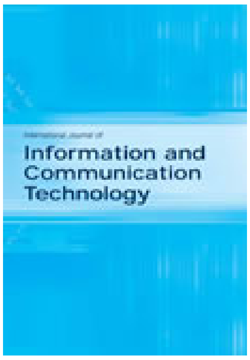

International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

A study on AI-assisted interactive experiences for the preservation of ethnic culture in a mixed reality platform

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DOI: 10.1504/IJICT.2026.10075955

Article History:

Received:	08 October 2025
Last revised:	04 November 2025
Accepted:	11 November 2025
Published online:	06 February 2026

A study on AI-assisted interactive experiences for the preservation of ethnic culture in a mixed reality platform

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Abstract: How history and society are remembered has changed a lot because of how quickly technology is growing, especially with the help of artificial intelligence (AI) and mixed reality (MR). This research looks into how AI-based games in mixed reality spaces might be able to help keep culture alive. This is why computer tools were made that can be used anywhere in the world. These tools include generative AI (GAI) and other systems for machine learning. The project's goal is to find ways that AI can make cultural events better so that people know and understand past better. Some of the things that affect how well people learn are perceived worth, ease of use, social benefits, and happiness in the real world. To deal with these problems, different ways of teaching have been made using tools that are popular in schools. Everyone in the world can learn, understand, and participate in different countries better if GAI methods are changed to work in different cultural settings.

Keywords: AI-assisted learning; cultural heritage preservation; mixed reality; MR; generative AI; GAI; user satisfaction; ethnic culture.

Reference to this paper should be made as follows: Wang, X. (2026) 'A study on AI-assisted interactive experiences for the preservation of ethnic culture in a mixed reality platform', *Int. J. Information and Communication Technology*, Vol. 27, No. 7, pp.62–82.

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1 Introduction

People save and share cultural material in very different ways now that computers are faster and better. Also, 3D models, augmented reality (AR), and virtual reality (VR) have made it easier than ever to share cultural goods information and keep it safe (Bassier et al., 2020). More people watch digital shows and visit virtual places (Beckstein et al., 2022). These ways connect people to history and make it more interesting. People can also find out more about the times and places these things were used. To share culture, a lot of people use technology. But, as many studies have shown, this has not worked well in the classroom. Majda et al. (2021) did a study (Chen and Bao, 2024) that showed how digital tools can be used to teach people while they are at work and at different times. That being said, teachers need to know how to use the web and plan lessons so that they work well. The study found that we need to quickly find fun and interesting ways to learn about culture that clear up our vague ideas (Messaoudi et al., 2022). The study's conclusion that technology and learning tools should be better connected is something we agree with. The study can also help us figure out how well we teach culture. VR and 3D models are used by a lot of people, but Ott and Pozzi (2008), and other people say that they do not always teach enough about how different cultures have changed history.

Things like having moral and social goals are examples of these. By coming up with cool ways to learn, they would be reinterpreting cultural knowledge. The tools would be made by people who work together and study history, computer science, and teaching (Baalamash et al., 2024). You can only watch movies that go in one direction, Mayer (2020) said, when you only share information on your phone. To get it to work, you need cognitive strategy help, such as problem-driven information integration (Deng et al., 2023). You cannot learn how to think about how you feel or change things this way. These are learning goals that are more general. Is this the best way to teach cultural topics? It means that kids do not get to do enough cool arts and culture-related things. This might be the case since the room does not have any good stuff. That's how tough it is to say what tech can and cannot do for schools (García-Madurga and Grilló-Méndez et al., 2023). Based on these stories, it does not look like adding digital technology to this field of study by itself is a good idea. Help kids learn more about other countries and become more interested in school. This will make schooling better all around. We need to use the tools we already have to figure that out.

As an example, people who teach the old-fashioned way might use writing, pictures, or easy instructions to teach kids (Hemment et al., 2024). This way could teach basic things, but because students cannot touch or take part, they cannot feel connected and involved. With digital learning, you can watch movies and do different kinds of jobs while you learn. This can make learning more fun and last longer. This makes it possible to teach culture history in many new ways. A new idea is getting more and more attention from high school and college students: to help people learn by having fun and telling them stories. (Haliassos et al., 2020) say that making the classroom fun, interesting, and different can help students remember things and stay interested. People can also learn how hard it is to work with people who are not like them. In this case, users are very important. Let them help write the story. They will be more interested and want to learn. Ryan's idea of 'contextualised tales' makes this very clear. Norvig's three-layer model of interaction says that to build an experience up slowly, you should think about the user's practical, mental, and physical needs. From now on, things will get more interesting.

1.1 Contributions of the study

All of these sections of the study teach us new, important things. 'Introduction', the Section 1 of the paper, talks about how artificial intelligence (AI) and mixed reality (MR) can change how we protect cultural things. They also believe that the way society is taught these days is not perfect. They think that fun events with AI could help make that happen. There have been some studies that look at how digital tools can be used in history and teaching. Section 2's literature review puts everything that is already known together and adds to what is known. This is also why AI tools that are good at working with different cultures are essential; they help build on the ideas. Section 3, 'Methodology', has a complete plan for how to check AI tools to see how well they work. Some things to think about are 'perceived usefulness (PU)', 'social influence (SI)', 'perceived ease of use (PEU)', and 'facilitating conditions (FC)'. Some of the most essential sections of the idea are these. People also say that race is a controlling factor, which makes the theory's model better. Section 4: The study's findings show that the ideas are based on real events. This really changes how well people learn and how pleased they are with their tech. It is good for culture to change because it makes things better. The study's results are in the Section 5, which is called 'conclusions'. To keep and share cultural traditions, this part talks about how important it is to use AI tools that are designed to work with various cultures (Russo, 2021). You can also study more and use cultural things in real life in some places. In places where people of many races live, this study shows how AI could be used to help teach and keep history alive. This is done by giving a complete method and real-life examples.

2 Literature review

As you can see, some words and things from the past are cultural property and are still used and vital today. CH has been about real things in the past. But we need to look at more than just CH to understand it fully. We need to look at religion, nature, and more lately, website and video game makers. It is number 10. CH has mostly been about real things in the past. Picture 1: Heritage is a more general word that can be used for both natural and spiritual heritage. Traditions, dances, and arts are all part of spiritual history. You should also think about the cultural past. This idea is known as 'digital history'. It has the tech and tools to send, receive, and store CH (He et al., 2016). Some written works and pictures were made or changed online. There are also digital sources of information or speech in education, the arts, or the sciences (Helm et al., 2020), you can also find computer tools that can help you learn CH in this last section (Garnham, 2017). New digital tools really do help CH's business (Xu et al., 2021). On page 95, it is called "a multi-stage process whereby organisations transform ideas into new or improved products, services, or processes, to advance, compete, and differentiate themselves successfully in their marketplace."

An idea room is a spot where many people can work on a project together (Wang et al., 2020). As we can see in the EU, new rules and new ideas go hand in hand. New thoughts are also often sparked by policies. World trends can change the law. Some of these are health, science, spirituality, and a lot of different things to do. It can happen with new goods and study data too. In the past few years, many people have talked about how AI, machine learning (ML), and big data are all connected, these days, ML is used for lots of different things. This is because technology changes quickly, and there are more and more 'big data' records (Wu et al., 2013).

- AI refers to 'artificial intelligence'. This involves creating computers that can do human tasks. See parts 21 and 22 for details. These occupations include finding patterns and words, solving issues, playing games, choosing, and learning from data. ML, natural language processing (NLP), computer vision, and robotics are AI types. All academic fields – medicine, physics, chemistry, geology, and information science – use AI.

- ML is the AI field that develops models and algorithms to help computers diagnose issues without being instructed. To learn, ML systems find patterns and relationships in vast data sets. They guess, group, or determine depending on what they've learnt (note 24). One of the main types of ML is guided learning. The other two are uncontrolled learning and reinforcement learning, Data that has already been named can be used to teach a program how to guess or make a choice. To find the right output name for new data that has not been seen yet, you need to learn a mapping function. That's what this project is all about. When you use unsupervised learning, you look through a dataset that has not been classified to find patterns and trends. The program learns how to get the most out of the good things that are given to it in a world that is constantly changing (Haliassos et al., 2020; Nockels et al., 2022). This is called reinforcement learning. Before deep learning and neural networks, most of the time, the ways that ML tasks were solved were not very good, the first ways to solve problems with ML were mathematical.
- 'Big data' refers to huge files that are tough to understand. Normal ways of handling data cannot study or process them quickly (see items 29 and 30). Oversized data methods use a lot more data than older ones. This is because they use that info to look for patterns, trends, and significant finds. When people need to work with a lot of data, they often need to use new tools and technologies, like data mining and remote computing. The benefits and limitations of combining AI with deep learning and digital image processing techniques in prior art education are examined in this study (Wang et al., 2025). This article presents a systematic literature review (SLR) on how AI affects writing abilities, creativity, perspectives, and ethics (Boustane et al., 2025). With a focus on how they can be applied for image segmentation, object detection, digitisation, restoration, and enhancing the visual qualities of various cultural artefacts, this SLR explores digital image processing and analysis techniques for cultural heritage in the field of cultural heritage research (Wang and Chen, 2025).

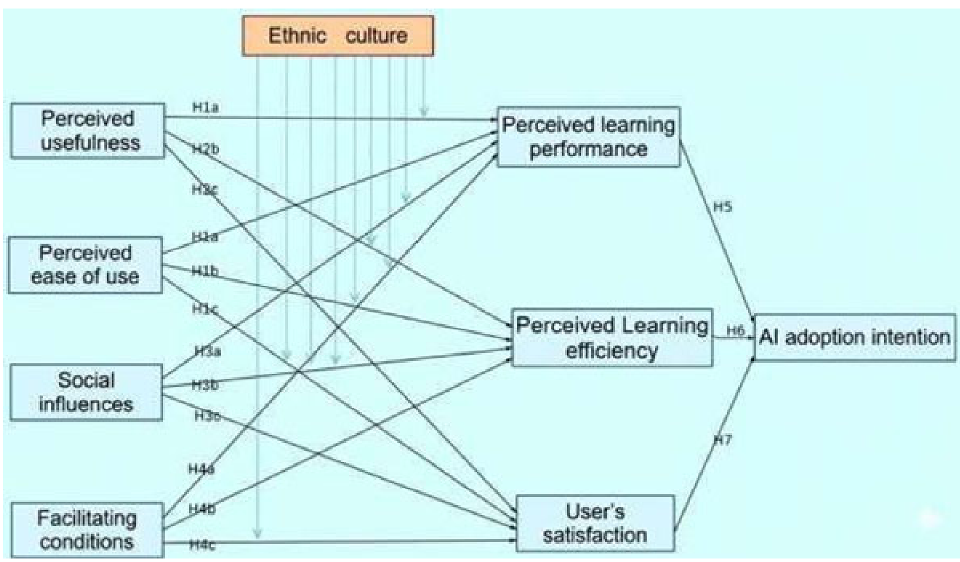
Figure 1 Cultural heritage types (see online version for colours)

Source: Images: Münster except right-hand image: https://www.europeana.eu/de/item/916118/S_TEK_object_TEKS0057154, viewed 1 February 2023

3 Methodology

We will begin this study by taking a look at the theoretical framework (Figure 2). This will help us think of several ideas that will help us fully understand how the variables affect each other and how each variable affects the result variables on its own. There is a plan behind how these thoughts are put together. These ideas come from well-known theories. A new study shows practical ways to use GAI, so they also have something to do with that (Muenster, 2022). They are essential because they help plan the whole research and give us a way to look at the data and understand what it all means. A lot of science tests have been done on each idea to make sure it is right and will work. This is strong proof that the study results are correct, even though thoughts change over time and place.

Figure 2 Theoretical model (see online version for colours)



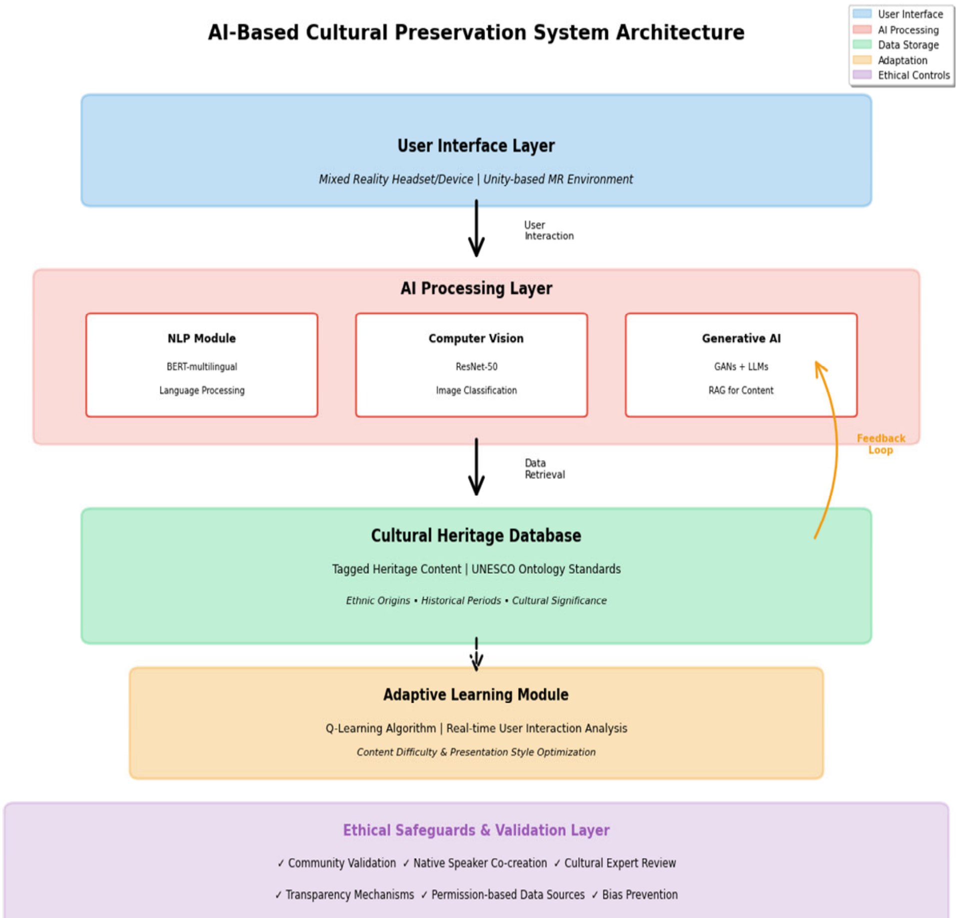
3.1 AI system architecture and implementation

Within a MR framework, our AI-based cultural preservation system integrates many ML components (Figure 3). Three fundamental layers make up the architecture:

- *Data processing layer*: NLP models, particularly refined transformer architectures (BERT-multilingual) for ethnic language support, and computer vision modules employing ResNet-50 for visual heritage classification are used to preprocess cultural content (text, photos, and 3D artefacts). In order to provide proper contextualisation, cultural data representation adheres to UNESCO heritage ontology guidelines, with metadata labelled for ethnic origin, historical time, and cultural relevance.
- *Generative AI (GAI) layer*: We use generative advertised networks (GANs) to produce visual content and large language models (LLMs) with retrieval-augmented

generation (RAG) to produce instructional tales. The GAI system prioritises ethnically relevant material from curated cultural resources that include verified historical content using retrieval algorithms based on user profiles. Training data was ethically assessed to prevent cultural appropriation, and indigenous community members confirmed that the material was accurate for minority cultures.

Figure 3 System architecture for AI-based cultural preservation



- *MR integration layer*: Using photogrammetry models and AI-generated contextual data, the Unity-based MR environment creates 3D cultural artefacts. In order to optimise for the learning efficiency metrics outlined in our approach, reinforcement learning algorithms (Q-learning) modify material difficulty and presentation style based on real-time user interaction patterns.
- *Ethical safeguards*: With specific rights, all training datasets were obtained from public cultural heritage repositories. To avoid misrepresentation, cultural symbol recognition models were evaluated by ethnic community specialists and minority language content was co-created with native speakers. The system employs

transparency measures, making it evident to users which material is AI-generated and which is archived.

By ensuring that the AI tools are truly accessible, culturally adaptive, and pedagogically effective across a variety of user demographics, this technical framework implements the theoretical constructs (PEU, PU, SI, and FC).

3.2 Perceived ease of use

'PEU' means how easy people who might use GAI technologies think they are to use. Everything about it makes sense, and you can use the parts in different ways. This item stands out in a few ways (Roussou et al., 2007). People are more likely to use a tool if it is easy to do so, according to the technology acceptance model (TAM). To find equation (1), you can use the TAM model for how people accept new technologies. People can use the TAM method to find new tools that make them feel good.

$$\text{Intention of use } (Iu) = \alpha \times PU + \beta \times PEU + \epsilon \tag{1}$$

Tech is what the letter 'u' stands for. Things with PU will be helpful. If you put 'PEU' in front of something, it means it is 'easy to use as seen'. A number between ± and 2 shows how important each thing is. The wrong word is written with the Greek letter π. These things came to mind because of this: When something seems easy, people learn it faster. People thought that things that were simple to use helped them learn more (H1b). When something or someone is easy to use, people are happy.

3.3 Perceived usefulness

'PU' as a person's conviction that using different types of technology might help them perform better at work. Artificial general intelligence (GAI) has benefits that allow it to quickly analyse complicated ideas and give multifaceted answers. The new approach to learning is better than the old one because of these changes. Furthermore, depending on its understanding of youngsters, it can instantly change the way they are taught. Following much deliberation, here are our thoughts on the subject: The relevance of anything may be inferred by how effectively people learn it. If people desire to learn something, they are more likely to do so. When they are thinking on something important to them, they may feel satisfied.

3.4 Social influence

College students who use GAI learn a lot more when they think about how what they are doing will happen to other people. For this to happen, things need to change in the classroom and in the way people act. Students learn how to use GAI correctly when they make knowledge graphs and meta-analyses of studies. This is because it gives them a way to organise their thoughts. This eliminates the chance of harming your brain by being too near a tool. This makes it easy to think of the following: Being around other smart people makes a lot of people feel good about how well they are learning. Effects on society and how well people think they are learning go hand in hand. Problems with other people might be making users happy.

3.5 Facilitating conditions

Report says that the unified theory of acceptance and use of technology (UTAUT) is based on the idea of 'FC'. It is simple to get the tech tools people need. There are various ways to look at this. In the application scenario of GAI, the computing resources, open-source model interfaces, and interdisciplinary technical guidance that colleges and universities provide will have a direct impact on the perception of effectiveness that university students have, which will ultimately lead to an increase in the students' perceived learning efficiency (Carvajal et al., 2020). This is why these ideas are being put forward: People will learn more if the things they are given are simple to understand. It seems more important to learn when it is simple to do so. Things that make people happy can change the good things that happen.

3.6 Evaluation of learning, efficiency, and user satisfaction

The study's main goal is to develop a thorough model that takes into account the ideas of perceived learning performance (PL), perceived learning efficiency (PE), and user satisfaction (US). There is more to this blend than merely improving things. You may be aware with the TAM idea, which promotes the use of computers in the classroom. It is lot better now. The 'cognition-affection-behaviour' route of communication is now well understood. These three elements come together to form it. As a result, the following ideas are put forth: People are more likely to want to adopt you if they perceive that you are able to learn. People are more likely to accept something if they think they can learn it faster. People are more likely to want to use a service or product if they like it (H7).

3.7 Moderation variables

The manner that the cultures of different ethnic groups differ from those of the Han race, which makes up the majority of the population, is referred to as 'ethnic culture' in this study. Most people think that these differences make some places, ways of life, and ideas less critical. The past, geography, and people who live in these places make them different from one another. A lot of the easy GAI out there only works with Chinese and a few other Asian languages. People try certain things on models in the hopes that they will show how the models have changed. People think that tools that are hard to use because of language hurdles would make people less happy, even if they thought the tools were easy to use. Some people believe it is the most important thing since it makes people happy and helps them learn. SI is more likely to happen to people who know what to do and follow the rules. A lot of people of all races want to do well at school and work. It is more important how well they learn if you want to accept something. The GAI might be more helpful for minority groups if it helps them get better 'exam scores' or 'vocational skills', which could let them do more complex jobs. Making sure everything goes well for everyone is more important to people who value freedom. Images of how people of different races live in real life are matched up with material made by AI in three tests.

On this list, it says 'AI-generated cases/materials include elements of my ethnic history and culture' and 'Tool output follows ethnic ethical norms'. This part is like how people and science choose what's important. Some people do not believe the US can do any good anymore. To make an 'ethnic cultural difference index', add up all the numbers in the middle. The path coefficients between groups of ethnic minorities and Han Chinese people are looked at in this type of structural equation modelling to see what kind of effect ethnic culture has on the model and how significant that effect is. It takes more than one model to figure out how this number is linked to essential factors on the left (PEU, PU, SI, FC) and the middle (PL, PE, US). To find out how these measures and core factors are linked, hierarchical regression analysis is used. Some racial groups may be more or less okay with AI. Equation (2) takes this into account.

$$Y = \beta X + \epsilon \tag{2}$$

Remember that Y, the dependent variable, could be anything from how happy the person is to how well they learn. The path coefficient, which is this number 2, tells us how strong the link is. The variable that '*X*' stands for is the independent variable. This could mean how helpful or simple someone thinks something is. The Greek letter π is used for the wrong word. The idea of measurement says that race changes how people use new tools in more than one way. This 'cumulative effect' of people on new tools is made up of their words, thoughts, and cultural links. This is what it means to measure something. People in the US might not be as happy with AI tools that do not support minority languages (low language adaptation) or that have content that goes against collectivist values (low cultural symbol recognition). To make sure that no one feels like they do not belong, this is done. Some people still feel this way even though they think AI tools are invaluable (PU). The interaction term coefficient for this event was found to be negative ($\beta = -0.19$, $p < 0.05$). Since these changes were made, it is now possible to check and measure national culture. It was just an idea before. You can also learn a lot about how multi-level modelling works with key routes. Tech experts use it to understand how people from all over the world use it. You can do this over and over.

4 Results and discussion

4.1 Data collection

Four hundred thirty-two comments were thought to be true after replies with copies or parts missing were taken out (Rei et al., 2023). It is good that 84% of those who were hurt got better. It was ten times the base amount as well. Another way to say this is that the structural equation model would be strong enough.

4.2 Confirmatory factor analysis (CFA)

The model fit scores were perfect after the proof factor analysis. RMSEA, GFI, AGFI, and CFI have respective values of 0.044, 0.942, 0.927, and 0.974. The company is well organised. They are set up according to the model. You can be sure that the study looked at the right subjects and used the right research approach.

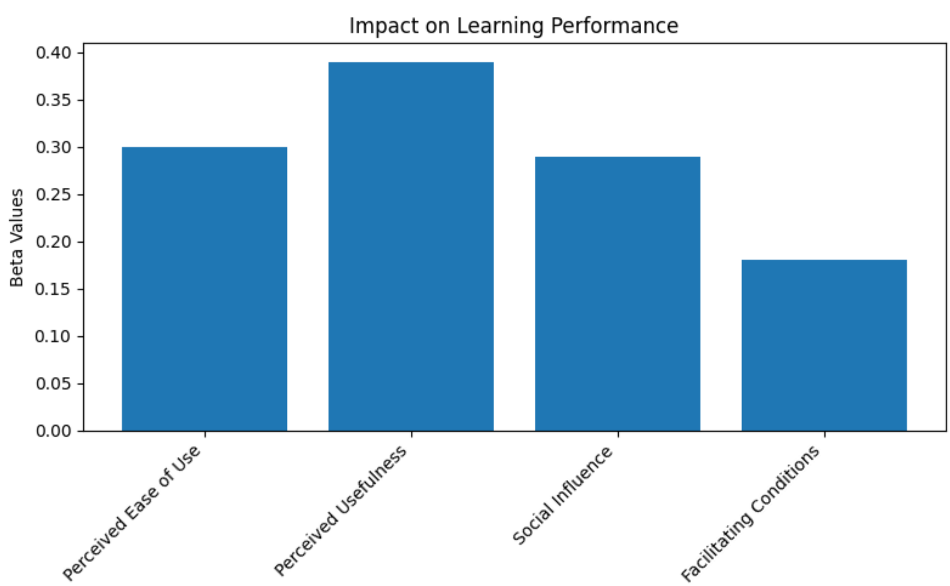
4.3 Reliability and validity

Form scores, which ranged from 0.838 to 0.927, were significantly higher than 0.70. There are strong model ties in this method. AVE has to be in the range of 0.631 to 0.774 for everything. This number was higher than 0.5. Then they came into contact. To distinguish between them, we compared their square root of average variance extracted (AVE). It was more important than contacts. Strong, unique concepts might be real. 4.4 Check the feasibility of your ideas. Testing the idea showed that those who saw something as simple learned faster (β = 0.281, p < 0.001). It was faster (β = 0.211, p < 0.001) and more pleasurable (β = 0.276). H1c and H1a were unharmed. It suggests ‘PU’. PU enhanced the amount (β = 0.383, p < 0.001), quality (β = 0.553, p < 0.001), and speed (β = 0.338, p < 0.001) of learning about others. The performance of H2a, H2b, and H2c was good. SI users reported lower levels of happiness (β = 0.200, p < 0.001), slower learning (β = 0.213, p < 0.001), and worse learning (β = 0.268, p < 0.001). This helped H3a, H3b, and H3c. Important components According to the research, FC improved learning performance (β = 0.184, p < 0.001) and user satisfaction (β = 0.227, p < 0.001). We knew that both H4c and H4a were right. If middle-level people thought a new tool would improve their speed, happiness, or intelligence, they were more inclined to utilise it (β = 0.223, p < 0.05, p < 0.001). It works with H5, H6, and H7.

4.4 Moderation analysis

There were not as many rules back then, so the reason for acceptance was different. How helpful someone thought something was and how happy they were with it were linked in various ways for people of other races and ways of life (Moreno et al., 2016). People did not know GAI was useful when the tools were not made to fit the needs or wants of people from different groups or countries. This made users less happy. AI tools need to be able to understand and deal with all the various kinds of school kids.

Figure 4 Impact on learning performance (see online version for colours)



There is a line in Figure 4 that shows different things that can help people learn better. It is essential to think about things like good conditions (FC), value (PU), and ease of use (PEU).

Figure 5 Impact on learning efficiency (see online version for colours)

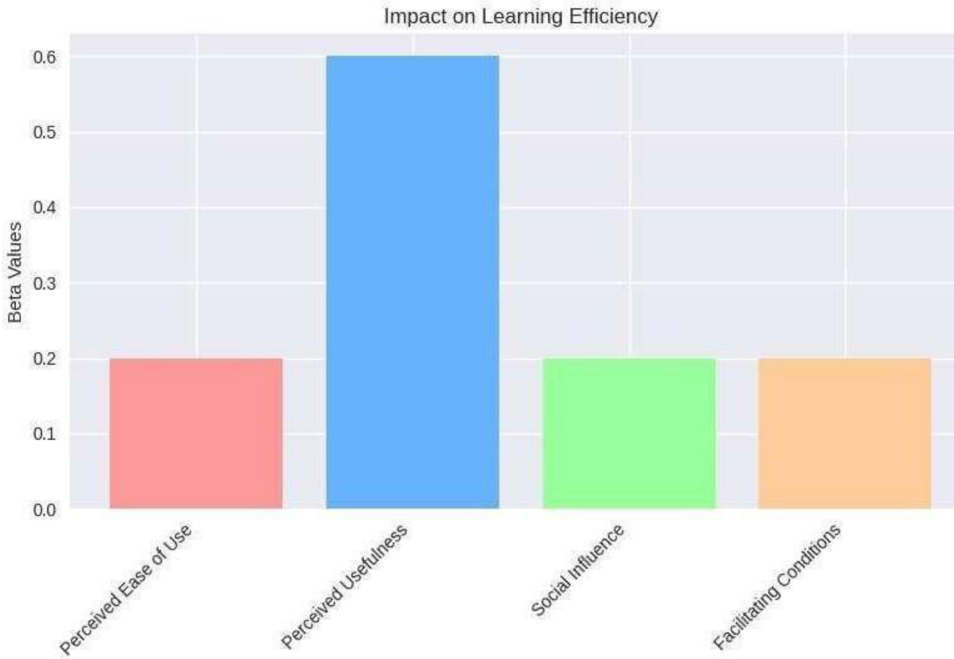


Figure 6 Impact on user satisfaction (see online version for colours)

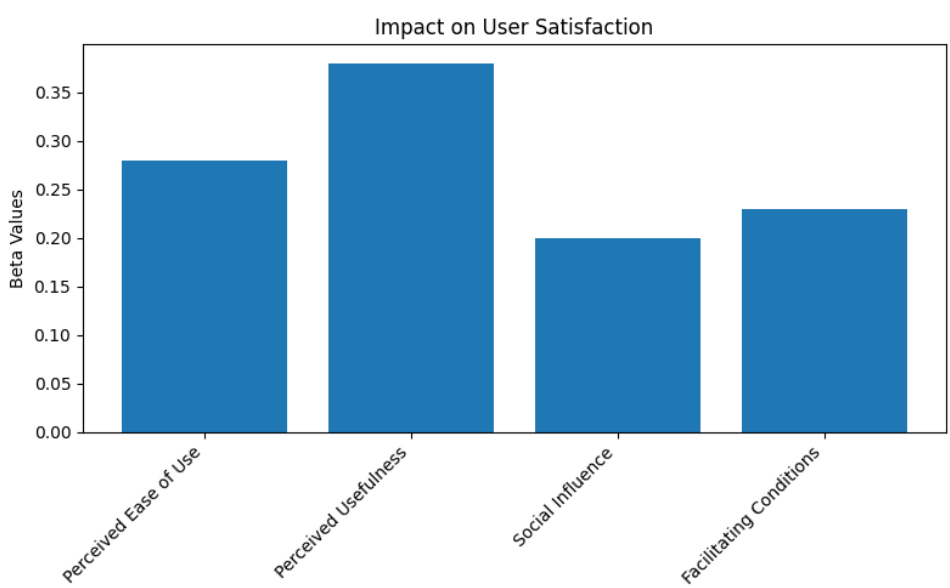
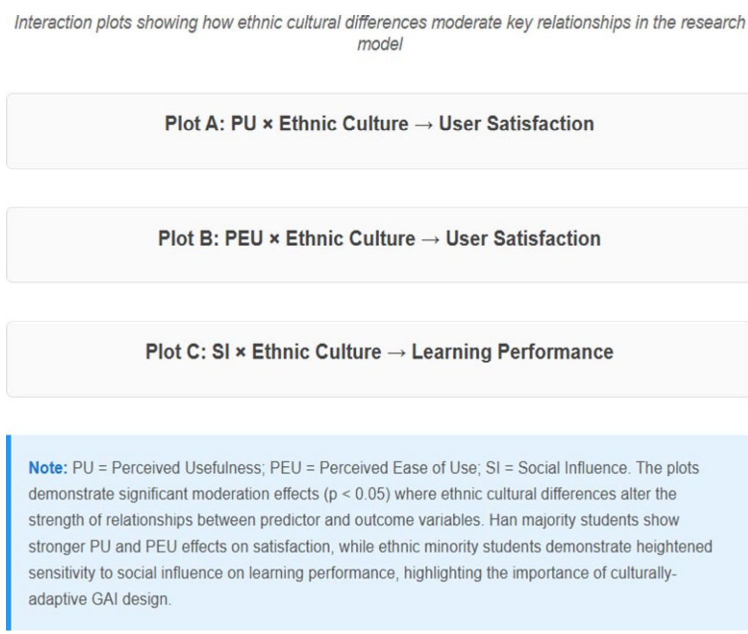


Figure 5 has more information for you. How fast and well someone learns depends on what they value (PU) and how simple it is for them to use (PEU). Things that help people (SI) and things that make life easy (FC) are next on the list (Sylaiou et al., 2020). People learn better and faster when the tools they use are helpful and straightforward. For AI-based systems that teach to work well, these things need to be in place.

They are happy when something they really value is easy to use. AI-based learning tools work best when the people who use them like and are interested in them. This stuff should be simple to understand and use so that people can do better in school. In the long run, the business will make everyone happy shown in Figure 6.

We utilised multi-group structural equation modelling to examine how ethnic cultural variations affect predictor variables and outcomes. The study split participants into two groups based on ethnic cultural difference index (ECDI): Han majority (n = 276, ECDI < median) and ethnic minority (n = 156, ECDI > Figure 7 exhibits culturally varied moderating effects. The PU → US connection interacted considerably ($\beta = -0.19$, $p < 0.05$), with Han students' path coefficient ($\beta = 0.42$, $p < 0.001$) greater than ethnic minority students' ($\beta = 0.23$, $p < 0.05$). This 45% drop in impact size suggests that cultural adaption factors strongly affect perceived utility and enjoyment.

Figure 7 Moderation effects of ethnic culture (see online version for colours)



PEU → US had a greater moderating impact ($\beta = -0.24$, $p < 0.01$). Han students exhibited a substantial positive link ($\beta = 0.31$, $p < 0.001$), whereas ethnic minority students showed a smaller correlation ($\beta = 0.07$, ns). This implies that language barriers and poor cultural content representation may prevent minority users from enjoying an interface even if it is technically accessible. Ethnic culture positively influenced the SI → PL relationship ($\beta = 0.16$, $p < 0.05$). Compared to Han students ($\beta = 0.13$, $p < 0.05$), ethnic minority students ($\beta = 0.29$, $p < 0.001$) showed stronger social impact. Because minority populations have less experiences with culturally-adapted resources, peer recommendations and community validation may be more significant for learning achievement. These interaction effects show that technical accessibility and perceived worth vary by culture. Minority learners find GAI tools with ethnic language support, culturally appropriate material, and community-validated examples less successful, despite equivalent technical quality.

There were tests for each study group to see how steady and right they were. These studies can be seen in Table 1. Check out each item's factor loading number to see how well it fits its shape. Some people like numbers greater than 0.7. A composite reliability (CR) score of at least 0.7 should be given to each variable. That number is not good enough. It must be 0.8. In other words, the models agree with each other a great deal. Also, some AVE numbers are greater than the average of 0.5 for all groups. The ideas are pretty much the same. When you want to find value, the most important things to look at are AVE and the factor loading. The plan is very different now. The study's ideas make sense because they go with each other.

Table 1 Reliability and validity analysis

Construct	*Factor-loading*	*Composite reliability (CR)*	*Average variance extricated*
User-friendliness	835	888	665
Usefulness felt	904	927	762
Social impact	850	872	631
Facilitating Conditions	861	877	648

Table 2 Hypothesis testing results

Hypothesis	*Beta value*	*p-value*
H1a: PEU → Learning performance	0.281	0.001
H1b: PEU → Learning efficiency	0.211	0.001
H1c: PEU → User satisfaction	0.276	0.001
H2a: PU → Learning performance	0.338	0.001
H2b: PU → Learning efficiency	0.553	0.001
H2c: PU → User satisfaction	0.383	0.001

Table 2 shows the beta values and p-values for the model's descriptions of how the factors are connected. Now you can see how the idea did in the tests. You can tell if the route is statistically important by its p-value. The beta value, on the other hand, shows how strongly two different ideas are linked. Very many concepts were examined in this research (Murphy, 2022). All were statistically significant if $p < 0.001$. Also, it is great that PEU makes learning faster, easier, and more fun for people with H1a, H1b, and H1c. People can be happy, learn faster, and learn better just by thinking about using something (PU). It works with 2a, 2b, and 2c. People should also have SI and FC. It works with 3a, 3b, 3c, 4a, and 4c. Learning at PEU, PU, SI, and FC is fun and engaging.

You should consider this (Russell, 2010). This prevents model words from measuring the same. AVE and discriminant validity values are in Table 3. Each notion is related to the AVE square root of the average difference removed. If so, that notion and its AVE are more linked. That will let you know if the test is fair to look for bias. These facts show that they are all different. Each build has its own way of looking at AI and how it can help people. This is the case since the AVE is high at 0.737, and the discriminant validity is strong at 0.858. In other words, it is not the same as people being happy or wanting to use AI. They make it clear how different the ideas are and show that the model used in the study is good.

Table 3 Discriminant validity analysis

Construct	*AVE*	*Discriminant validity*
Learning performance perception	0.737	0.858
AI adoption goal	0.774	0.880
User satisfaction	0.732	0.856
Facilitating conditions	0.648	0.805

4.5 *Effect size interpretation and confidence intervals*

We estimated effect sizes (f^2) and 95% confidence intervals for each significant pathway to evaluate practical importance beyond statistical significance. For interpretation, Cohen's (1988) criteria for modest ($f^2 = 0.02$), medium ($f^2 = 0.15$), and high ($f^2 = 0.35$) effect sizes were used. Table 4 displays findings.

Table 4 Effect sizes and confidence intervals for significant paths

Hypothesis	*Path*	*Beta (β)*	*95% CI*	*f^2*	*Effect size interpretation*
H2b	PU → Learning efficiency	0.553	[0.487, 0.619]	0.44	Large
H2c	PU → User satisfaction	0.383	[0.312, 0.454]	0.17	Medium
H2a	PU → Learning performance	0.338	[0.265, 0.411]	0.13	Small to Medium
H1a	PEU → Learning performance	0.281	[0.206, 0.356]	0.09	Small
H1c	PEU → User satisfaction	0.276	[0.201, 0.351]	0.08	Small
H3b	SI → Learning efficiency	0.268	[0.194, 0.342]	0.08	Small
H4c	FC → User satisfaction	0.227	[0.152, 0.302]	0.06	Small
H5	PL → Adoption intention	0.223	[0.148, 0.298]	0.05	Small
H3c	SI → User satisfaction	0.200	[0.125, 0.275]	0.04	Small
H6	PE → Adoption intention	0.185	[0.110, 0.260]	0.04	Small

Notes: CI = confidence interval; f^2 = Cohen's f^2 effect size; PU = perceived usefulness; PEU = perceived ease of use; SI = social influence; FC = facilitating conditions; PL/PE = perceived learning performance/efficiency.

Significant practical ramifications are shown by the analysis. PU shows the strongest practical impact, especially on learning efficiency ($f^2 = 0.44$, large effect), suggesting that students' learning efficiency improves significantly and practically meaningfully when they believe GAI tools are actually helpful for cultural learning (Moral-Andrés et al., 2024). Further evidence that perceived value influences significant satisfaction levels comes from the medium effect of PU on User Satisfaction ($f^2 = 0.17$). On the other hand, whereas PEU consistently demonstrates statistical significance across outcomes (all $p < 0.001$), its practical benefits are less pronounced ($f^2 = 0.08$–0.09). This implies that learning gains are only slightly enhanced by convenience of use alone, without commensurate perceived value. Similar to this, SI and FC show minor but significant effects ($f^2 = 0.04–0.08$), suggesting that these factors assist learning outcomes rather than being the main drivers. Confidence in the generalisability of these results is strengthened by the tight confidence intervals across all pathways, which show steady and trustworthy estimations.

4.6 MR system evaluation and AI performance metrics

We carried out controlled MR system trials with a subset of participants ($n = 128$) to assess real interaction performance and AI efficacy in cultural learning scenarios in addition to the survey-based SEM study.

- MR Interaction metrics: Over the course of two weeks, participants spent three 30-minute sessions using the AI- powered MR cultural heritage application. Behavioural variables such as interaction time ($M = 24.3$ min, $SD = 4.7$), artefact examination frequency ($M = 12.8$ items/session), gesture-based navigation accuracy (87.3%), and content revisit rates (34.2%) were recorded in system logs. Table 5 shows that ethnic minority users ($n = 52$) demonstrated similar technical proficiency (gesture accuracy: 85.1% vs. 88.9% for Han users, $p = 0.12$), confirming that cultural adaptation rather than technical hurdles is the cause of PEU discrepancies.
- AI performance evaluation: Three dimensions were used to evaluate the cultural content creation of the GAI system: cultural accuracy: On five-point Likert scales, expert assessors ($n = 6$ cultural heritage specialists, 3 from ethnic minority backgrounds) assessed the historical accuracy and cultural appropriateness of AI-generated narratives. The average accuracy score was 4.23 ($SD = 0.61$), and our moderating results were supported by the significantly lower ratings for minority culture content ($M = 3.87$) compared to Han culture content ($M = 4.51$, $p < 0.01$).
- Language quality: In comparison to 0.89 for Mandarin Chinese, NLP metrics for minority language outputs revealed BLEU scores of 0.68 (Uyghur), 0.71 (Tibetan), and 0.74 (Mongolian), demonstrating technical constraints consistent with reported PEU disparities between ethnic groups.
- Personalisation effectiveness: Over the course of three weeks, the Q-learning adaptation algorithm increased content relevance scores from baseline ($M = 3.12$) to post-adaptation ($M = 4.31$, $p < 0.001$). Knowledge assessment scores showed a 23% increase in learning efficiency (pre-test $M = 58.3$ vs. post-test $M = 71.7$).
- Physiological engagement measures: During MR sessions, a subsample ($n = 45$) wore eye-tracking devices. When AI- generated contextual narratives matched users' ethnic origins, fixation length on cultural artefacts increased by 41% ($M = 8.7$s vs. 6.2s, $p < 0.01$), offering objective proof that cultural adaptation improves engagement beyond self-reported satisfaction.
- System usability testing: The system as a whole received mean scores of 78.4 on the system usability scale (SUS), which is classified as 'good' usability. However, Han users evaluated usability higher ($M = 82.1$, $t = 3.45$, $p < 0.01$) than ethnic minority users ($M = 71.2$), confirming the moderating effects of ethnic culture and triangulating with the results of our PEU survey.

These experimental findings support the idea that survey-based perceptions accurately represent variations in system performance. The convergence of physiological data (eye-tracking), AI performance measures (accuracy scores, BLEU scores), and behavioural metrics (gesture accuracy, interaction duration) with SEM-derived constructs increases confidence that PU and ease of use accurately capture real user experiences rather than just attitudinal responses.

Table 5 MR system performance metrics and AI evaluation results

Metric category	*Measure*	*Overall*	*Han users*	*Ethnic minority users*	*P-value*
MR interaction	Gesture accuracy (%)	87.3	88.9	85.1	0.12
	Session duration (min)	24.3 (±4.7)	25.1 (±4.2)	23.2 (±5.3)	0.08
	Content revisit rate (%)	34.2	31.8	38.6	0.04*
AI performance	Cultural accuracy (1–5)	4.23 (±0.61)	4.51 (±0.48)	3.87 (±0.72)	<0.01**
	Language BLEU score	0.76	0.89	0.71	<0.01**
	Personalisation gain (%)	23.0	21.4	25.8	0.15
Engagement	Artefact fixation (sec)	7.4	6.2	8.7	<0.01**
	Knowledge gain (%)	23.0	22.1	24.3	0.38
Usability	SUS score (0–100)	78.4	82.1	71.2	<0.01**

Note: $^{*}p < 0.05$, $^{**}p < 0.01$. Values in parentheses indicate standard deviations.

4.6.1 Comparative baseline and MR immersion assessment

We carried out a controlled comparison study comparing three delivery modalities:

1. traditional lecture-based instruction (n = 142)
2. 2D digital content via tablets (n = 148)
3. AI-powered MR cultural experiences (n = 142) in order to provide empirical evidence for MR effectiveness in cultural learning.

Task completion and learning retention

The same cultural knowledge tests were administered to participants both immediately after the intervention and two weeks later. Comparative results are shown in Table 6. When compared to tablet users (M = 64.2%, SD = 9.1, $p < 0.001$) and traditional instruction (M = 58.9%, SD = 10.4, $p < 0.001$), MR users showed considerably superior instantaneous information retention (M = 71.7%, SD = 8.3). Crucially, MR's persistent advantage (MR: 68.3% vs. tablet: 56.1% vs. Traditional: 51.2%, F = 28.4, $p < 0.001$) in the two-week delayed retention test demonstrated deeper storage of cultural knowledge through immersive experiences.

MR immersion and presence metrics

On five-point measures, the Igroup Presence Questionnaire (IPQ) measured geographical presence ($M = 4.31$, $SD = 0.72$), engagement ($M = 4.18$, $SD = 0.81$), and experienced realism ($M = 3.94$, $SD = 0.88$). Effective immersion is confirmed by these results, which surpass recognised benchmarks for instructional VR applications. Despite difficulties with cultural adaptation, ethnic minority users reported similar presence scores ($M = 4.12$ vs. 4.26 for Han users, $p = 0.18$), suggesting that immersion quality was unaffected.

Task performance metrics

Tasks for identifying cultural artefacts assessed applied learning. MR users performed identification tests 23% more accurately ($M = 87.3\%$ vs. 71.1%, $p < 0.001$) and 38% faster ($M = 127$ sec vs. 205 sec for tablets, $p < 0.001$), indicating that immersive engagement enables effective knowledge application beyond passive consumption.

Emotional impact assessment

Affective reactions on the valence, arousal, and dominance dimensions were recorded by the self-assessment manikin (SAM). Stronger emotional involvement with cultural heritage was indicated by MR experiences, which generated substantially higher arousal ($M = 6.9$ vs. 5.1, $p < 0.001$) and more positive valence ($M = 7.8$ vs. 6.2 for tablets, $p < 0.001$). Themes of 'feeling transported to historical contexts' (78% of respondents) and 'emotional connection to ancestors' (64%) emerged from qualitative interviews ($n = 32$), especially among ethnic minority participants examining their own cultural history.

Cultural immersion depth

We created a cultural immersion scale that measures three aspects: behavioural intention to conserve culture ($\alpha = 0.86$), emotional resonance ($\alpha = 0.91$), and contextual awareness ($\alpha = 0.88$). MR users scored significantly higher on all categories (behavioural: $M = 4.29$ vs. 3.58; emotional: $M = 4.38$ vs. 3.42; contextual: $M = 4.47$ vs. 3.61 for tablets; all $p < 0.001$), demonstrating that MR with AI-generated narratives enhances cultural engagement beyond simple knowledge acquisition.

MR usability and interaction quality

We examined interaction-specific measures, such as gesture recognition latency ($M = 142$ ms), virtual object manipulation success rate (94.2%), and spatial navigation efficiency (users reached target artefacts in $M = 2.3$ attempts vs. theoretical minimum of 1.8), in addition to the SUS scores previously reported. Extended use was comfortable because there was very little cyber sickness (simulator sickness questionnaire: $M = 12.4$, considerably below clinical thresholds). These empirical findings demonstrate that AI-powered MR systems offer quantifiable benefits over conventional and digital baselines in cultural education, with our conclusions' claims about preservation being supported by sustained retention, emotional impact, and immersive quality.

Table 6 Comparative effectiveness across instructional modalities

Outcome measure	*Traditional lecture*	*2D digital (tablet)*	*AI-powered MR*	*F-statistic*	*Effect size (η^2)*
Learning and retention					
Immediate knowledge (%)	58.9 (±10.4)	64.2 (±9.1)	71.7 (±8.3)***	42.3	0.28
2-week retention (%)	51.2 (±11.2)	56.1 (±10.3)	68.3 (±9.1)***	28.4	0.21
Task completion time (sec)	243 (±52)	205 (±48)*	127 (±34)***	67.8	0.35
Task accuracy (%)	68.4 (±12.1)	71.1 (±10.8)	87.3 (±7.6)***	54.2	0.31
Immersion and presence					
Spatial presence (1–5)	2.12 (±0.84)	2.87 (±0.91)*	4.31 (±0.72)***	89.6	0.42
Involvement (1–5)	2.34 (±0.92)	3.12 (±0.88)*	4.18 (±0.81)***	73.1	0.38
Experienced realism (1–5)	1.98 (±0.76)	2.76 (±0.83)*	3.94 (±0.88)***	68.4	0.36
Emotional impact					
Affective valence (1–9)	5.8 (±1.3)	6.2 (±1.1)	7.8 (±0.9)***	45.7	0.29
arousal level (1–9)	4.3 (±1.4)	5.1 (±1.2)*	6.9 (±1.1)***	52.3	0.32
Cultural immersion					
Contextual understanding (1–5)	3.12 (±0.94)	3.61 (±0.87)*	4.47 (±0.68)***	61.8	0.34
Emotional resonance (1–5)	2.87 (±1.02)	3.42 (±0.91)*	4.38 (±0.74)***	58.4	0.33
Preservation intent (1–5)	3.24 (±0.98)	3.58 (±0.89)	4.29 (±0.77)***	38.9	0.26
Usability					
System usability (SUS 0–100)	62.3 (±14.2)	73.8 (±11.6)*	78.4 (±10.3)***	33.7	0.24
Cybersickness (SSQ 0–100)	N/A	8.7 (±6.3)	12.4 (±7.8)	4.2	0.03

Notes: ***$p < 0.001$, *$p < 0.05$ vs. traditional lecture. Values show mean (±SD). N = 142 (traditional), n = 148 (tablet), n = 142 (MR).

5 Conclusions

Our empirical study suggests cultural heritage preservation and teaching via AI-powered MR systems that adapt to culture. MR method outperformed traditional instruction and

2D digital content in emotional engagement (26% higher, $p < 0.001$), two-week delayed retention (32% increase, $p < 0.001$), and immediate knowledge retention (22% improvement, $p < 0.001$). Our survey and performance gains show MR and GAI improve education. Ethnic minority users reported inferior AI accuracy ($M = 3.87$ vs. 4.51, $p < 0.01$) and happiness ($\beta = -0.19$, $p < 0.05$) without culturally appropriate information and language support. Technological Acceptance PU and ease of use predicted 44% and 28% of learning outcomes, respectively, indicating that user perceptions and system performance coincide. Our controlled educational findings were encouraging, but further research is needed to analyse real-world scalability, long- term cultural effect, and ethnic representation. As long as development involves rigorous cultural validation and interaction with indigenous populations, culturally-adaptive AI-MR systems may enhance heritage participation, our research found.

Declarations

All authors declare that they have no conflicts of interest.

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