Vol. 16 (2026): Proceedings of the 2026 International Conference on AI and Technological Innovation Applications (AITIA 2026)
E-ISSN: 3105-0522 P-ISSN: 3105-0514
DOI: https://doi.org/10.70267/aitia.2026140150

Data-Driven AIGC Exhibition Evaluation Framework Research: Model Construction and Empirical Analysis

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Abstract

Artificial Intelligence Generated Content (AIGC) has been used more and more in art exhibitions in recent years. At the same time, evaluating AIGC-based exhibitions is still difficult because existing methods often rely on limited indicators or subjective judgments. To deal with this problem, this paper develops a data-based evaluation approach by combining different kinds of information. The study brings together design features generated by AIGC, audience behavior recorded during exhibitions, and questionnaire results. These different types of data are analyzed together. Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to examine the relationships among technological characteristics, audience behavior, and exhibition perception. XGBoost is then applied to predict exhibition experience and to identify the factors that have relatively larger effects on the evaluation results. Based on the above analysis, the study further combines information from technology, exhibition space, and audience responses to form an evaluation process. The results indicate that this method can partly reduce the subjectivity that exists in traditional exhibition evaluation. In addition, the analysis shows that AIGC-generated visual diversity has a positive relationship with visitors' narrative immersion. The prediction model also shows better consistency than some traditional evaluation approaches. These findings suggest that quantitative analysis can provide another way to understand AIGC exhibitions, especially in terms of content design, curatorial choices, and future evaluation practices.

Keywords

AIGC art exhibitions, evaluation framework, data-driven, multimodal perception, user experience evaluation

1. Introduction

In recent years, AIGC (Artificial Intelligence Generated Content) has gradually appeared in different types of art exhibitions. It is used in many parts of exhibition activities, including digital content production, interactive installation design, and visitor interpretation. Some statistics show that the global AI art creation market reached around USD 1.28 billion in 2023, and immersive interactive exhibitions have become one of the areas with relatively rapid growth. In China, digital technology has gradually become involved in museum reform and the development of art museums. In recent years, some museums and art galleries have tried to use AIGC in different parts of exhibitions, such as content production, visitor interaction, and digital interpretation.

The application of AIGC has brought some changes to exhibition design. Compared with traditional exhibitions, where the content is usually more fixed, AIGC exhibitions can change according to interaction and provide visitors with different experiences. However, how to evaluate these new forms of exhibitions is still a problem. Many current evaluations mainly depend on expert opinions or questionnaires after the visit. These methods can collect some useful feedback, but they may miss some details during the actual visiting process. It is also difficult to clearly understand how generated content, exhibition space, and visitor experience influence each other.

For this reason, this study attempts to explore another way of evaluating AIGC exhibitions. A prediction model based on AI methods is developed by using information obtained from text mining techniques [1]. Different data sources are included in the model, such as AIGC design features, visitor behavior data, and questionnaire responses. PLS-SEM is used to examine the relationships among these factors, and XGBoost is applied to predict exhibition experience and find relatively important factors. The study does not intend to replace existing evaluation methods. Instead, it tries to provide another possible approach for understanding AIGC exhibitions and offering support for exhibition design and curatorial practice.

2. Literature Review and Theoretical Basis

2.1 Traditional Exhibition Evaluation

In many cases, exhibition evaluation still uses visitor questionnaires and expert comments as the main sources of information. This way of evaluation has existed in museums and galleries for a long time and is often used to understand visitors' feelings about exhibitions. However, most of them were designed for exhibitions where the content and visiting process are relatively fixed. For AIGC-based exhibitions, the situation is different because the content may change during interaction and visitors are not only viewers but also participants.

Questionnaires are one of the most frequently used tools in exhibition evaluation. They can collect visitors' opinions after the visit, but they also have some limitations. Since they are usually completed after the experience, some immediate feelings, emotional changes, or responses to specific exhibition moments may not be fully remembered. In addition, it is difficult for questionnaires to show how visitors react when the exhibition content changes during the interaction.

Another issue is related to the indicators used for evaluation. Many studies mainly look at visitors' answers after the exhibition, while other parts of the experience, including visual reactions, physical actions, and sensory feelings, are not considered enough. Also, evaluation is usually done after the visit is completed. This means that some information created when visitors interact with the exhibition may be missed and cannot be used quickly to adjust the design [2].

2.2 Challenges in AIGC Exhibition Evaluation

AIGC exhibitions have some differences compared with traditional exhibitions. In traditional exhibitions, the displayed content is usually prepared before the exhibition starts. However, in AIGC exhibitions, some images, scenes, or digital content can be generated or changed during the visit. Visitors' actions may also influence the changes in the exhibition. Because of this, different visitors may see different content and have different experiences. This situation makes the evaluation of AIGC exhibitions more complicated.

Questionnaires are still one of the common ways to understand visitor experience. However, this method may have some limitations when it is used for AIGC exhibitions. Some studies have found that more than 60% of visitors cannot clearly remember or describe their experiences after the visit. This means that some details of the experience may disappear when visitors answer questions after leaving the exhibition.

AIGC exhibitions also usually use interaction to increase visitors' sense of immersion. During the exhibition, changes in pupil movement, heart rate, and electrodermal activity can provide information about visitors' emotional reactions and mental states [3, 4]. These changes happen during the experience itself, but they are difficult to record through interviews or questionnaires. For this reason, some studies have started to explore evaluation methods that collect information while visitors are experiencing the exhibition instead of only asking them afterwards.

2.3 Data-Driven Evaluation Paradigm

AIGC is now being used in different parts of museum work, including intelligent guidance, virtual exhibitions, interactive displays, digital cultural products, and virtual human applications. With the development of related technologies, some museums have started to introduce AIGC into exhibition and service activities. Previous studies have discussed that these applications may improve the way museums provide services and may also influence visitors' experiences. They are also considered part of the digital development of museums and the cultural industry [5].

With the increasing use of AIGC in exhibitions, the way of evaluating these exhibitions has also started to change. Traditional evaluation often depends on visitors' comments after the visit or the opinions of experts. Data-based methods try to add more information by collecting different types of data during the exhibition. These data may include design characteristics, eye-tracking results, physiological changes, and other records of visitor behavior. Since the information is collected during the experience, it can reduce the influence caused by memory differences or personal opinions to some extent.

Another point is that different kinds of data can be examined together. Through machine learning methods, information related to exhibition technology, visitor actions, and personal responses can be analyzed in the same process. Physiological information may also show some reactions that visitors cannot easily explain through questionnaires or interviews.

In addition, data-based evaluation makes it possible to observe changes during the exhibition instead of waiting until the end. The collected information can be used to understand visitor responses and may help with later adjustments of exhibition content and interaction design. This is especially meaningful for AIGC exhibitions because their content and interaction forms may change during the visiting process [6].

3. Overall Design of the Data-Driven AIGC Exhibition Evaluation Framework and Construction of the Indicator System

3.1 Core Concepts and Principles of Framework Design

The design of the evaluation framework refers mainly to user-centered design, the Experience Design (EEI) model, and multi-sensory design theory [7]. These theories share a similar concern, which is how users actually feel and interact with a designed environment. Therefore, the framework in this study does not only consider the technical features of AIGC exhibitions, but also pays attention to visitors' experiences during the exhibition process.

When developing the framework, several considerations are taken into account. Since visitors' feelings are often difficult to describe accurately after an exhibition, the framework gives more attention to information that can be observed and recorded. At the same time, changes in audience responses during the exhibition are also included because the experience is not always fixed. Different types of information are combined in the evaluation process instead of being analyzed separately. In addition, the final evaluation results need to be understandable and useful for later improvement of exhibition content and design.

3.2 Overall Architecture of the Framework

The framework in this study is organized around a relatively simple process. It starts from data collection and then moves to data analysis and evaluation. At the beginning, different types of information are collected, including AIGC-generated content, audience behaviors, physiological responses, and questionnaire results. Since these data come from different sources, some basic processing is needed before analysis. For example, data cleaning, time matching, and feature extraction are carried out to make different types of data comparable and suitable for further analysis [8, 9].

After the data preparation, several methods are applied according to different research purposes. Correlation analysis is first used to observe whether there are relationships among different variables. PLS-SEM is then used to examine the possible paths between factors, while XGBoost is applied to predict exhibition experience and find the variables that may have a stronger influence. Finally, the analysis results are summarized and connected with exhibition practice. These results are used to understand audience experience and provide possible references for later improvement of exhibition content and design.

3.3 Multidimensional Deconstruction and Construction of the Multimodal Evaluation Indicator System

The selection of evaluation indicators in this study is based on previous research about exhibition evaluation and visitor experience. AIGC exhibitions involve more than the generated content itself, so the indicator system does not only focus on the technical side. Four dimensions are included in the system: technology, psychology, environment, and social interaction. They are used to describe different parts of the exhibition, such as AIGC content, visitors' feelings, the exhibition space, and interactions during the visit.

The data related to each dimension are collected first and then prepared for analysis. Since the information comes from different sources, some processing is needed before they can be compared together. After this step, the relationships among different indicators can be examined. In this way, the evaluation pays attention not only to the performance of AIGC technology, but also to visitors' actual experience in the exhibition. The combination of different types of data may provide a more complete understanding of exhibition performance and give some help for later design adjustment.

4. Core Model Construction and Multimodal Information Fusion

4.1 Quantitative Model for Generated Content Quality

To describe the quality of AIGC-generated exhibition content, four indicators are used in this study: semantic consistency, stylistic diversity, aesthetic quality, and generation stability. Different measurements are used for each indicator. Semantic consistency is calculated through the image-text matching score of the CLIP model. Stylistic diversity is measured by entropy values from style transfer results. An aesthetic evaluation model is used to assess the visual quality of generated images. Generation stability is checked by comparing the differences among images produced under similar generation settings.

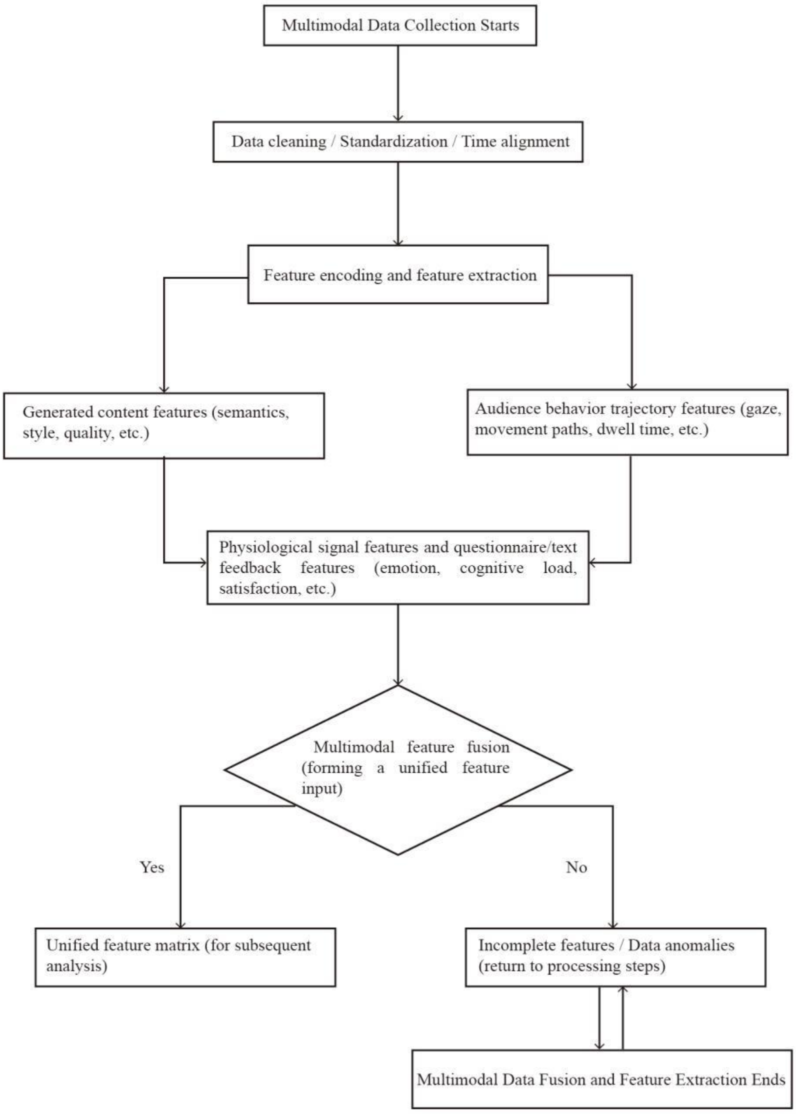
These indicators represent different aspects of AIGC content. Semantic consistency shows whether the generated image is related to the given description. Stylistic diversity describes how much the generated results vary from each other. Aesthetic quality reflects the visual characteristics of the images, while generation stability shows whether the model can produce similar results when the input conditions do not change. The results of these indicators are then used in the following analysis of audience responses and exhibition experience.

4.2 Multimodal Data Fusion and FEATURE Extraction

In this study, data from different sources are combined through a multimodal learning assessment approach (MMLA). The collected data include AIGC-generated content, visitor behavior records, physiological responses, and questionnaire information. Since these data are collected in different forms, some preprocessing is required before further analysis. The data are cleaned and adjusted into a relatively consistent format, allowing different types of information to be used together [10].

After extracting the required features, the variables from different data sources are integrated into a multimodal feature dataset. This dataset is used for the later modeling process. It provides the data input for PLS-SEM and XGBoost, which are applied to explore the relationships among variables and to evaluate factors related to exhibition experience quality [11].

Figure 1: Overall Research Framework (Source: Author-created)

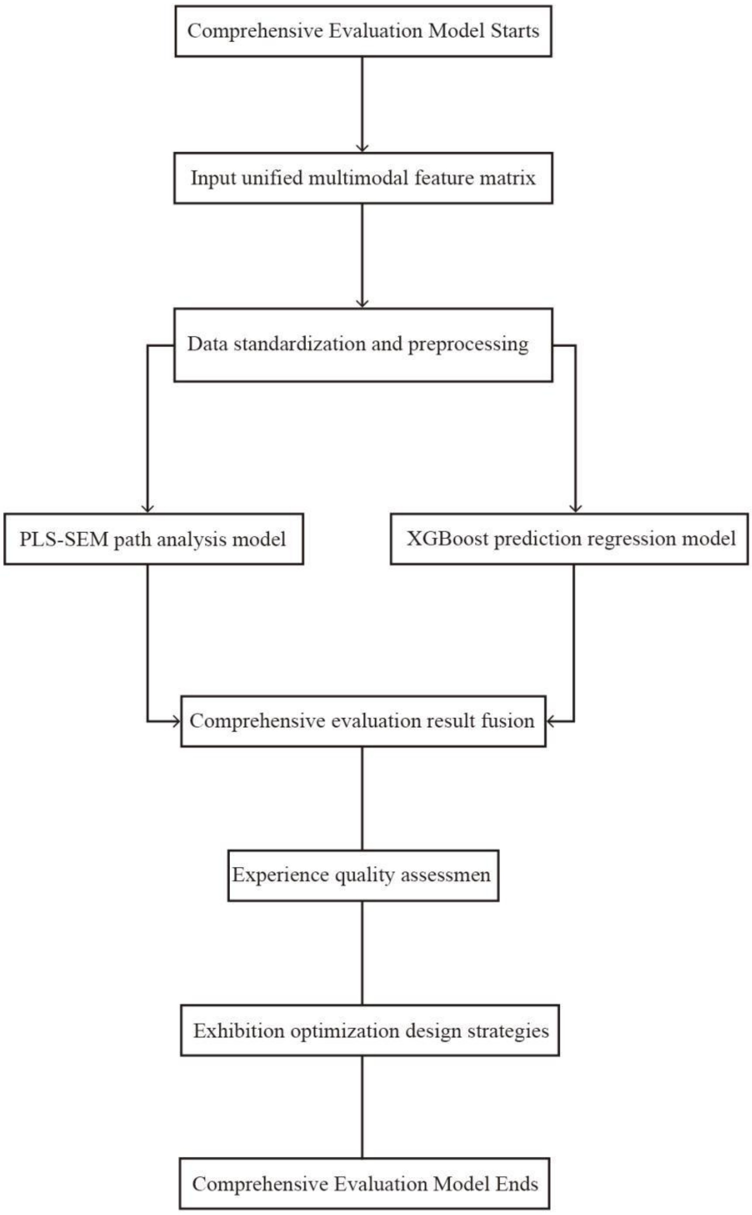


4.3 Comprehensive Evaluation Algorithm Model

The evaluation model is built on the multimodal feature set described above. Five types of information are included in the analysis: text, images, physiological signals, human-related data, and environmental records. These different types of data are analyzed together rather than separately.

PLS-SEM is mainly used to examine the relationships among technology, audience behavior, and exhibition experience. XGBoost is then used to predict experience quality and identify the variables that have a stronger influence on the results. After the analysis is finished, the results are compared with the evaluation criteria to identify possible problems. The findings can then be used to improve exhibition design and audience interaction. In this way, the evaluation process can be repeated after changes are made, so the exhibition can be adjusted step by step [12].

Figure 2: AIGC Content Quality Evaluation Process (Source: Author-created)



5. Case Validation of the Evaluation Framework and Design Strategies

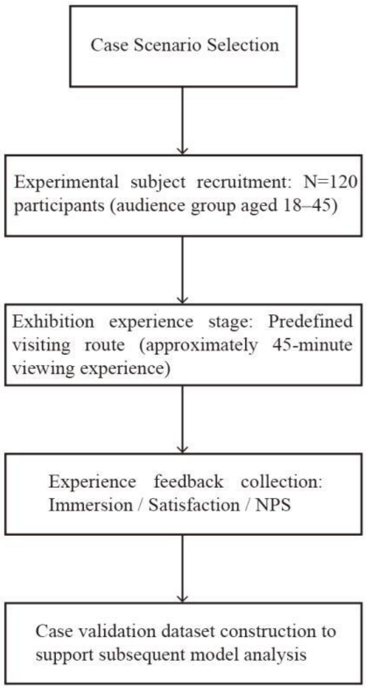
5.1 Case Description and Experimental Design

To examine whether the proposed evaluation method can be used in practice, this study selects TeamLab Borderless in Tokyo, Japan, as the case. The case selected in this study is a digital exhibition in a museum. The exhibition has attracted attention because of its use of digital technology in exhibition design. It includes algorithm-generated visual content, interactive installations, and immersive spaces. During the visit, visitors can interact with the exhibition, and their actions may cause changes in the displayed content or the surrounding environment. Because of these features, the exhibition provides a suitable case for studying AIGC exhibition experience.

The evaluation method proposed in this study was tested through this case. A total of 120 visitors joined the experiment, including 56 males and 64 females. Most participants were between 18 and 45 years old. They came from different groups, including people with backgrounds in art and design, technology fields, and general visitors. This was intended to include different types of exhibition users.

The experiment mainly included three parts: exhibition visiting, data collection, and experience feedback. Each participant spent about 45 minutes visiting the exhibition and followed the same route in the main exhibition areas. The exhibition conditions were not changed during the experiment. During the visit, information about visitor movement, physiological changes, and interaction behaviors was recorded. After the visit, participants completed questionnaires about exhibition content, immersion, and satisfaction. All collected data, including generated content, behavior records, physiological information, and questionnaire results, were organized as a multimodal dataset for later analysis [13].

Figure 3: Case Validation Experimental Design Process (Source: Author-created)



5.2 Multimodal Data Collection Scheme and Indicator Mapping

In this case study, data were collected from four aspects: exhibition content, visitor behavior, physiological responses, and questionnaire feedback. The content data mainly included exhibition images and interactive digital works. To examine the features of AIGC-generated content, this study used several indicators, such as semantic consistency, stylistic diversity, and aesthetic quality. The CLIP model and an aesthetic evaluation model were applied to obtain the related results.

Visitor behavior data were collected through eye-tracking equipment and indoor positioning devices. The recorded information included where visitors looked, how long they stayed, their movement paths, and the frequency of interaction. These data were used to observe visitors' attention and behavior during the exhibition.

Physiological data were collected using heart rate devices and electrodermal activity (EDA) sensors. The data were mainly used to observe changes in visitors' emotional and cognitive responses. After the exhibition, visitors also completed questionnaires. The questions included immersion, satisfaction, and Net Promoter Score (NPS), which provided additional information about their experience.

After collection, the different types of data were organized according to the four dimensions of the evaluation system: technology, psychology, environment, and society. Since the data came from different sources, they were combined before the following analysis. The evaluation therefore considered both the characteristics of AIGC content and the responses generated during visitors' actual exhibition experience.

Table 1: Multimodal Data Collection and Indicator Mapping Relationship (Source: Author-created)

Data Type	Data Acquisition Method	Representative Indicators	Evaluation Dimension
Generated Content Data	AIGC artwork analysis, CLIP model computation	Semantic consistency, stylistic diversity, aesthetic quality, generation stability	Technical Dimension
Behavior Trajectory Data	Eye-tracking devices, spatial positioning systems	Gaze hotspots, dwell time, browsing paths, interaction frequency	Environmental Dimension
Physiological Feedback Data	Heart rate monitoring devices, EDA sensors	HRV, EDA, cognitive load index	Psychological Dimension
Subjective Evaluation Data	Questionnaire surveys and experience feedback	Immersion, satisfaction, NPS	Psychological Dimension, Social Dimension

5.3 Validation of the Comprehensive Evaluation Model and Results Analysis

5.3.1 Correlation Analysis

Correlation analysis was first carried out to explore the relationships between AIGC exhibition content and audience experience. The results show that electrodermal activity (EDA) is positively related to spatial dwell time (r=0.62) and is also associated with narrative immersion reported by participants (r=0.58). Spatial dwell time is also positively related to immersion (r=0.71).

These results suggest that visitors tend to stay longer when the exhibition content is more visually attractive and interactive. A longer stay is often accompanied by a stronger sense of immersion during the visit, which may further improve the overall exhibition experience [14].

Taken together, the results suggest that audience experience is influenced by several factors rather than by visual content alone. Exhibition content, spatial experience, and psychological responses all seem to play a role, providing the basis for the following path analysis.

5.3.2 Comprehensive Evaluation Results and Discussion

PLS-SEM and XGBoost were then used to further analyze the collected data. The results suggest that experience quality is not determined by a single design factor. Instead, different factors appear to work together during the exhibition process.

Semantic consistency of AIGC content seems to influence visitors at the beginning of the experience by making the generated content easier to understand and more visually acceptable. As visitors continue to interact with the exhibition and move through the exhibition space, their level of immersion gradually changes. These experiences together finally affect their overall evaluation of the exhibition.

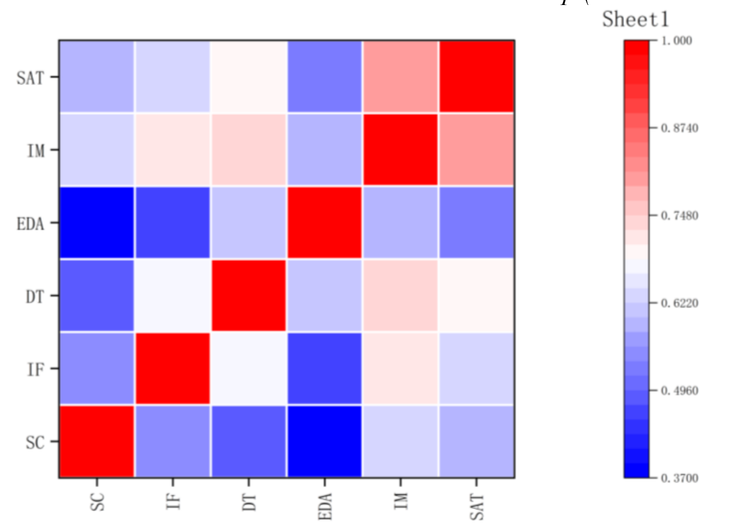
The XGBoost results also show that semantic consistency (0.26), interaction response frequency (0.23), and spatial dwell time (0.21) have relatively higher importance than the other variables. This suggests that these factors may deserve more attention when designing AIGC exhibitions. They may also provide some reference for adjusting exhibition content, spatial arrangement, and interaction design [15].

5.3.3 Validity Testing

The case study suggests that the four dimensions used in this study—technology, psychology, environment, and society—can describe the main characteristics of AIGC exhibitions from different perspectives.

The proposed method was also compared with a traditional evaluation approach based only on questionnaire data. The results indicate that questionnaire-based evaluation is more easily affected by participants' memory and therefore provides relatively lower prediction accuracy (R^2=0.72). After adding behavioral information, physiological signals, and questionnaire data into the model, the prediction result reached R^2=0.89. The result was higher than the model based on only one type of data. This may be because different data sources describe different parts of visitors' experiences. Therefore, using several types of information together can reduce the limitation caused by relying on only one source of data. In this case, the proposed method shows some potential for AIGC exhibition evaluation and later design improvement [16].

Figure 4: Multimodal Evaluation Indicator Correlation Heatmap (Source: Author-created)



*Note: *p<0.05, **p<0.01.*

5.4 Optimization Design Strategies Based on Evaluation Results

The case results show that the influence of different design factors on visitor experience is not exactly the same. One problem found in the exhibition is that some AIGC-generated content does not fully fit the theme of the exhibition. When the relationship between the generated images and the exhibition idea is weak, visitors may need more time to understand the meaning behind the content, and this may also influence their satisfaction. For this reason, AIGC content may need to be checked and adjusted before being used in an actual exhibition. In some cases, better prompt design and human modification can be used together to make the generated content closer to the exhibition theme.

The behavioral data also show that spatial design has an important role in visitor experience. Some exhibition areas can attract visitors because of their visual effects, but visitors do not always stay there for a long time. This means that attractive content does not always lead to deeper engagement, and the connection between display design and spatial arrangement still needs attention [17]. One possible improvement is to consider visitor routes together with exhibition narratives. In this way, different parts of the exhibition may connect better and visitors may experience the exhibition in a more continuous way.

The analysis of physiological data suggests that emotional response is related to immersion during the visit. This means that visual effects alone cannot explain the whole experience. Sound, lighting, and interactive design may also influence how visitors understand and feel the exhibition. For some important exhibition spaces, combining different sensory elements may help strengthen visitors' emotional reactions and make the experience more memorable.

These design suggestions come from the problems found in the case analysis. Instead of changing only one element, they consider the relationship among AIGC content, exhibition space, and visitor experience. A closer connection among these parts may help improve the design of future AIGC exhibitions [18].

6. Conclusion

6.1 Research Conclusions

This study discusses the experience of AIGC exhibitions and tries to build a multimodal way for evaluation. The findings show that visitor experience is not caused by one single element. In fact, it is influenced by several parts of the exhibition, such as the quality of generated content, the interaction between visitors and exhibition space, and the emotional changes during the visiting process.

From the analysis, semantic consistency plays a role in helping visitors understand the content and meaning of the exhibition. Spatial dwell time can partly show visitors' attention and participation in different areas. At the same time, emotional arousal is also connected with the formation of immersion. These factors together show a possible process of experience formation, which can be understood as a relationship among "content–behavior–experience."

The results also suggest that AIGC exhibition experience is not simple and cannot be explained by only one kind of data. If the evaluation only depends on questionnaires or behavioral information, some parts of visitors' actual experience may not be fully reflected. By combining generated content features, visitor behavior records, physiological responses, and subjective feedback, the multimodal method provides another way to understand how exhibition experience is formed.

Besides evaluating the final experience, the evaluation results can also provide information for exhibition improvement. Through the analysis of different factors, it becomes possible to find which design aspects may have a stronger relationship with visitor experience. These findings may provide some reference for the adjustment of AIGC content generation and future exhibition space design.

6.2 Research Contributions and Future Prospects

Compared with some previous studies that mainly focus on the quality of AIGC-generated content or simple feedback from users, this study pays more attention to the process of how visitors experience AIGC exhibitions. Different types of information, including content features, visitor behaviors, physiological responses, and questionnaire results, are considered together in the evaluation. Through this combination, the study tries to provide another possible view for understanding AIGC exhibition experience.

In terms of the research method, the use of PLS-SEM and XGBoost helps to examine the relationships between different factors and visitor experience. The model does not only show the possible connections among variables, but also helps find some factors that may influence experience quality more than others. Besides this, the evaluation results can also be related to exhibition design. They may provide some useful information for changing generated content, improving spatial arrangement, and adjusting interaction design.

However, this study also has some limitations. The case used in this research is from a museum exhibition, so the indicators and models may be affected by the features of this kind of exhibition. Some physiological information also needs specific devices to collect, which may make the method harder to apply in some other exhibition environments.

At present, AIGC technology is still changing quickly. Its application is not only limited to content generation but also appears in interactive systems, intelligent navigation, and dynamic exhibition management. These new applications may bring some new questions for future research. Future studies can include more real-time visitor information and data related to intelligent agents. Also, continuous observation of visitor experience in changing exhibition situations may help improve the evaluation method and make it more suitable for different AIGC exhibition cases.

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Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.