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A Modeling Study of Non-Heritage Cultural Communication Behavior under the Framework of Situational Cognition Based on Time Series Data Mining

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ABSTRACT

Participatory culture, as one of the characteristics of audience performance in the current communication environment, provides imaginative space for stimulating the power of audience participation in the communication of non-heritage culture, and at the same time provides new thinking direction and inspiration for the current communication of non-heritage culture. In this paper, we mainly apply recurrent neural networks to model sequence data, and control the flow of information by adding special gating structures, so as to be able to effectively memorize and process long sequence data. Self-attention is constructed so that the network can better focus on the important parts of the sequence while ignoring the irrelevant information in the sequence. Identify non-heritage communication behaviors based on time-series data, and model non-heritage cultural communication behaviors based on the length of time the behaviors occur under the framework of situational awareness. The research experimental model is designed, relevant hypotheses are proposed, and examined through empirical evidence. The number of borrowings by visitors under 18 years old, which is the main group of visitors, declined from 737 in 2016 to 357 in 2022, with an overall decline of 51.56%, and the overall visiting behavior also showed a declining trend. In order to test the mediating role of perceived value in the relationship between interactive behavior and the communication effect of intangible cultural heritage, the benchmark model M3 model was constructed with the communication effect as the dependent variable and gender and whether the only child was the controlling variable, and the independent variables "interactive behavior" and "perceived value" were added on this basis, and the perceived value had a significant positive impact on the communication effect, $\beta=0.485$, $p<0.001$. The influence of interactive behavior on communication effect remains significant, at this time the β-value is 0.487 and $p<0.001$, the mediating role of perceived value between interactive behavior and non-heritage culture communication effect.

Keywords: Recurrent neural network; Self-attention, Time-series data recognition, Contextual cognition, Non-heritage cultural communication behavior

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1. Introduction

With the continuous development of emerging science and technology, situational cognition theory has been continuously emphasized in the fields of human-computer interaction, computer design and product design, which provides a new research direction for the fields of computer information and human-computer interface design. Situated cognition theory was developed in the late 20th century, and its core view is that all knowledge and learning are situational, and that knowledge and action are interactive and inextricably linked [1-2]. Knowledge cannot be talked about without context; contextuality is a characteristic and integral part of knowledge and learning; once knowledge is taken out of context it becomes artificial intelligence, inauthentic and not characterized by actual behavior [3-5]. Effective learning must link the content of knowledge, and the methods of acquiring and using it, to authentic contexts in which learners construct knowledge and develop competence [6-7].

Since knowing and doing are interactive, this provides a theoretical basis for realizing the reorganization and merger of information technology and learning content, for applying computer technology in the field of educational technology such as virtual learning and collaborative learning, and also for the digital inheritance and innovation of intangible cultural heritage [8-11]. Combining digital technology with the “real situation” of intangible cultural heritage to convey the knowledge, content, value and significance of intangible cultural heritage, allowing the audience to construct knowledge and develop their abilities in the context [12-14]. It can effectively alleviate the serious intergenerational imbalance in the current cognition of the audience of non-heritage culture, the single form of communication and the coordination of “culture” and “technology” [15-17]. The construction of “real situation” can be realized with the help of virtual reality technology, by generating a digital environment that is highly similar to the real environment, so that the experiencers can interact with the objects in the digital environment in real time with the help of equipment and produce an immersive and unique experience, which can enhance the contemporary people's cognition and love of the non-heritage culture [18-21].

In this paper, the recurrent neural network model is used to model sequence data, and in order to solve the problem of long-term information preservation in the RNN model, the long and short-term memory network model is proposed, so as to achieve effective memory and processing of long sequence data. On this basis, a self-attention model is formed to better capture the global relationships and important information in the sequence. A new time-domain feature mapping structure is obtained by integrating the modified time-domain convolution operation with the unfolded RNN unit structure, and the time-domain feature mapping expression is represented by the subset structure to recognize the propagation behavior. Based on the short-term and long-term of the occurrence time of tourists' behaviors, a non-heritage culture propagation behavior mining model is established. Under the contextual framework, the study of NRH culture tourists' participation behavior is designed, relevant research hypotheses are proposed, and verified one by one by means of practical research.

2. Time-series data mining based on the dissemination behavior of non-heritage culture

2.1. Sequence data modeling

2.1.1. Recurrent Neural Networks. Recurrent Neural Network (RNN) is a neural network with a memory function that can model sequential data, such as text, speech, video, etc. [22]. The main feature of RNN is that it has a hidden state, which preserves the sequence information from the previous time step. This structure allows the RNN to better capture the dependencies in the sequence. The basic structure of an RNN is a loop unit that accepts the current input and the hidden state of the previous time step and outputs the hidden state and the predicted value of the current time step.

In traditional neural networks, every two layers are fully connected to each other, but in recurrent neural networks, there is a circular connection between the input layer and the hidden layer, which means that the hidden layer will not only receive the current input, but also the previous hidden state information. The recurrent neural network receives a sequence of inputs and processes the inputs for each time step in turn. Specifically, the sequence step update is computed as follows:

$$H_t = f(W_{xh}X_t + W_{hh}H_{t-1} + b_h) \tag{1}$$

$$O_t = g(W_{hy}H_t + b_y) \tag{2}$$

where W_{hh}, W_{xh} and bias b_h are the weights of the hidden layer, W_{hy} and bias b_y are the weights of the output layer. X_t is the input of time step t, H_t denotes the hidden variable of time step t, and O_t denotes the output of time step t.

RNN models may suffer from the problem of long-term information preservation when dealing with long sequences, i.e., the network is unable to memorize the previous information efficiently, and thus is unable to predict the subsequent output correctly. This is due to the fact that in the backpropagation process, the gradient can only be passed layer by layer through each time step. Whereas in long sequences, the gradient fades away, thus preventing the network from retaining long-term memory.

2.1.2. Long and short-term memory networks. In order to solve the problem of long-term information preservation that exists in RNN models, LSTM controls the flow of information by adding a special gating structure, so that it can effectively memorize and process long sequential data.

The basic unit of LSTM's structure contains three gates: an input gate, a forgetting gate, and an output gate, as well as a memory unit [23]. Together, these gates and the memory unit control the flow of information, thus enabling the LSTM to better process long sequential data. Specifically, the computational steps of LSTM are as follows:

$$I_t = \sigma(W_{xi}X_t + W_{hi}H_{t-1} + b_i) \tag{3}$$

$$F_t = \sigma(W_{xf}X_t + W_{hf}H_{t-1} + b_f) \tag{4}$$

$$O_t = \sigma(W_{xo}X_t + W_{ho}H_{t-1} + b_o) \tag{5}$$

$$\tilde{C}_t = tanh(W_{xc}X_t + W_{hc}H_{t-1} + b_c) \tag{6}$$

$$C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t \tag{7}$$

$$H_t = O_t \odot \tanh(C_t) \tag{8}$$

Where, W is a weight parameter, b is a bias parameter, σ is a sigmoid function, and $\odot$ denotes multiplication by elements. I_t is the input gate, which determines how new input information is added to the memory cell. F_t is the forget gate, which determines what information needs to be removed from the memory cell. O_t is the output gate, which determines what information needs to be output from the memory cell. C_t is the memory cell that controls how much of the past content of the memory cell C_{t-1} is retained via the forget gate F_t and how much new data from $\tilde{C}_t$ is adopted via the input gate I_t. Finally, the hidden state H_t is controlled by an output gate to control which memory information from the memory unit is passed to the prediction part. Because LSTMs can effectively model long sequential data, they have been widely used in natural language processing, speech recognition, image processing, and other fields.

2.1.3. Self-attention. The computational process of self-attention is shown in Fig. 1. Self-attention is a model based on the attention mechanism, which uses each element in the input sequence as a query, key, and value in the attention mechanism at the same time, so that each element in the sequence can fully interact with the other elements in the sequence, and thus be able to better capture the global relationships and important information in the sequence [24]. The self-attention model is able to assign different weights to each element in the sequence by learning the attention weights, enabling the network to better focus on the important parts of the sequence while ignoring irrelevant information in the sequence.

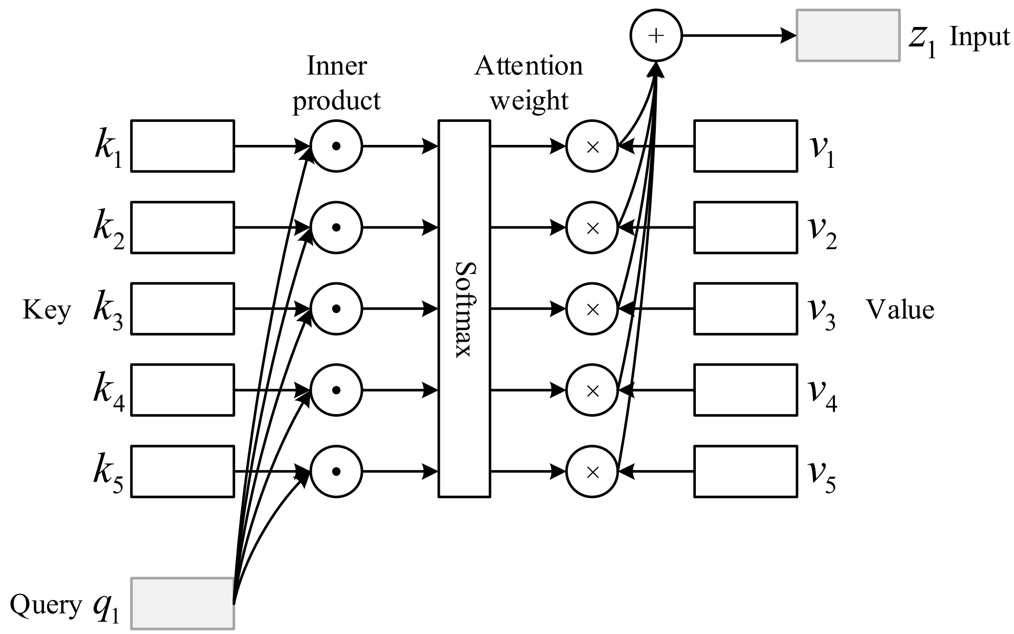

Fig. 1. Self-attention calculation process

Assume that the input sequence data is $[x_1, x_2, \ldots, x_n]$. First, for each input vector x_i, three fully connected layers are used to compute its query vector q_i, key vector k_i, and value vector v_i, respectively:

$$q_i = W_q x_i k_i = W_k x_i v_i = W_v x_i \tag{9}$$

where W_q, W_k and W_v are the parameter matrices of the query, keys and values, respectively. Then, the similarity between each query vector and all key vectors is calculated for computing the attention weights:

$$\alpha_{ij} = \frac{q_i^T k_j}{\sqrt{d}} \tag{10}$$

$$\beta_{i,j} = \frac{\exp(\alpha_{ij})}{\sum_{k=1}^{n} \exp(\alpha_{ik})} \tag{11}$$

where $\sqrt{d}$ is to scale the size of the similarity so that the similarity ranges between [0, 1]. Finally, each value vector v_i is multiplied by the corresponding attention weight $\beta_{i,j}$ and summed to obtain the output vector z_i for each query vector q_i. The output of the input sequence after the self-attention layer is $[z_1, z_2, \ldots, z_n]$, and z_i denotes the coded representation of the ith element of the input sequence.

2.2. Identification of propagation behavior based on time-series data

2.2.1. Design of Time Domain Graph Representation Structure. Theoretical derivation of time-domain feature extraction operation: The time-domain feature extraction operation integrates the time-domain convolutional operation and the recurrent neural network structure, which makes it possible to extract the time-dependent features between different moments in time series data with high computational efficiency. This subsection mainly focuses on the theoretical derivation of formulas involved in the improvement of the time domain feature extraction operation to prove the feasibility of the proposed method from the theoretical level. Firstly, for the time-domain convolution operation, given that the feature input of any t moment in the time series data is x_t, the size of a single convolution kernel is 3×1, and the weight parameter is W_{conv}, the time-domain convolution operation can be expressed in the following generalized form:

$$f_{conv}(x_t)=[x_{t-1},x_t,x_{t+1}]\cdot W_{conv} \tag{12}$$

where x_t-1 and x_{t+1} denote the input at moment $t-1$ and moment $t-1$ respectively, and the $\cdot$ symbol denotes the convolution operator. Meanwhile, in order to avoid information leakage caused by future information flowing into the current moment, we restrict the scope of the time-domain convolution kernel to the current and previous moments, so as to retain the temporal dependency of the time dimension, and obtain the modified time-domain convolutional computation:

$$\hat{f}_{conv}(x_t)=[x_{t-1},x_t]\cdot\hat{W}_{conv} \tag{13}$$

For the time-domain RNN unit, the setting of the hidden state is introduced into the cyclic structure, and the time-series dependent feature extraction between the input data at different times is realized through iterative calculation, assuming that s_t represents the current Implicit state corresponding to the input information at t times, o_t represents the feature output representation corresponding to the input information at the current time, U represents the mapping transformation weight parameters input to the hidden state, V represents the weight parameters corresponding to the mapping transformation between the hidden state and the feature output, W represents the transformation weights between the hidden states, Then the corresponding state transition at this time under RNN operation can be expressed by the following formula:

$$\begin{aligned} s_t &= Ux_t+Ws_{t-1} \\ o_t &= Vs_t \end{aligned} \tag{14}$$

Where s_{t-1} denotes the implied state information at moment $t-1$. At this time, due to the existence of the implied state, the mapping transformation between the input information to the feature output cannot be obtained directly, making the computation process of the RNN unit cannot be carried out in parallel. In order to realize a more efficient parallel computation method, the implied state computation involved in the RNN unit is looped in the time dimension, so as to overcome the disadvantage of its serial computation, thus obtaining the mapping transformation from input to feature output directly, independent of the implied state:

$$\begin{aligned} o_t &= V(Ux_t+Ws_{t-1}) \\ &= VUx_t+VWs_{t-1} \\ &= VUx_t+VW(Ux_{t-1}+Ws_{t-2}) \\ &= VUx_t+VWUx_{t-1}+VW^2s_{t-2} \\ &= \ldots\ldots = VUx_t+VWUx_{t-1}+\ldots\ldots+VW^{t-1}Ux_1 \end{aligned} \tag{15}$$

A new time-domain feature mapping structure is then obtained by fusing the modified time-domain convolution operation with the unfolded RNN cell structure, which is expressed as:

$$f_{out}(x_t) = [x_t, x_{t-1}, \ldots, x_1] \cdot W_{conv_t} \tag{16}$$

where W_{conv_t} denotes the time-domain mapping weight corresponding to moment t. It can be seen that the new time-domain feature extraction operation uses the convolution operation instead of the matrix cyclic multiplication operation to extract the long- and short-term time-dependent features, which can reduce the model complexity and accelerate the model training process by the shared parameter and local computation of the convolution structure while keeping the time-domain time-varying relationship unchanged.

2.2.2. Time-domain graph representation implementation. Selection of subset partitioning strategy: since the feature representation of time series data at different moments corresponds to the influence of different time domain ranges in the time dimension, after obtaining the adjacency matrix representation that can express the relationship of such time domain influence, how to reasonably set up the allocation strategy of the mapping weight is a key step in realizing the convolutional operation of time domain maps. As can be seen from Eq. (17), when calculating the feature representation of the skeleton data at a particular moment, the input information of all relevant moments corresponds to their respective mapping weights, so the size of the convolution kernel of the time-domain map convolution mapping needs to be set reasonably, so as to ensure that the majority of the convolution kernel parameters can be activated when traversing the input information of different moments. Here, in order to facilitate the computation, the pairs of momentary influence relations conforming to the same mapping transformation rules are divided into a subset, so as to obtain the time-domain feature mapping representation using the subset structure:

$$f_{out}(x) = [sub_1(x), sub_2(x), \ldots, sub_S(x)] \cdot W_{sub} \tag{17}$$

Where S denotes the number of subsets divided, $sub\_S(x)$ denotes the Srd node subset, and W_{sub} denotes the time domain mapping weights corresponding to different node subsets. From this, it can be seen that the sets composed of input information at different moments follow the same set representation structure after subset structuring, so each subset can be regarded as an element to be operated, and from another natural division strategy is to divide the subsets based on the temporal distances between the relevant node pairs in the time-domain mapping, taking into account that there is a detailed or non-detailed definition of the distance information, and that the division method can be divided into two ways: localized division and independent division. In the local division strategy, three modes are defined according to the local distance range of the temporal distance between nodes, such as own node subset, near interval subset and far interval subset, and the judgment basis for dividing node connections into a specific subset is as follows:

$$sub_i dx(x_i, x_j) = \begin{cases} 0 & \text{if } d(x_i, x_j) = 0 \\ 1 & \text{if } 1 \le d(x_i, x_j) < D \\ 2 & \text{if } D \le d(x_i, x_j) \end{cases} \tag{18}$$

where $d(x_i, x_j)$ denotes the temporal distance between node x_i and node x_j, and D denotes the threshold value corresponding to the local distance. The neighbor matrix representations corresponding to each of the three subsets when the threshold D is set to 2. The self node subset contains self-connection relation pairs of each node, and its corresponding neighbor matrix representation is in the form of a unit matrix; the near runaway interval subset and the far runaway interval subset contain connection relation pairs with smaller and larger temporal runaways, respectively.

The independent division strategy defines the corresponding independent subset structure according to the detailed temporal distance between the time domain nodes, assigns independent mapping transformation weights to each temporal connection of a specific time domain interval, and realizes the determination of node connection division to a specific subset based on the following formula:

$$sub_i dx(x_i, x_j) = \begin{cases} 0 & if\ d(x_i, x_j) = 0 \\ 1 & if\ d(x_i, x_j) = 1 \\ \cdots & \cdots \\ T-1 & if\ d(x_i, x_j) = T-1 \end{cases} \tag{19}$$

where $d(x_i, x_j)$ represents the temporal distance between time domain node x_i and time domain node x_j, T represents the time domain duration length of the behavior sequence, and $sub\_idx(x_i, x_j)$ represents the index of the subset to which the temporal connection from time domain node x_i to time domain node x_j belongs.

Construction of time-domain graph convolution layer: after obtaining the subset structure and adjacency matrix representation corresponding to different feature mapping transformations of the behavioral sequence data in the time dimension, how to implement the time-domain graph convolution operation shown in Eq. (19) on this basis is the next issue to be explored. Since the computational process of graph convolution is not as straightforward as traditional convolution on images, which often involves computationally structurally variable multiply-add operations at the elemental level, the computational approach of element-by-element processing is generally not chosen. Considering that all node connections in a particular subset share a single weight parameter, the element-by-element multiply-and-add operation on the subset can be transformed into an add-and-multiply operation on all elements in the set.

The introduction of the adjacency matrix corresponding to the subset of node connections can facilitate the summing operation of the elements in the set, which can then be combined with the traditional convolution operation to realize the time-domain graph convolution operation at the level of the subset structure:

$$f_{out} = \sum_{s=1}^{s} \Lambda_s^{-\frac{1}{2}} A_s \Lambda_s^{-\frac{1}{2}} X W_s \tag{20}$$

where S denotes the number of subsets into which the temporal connection is divided, X denotes the input data, W_s denotes the mapping weight corresponding to the s th node connecting the subset, A_s denotes the time-domain adjacency matrix representation of the subset, $\Lambda_s^{ii} = \sum_j A_s^{ij} + \theta$ denotes the corresponding degree matrix, and θ denotes an extra increment with a value of 0.001.

2.3. *Modeling Non-heritage Cultural Communication Behavior Based on Time Series Data Mining*

2.3.1. Short-term behavior. Tourist short-term behavior describes the current behavioral trajectory and state of tourists. In order to adequately model the semantic information in tourists' short-term behaviors, this paper uses the tourists' behavioral sequence data (including three types of multimodal data, including x_a, x_m and x_w) collected from mobile devices to construct a heterogeneous information network of tourists' short-term behaviors, so as to realize the fusion of the three types of multimodal data.

The node representation in the heterogeneous information network is aggregated from the representations of its surrounding neighbor nodes and the initial representation of the node, i.e., for a node $v, A \in \{x_a, x_m, x_w\}$ of type A in the network, its representation is:

$$\tilde{x}_v^A = W_a x_v^A + W_b \sum_{i \in N_v^A} W_{vi}^A x_i \tag{21}$$

Where: $\tilde{x}_v^A$ is the node representation obtained by aggregation of neighbor node representations with dimensions d, W_a and W_b are trainable weights, x_v^A is the initial representation of the node, generated using word embedding, N_v^A is all the neighbors of the node, W_{vi}^A is the weight influence of each neighbor on the node, and x_i is the node representation of each neighbor.

An edge representation in a heterogeneous information network consists of a collocation of the 2 node representations that make up the edge. The representation has a temporal association between the 2 nodes. That is, for an edge constructed by a node j of type A and a node v of type B in the network, $A, B \in \{x_a, x_m, x_w\}$, the edge is represented as:

$$e_{jv} = W_c \cdot concat(\tilde{x}_j^A, \tilde{x}_v^B) \tag{22}$$

Where: e_{jv} is the representation of the obtained edges. W_c is the trainable weights $\tilde{x}_j^A$ and $\tilde{x}_j^B$ are the representations of node j and node v respectively.

The short-term behavior representation of tourists can be obtained by representing the tourists' short-term behavior heterogeneous information network: The whole heterogeneous information network graph representation is obtained by splicing all node representations in the network with edge representations, Eq:

$$S_u = concat\left(\sum_{v,A} \alpha_v^A \tilde{x}_v^A, \sum_{j,v} \beta_{jv} e_{jv}\right) \tag{23}$$

Where: $\tilde{x}_v^A$ and e_{jv} are node representations and edge representations, respectively; α_v^A and β_{jv} are the weights assigned when aggregating each node representation and each edge representation, respectively, and S_u is the final generated short-term behavioral representation of the tourists, which has the same dimensions as the node representations and is also d.

The short-term behavior modeling module obtains the short-term behavior representation by representing the short-term behavior heterogeneous information network. The heterogeneous information network is used to fully model the potential information in the tourist behavior, so as to enhance the semantic information representation in the tourist behavior.

2.3.2. Modeling long-term behavior. Cultural communication behaviors are usually guided by their personal habits, and modeling long-term behaviors can consider the changes and regularity of cultural communication behaviors in the time dimension, which is conducive to the enhancement of model prediction effects. Considering that the attention mechanism can effectively capture the potential relationship between short-term behaviors, this paper introduces the behavioral attention mechanism to extract the long-term habits in cultural communication behaviors.

In this study, the weights of the attention mechanism are trained to obtain behavioral representations of non-heritage cultural communication focused on describing tourists, and the attention scores of short-term behaviors on different dates are calculated according to the importance of the generated behavioral representations to the prediction results I_u^k, with the formula:

$$I_u^k = \tanh(W_d S_u^k) \tag{24}$$

Where: S_u^k is the short-term behavioral representation of the tourist on day k; W_d is the trainable weight.

In this paper, the Softmax function is used to normalize the attention scores, and the normalized result is the distribution of attention on each short-term behavioral input when the long-term behavioral patterns are aggregated, where each value corresponds to the original input, Eq:

$$\alpha_u^k = \frac{\exp(I_u^k)}{\sum_{j=1}^{n} \exp(I_u^j)} \tag{25}$$

Where: α_u^k is the attention weight normalized to each short-term behavior, and n is the total number of tourists' short-term behaviors. The attention weights are weighted and summed with each short-term behavioral representation to obtain the long-term behavioral representation of tourists, Eq:

$$L_u = \sum_{j=1}^{p} \alpha_j^k S_u^k \tag{26}$$

L_u that is, the long-term behavioral representation of tourists obtained from the final modeling with dimension d.

3. Modeling of Non-Heritage Cultural Communication Behavior in a Contextual Framework

3.1. Research on Situated Cognition Theory

3.1.1. Definition and Composition of Situations. “Situation” is the core word of situational cognition theory, and the research of situational cognition theory is based on situation. In the Modern Chinese Dictionary, context is defined as situation, environment. From a design perspective, the term context in situated cognition theory cannot be completely replaced by situation or environment. Before examining the definition of the term “context”, we distinguish and understand it in relation to the meaning of its close synonym, “situation”. Scenario means situation and scene, it focuses on describing things, the environment and other things that can be directly seen by the external performance, is a specific visualization of the scene. The word “situation” in context elevates the meaning of the word situation to something more complex, comprehensive and abstract than a scenario. Situation in the “realm”, can be understood as the environment and the realm, the environment is the external conditions in which people live, and the realm is the subjective feelings of people on the objective world. Context encompasses a whole system of both intuitive situational components and implicit components and their interrelationships.

The term context appears in a variety of disciplines such as psychology, philosophy, linguistics, sociology, management and so on, and there are some differences in the interpretation of context in different disciplinary fields. The conceptual definition of context has gone through three main stages: the objective environment stage of the behaviorist school, the objective environment and subjective consciousness stage of the cognitive-behaviorist school, and the subjective consciousness stage of the Gestalt school. The meaning of context in situational cognitive theory is more in favor of the cognitive-behaviorist school of interpretation.

3.1.2. Contextual cognition theory connotations. Contextual cognition can replace the previous information processing theory. Information processing theory overemphasizes the human brain's description of rules and information, focuses only on conscious reasoning and thinking, and ignores the influence of cultural as well as physical contexts on human cognitive processes. Situated cognition theory places individual cognition in a larger cultural environment and social context, i.e., interaction and culture influence the construction of cognition, and the theory intertwines individual cognition and social behavior. “Contextual” does not mean that something is specific or concrete, nor does it mean that it is not generalizable. “Context” implies that a given social practice is multiply related to other aspects of ongoing social processes in the activity system at many levels of specificity and universality.

The theory of situated cognition is generally used in conjunction with learning as a comprehensive concept of “situated learning”. Contextual learning requires learners to genuinely engage in cultural practices, relying on different practices in different contexts for the construction of knowledge, meaning and identity. Knowledge is a dynamic construction and organization, and human behavior is based on social membership, and human thoughts, words and actions are influenced by the social contexts in which they are embedded. In other words, behavior is rooted in the social roles that individuals assume.

3.1.3. Application of Situational Cognition Theory in the Communication of Non-Heritage Culture. Contextual cognition theory has been applied in many fields, among which the research in the field of education is the most common, and contextual cognition theory plays a significant role in guiding teaching, curriculum design and so on. In the field of non-heritage cultural communication, there are not many studies on non-heritage cultural communication based on situational cognition theory, and even fewer studies on non-heritage cultural communication behavior.

3.2. Research on Tourist Participation Behavior of Non-Heritage Culture

3.2.1. Research design:

1) Research Methodology. The research goal of this paper is to generalize and analyze the phenomenon of visitor participation behavior of non-heritage thematic exhibitions and construct theories. However, there is no mature scale available for reference in the related research, so the SOR model combined with the rooted theory will be used as the main research method. In the specific operation, the semi-structured interview method is chosen, and combined with time series data mining to obtain the original communication behavior data information. NVivo12 software is used to conduct open, spindle and selective coding analysis on the interview data, to study the factors affecting visitors' participation behavior and the relationship between them through a step-by-step induction method, and to construct a model of the factors affecting visitors' participation behavior, with a view to providing a reasonable reference for the study of visitors' participation behavior in the thematic exhibition of non-heritage.

2) Research Objects. The China Grand Canal Museum (hereinafter referred to as “CCM”) has three permanent exhibitions, six thematic exhibitions and two temporary exhibitions. This paper takes the “Grand Canal Intangible Cultural Heritage” special exhibition in Hall 7 (hereinafter referred to as the “Intangible Cultural Heritage Special Exhibition”) as its object, and refines the canal's cultural heritage in three types: music, handicrafts and folklore. "Music and Rhyme" displays traditional music, opera and other performance intangible cultural heritage, "Shape and Color" displays traditional art, carving, weaving and embroidery and other handicraft intangible cultural heritage, and "Folk Customs" displays festivals, temple fairs, etiquette and other festival folk intangible cultural heritage. The pavilion combines static graphics and dynamic media scenes, utilizes interactive narrative techniques to interpret the relationship between “space, process, and people”, and highlights the process of displaying and multi-sensory experience of non-heritage culture. However, on-site research found that the non-heritage thematic exhibition compared with other exhibition halls, the flow of people is relatively small, and the enthusiasm of visitors to experience is not high. Visiting behavior by the time period, the flow of people and the interest of tourists and other factors have a greater impact on what form of mobilization of tourists to participate in the enthusiasm of this issue is worth exploring.

3) Interview Sample and Data Collection. This paper adopts rooted theory to study tourists' perceptions and evaluations of non-heritage thematic exhibitions, and generates text to provide data support for subsequent refinement and generalization of conceptual categories. To ensure the authenticity and extensiveness of the data, the data collection was obtained multiple times between March and October 2023, covering periods of high foot traffic such as Labor Day, summer vacation,

and National Day, which facilitated a wider selection of interviewees. Based on on-site observation and semi-structured interviews, on the one hand, we observed and recorded the time that visitors stopped at the location of the exhibits, the exhibits that could arouse conversations and interests, and the visitors' participation in interactive behaviors. On the other hand, following the tour route of pre-interview subjects and observing their visiting behavior, combined with the interview content can make the data more authentic. The semi-structured interview content centers on the interviewees' perception of the exhibition hall context, the layout of the exhibits, the feeling of visiting experience, and the behavioral willingness of the non-heritage exhibitions.

3.2.2. Theoretical models. The model of influencing factors of tourists' participation behavior in NRH thematic exhibition is constructed around the three dimensions of "Situation-Cognition-Behavior" of the SOR theory, and it can be seen from the results of the above data analysis that the influences mainly come from the factors of exhibition, exhibition hall, tourists and environment factors, which are the results of the combined effect of interactive narrative situation, internal drive and external role and cultural environment. The influence mainly comes from the exhibition viewing factors, pavilion factors, visitor factors and environmental factors, and is the result of the combined effect of the interactive narrative context, visitors' perception level, internal drive and external role, and cultural environment, and constitutes a causal, mediating and regulating relationship in this process.

3.2.3. Model extension analysis. It can be seen through the model interpretation that tourists are eager to find the true nature of culture in the museum's non-heritage thematic exhibition, and contextual cognition can extend the non-heritage memory to the social, cultural and tourism scenes, as shown in Fig. 2. From the demand angle, tourists want to experience local non-heritage culture through the exhibition space, and from the cultural supply angle, the museum's non-heritage thematic exhibition hopes to enhance the dissemination of non-heritage folk culture, and drive the museum's tourism economy, and from the design angle, the path of enhancing tourists' situational awareness and participation experience is taken as the research direction to effectively promote the interaction between tourists and non-heritage culture.

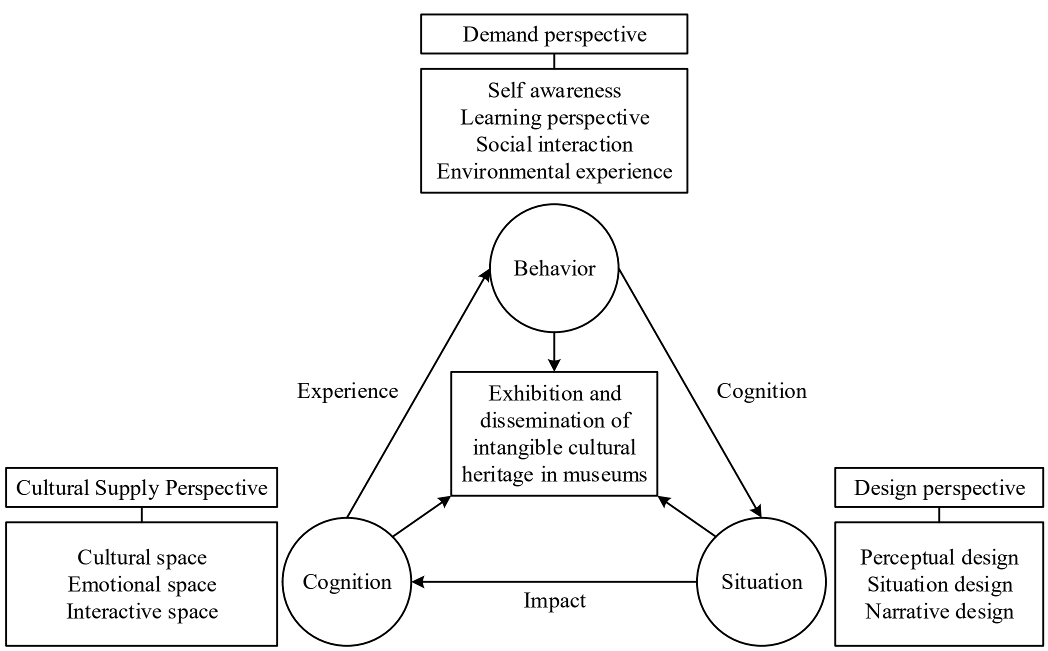

Fig. 2. Model expansion analysis

3.2.4. Research hypotheses:

1) Perceived value and interactive behavior. Perceived value is a kind of customer value based on consumer experience in the era of experience economy, which is the consumer's preference for product attributes or service performance in the process of interaction with the product or service. It has been proved that interactive behavior can influence tourists' perception and bring better experience to tourists, so that tourists can gain experience, grow, insinuate themselves and discover themselves in the process of feeling the environmental atmosphere of tourist places and interacting with people. Therefore, this study proposes the hypothesis:

H1: There is a significant positive effect of interaction behavior on perceived value

2) Cultural Communication. Cultural communication is mainly composed of five basic elements: communicator, communication medium, communication content, contact audience and communication effect. The theory of value co-creation holds that the consumer's consumption experience is the basis of value co-creation, and the interaction among members of the consumption network is the form of value co-creation.

H2: There is a significant positive influence of interaction behavior on the communication effect of non-heritage culture.

H3: There is a significant positive influence of perceived value on the communication effect of non-heritage culture.

On the one hand, in the process of value co-creation, the interaction between individuals and natural and social situations is the fundamental way for "experience" to be realized, and experience is the important basis for the generation and transmission of perceived value; in other words, interactive behavior is the prerequisite for the generation of perceived value. On the other hand, positive interactive behavior can improve tourists' satisfaction and sense of experience, and tourists can stimulate "information search, information exchange, interpersonal interaction and cooperation" and "feedback, publicity, and helping others" through positive experiential value, which in turn promotes the co-creative behavior of tourism. Co-creation behavior, thus promoting the promotion and cultural dissemination of tourist destinations. Similarly, tourists continuously obtain perceived value through communication and interaction with people or objects, and then generate a series of autonomous value co-creation behaviors such as information search, information sharing, feedback and publicity to promote the effective dissemination of NRH culture. Therefore, this study proposes the hypothesis:

H4: Perceived value mediates between interactive behavior and the effects of non-heritage cultural communication.

3) Cultural identity. Cultural identity is essentially a collective identity that binds people together based on shared history and cultural heritage. Tourists' heritage identity has a positive effect on their post-trip behavioral intentions such as promoting and protecting heritage, and cultural identity can play a moderating role between the quality of cultural heritage interactions and tourists' behavioral intentions.

Therefore, this study proposes the hypothesis:

H5: There is a moderating role of cultural identity in the relationship between interaction behavior and the effects of non-heritage cultural communication.

When tourists' cultural identity is high, the role of perceived value in influencing communication effects is strengthened. Therefore, this study proposes the hypothesis:

H6: There is a moderating role of cultural identity in the influential relationship between perceived value and the communication effect of non-heritage culture.

3.2.5. Summary of measured variables in the conceptual model. Table 1 shows the measurement indexes, and the non-heritage cultural communication behavior of tourists and its influence effect are quantitatively analyzed using the non-heritage cultural communication behavior model based on time-series data mining constructed in this paper.

Table 1. Measuring index

Measuring index	
Interactive behavior	Product interaction
	Interpersonal interaction
	Service interaction
Perceived value	Educational value
	Emotional value
	Social value
Cultural identity	
Non-heritage propagation effect	

4. Study on the dissemination behavior of non-heritage culture

4.1. Model Evaluation and Testing

4.1.1. Analysis of non-heritage cultural communication behaviors based on temporal changes. The 7-year museum visits of 4 categories of tourists obtained through time series data mining are plotted in time series, and the overall trend of change in the participation of NRM cultural communication behavior can be obtained. Figure 3 shows the annual communication behavior change trend of the time series of 4 categories of tourists, from which it can be seen that the overall museum visit behavior shows a trend from 797 times in 2016 to 402 times in 2022, with a total decrease of 49.56% and an average annual decrease of 7.08%. Borrowing by visitors under 18 years of age, which is the main group of visitors, declined from 737 visits in 2016 to 357 visits in 2022, an overall decline of 51.56%, and was the main contributor to the overall change.

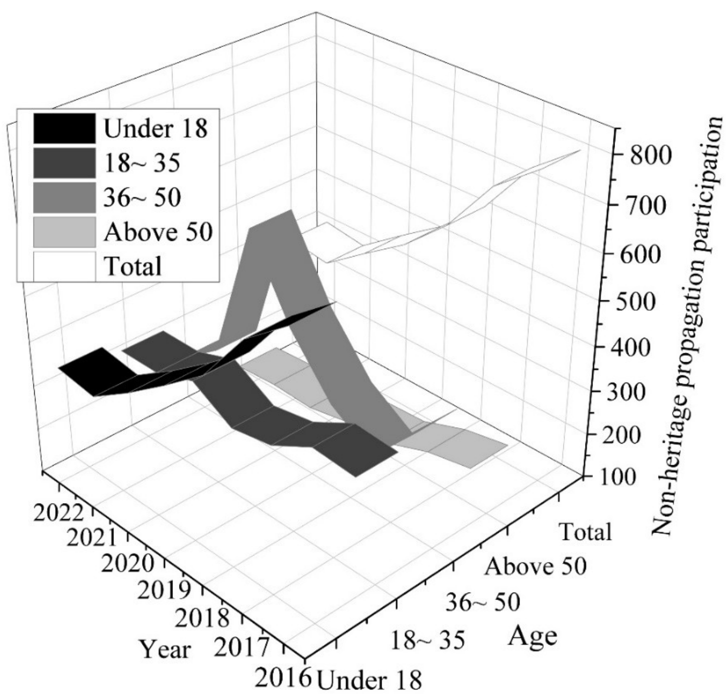

Fig. 3. The trend of the annual transmission behavior of four kinds of tourists

4.1.2. Test results. This phase of the test was conducted in a way that combined online and offline experiments, and 30 typical tourists were selected for this test. Firstly, the tourists were asked to complete the test of the knowledge content related to non-heritage cultural skills. The tourists experience the non-heritage cultural and technical communication, and during the tourists' experience, the non-heritage cultural communication behavior model is mined using time-series data to get the behavior and reaction of the test subjects and recorded. After the tourists' experience, the questionnaire is used again to complete the test of knowledge content related to NRH cultural skills. The scores of the two tests were compared to test the effectiveness of digital communication of NRH cultural skills based on contextual cognition theory. According to the score comparison results of the two tests of 30 tourists, as shown in Figure 4, the average scores of the first and second tests are 63.38 and 88.93 respectively, which shows that the knowledge dissemination effect of the non-heritage cultural skills dissemination based on the contextual cognition theory is significant.

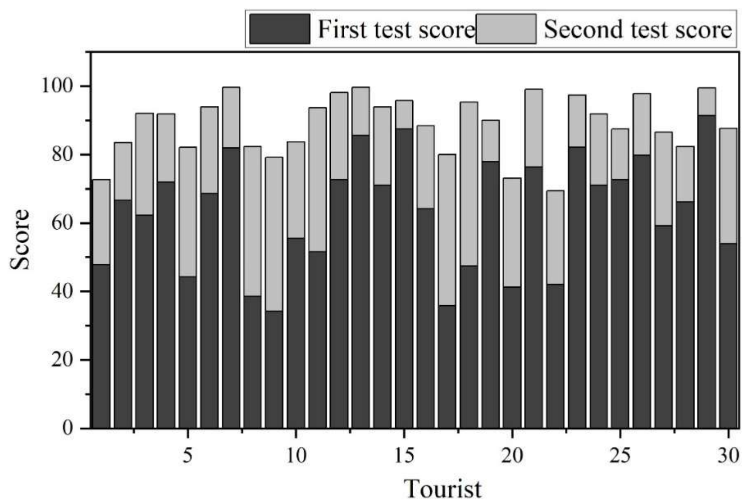

Fig. 4. Comparison of two test scores

4.2. Findings and Analysis

4.2.1. Necessity. The Theory of Planned Behavior seeks to predict and explain an individual's intentional behavior in a given situation. The theory suggests that an individual's intention to behave is the most direct predictor of behavioral occurrence, and that the intention to behave itself is influenced by three main factors: attitudes, subjective norms, and perceived behavioral control. The digitization of NCS may require specific technical support and resources. By applying the Theory of Planned Behavior, it is possible to gain insights into the psychological and social factors that influence users' adoption of digital communication models for NRM culture. This can help in designing more appealing and easy-to-use digitization, as well as in developing effective communication strategies to facilitate the widespread dissemination and preservation of NRM culture.

Figure 5 shows the necessity analysis, according to the necessity of the audience adoption behavior willingness factor of the digital communication model of non-heritage culture, the results of two analyses were carried out, and the average values of consistency and coverage in the two necessity analyses were 0.6436 and 0.5006, respectively. Each single variable is not a necessary factor influencing the audience's willingness to accept, which in turn indicates that the audience's willingness to accept the digital communication of non-heritage culture is affected by a combination of factors.

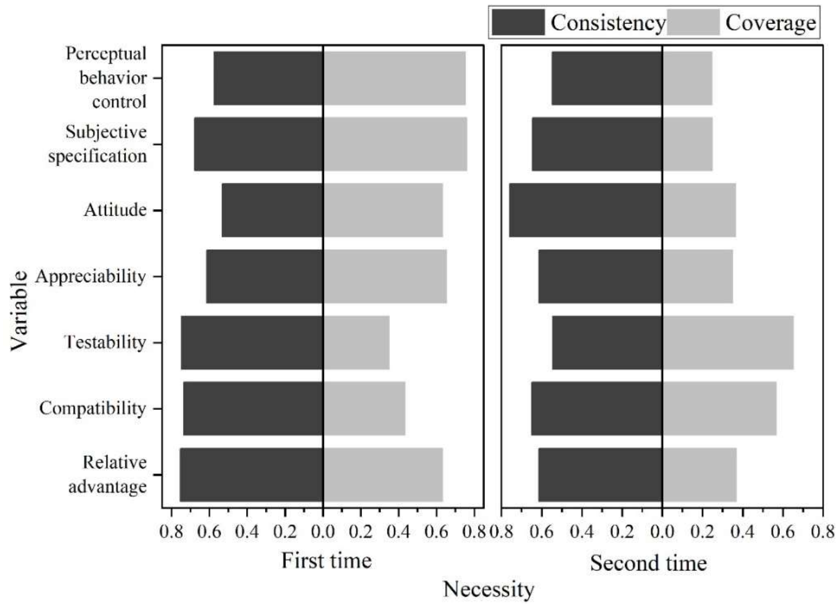

Fig. 5. Necessity analysis

4.2.2. Configuration path analysis. Further using group state analysis and selecting the intermediate solution with a better explanation situation as the basis of the study, according to the results, the tourists' willingness to adopt the behavior of non-heritage cultural communication can be composed of a total of three group states as shown in Table 2.

The consistency, original coverage and unique coverage for grouping I, II and III are 1.035, 0.169, 0.169, 0.853, 0.179, 0.179, 0.861, 0.128, 0.128, respectively. Configuration 1 is a "technology-driven-value identity" path, which is composed of three factors: "comparative advantage", "compatibility" and "attitude". This grouping suggests that when NRM cultural communication has obvious advantages on the technological level, such as higher information transfer efficiency, richer interactivity and better user experience, and these advantages are recognized by the audience, the audience's willingness to adopt will increase. Group II is the “social influence-imitative behavior” pathway, which consists of two factors: “observability” and “subjective norms”. This grouping suggests that audiences who observe others using and benefiting from the NRM cultural communication model are socially influenced and tend to emulate these behaviors. This observability allows audiences to directly see the positive results of adopting the model, thus reducing uncertainty of adoption. Configuration 3 is a "comprehensive synergy-comprehensive consideration" path, which is composed of four factors: "comparative advantage", "compatibility", "observability" and "perceptual behavior control". This grouping suggests that when the NRM model of cultural communication has a clear technological comparative advantage and is highly compatible with the cultural values and lifestyles of the audience, these two factors work together to provide a strong incentive for the audience to adopt the new model.

Table 2. Analysis of non-legacy propagation behavior

Variable	Configuration one	Configuration two	Configuration three
Relative advantage	●		●
Compatibility	●		●
Testability			
Observability		●	●
Attitude	●		
Subjective specification		●	
Perceptual behavior control			●

Consistency	1.035	0.853	0.861
Original coverage	0.169	0.179	0.128
Unique coverage	0.169	0.179	0.128
Consistency of solutions		0.846	
The coverage of the solution		0.569	

Note: ● Indicates that the condition exists

4.2.3. Robustness Tests. Table 3 shows the results of the robustness test, 20 samples were randomly screened and further analyzed using grouping analysis found that three groupings can still be formed and the constitutive factors are the same as above. And the differences in consistency, original coverage, and unique coverage are not significant, and the consistency, original coverage, and unique coverage of grouping state I, grouping state II, and grouping state III are 1.036, 0.154, 0.154, 0.749, 0.186, 0.186, 0.769, 0.119, and 0.119, respectively.In this formulation, the grouping analysis of the present study has a certain degree of scientific validity and reliability.

Table 3. Robustness test results

/	Configuration one	Configuration two	Configuration three
Relative advantage	●		●
Compatibility	●		●
Testability			
Observability		●	●
Attitude	●		
Subjective specification		●	
Perceptual behavior control			●
Consistency	1.036	0.749	0.769
Original coverage	0.154	0.186	0.119
Unique coverage	0.154	0.186	0.119
Consistency of solutions		0.763	
The coverage of the solution		0.516	

4.3. Hypothesis testing

4.3.1. Main effects mediation effects analysis:

1) Direct effect test. Table 4 The main effect and mediating effect tests, constructing the baseline model M1 with perceived value as the dependent variable and gender and whether or not it is an only child as the control variables, and constructing the baseline model M3 with the communication effect as the dependent variable and gender and whether or not it is an only child as the control variables.

The independent variable "interactive behavior" is added to M1 to form model M2. The results showed that interactive behavior had a significant positive effect on perceived value (β=0.918, $p<0.001$), and H1 was validated. The independent variable "interactive behavior" was added to M3 to form model M4. The results show that interactive behavior has a significant positive effect on the communication effect of NRM culture (β=0.925, $p<0.001$), and H2 is validated.

The independent variable "perceived value" is added to M3 to form model M5. The results showed that perceived value had a significant positive effect (β=0.948, $p<0.001$) on the communication effect of NRM culture, and H3 was validated.

2) Mediation effect test. In order to test the mediating effect of perceived value between interactive behavior and the communication effect of non-heritage culture, model M3 is taken as the benchmark, and independent variables "interactive behavior" and "perceived value" are added to form model M6. The results showed that perceived value had a significant positive impact on the communication effect (β=0.485, $p<0.001$), and the impact of interactive behavior on the communication effect was

still significant (β=0.487, p<0.001), but the coefficient decreased from 0.925 to 0.487, so the "perceived value" played a partial mediating role in the "influence of interactive behavior on the communication effect of intangible cultural heritage", and H4 was verified.

Table 4. Master effect and mediation effect test

Dependent variable model		Perceived value		Communication effect			
		Benchmark M1	M2	Benchmark M3	M4	M5	M6
Control variable	Gender	0.178**	-0.005	0.189**	0.008	0.016	0.013
	The only child	0.186**	-0.004	0.269**	0.032	0.046	0.046
Independent variable	Interactive behavior		0.918***		0.925***		0.487***
	Perceived value					0.948***	0.485***
Fitting degree	R^2	0.065	0.948	0.084	0.848	0.869	0.859
	$\triangle R^2$		0.848***		0.766***	0.748***	0.849***
	F	7.826*	1597.265***	9.835***	506.482***	518.484***	415.548***

Note: * means p<0.05, ** means p<0.01, *** means p<0.001.

4.3.2. Moderating effects test. The results show that after the moderating variable "cultural identity" is put into the model, the interaction between interactive behavior and cultural identity has a significant impact on the transmission effect of intangible cultural heritage (β interactive × culture=-0.3548, t=-2.3148, p<0.05), and H5 is verified. The interaction between perceived value and cultural identity also had a significant effect on the communication effect of NRM culture (β perception × culture = 0.3499, t = 2.2978, p<0.05), which was verified by H6. To further analyze the effects of different levels of cultural identity, slope analysis was conducted.(see Table 5)

Table 5. Regulatory effect test

Dependent variable	Independent variable	Overall fit index			Significance of regression coefficient	
		R	R^2	F	B	t
Propagation effect		0.9187	0.9248	354.4785***		
	Gender				0.0178	0.2648
	The only child				0.0599	1.2648
	Interactive behavior				0.4152	3.4584***
	Perceived value				0.1896	1.8594
	Cultural identity				0.3848	8.2648***
	Interactive × Culture				-0.3548	-2.3148*

	Perception × culture				0.3499	2.2978*

Figure 6 shows the moderating role of cultural identity between interaction and communication as well as perception and communication, Figure (a) shows interaction and communication and Figure (b) shows perception and communication. As can be seen from Figure (a), for tourists with a lower level of cultural identity, interactive behavior has a significant positive effect on the communication effect (β=0.7348, t=3.2754, p<0.01), whereas for tourists with a higher level of cultural identity, interactive behavior does not have a significant effect on the communication effect (β=0.1158, t=0.7485, p>0.05). Therefore, with the increase in the level of cultural identity, the influence of interactive behavior on the communication effect of non-heritage culture is weakened.

From Figure (b), it can be seen that for tourists with a lower level of cultural identity, the effect of perceived value on the dissemination effect of non-heritage culture is not significant (β=-0.1459, t=-0.6485, p>0.05), whereas for tourists with a higher level of cultural identity, perceived value has a significant positive effect on the dissemination effect of non-heritage culture (β=0.5261, t=3.2786, p< 0.01). Therefore, with the increase in the level of cultural identity, the influence of perceived value on the dissemination effect of non-heritage culture is enhanced.

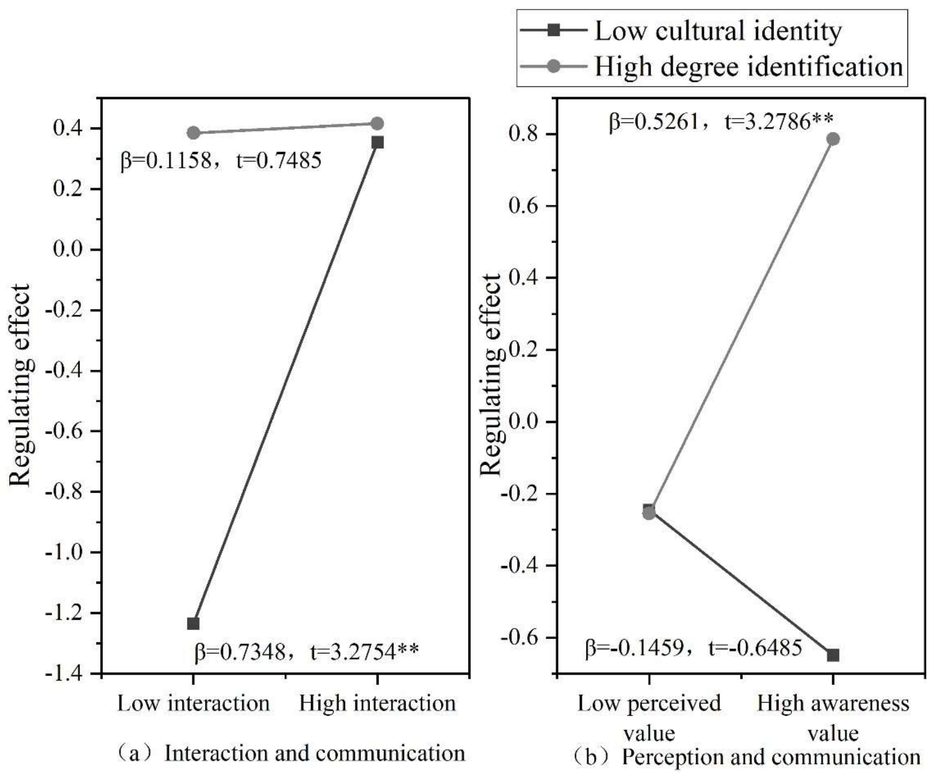

Figure 6. Adjustment analysis

5. Conclusion

This paper models the sequence data, identifies the communication behavior based on the chronological data, divides the non-heritage culture communication behavior into long-term and short-term, and constructs the non-heritage culture communication behavior analysis model under the contextual framework, proposes the relevant variable measurements and research hypotheses of the non-heritage culture tourists' participation behavior, and verifies the validity of the hypotheses by means of experiments.

The 7-year non-heritage museum visit chronological change behavior of 4 types of tourists is analyzed, and the overall museum visit behavior shows a trend from 797 times in 2016 to 402 times in 2022, with a total decrease of 49.56% and an average annual decrease of 10.545%. Thirty visitors were selected and their experiential behaviors and reactions were recorded and analyzed, and the average scores of the first and second tests were 63.38 and 88.93, respectively, indicating that the knowledge dissemination effect of non-heritage cultural and technological communication based on situational cognition theory is significant.

The constructed model was tested for main and mediation effects, and the independent variable "interactive behavior" was added to the baseline model M1, which has perceived value as the dependent variable and gender and whether it is an only child as the control variables, to form the model M2, and the results show that the interactive behavior has a significant positive effect on perceived value $\beta=0.918$, $p<0.001$, indicating that there is a significant positive effect of interaction behavior on perceived value, and cultural interaction contributes to the dissemination of non-heritage culture.

References

[1] Kirshner, D., & Whitson, J. A. (Eds.). (2021). Situated cognition: Social, semiotic, and psychological perspectives. Taylor & Francis.

[2] Young, M. F., & McNeese, M. D. (2018). A situated cognition approach to problem solving. In Local applications of the ecological approach to human-machine systems (pp. 359-391). CRC Press.

[3] binti Pengiran, P. H. S. N., & Besar, H. (2018). Situated learning theory: the key to effective classroom teaching?. HONAI, 1(1).

[4] Shilling, C. (2017). Body pedagogics: Embodiment, cognition and cultural transmission. Sociology, 51(6), 1205-1221.

[5] Cerulo, K. A., Leschziner, V., & Shepherd, H. (2021). Rethinking culture and cognition. Annual Review of Sociology, 47(1), 63-85.

[6] Kashima, Y., Bratanova, B., & Peters, K. (2018). Social transmission and shared reality in cultural dynamics. Current opinion in psychology, 23, 15-19.

[7] Norton, M. (2020). Cultural sociology meets the cognitive wild: advantages of the distributed cognition framework for analyzing the intersection of culture and cognition. American Journal of Cultural Sociology, 8(1), 45-62.

[8] Dagnino, F. M., Ott, M., Pozzi, F., Yilmaz, E., Tsalakanidou, F., Dimitropoulos, K., & Grammalidis, N. (2015). Serious games to support learning of rare 'intangible'cultural expressions. In INTED2015 Proceedings (pp. 7184-7194). IATED.

[9] Wu, J., Ju, L. H., Lin, P. H., & Lyu, Y. (2022). The relationship between form and ritual in cultural sustainability. Sustainability, 14(15), 9157.

[10] Io, M. U. (2019). Understanding the core attractiveness of performing arts heritage to international tourists. Tourism Geographies, 21(4), 687-705.

[11] Sun, T., Jin, T., Huang, Y., Li, M., Wang, Y., Jia, Z., & Fu, X. (2024). Restoring dunhuang murals: crafting cultural heritage preservation knowledge into immersive virtual reality experience design. International Journal of Human–Computer Interaction, 40(8), 2019-2040.

[12] Ma, Y., Zhao, W., Zhang, X., & Gao, Z. (2023, December). Embodied Cognition Guides Virtual-Real Interaction Design to Help Yicheng Flower Drum Intangible Cultural Heritage Dissemination. In 2023 Asia Conference on Cognitive Engineering and Intelligent Interaction (CEII) (pp. 1-7). IEEE.

[13] Alkhafaji, A., Fallahkhair, S., & Haig, E. (2020). A theoretical framework for designing smart and ubiquitous learning environments for outdoor cultural heritage. Journal of cultural heritage, 46,

244-258.

[14] Tan, P., Hills, D., Ji, Y., & Feng, K. (2020, April). Case study: creating embodied interaction with learning intangible cultural heritage through WebAR. In Extended abstracts of the 2020 CHI conference on human factors in computing systems (pp. 1-6).

[15] Sun, S., & Deng, J. (2024, January). Multidimensional Knowledge Representation and Semantic Enrichment of Linear Cultural Heritage Resources. In Knowledge Organization for Resilience in Times of Crisis: Challenges and Opportunities (pp. 411-420). Ergon-Verlag.

[16] Li, X. Z., Chen, C. C., Kang, X., & Kang, J. (2022). Research on relevant dimensions of tourism experience of intangible cultural heritage lantern festival: Integrating generic learning outcomes with the technology acceptance model. Frontiers in Psychology, 13, 943277.

[17] Bertrand, S., Vassiliadi, M., Zikas, P., Geronikolakis, E., & Papagiannakis, G. (2021). From readership to usership: communicating heritage digitally through presence, embodiment and aesthetic experience. Frontiers in Communication, 6, 676446.

[18] Zhang, J., & Jing, Y. (2022). Application of artificial intelligence technology in cross-cultural communication of intangible cultural heritage. Mathematical Problems in Engineering, 2022.

[19] Sabie, D., Sheta, H., Ferdous, H. S., Kopalakrishnan, V., & Ahmed, S. I. (2023, April). Be our guest: intercultural heritage exchange through augmented reality (AR). In Proceedings of the 2023 CHI conference on human factors in computing systems (pp. 1-15).

[20] Pietroni, E., & Ferdani, D. (2021). Virtual restoration and virtual reconstruction in cultural heritage: Terminology, methodologies, visual representation techniques and cognitive models. Information, 12(4), 167.

[21] Ćosović, M., & Brkić, B. R. (2019). Game-based learning in museums—cultural heritage applications. Information, 11(1), 22.

[22] Saurabh Balkrishna Tandale,Prashant Sharma,Vasileios Polydoras & Marcus Stoffel. (2024). Recurrent neural networks as a physics-based self-learning solver to satisfy plane stress viscoplasticity undergoing isotropic damage. Mechanics Research Communications104347-104347.

[23] Satoshi Hoshino,Yu Kubota & Yusuke Yoshida. (2024). Motion planner based on CNN with LSTM through mediated perception for obstacle avoidance. SICE Journal of Control, Measurement, and System Integration(1),19-30.

[24] Ru Zhao,Chaozhu Zhang & Dan Xue. (2024). A multi-scale multi-channel CNN introducing a channel-spatial attention mechanism hyperspectral remote sensing image classification method. European Journal of Remote Sensing(1),