AAEGS.	0.567	0.908	0.908
EA2. I have the intention to use the AAEGS as frequently as possible.	0.518	0.909	
EA3. I will persistently use the AAEGS in the future.	0.594	0.908	
Standardized Cronbach α coefficient： 0.913			

The discriminant validity is confirmed when the square root of AVE for each construct is higher than its inter-construct correlations (Cheung et al., 2023). The diagonal elements in Table 5 represent the square roots of AVEs, which are all in italics and exceed their corresponding off-diagonal inter-construct correlation values. For instance, the square root of AVE for Informativeness ($\sqrt{0.605}$) is 0.778, which is higher than all its correlations with other constructs. This holds true for all the constructs which support the contention that each construct is unique and measures things not encompassed by other constructs in the model (Cheung et al., 2023; Hulland, 1999).

Finally, the results showed that the measures of informativity, personalization, interactivity, cognitive involvement, affective involvement, and AAEGS acceptance confirm both convergent and discriminant validity. High CR values suggest that the constructs are adequately defined or measured. Therefore, the results of validity and reliability analysis provide substantial support for measuring the strength and reliability of the model to support analysis and hypothesis testing of the structural model.

Table 4 Results of validity analysis

Scale items	Factor loading						Commonality
	IF	PER	INT	CI	AI	EA	
Informativeness (IF)							
IF1.I appreciate various aspects of this museum exhibitthrough the AAEGS.	0.769	0.421	0.237	-0.093	0.126	0.671	0.71
IF2.I have a variety of experiences while exploring this museum exhibit with AAEGS.	0.678	-0.079	0.28	-0.072	0.176	0.169	0.57
IF3.I get varied knowledge about this museum exhibit through using AAEGS.	0.806	0.018	0.042	0.074	0.179	0.669	0.65
IF4.I collect diverse information about this museum exhibit from using AAEGS.	0.597	0.662	0.134	0.067	-0.019	0.281	0.579
Personalization(PER)							
PER1. AAEGS allowed me to receive tailored information about this museum exhibit.	0.105	0.751	0.495	0.142	0.172	0.286	0.626
PER2. I could interact with AAEGS to get personalized information about this museum exhibit.	0.174	0.779	0.535	0.143	0.376	0.065	0.607
PER3. The personalized information about this museum exhibitprovided by AAEGS met my need.	0.144	0.747	0.436	0.211	0.421	0.216	0.558
Interactivity(INT)							
INT1.While exploring this museum exhibit， I can access a variety of other visitors' questions and answers through the AAEGS platform.	0.257	0.368	0.755	0.066	-0.081	-0.108	0.544
INT2. AAEGS are highly responsive during this museum exhibit.	0.49	0.232	0.709	0.139	0.188	0.162	0.528
INT3. AAEGS is interactive when I am exploring this museum exhibit.	0.1	0.621	0.758	0.143	0.315	-0.005	0.535
INT4. It is easy to share information and content on AAEGS during this museum exhibit.	0.333	0.17	0.706	0.38	0.04	-0.099	0.584
Cognitive involvement(CI)							
CI1. The information provided by AAEGS can draw my attention during this museum exhibit.	0.298	0.203	0.041	0.662	-0.104	0.546	0.581
CI2. I process the content delivered by AAEGS with considerable attention while exploring this museum exhibit.	0.542	0.269	-0.119	0.617	0.206	0.005	0.502
CI3. I am able to remember the information from AAEGS for a long time after this museum exhibit.	0.102	0.031	0.249	0.735	0.154	0.119	0.765
CI4. My thoughts on the information provided by AAEGS can last for a long time following this museum exhibit.	0.122	0.366	0.168	0.746	0.288	0.068	0.653
CI5. AAEGS is needed for my engagement with this museum exhibit.	0.475	0.018	0.195	0.733	0.099	0.331	0.552
CI6. AAEGS is valuable to my experience of this museum exhibit.				Dropped			
CI7. AAEGS offers features that are relevant to this museum exhibit I am interested in.				Dropped			
Affective involvement (AI)							
AI1. AAEGS is fascinating and captures my interest in this museum exhibit.	0.348	0.531	0.056	0.206	0.724	0.13	0.524
AI2. AAEGS is interesting， making me want to learn more about this museum exhibit.	0.616	0.032	0.114	0.3	0.701	0.223	0.577
AI3. AAEGS is appealing， enhancing this museum exhibit experience.	0.567	0.261	0.167	0.014	0.732	0.09	0.533
AI4. AAEGS is involving， drawing me into a deeper engagement with this museum exhibit narratives.	0.446	0.252	0.371	0.257	0.754	0.137	0.569
AAEGS Acceptance (EA)							
EA1. I have the intention to use again the AAEGS.	0.414	0.393	-0.045	0.051	0.36	0.772	0.596
EA2. I have the intention to use the AAEGS as frequently as possible.	0.232	0.118	0.081	0.246	0.712	0.768	0.647
EA3. I will persistently use the AAEGS in the future.	0.346	0.287	0.178	0.009	0.61	0.846	0.716
Eigenvalues	3.52	2.261	2.215	1.925	1.876	1.834	-
% of Variance	14.079%	9.04%	8.858%	7.698%	7.505%	7.336%	-
Cummulative %	14.079%	23.123%	31.982%	39.680%	47.185%	64.52%	-
KMO			0.932				-
Bartlett			3196.729				-
df			300				-
p			0				-

Table 5 Inter-Construct Correlations and AVE values

	Composite Reliability	Average Variance	IF	PER	INT	CI	AI	EA
Informativeness (IF)	0.821	0.605	**0.778**					
Personalization(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**

Note: Squared root of AVE's are presented in the diagonal for each construct in italics.

4.4 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 3. The results of structural equation modeling output highlighted in this paper clearly describe the interrelationships between various constructs in the context of accepting of AAEGS, as postulated by Gironda (2024). All path coefficients in the model represent the direct effects of the constructs,with all paths showing significant impacts at p<0. At the 01 level, there is concern about the reliability of the proposed model to explain trends accepted by AAEGS (Hair et al. , 2019).

In the exploration of AAEGS within museum settings, 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. This path helps to establish the significance of informality in enhancing the cognition of users. In this case, we can define the information as the value of the content that adds to the existing information set that the user can gain from the museum exhibition (Davis, 1985). This path is important because it provides specific and relevant information that will satisfy the curiosity

of museum visitors and keep them engaged for longer than the information generally provided (Lowry et al., 2012). This is consistent with academic literature, as Marangunić and Granić (2015) explain that the depth and relevance of information greatly improve the user engagement with digital systems. Such interactions are not just on the surface level, but interactive, helping users move through cognitive modes of information processing which are crucial for meaningful learning (Marangunić & Granić, 2015).

The relationship between personalization and cognitive engagement (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. This strong relationship emphasizes the importance of personalization in increasing the degree of the cognitive presence, which refers to the extent to which content is customized to meet the needs and preferences of users, in this case visitors to museums. This kind of customization makes the visitor attentive and enhances the level of thinking in relation to the content of the exhibit. Theoretical backup from Hair (2019) supports the observed effects, arguing that not only does the use of personalized content capture the user's attention, but also helps the brain to process relevant information more effectively due to the direct relevance of the information provided to the user.

The influence of personalization on affective involvement (H5: PER→AI) is evident in the standardized coefficient of 0.338, which highlights a significant and highly essential effect ($p < 0.01$). Thus, the Cronbach's alpha coefficient calculated above is 0. Mo et al. (2023) noted that personalization heightens user satisfaction and emotional commitment due to the fact that its targets are based on individual preferences and interests. Such customized experience can reach out to the users more effectively, and it can be argued that it may change the way users interact from mere curiosity to passion (Mo et al., 2023). This emotional connection also helps enhance the chances of repeated usage, in addtion to enhancing the overall satisfaction level of the museum visit.

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. Lee (2010) pointed out that interactivity helps to improve cognitive processing since it creates an environment that demands engagement as well as critical thinking from users. It is in this regard that touch screens, augmented reality layers, and other multimedia elements that encourage visitors to participate more actively in the museum experience are added. In this case, active involvement enables users to analyze the presented information, relate it to prior knowledge, and enhance overall knowledge and understanding.

The relationship between interactivity and affective involvement (H7: INT→AI), as suggested by a standardized coefficient of 0.429 ($p < 0.01$). Hypothesis 7: Interactive elements in AAEGS positively influence users' emotional engagement. Which indicates that the use of interactive elements in AAEGS significantly increases the level of users' emotional engagement. This substantial impact reflects the theory of flow as described by Csikszentmihalyi (1990), where deeply engaging and interactive environments can lead to a state of heightened focus and enjoyment, termed “flow”. Such interactivity may refer to the ability to navigate through the content created by users, multimedia interactions, or some augmented reality features where the content responds to the inputs given by the users (Engeser et al., 2021; Nakamura & Csikszentmihalyi, 2002). These elements not only attract the visitors, but also involve them emotionally, which makes the entire experience more appealing and memorable (Corrêa & Gosling, 2021). When users engage with such systems, their emotional state is influenced, thus, resulting in increased satisfaction and the “emotional bond” with the technology. It is important to note that this significant emotional attachment contributes to the technology acceptance model because it increases the user satisfaction and their commitment to the system, which in turn affects their likelihood that they will use it and recommend it to others. This result suggests that in the future, more interactive features should be incorporated into the design of AAEGS to enhance users' sense of social intimacy with the system.

The path from cognitive involvement to AAEGS acceptance (H1: The path from CI to EA)

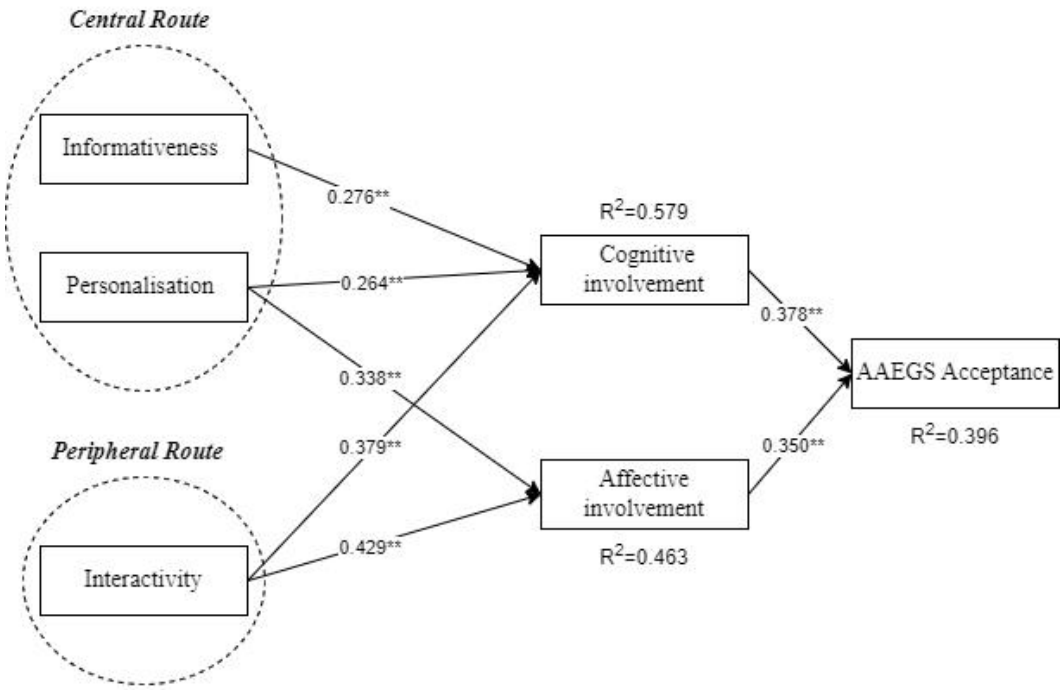
was significant, as indicated by a standardized coefficient of 0.378 and a highly significant p-value ($p < 0.01$), show that level of cognitive engagement has substantial effect on the level of user acceptance. Such relationship is well founded in the ELM model postulated by Petty and Cacioppo (1986) where central and elaborate processing of information results to more permanent change in attitudes and behaviors. This observation implies that when viewers of these systems are intellectually stimulated by the information presented to them, they are more likely to adopt its utility in their museum visiting behavior. Advanced cognitive processes that might be associated with AAEGS might include the ability to comprehend textual or visual information presented about an exhibition, grasp more detailed background information about the exhibition, or engage with the AR components of the experience. As you can imagine, when visitors take their time to read this information, they not only comprehend it, but also appreciate the improved learning outcomes, thus increasing the likelihood of accepting it. Such cognitive involvement is essential as it ensures that acceptance is not merely superficial or temporary, but is based on a solid appreciation of the system's utility and impact (Perse, 1998). Hence, there is a need to incorporate elements that will ensure that AAEGS is intellectually stimulating, which will include the use of interesting, challenging and informative content that will help ensure that the concept gains permanent acceptance by museum visitors (Su et al. , 2019). This is particularly relevant to the design of technological solutions that not only require novel approaches but also engage users on a cognitive level to meet empirical needs.

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. Especially where users' cognitive processing might not be the primary focus or they may not likely to invest significant time and effort in their interactions with content, affective responses play an important role in allowing them to form acceptance attitudes towards the technology (Liu et al. , 2015). This approch suggests that affective factors, such as pleasure, beauty, and

availability, actually contribute positively to visitor acceptance. The appeal to emotion in these systems, through the graphical appeal or the narrative appeal of AR, makes people curious about the technological possibilities (Zhang et al., 2006). This emotional connection is not only complementary to cognitive engagement, but can also serve as a sole persuasion reason, especially useful in situations where users prefer affective experiences over utilitarian content (Zhang et al. , 2006).

In the context of structural modeling, R^2 value is the measure that is used to determine the goodness of fit of a structural equation model, the value which may range between 0 and 1. It establishes the capacity of the model to account for the variation in the observed data and enables the researcher to determine the extent of the model fit, compare models, and further understand the relationship between the variables (Purwanto, 2021). 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 (Memon et al. , 2021). The above results indicate that the proposed model is able to incorporate key factors that influence visitors' acceptance of AAEGS. What's more, the R^2 values suggest that significant variability in how visitors perceive and interact with AAEGS can be explained by the variables included in the model. This enhancement of explanatory power further enhances the credibility of the ELM framework used in this research and reveals the importance of both cognitive and affective routes in determining user acceptance. The results support the hypothesized relationships stated in ELM, that the features of AAEGS are indeed affecting the level of interaction of visitors (Kizito & Sun, 2018). By providing detailed and relevant materials that promote cognitive involvement and enhance emotional engagement through emotionally engaging interactions, AAEGS can greatly improve the museum experience and thus, improve acceptance of the technology by the museum visitors.

Figure 3 Structural regression model



Note: Numbers are standardized path coefficients, * indicates significance at level of 0.05,**p<0.01)

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 (Mulaik et al., 1989; Singh, 2009). It is also important to note that the results provided in the Table 6 indicate several such indicators which when combined together, point towards a relatively satisfactory fit of the proposed model in terms of the data collected for assessing the acceptance of AAEGS in museums. 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. The Root Mean Square Error of Approximation (RMSEA) is 0.05, which is comparable to the ideal situation of being below 0.1 (Morgan et al., 2004). 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. However, it is also falls within the acceptable limit of 0.05, which again proved that the chosen model is quite sufficient. 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). These indices are particularly useful since they incorporate the model complexity since parsimony is valued.

However, as strong as these findings may appear, it is important to appreciate the shortcomings of using fit indices only as a measure of model fit. The use of fit indices can also be problematic at times, especially in the larger and more complex models, where the indices will always turn out to be a better fit regardless of the actual theoretical accuracy of the model in question (Goretzko et al., 2024). In addition, according to the Default Model, the X^2 (300) is 3374.175, which is much higher than desirable, p-value of 1. 000, implying model misspecification or the need for model respecification, it should not be overemphasised because this aspect often captures an "in principle" idea rather than a "real world" application (Marsh et al., 1988).

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.

4.5 Mediating effect test

Table 7 offers the mediation effect analysis from our study, where cognitive and affective engagement are considered as potential mediators. A total of 417 respondents were analyzed using percentile bootstrap method. To increase the accuracy of the estimated confidence interval, a large number of bootstrap samples were created, in fact, 5,000 samples in total (Valente et al., 2016). This methodological rigor assists in strengthening the observed mediation effects' credibility, thus building a statistical basis for understanding how cognitive and affective engagement affects the system acceptance process (MacKinnon, 1994).

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 engagement and cognition. This supports the Cognitive Mediation Theory which states that the cognition and handling of information influence subsequent attitudes and behaviors, hence supporting the importance of informativeness in increasing user acceptance of technology systems like AAEGS (Eveland Jr, 2001). This pathway focuses on the idea of designing information content that would positively appeal to the higher cognitive abilities in order to increase overall system acceptance.

Figures 3 show that personalization has a positive and significant impact on both the cognitive and affective beliefs that influence the acceptance of AAEGS, thus providing support for H1 and H2. Therefore, the partial mediator from personalization to cognitive engagement to AAEGS acceptance is 0.334, accounting for 61.05%. This strong 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. Personalization, on the other hand, affects the consumer through affective engagement with the brand, and has a mediating effect (ab) of 0.305, which represents 55.82%. This pathway highlights how personalization elicits strong emotional responses from users, since users feel more emotionally engaged and content with a system that adapts to their tastes. These findings are consistent with Norman's (2010) perspective about the anthropomorphism of user experience, namely that personalised interactions can lead to high levels of emotional investment, which in turn will increase the rate of acceptance of the technology (Norman, 2010).

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 → CI → 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→AI→EA pathway illustrates interactivity's 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 engagement but also significantly affects emotional responses which in turn influence acceptance. These results underscore the dual pathway through which interactivity impacts AAEGS acceptance, aligning with the multi-faceted approach of technology acceptance where both cognitive and emotional engagements are crucial.

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 (Mallinckrodt et al., 2006; Steffener, 2021). This methodological approach is based on contemporary statistical approaches to mediation analysis, as Steffener (2021) suggested, such as the use of the bootstrap technique for deriving more precise confidence intervals around indirect effects. This is especially important when making assumptions about the distribution of indirect effects in different models, where conventional assumptions can be a problem.

Table 6 Fit indices results

Fit Indices	χ2	df	p	χ2/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: $\chi2(300)=3374.175$, p=1.000

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.

5. 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, personalization and interactivity regarding the acceptance of AAEGS is mediated by cognitive and affective involvement. Each of these mediational pathways implies that in purposes to enhance acceptation of AAEGS, it is necessary to involve not only the content that would be interesting to the user cognitively, but also emotionally. These findings provide the empirical support for adopting UX design features to enrich the visitors and facilitate their engagement as well as to promote the acceptance of technology within the museum context. Personalization measures the extent to which the information system can present different pieces of information and experiences that are relevant to these users, proposing that higher levels of personalization can enhance both cognitive and affective engagement (Ho & Bodoff, 2014). Finally, interactivity is the degree to

which users can meaningfully engage with the system; the authors propose that high interaction enhances affective involvement because the interactions are more appealing and emotionally stimulating (Alnawas & Hemsley-Brown, 2018). In light of these factors, the study aims to provide an understanding of the various processes by which the visitors to museums in China are persuaded to accept and adopt these innovative technological guides.

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, the findings of the present study are in line with Eveland's (2001) Cognitive Mediation Model in that the depth and clarity of the content provided on AAEGS are critical determinants of the level of cognitive engagement. Eveland believes that the flow from information exposure to knowledge acquisition is influenced by cognitive activities, where higher quality information enhances the odds of performing more cognitive activities, such as elaboration and reflection (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 (Petty & Cacioppo, 1986). 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. For instance, research carried out by Mayer (2005) on multimedia learning also bear this research. Mayer also points to coherence and signaling as two of the biggest factors in educational content, as they help eliminate extraneous processing and provide the foundation for basic processing (Mayer, 2005). This is directly relevant to our study as the informativeness of AAEGS can be linked to signaling which helps users navigate through the cognitive structure of learning in a museum environment.

Theoretical implications of these findings for management of museums and design of exhibitions are thus far reaching. To increase the acceptance and efficiency of AAEGS, the curators in the museums and content developers should ensure that the information provided by these systems is correct and must also be coordinated in a way that is understandable to various visitors. This entails incorporating various forms of media that are informative and also interesting so as to meet the needs of all learning styles (Smith, 2020). 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 (Craig & Choi, 2024). Therefore, our study implies that while informativeness is indeed a critical factor (Gregg et al., 2001), it is not enough to ensure that visitors are informed and receive the information given to them; there are other factors, such as personalization and interaction, that also come into play in influencing visitor experiences. 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.

I also found that personalization has significant and positive impact on cognitive and emotional engagement, which means that users are more engaged when their experience is personalized, and therefore, personalization strategies should be encouraged. This finding supports Kim's (2016) observation that personalization improves satisfaction and emotional attachment, which are the key factors influencing the adoption of technologies in contexts such as museums where relevance and the ability to elicit emotional responses from visitors are critical determinants of satisfaction. Thus, the quantitave data revealed in our research confirms that personalization influences cognitive engagement as well. Findings from a sample of 417 museum visitors showed that personalization 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 engagement is particularly useful in museums, which provide a great deal of information to the audience.

Personalization helps to avoid this problem as the user is exposed to information that is not only relevant to the search but also adjusted to the knowledge level. These findings support the contention of Mo et al. (2023) that systems that can adjust with the user preferences are critical to enhancing the usability and effectiveness of the information presented. 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. This emotional appeal is important because it takes the simplest experience, such as a visit and makes it more meaningful and even emotionally moving (Mo et al. , 2023). Such engagement is not just an information processing task, but a meaningful personal experience with the content, which can make a huge difference in the process, and therefore in the impact, Csikszentmihalyi and Robinson (1990). These findings hold important lessons for museum curators and administrators. Thus, by providing customized AAEGS, museums can not only address the information demands of visitors, but also design the appealing stories based on the shared emotions. It should be stressed that such systems should utilize visitor data to adjust content and design based on the interactions and preferences of the visitor, and this must be done in real-time.

Therefore, it is evident that while personalization has numerous advantages, there are issues in designing efficient personalization systems. Such as the technological constraints that enable personalisation of the user preferences, privacy issues arising from the data collection, and the necessity of the content management system that would be capable of responding to the varying user profile (Roussou & Katifori, 2018) This is a call for future research to further investigate and seek to find better approaches to machine learning for personalization, invent better ways to collect data that will preserve privacy and to assess the effects of personalized museum experience on the satisfaction of the visitors and their learning (Ho & Bodoff, 2014). The overall effect of personalization of cognitive and affective involvement enhances the experience for visitors of museums that are fitted with AAEGS. Museum can attain

greater levels of guest satisfaction while at the same time promoting appreciation and understanding of cultural and historical pieces through creating a more effective experience.

This study also points out that interaction has a powerful regulatory capacity to increase levels of cognitive and emotional engagement in a museum environment, as supported by the incorporation of interactive elements into AAEGS. 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 (Liu & Shrum, 2002). 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 organisational 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 (Duguleană et al., 2020). Other interactions, such as quizzes, maps, and augmented reality overlays, transform the "Passive reception" of visitors from reception to participation (Chaturvedi et al., 2023). These tools enhance the processes through which the visitors interact with the exhibition and make these processes involve augmented mental effort.

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 (Ponsignon & Derbaix, 2020). Ricotta et al. (2007) echoes this assertion, pointing out that levels of interaction promote cognitive absorption in a way that fosters better learning. In the context of AAEGS, this means that when visitors are provided with tools that they can actively manipulate

content, they not only have better access to information, but they also manage to memorize it for a longer period of time (Ricotta & Costabile, 2007). In addition, Mayer (2005), who has investigated the multimedia learning theory also found that interactive elements can help reduce the cognitive load because they partition and present information in small chunks. This approach enables visitors to understand information at their own pace, which is very important, especially when they are exposed to areas of high information density, such as museums.

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. Additional features that enable the visitor to have an individual approach or be able to have an emotional relationship with the content will help to achieve better results and increase the level of emotional involvement. In the museum setting, when a visitor is an active participant in the learning process, he or she is more likely to develop an emotional connection to the content. This emotional bond is important because it can turn a routine visit into an extraordinary one, which according to Kim (2009), is significant to the formation of a strong emotional bond. Multimedia in museums can be shown to be effective in creating individual associations with the pieces, which can result in higher levels of self-reported emotions. Furthermore, Smith (2020) posits that in interactive systems, emotional design can have a significant impact on a user's perspective of the technology. In museums, people can have certain types of emotional reactions that can enhance or dinimish the overall visit, and interaction can be the determining factor between an ordinary visit and an extraordinary one. Thus, using technology to provide visitors with a sense of agency and engage them in content that is meaningful on a personal level can museum visitors who are not only knowledgeable, but also emotionally engaged (Smith, 2020).

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. The findings presented in this study suggest that emotional involvement seems to have a greater impact than cognitive involvement on visitor acceptance of AAEGS. Cognitive Involvement traditionally focused on the intellectual engagement that visitors experience when interacting with AAEGS (Perse, 1998). 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 (Su et al. , 2019). 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. It is in the category of Affective Involvement that we witness a more apparent effect. Perceived interactivity, and hence, a key antecedent of emotional engagement, 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. This type of involvement involves the feelings that visitors get from their experience, including a sense of enjoyment, satisfaction, and emotional engagement, which is highly beneficial since AAEGS has the capability of providing individualized and interactive experience.

This means that 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 (Faisal et al., 2020). This focus on visitor experience in educational technology goes beyond the technical needs of educational technology to address the psychological and experiential needs necessary for the integration of new technologies in complex cultural and historical institutions such as museums. This study leads us to recommend that museum administrators and exhibition designers

should consider not only cognitive but also affective factors when adopting AAEGS to improve the educational value of museums as well as the hedonic experience of museum visits. More such studies should be conducted in the future, perhaps even focusing on how particular emotions can be triggered and utilised to improve the uptake and usage of technology in cultures.

Taking advantage of the benefits of the integration of AI and AR, this paper will discuss how these technologies have not only impacted the manner in which visitors engage with the exhibitions, but also enhanced the value of the museum visit. Thus, this paper hypothesizes, based on ELM's findings, that the integration of AI and AR in AAEGS engenders dual-path learning – cognitive and affective – resulting in enhanced learning experience and a deeper appreciation of cultural heritage. The implementation of these systems in museums brings some innovations in the field of tourism, namely personalization, interactivity, and informativeness as fundamental to adapting to the new expectations of today's museum visitors and securing their long-term acceptance of museums.

6. Conclusion and limitations

In this research, I seek to examine how AAEGS affect visitor acceptance in Chinese museums with reference to informativeness, personalization, 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 engagement. 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 (Caputo & Evangelista, 2019). This is not a passive engagement, where one is simply receiving information, but an active one that requires both cognition and

understanding, and is required for an enriching tourism experience (Tung et al., 2017). These museums include technologies that provide different views on the same object, helping the viewer to construct a more substantial perception. This is a key factor since it leads to higher satisfaction and can greatly influence the possibility of visitor's decision about the return or recommendation of the museum, as stated by Eveland (2001), whose argument was that information quality engages the user cognitively.

One of the most striking points in the paper is the fact that the use of personalization has an impact on both cognitive and affective dimensions of the visitors (Mo et al. , 2023). 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 (Ho & Bodoff, 2014). This relevance enhances cognitive engagement, as viewers are more likely to engage their ears by focusing on the content they are interested in. More critically, affective involvement is facilitated by personalization since this makes visitors feel almost personally attached to the exhibition (Enopadria & Putri, 2022). This is accomplished via storytelling that targets the visitor and entrenches a positive affective bond that makes the experience enjoyable and memorable, hence the hedonic appeal of the exhibition as postulated by Faisal et al. in 2020. The importance of personalization in the context of promoting the feeling of an emotional bond and overall satisfaction is discussed, for example, in the study of Kim (2016) who pointed out that such a strategy increases the involvement of visitors.

AAEGS is a useful platform for creating interactivity and it is effective in engaging the visitors both in terms of their cognition and emotions. Augmented reality overlays and virtual tours make the viewers not only observers of the content, but active participants in the process of learning. Such an active engagement is helpful for learning, as it stimulates the brain to work and pay more attention to what is being offered. From an affective standpoint, interaction adds the value of a visit because it has the potential to create a more engaging experience. This type of engagement is

consistent with Csikszentmihalyi's (1990) flow theory, which states that immersion in pleasurable activities can lead to a state of optimal experience. This not only enhances the learning process and makes it more fun, but also creates an emotional association with the technology, which in turn would contribute to its acceptance (Nakamura & Csikszentmihalyi, 2002).

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. The short-term affective responses generated by personalization and interaction can play a critical role in shaping the visitors' impressions and willingness to engage, erasing any other long-term rational evaluation. This is consistent with the Dual Process Theory described by Morewedge and Kahneman (2010), where the authors suggest that decisions involving emotions are likely to be made in the absence of a comprehensive rational analysis. Thus, since cognitive and affective involvement represent critical moderators of technology acceptance in museums, the role of affective involvement is particularly significant for settings where people's experiences and emotions are paramount (Morewedge & Kahneman, 2010). As museums continue to adopt new technologies such as AAEGS, the multifaceted dynamics of these mediators will be crucial considerations when creating emotional learning experiences for the public.

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. Accordingly, this research reveals static significance hence providing an insight into how visitors perceive technological features through the central (cognitive) and

peripheral (affective) routes. Such dual routes support Petty and Cacioppo's (1986) initial propositions of the ELM, which holds that acceptance may entail elaborate and thought-out processing of the information or simple feelings for such information. In terms of the expansion of these concepts, our research builds up evidence that while both are important for museum technology, both are mutually interconnected, and imply that visitor acceptance is optimised when both imperative cognitive and affective appeals are optimised.

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, personalization, and interactivity, the positive impact on visitors' engagement and acceptance, it would be crucial for museums to focus on these features in further development of digital components. Some examples are: making digital guides or AR applications as content rich as possible will not only increase interest, but will also propagate information deeper into the visitors' minds and provide them with the feelings of satisfaction from the enriched learning process. Based on our previous analysis, personalization is among the leading factors that set value and perceived quality during visitor interactions. Through this opportunity, museums gain valuable data analysis, which also entails the users' profile information – this would help in tailoring the tour and knowledge being presented to be unique and relevant to the customer each time (Khalil et al., 2023). It is interesting to note that this approach is not only useful for enhancing visitors' satisfaction, but also for bringing them back and recommending the sites to their acquaintances – all of this being crucial to the survival and development of cultural facilities. As found in this research, interaction plays an important part in stimulating cognitive and affective engagement and, therefore, it can be seen that a museum must seek out and incorporate interactive tools that stimulate curiosity and positive interaction with artifacts (Hellgren, 2015). This type of project can include such forms of amusement as virtual reality scenarios, special kiosks, augmented reality treasure hunts, etc. , which make the traditional viewings in the museums more exciting for

mass, especially for the young and informed generations. Furthermore, it extends the knowledge of cognitive and affective involvement's intermediation in technology acceptance, thus emphasizing the significance of developing engrossing exhibits, which would appeal not only to visitors' rationality, but also to their emotions (Morewedge & Kahneman, 2010). Museums should consider engaging the hearts of their visitors so they leave with more than just intellectual nuggets and aesthetic pleasure but something more profound; a cultural acquisition that will change them forever.

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 (Kokash et al. , 2024). Further research on cultural differences in museum and interacting with cultural differences the visitor experience through technology could be useful in exploring how different cultural challenges contribute to the efficiency of technological intercessions in altering visitor perception (Pai et al. , 2020). Another limitation is the reliance on self-reported data, which is susceptible to response bias. This could be due to either social desirability or bias in participants' perception of the questions posed in survey, which may not be true to their behavioral intention or attitude. In order to overcome this limitation in future researches, a mixed method approach could be employed, that both qualitative and quantitative data could be gathered concurrently. Quantitative methods can also be employed which includes

observational approach whereby the researcher cre > Studies done with participants' survey results could also be complemented by follow-up through observational studies or through experimental designs whereby different aspects of informativeness, personalization, or interactivity are manipulated, as well as getting validation on whether people really behave as they said in the survey (Lin et al. , 2022). In addition, we can include physiological data like eye-tracking or heart rate variability to gain a more profound understanding of visitors' deep cognitive and emotional processes within the encounters with AAEGS (Bloomfield & Fisher, 2019). This paper employs a cross-sectional design to survey its participants, suggesting that the data collected reflect a snapshot of visitors. Despite this advantage, this snapshot approach does not consider how perceptions and behaviors may change as visitors become familiar with AAEGS, or how visitors may get bored or stagnant over time for novelty or stimulating reasons of the event (Clark, 1998). The assessments of changes in visitor acceptance in different elements of the museum over time would give a dynamic analysis in the process of adoption and the impact of AAEGS in the long run. Such studies could also plug the knowledge gap on the effectiveness of multiple exposures to exhibits within AAEGS by ascertaining the effects on visitors' knowledge and perceptions.

Another factor of the fast pace of society caused by technology advancement is also a challenge to the long-term applicability of this study. 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. This means that closely related research referred to in the subsequent section, can be particularly valuable for investigating the use of new technologies including virtual reality, artificial intelligence, and machine learning in the context of the enhancement of museum experience. Last but not least, it is important to note that while the study

focuses on museums, the conclusions drawn can be generalized on other institutions in the field of tourism and culture that attempt to use technology to complement the visitor's experience. 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 informationa, personalization and interaction impact of such environments.

Lastly, it presents the findings of this study to explore how cognitive and affective involvement can help to influence the impact of information, personalization and interactivity on the levels of acceptance of AI-enabled AR technology in museums. This highlights the imperative of museums incorporating elements of effective design in exhibitions and also ensuring that such designs are accepted and enjoyed by the visitor. Furthermore, it will also be pointed out that how museums are able to make use of the opportunities of technology and create meaningful environments that on the one hand intellectual curiosity can be sparked, but on the other hand emotions can also be enjoyed to create a meaningful experience with today’s visitors. As this study provides a framework for understanding the factors supporting the acceptance of AR systems in museums, the above limitations and future research directions will further investigate this rapidly growing field.

7. References

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8. Appendices

Massey University ethics approval

Date: October 18, 2023

Kia ora, Zuguo Fu

Ethics Notification Number: 4000028132

Project Title: AI-enabled Augmented Reality Exhibition Guide Systems and Their Acceptance in Chinese Museums

Thank you for your notification which you have assessed as low risk.

Your project has been recorded in our database for inclusion in the Annual Report of the Massey University Human Ethics Committee. The low risk notification for this project is valid for a maximum of three years. Please notify the Human Ethics Team if situations subsequently occur which cause you to reconsider your initial ethical analysis that it is safe to proceed without approval by one of the University's Human Ethics Committees.

Please note that travel undertaken by students must be approved by the supervisor and the relevant Pro Vice-Chancellor and be in accordance with the Policy and Procedures for Course-Related Student Travel Overseas. In addition, the supervisor must advise the University's Insurance Officer.A reminder to include the following statement on all public documents:

"This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher(s) named in this document are responsible for the ethical conduct of this research.

If you have any concerns about the conduct of this research that you want to raise with someone other than the researcher(s), please contact the Research Ethics Office, email humanethics@massey.ac.nz."

Please note:

If a sponsoring organisation, funding authority or a journal in which you wish to publish require evidence of committee approval (with an approval number), you will have to complete the application form again, answering “Yes” to the publication question in order to complete a full application for review by one of the University's Human Ethics Committees. You should also note that such an approval can only be provided prior to the commencement of the research.

Yours sincerely

Professor Tracy Riley

Acting Chair, Research Ethics Chairs' Committee and Acting Director, Research Ethics