

## Article

# A Semantic Analysis Method of Public Public Built Environment and Its Landscape Based on Big Data Technology: Kimbell Art Museum as Example

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**Abstract:** Based on big data, a new public space evaluation method is proposed. Using programming technology to collect visitor reviews from the travel website TripAdvisor to build a database, based on the data of 99,240 words in 1573 visitor reviews in 10 years, the connection between data and reality is established through systematic data classification and visualization. Following an assessment of the Kimbell Art Museum's functionality, architectural design, and landscape design, along with visitor feedback, a new evaluation methodology was formulated for application to public buildings with landscapes. By utilizing the unique advantages of big data, it provides convenient and efficient analysis methods for public spaces with similar data foundations and opens the way for the optimization of the built environment in the information age.

**Keywords:** space evaluation method; big data mining; public architecture evaluation; Kimbell Art Museum



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## 1. Introduction

A knowledge base representing semantic relations between concepts in a network is termed a semantic network or frame network [1]. The concept of “semantic networks” in propositional calculus had its embryonic origins as early as 1956 (Richard H. Richens). Rooted in Computational Linguistics, research emerged utilizing phrase-structure grammar algorithms for sentence generation (Victor Yngve, 1960) [2]. Sheldon Klein and Robert F. Simmons encapsulated it as “a method for controlling the sense of what was generated by respecting the semantic dependencies of words as they occurred in the text”. Subsequently, through practical research efforts led by numerous scholars, including M. Ross Quillian, semantic network analysis gradually formalized its framework [3]. According to visual analysis, semantic networks have the capacity to be automatically extracted from unstructured textual data, serving as a platform for visual text analysis. It also involved modeling semantic relationships (Sowa, 1991) and visualizing patterns of labeled nodes and edges (Di Battista, 1999) [1]. In recent years, this research has evolved towards social semantic networks [4].

Currently, a single public building post-occupancy evaluation based on user reviews is a scientific method [5–8]. Since the early 21st century, the development of big data technology has promoted the gradual application of semantic network analysis in post-occupancy evaluation, which has the advantages of sufficient data, rich diversity, and spontaneity [9].

In the past 20 years, there have been more than one thousand articles on semantic network analysis [10], but the focused fields are limited: in addition to technology research, this method is mainly used in the landscape planning of scenic spots (accounting for

24.6%) [11,12], whereas in the field of architectural science and engineering, related articles only account for 1.18% [13,14], and the research usually stops at the data sorting level, such as semantic classification and word frequency extraction, with no mature evaluation system that can establish connections between the complex network semantic data and actual usage based on a continuous logic [15,16]. This article summarizes a method of identifying problems from data and converting them into design guidance, making the structural evaluation open; therefore, the traditional top–bottom presupposition is replaced by bottom–top spontaneity, making up for the shortcomings of traditional methods such as lack of soft experience and visitors’ spontaneity. The method proposed in this article truly based public building post-occupancy evaluation on the visitors’ experiences.

Python was adopted to acquire, filter, classify, and visualize the data [17]. By analyzing the internal relation of the data, this article summarizes public building design guidance based on semantic network analysis [18]. The classification, visualization, and analysis approaches adopted are all original ones proposed by the study team, and they addressed the issue of a lack of visitors’ soft experience analysis that haunts existing semantic analysis methods and a scientific method of establishing analysis logic with big data semantic text as the data source was proposed [19]. A pure visitor perspective was adopted to explore architectural characteristics. The research subject can be built public buildings that have been put into use for a certain period, available for public review and with good landscapes, such as libraries, art galleries, etc. [20]. Urban scenic spots in major cities are predominantly occupied by museum-type public buildings, making them prime candidates for researching assessment methods, as indicated by evaluation rankings (Figure 1) [21].

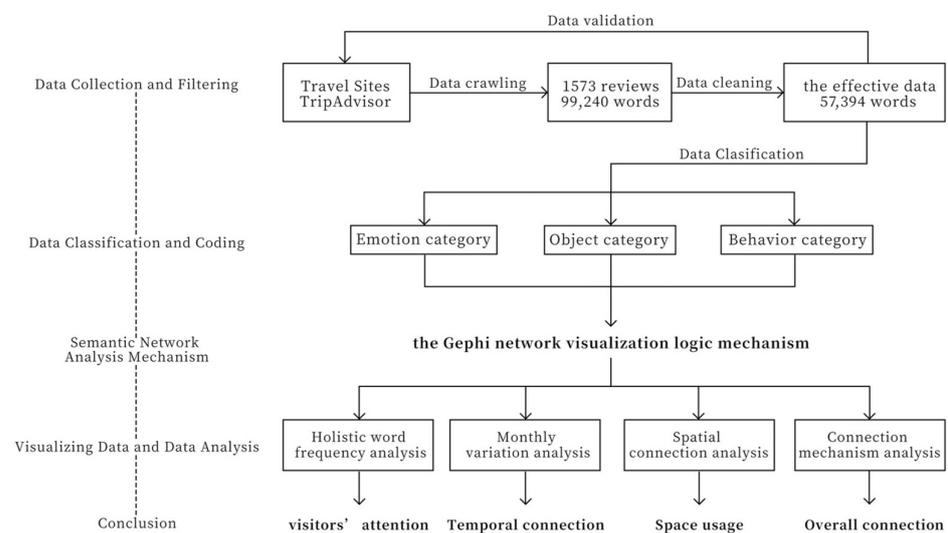
	Westminster Abbey	Chunshan Villa	Sacre-Coeur	Broadway	John Kennedy International Airport	Wangfujing Street	Ocean Park
	W & A Museum	Nation Technology Museum	Notre Dame Cathedral	StatensIslandFerry	Fort Worth Botanic Garden	ZOO	Shanghai Tower
	Houses of Parliament	The New Tokyo City Hall	Malai District	Public library	ZOO	National Tsinghua University	Shanghai Disneyland
	The British Museum	Edo-Tokyo Museum	Rodin Museum	Grand Central Terminal	Fort Worth Stockyards Historic District	Capital Museum	Shanghai Museum
	Hyde Park	Meiji Temple	Orangerie Museum	Brooklyn Bridge	Sid Richardson Museum	National Museum of China	The Bund
	Tower Bridge	Sensoji Temple	Pont Alexandre III	St.Patrick's Cathedral	Fort Worth Botanic Garden	Yi-He Yuan Imperial Garden	Oriental Pearl Tower
	Tower of London	Muzu Museum	Paris Opera	Metropolitan Museum of Art	Bureau of Engraving and Printing	Happy Valley Beijing	Shanghai Wild Animal Park
	Churchill War Rooms	Samurai Museum	Luxembourg Gardens	Central Park	National Gallery of Art	Badaling Great Wall	Science & Technology Museum
	St.James' s Park	Shinjuku Royal Garden	La Sainte-Chapelle	National Memorial Museum	Kimbell Art Museum	Universal Beijing Resort	Happy Valley Shanghai
	The National Gallery	H.I.S	ORSAY MUSEUM	Manhattan Skyline	Bass Concert Hall	The Imperial Palace	Shanghai Disney Resort
40%	London	Tokyo	Paris	New York	Fort Worth	Beijing	Shanghai

Figure 1. Urban Scenic Spots Evaluation Ranking.

Evaluation systems based on computer technology have all developed from independent case analysis to a standard system [9]. Under this background, this article takes the Kimbell Art Museum in Fort Worth, Texas, USA as the subject, based on the reviews gained through big data python, builds a network data and programming technology-based evaluation system that uses semantic classification and word frequency extraction as the basis for analysis to dig deep into the systematic spatial–temporal connection of behavior, objects, and emotions inside the building. The Kimbell Art Museum was chosen for study because of its distinctive blend of public functionality, curated indoor spaces, and meticulously maintained outdoor landscapes [22]. Analyzing these elements enables the assessment of how functional activities, indoor spaces, and outdoor environments influence visitors in public buildings, leading to the development of a comprehensive evaluation framework [23]. The richness of big data enables the study team to deeply explore the correlation mechanism behind the use of buildings, therefore forming a semantic network evaluation framework for public buildings and their landscapes, which can guide and optimize the operation and design of the Kimbell Art Museum and similar buildings and open up new development directions for such research.

## 2. Materials and Methods

The method proposed in this study classified the effective data into three categories: human emotions (emotion), human behavior (behavior) and objects in the building that interact with people (object) and established a one-to-one corresponding relationship between visitors' reviews and the building. Following the Gephi network visualization logic mechanism, basic data analysis (overall word frequency analysis), temporal correlation analysis (analysis by month), spatial correlation analysis (spatial correlation analysis), and correlation analysis with others (Gephi correlation mechanism analysis) were performed on the three categories of reviews [24]. Data analysis covers the basic experience and attention of visitors, the influence of time factors such as seasons on the evaluation and landscape, and the overall relationship between the focus of the reviews in specific spaces and emotion, behavior, and object [25]. The data analysis provided a thorough evaluation of the building's advantages, disadvantages, and future development trends, which is of theoretical support for the selection of the building's development focus, seasonal activity planning, space quality improvement, and interaction detail improvement (Figure 2).



**Figure 2.** Research Framework.

### 2.1. Data Collection and Filtering

The data source of this method was the reviews published by visitors on a tourism website after visiting the building. Four advantages that distinguish this method from traditional data research have been given full play in this study (Table 1) [26]:

1. Large amount of data: 1573 reviews were collected with a total of 99,240 words;
2. Data accumulation: the data covers a period of 9 years from January 2011 to December 2019;
3. Diversified data: In addition to the overall visiting experience reviews, single-data content also includes tour time, ratings, and user information;
4. Data spontaneity: the content is not guided by questionnaire questions or interviews, so it can provide a subjective evaluation from many aspects.

Since there is a lot of secondary information in the data, meaningless conjunctions, pronouns such as such as "And", non-associated references such as "TripAdvisor (TripAdvisor)", basic information such as "Kimbell (Kimbell)", and words that appear too few times were screened out, leaving 45,732 words as valid data (53,508 words were screened out) (Figure 3).



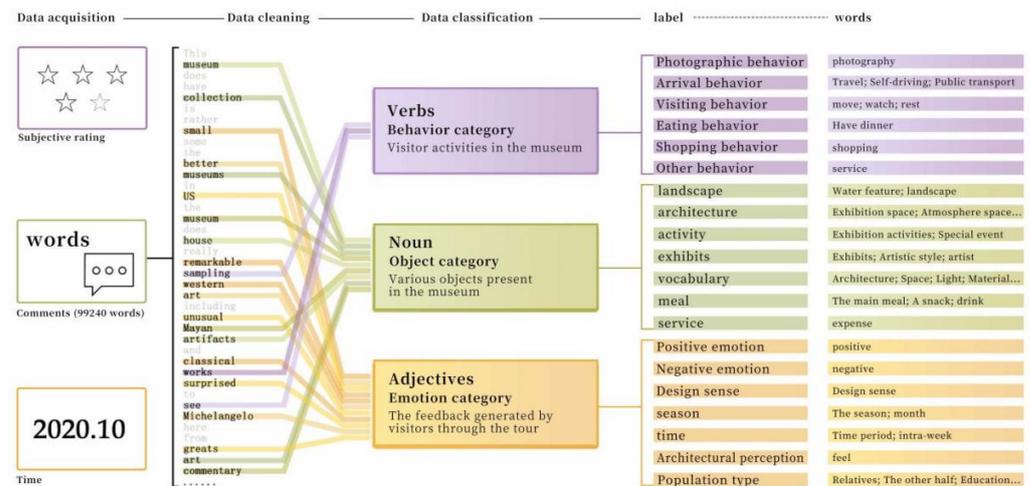


Figure 4. Data Processing.

The process of building a database refers to collecting and dividing data into word lists with the aid of programming technology. After data filtering, the effective data were divided into three categories, and the initial connection between the data and the use of the environment was established. Finally, each piece of data was linked to the specific circumstance in reality through coding.

### 2.3. Semantic Network Analysis Mechanism

The open-source data visualization software Gephi-0.10.1 was adopted in this study to analyze the connection status of the 44 tags and demonstrate the causal mechanism of exploring space use. The reviews were split into sentences (ending with “.”, “?”, “!”, etc.) to explore the correlation mechanism between the different factors (Figure 5).

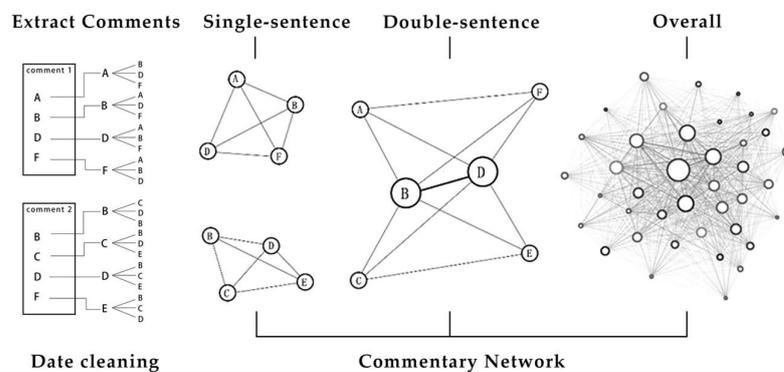
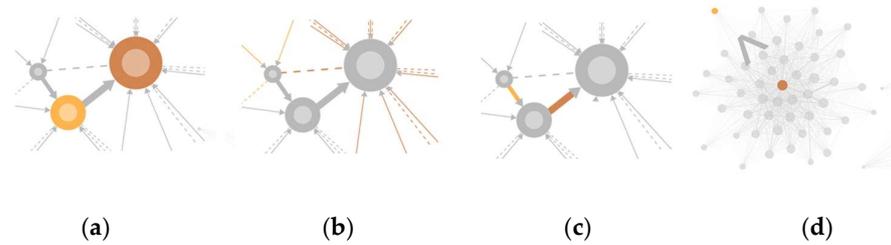


Figure 5. Gephi Visual Network Logic.

1. The size of the point: reflects the number of occurrences of the tag in the database. The larger the point, the more attention the tag has received from visitors;
2. Number of lines: reflects the influence dimension of the tag in the network. The more lines on the tag, the bigger the influence dimension of the point in the overall network;
3. Line width: reflects the intensity of the influence between two tags. For example, the more pairs of two words found in the same review, the thicker the edge between the two points, and the higher the mutual influence, and vice versa;
4. The position of the point: reflects the position of the tag in the whole network. The closer the point is to the center of the network, the more attention the tag receives and the bigger impact it has on other tags. On the contrary, tags at the edge of the network are relatively unnoticed by visitors and are not an important factor affecting their museum tour experience (Figure 6).



**Figure 6.** Gephi Grammar. (a) The size of the point; (b) Number of lines; (c) Line width; (d) The position of the point.

### 3. Visualizing Data and Data Analysis

#### 3.1. Overall Word Frequency Analysis

Overall word frequency analysis can reveal the focus of visitors’ attention in the museum. This analysis serves to validate whether the museum’s functions and positioning align with its intended goals while also facilitating the identification of areas ripe for future development.

At the category level, when the proportion of behavior is the highest, visitors’ activities in the museum are mainly behaviors such as shopping and dining. When the proportion of object is the highest, visitors’ activities are usually connected with objects, such as buildings and exhibits. When the proportion of emotion is the highest, visitors’ activities in the museum usually center on the design, the season, or the extreme emotional evaluation of the building.

At the subcategory and tag level, taking the behavior category as an example (Figure 7), word frequency (word frequency/average word frequency within the category) was compared using 1 as the ratio limit, thus quantifying the intensity of the focus, and the elements with the highest and lowest concern were identified.

Behavior category	Average value	Photographic behavior	Arrival behavior				Visiting behavior				Eating behavior	Shopping behavior	Acceptance behavior
	189	0.19	3.17				4.69				0.37	0.13	1.46
	×	√				MAX				×	MIN	√	
		Average value	travel	self-drive	Public transport	Average value	move	see	rest				
		200	2.3	0.66	0.08	295	0.38	2.32	0.29				
			MAX	×	MIN		×	MAX	MIN				

**Figure 7.** Overall Word Frequency Analysis (word frequency/average word frequency within the category).

The word frequency analysis was then visualized, and the attention to different data was represented by the bar graph of 20 subcategories under the three categories of behavior (purple), object (green), and emotion (yellow). The following conclusions can be drawn from Figure 8:

1. Under the behavior category, the behavior that received the most attention was “visiting behavior”, followed by “arrival behavior”. Among them, the elements that visitors were mostly concerned with were “tourism”, “viewing”, and “service”, indicating a strong emphasis on the overall tour experience.
2. Under the object category, the object that received the most attention was “exhibits”, followed by “glossary”. Among them, “art”, “exhibits”, “cost”, and “architecture” were the elements that attracted more attention from the visitors, underscoring their appeal within the museum context.
3. Within the space, the areas that received a high degree of attention from the visitors were “dining space” and “shopping space”, reflecting the importance of amenities and facilities catering to visitors’ needs and preferences.
4. The visitors paid a lot of attention to the architectural design content, such as “lighting”, “hard decoration”, and other elements. The visitors also cared about architectural details, on which more comments and feedback can be found. Such insights

emphasize the significance of architectural aesthetics in shaping visitors’ perceptions and experiences within the museum environment.

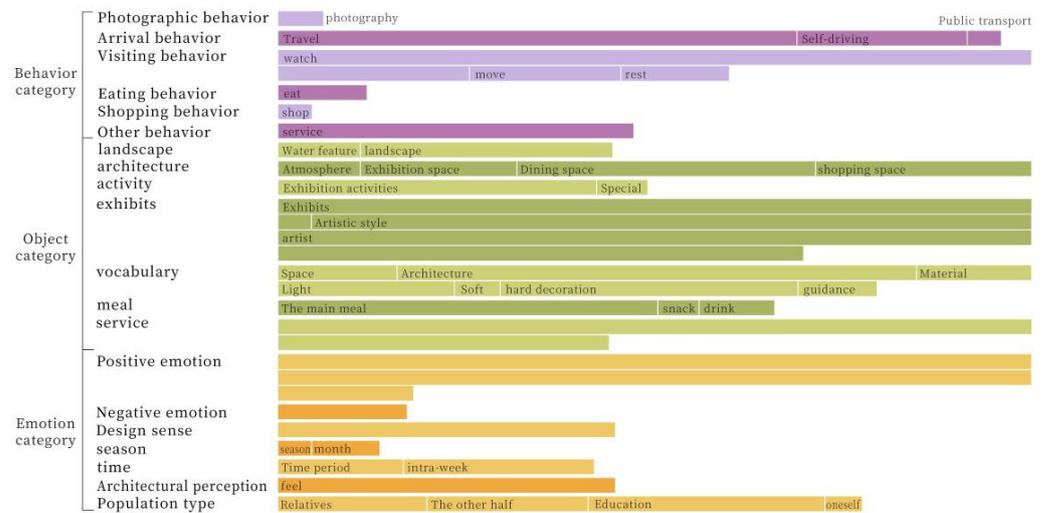


Figure 8. Overall Word Frequency (number of occurrences of each word).

### 3.2. Temporal Connection (Change of Month) Analysis

A frequency connection was established between each item and the time node to analyze the word frequency changes, reflecting the differences in attention across different months and the correlation between the changes in elements with the change in time. The following conclusions can be drawn from Figure 9:

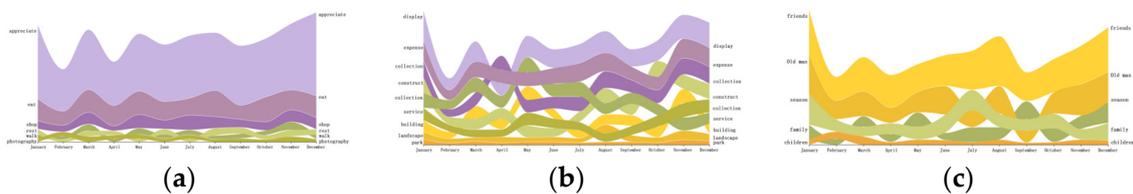


Figure 9. Word Frequency by Month. (a) Behavior in relation to time nodes; (b) Object in relation to time nodes; (c) Result data in relation to time nodes.

1. Under the behavior category, “having meals” is the element that attracted more attention, and was stable throughout the year and did not fluctuate greatly with the change of months.
2. Under the behavior category, a noteworthy correlation was observed between “rest” and “walking”, where the prominence of one corresponded inversely with the prominence of the other, suggesting a trade-off in visitor activities.
3. Under the object category, “display” was the most stable element, maintaining consistent attention levels across varying time nodes.
4. Under the object category, “construction” received more attention than “architecture”, except for a few time nodes.
5. The result data also reflect the relationship between group tours and seasonal changes. Only in the month of August, the number of family visitors as groups increased faster than that of individual visitors, highlighting the influence of seasonal dynamics on visitor behavior and preferences.

### 3.3. Spatial Connection Analysis

In addition to the aforementioned analysis, a direct correlation was established between each item and the architectural space to precisely quantify the rate of space utilization, thereby offering insight into visitors’ inclination towards evaluating the spatial layout. By

meticulously computing both the spatial area and the frequency of words employed in spatial commentary, a comprehensive understanding of visitors’ perceptions of the space was attained. Furthermore, by leveraging the spatial scale of the subject under review, the spatial area corresponding to a predetermined number of reviews was meticulously delineated.

With all the above steps finished, a pivotal review-to-space area ratio was derived, enabling a rigorous quantitative examination. This ratio not only provides a metric for assessing the intensity of visitor engagement within specific spatial contexts but also furnishes valuable insights into the spatial dynamics that shape visitor experiences. The relationship between the number of reviews and the corresponding spatial area is illustrated in Figure 10, offering a visual representation of the nuanced interplay between visitor feedback and architectural space utilization.

1. Among the various areas assessed, “Landscape” occupied the largest overall area within the museum premises, while the “exhibition hall” stood out as the area garnering the highest number of reviews. This highlights the significance of both outdoor ambience and curated exhibition spaces in shaping visitors’ experiences.
2. “Office” had the lowest reviews/area ratio, indicating relatively fewer reviews in proportion to its spatial extent. Conversely, “restaurant” had the highest reviews/area ratio, underscoring the heightened attention and engagement it elicits from visitors. Following closely were the “exhibition hall” and “service area”, further emphasizing the importance of amenities and exhibition spaces within the museum environment.
3. Across all areas except for the “office”, the reviews predominantly focused on “behavior” over “object” and “emotion”. This suggests that visitors tend to prioritize their interactions and experiences within these spaces. Conversely, reviews of the “office” area primarily centered on “object”, with a notable emphasis on the “layout” element. This deviation underscores the functional and design considerations associated with administrative spaces within the museum.

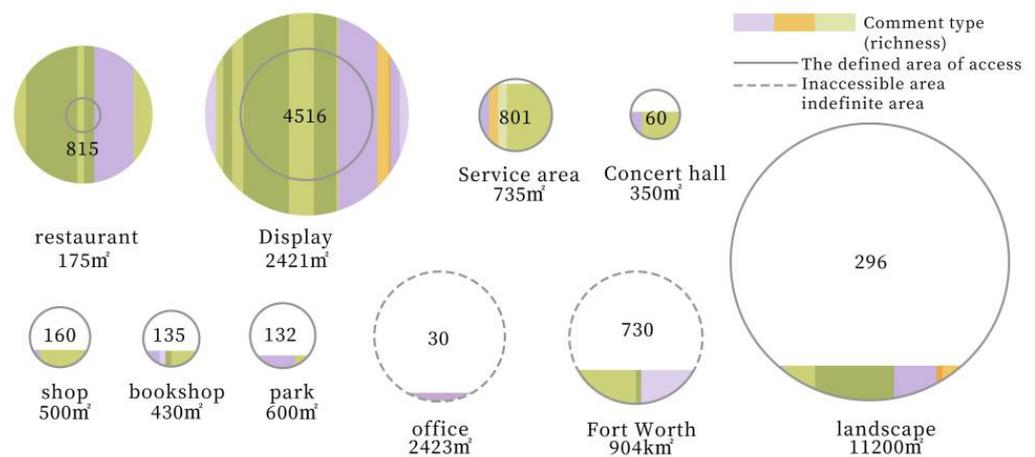


Figure 10. Space Area/Number of Reviews (space evaluation intensity).

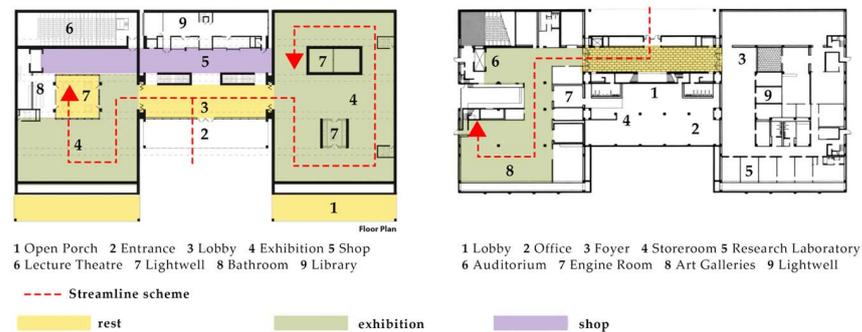
### 3.4. Gephi Connection Mechanism Analysis

The ring diagram (Figure 11) presents the interplay among different categories of data, establishing a comprehensive relationship between behavior, object, and emotion. This supplementary analysis enriches the overall study by offering a nuanced perspective on visitor engagement within the museum environment. Aligned with the findings from the overarching word frequency map, the diagram underscores that visitors predominantly concentrated on eight key elements: “appreciation”, “architecture”, “construction”, “exhibition”, “exhibits”, “collection”, “ticket price”, and “positive emotion”. Notably, “positive emotion” emerged as the focal point, serving as the linchpin of the entire word frequency map. The remaining seven elements exhibited close associations with “positive emotion”,





Chen Xiaotang (2016) in the post-occupancy evaluation of the museum: “A good rest space can help visitors recover their physical strength and improve their attention, so as to better finish the tour”.



**Figure 13.** Floor Plan of the Kimbell Gallery (building layout and visitor routes).

#### 4.2. Service Functions

The Kimbell Art Museum is equipped with service space, accounting for 17.37% of the total area of the venue (Figure 14). In terms of space evaluation intensity, “restaurant” (4.7 pieces/m<sup>2</sup>) surpassed “exhibition” (1.9 pieces/m<sup>2</sup>) to become the area with the highest space evaluation degree. In terms of temporal connection, “dining” and “shopping” both showed stable performance throughout the year, and the activity frequency did not fluctuate greatly with the change in the month. In terms of overall connection, “eating”, second only to “seeing”, was the most closely associated factor with “positive emotion” and is an important behavior in providing a quality sightseeing experience. It can be seen that the commercial attached space of the Kimbell Art Museum is well created, which improves the tour experience and has the potential for sustainable development [28].



**Figure 14.** Shopping and Dining Places.

#### 4.3. Exhibition Environment Design

The Kimbell Gallery uses 16 unit vaults, two interior courtyards, and three light wells to bring in outdoor natural light (Figure 15) [29]. This design optimizes the viewing environment and seamlessly integrates with exhibits, contributing to its prominence among visitors, second only to functionality [30]. In terms of visitors’ attention, showroom, which had 4561 comments, was the space with the highest number of comments. In addition, art exhibition, accounting for 44.52% of the attention, was the core visiting content of the museum. In terms of temporal connection, “exhibition” was the most stable among various factors in the object category. Unique activities and exhibitions avoid the off-season of visits brought about by seasonal changes. In terms of overall connection, “exhibition” in the object category was the core factor affecting the experience of art museums and was also the factor most closely associated with “positive emotion”. It can be seen that the Kimbell Art Museum has a good exhibition environment, and visitors’ attention is paid to proper places. According to the analysis, exhibition halls can be designed and opened around the lobby, park, catering area, and workshop to display exhibits of high attention. The exhibition area is used to presuppose people’s tour paths to improve the overall attention of visitors to the non-exhibition space [31].



**Figure 15.** Exhibition Environment.

#### 4.4. Architecture Appreciation

The Kimbell Art Museum is highly regarded in the field of architectural design. In terms of visitors' attention, visitors paid more attention to "construction" (door, window, column, etc.) than "architecture" (light and shadow, material, etc.). Different from the analysis of light processing, spatial prototype, and form selection from a professional perspective, visitors were more interested in visible architectural elements such as structural style and decorative details [32]. There was little feedback on the overall appearance and design logic of the building. In terms of overall connection, the connection between "construction" and "positive emotion" was stronger than that of "space". However, in addition to being closely connected to "collection" and "exhibits", exhibition was mainly connected to "space", and "construction", "sense of design", and "space" constituted the second source of positive emotion for visitors in the museum. It is known that visitors are more sensitive to visible design elements in the process of visiting, and it is easier to obtain satisfaction through visible design elements. Therefore, formal and visible design should be properly retained in architectural details. Moreover, the frequency of "photography" behavior in the interior of buildings is low, and visitors are more inclined to perceive these buildings with their eyes. It can be considered that by combining with the building itself, an appropriate photography space can be created to guide visitors' attention to the building itself [33].

#### 4.5. Landscape Design

The Kimbell Art Museum has a large landscape. (Figure 16) The construction area of the Kimbell Art Museum (9982 square meters) is similar to the landscape area (8600 square meters), but in terms of visitors' attention to the landscape, the visitors' attention was the lowest among those in the object category. In terms of temporal connection, visitors' evaluation of the landscape had an obvious peak in August, and August was the only month in which the rising trend of family visitors was higher than that of individual visitors. In terms of spatial evaluation intensity, the overall area of "landscape" was the largest, but the evaluation ratio was the lowest in the open space facing visitors. In terms of overall connection, only 3.5% of visitors' shared experiences of walking took place in the landscape. Among the 145 walking behaviors in the behavioral data, only 5 walking behaviors were directly connected with the landscape, and the landscape evaluations of "lawn", "sky", "trees", and "surrounding environment" were marginalized in the whole evaluation network. It can be seen that the spatial evaluation degree of the "landscape" area was very low, the temporal connection was strong, and it had almost no correlation with other behaviors such as exhibits and dining. The modernist landscape design effect of the Kimbell Art Museum failed to make good use of the advantages of the area, and its attraction to visitors is relatively weak. Food and beverage activities, commercial spaces, and exhibitions can be considered to break through the seasonal limitations and enhance the vitality of the landscape area.



Figure 16. Landscape of the Kimbell Art Museum.

## 5. Application Prospect

Big data mining technology and a semantic analysis concept are adopted in this study to establish an effective evaluation framework for the use of buildings and their landscapes (Figure 17), which has a broad application prospect.

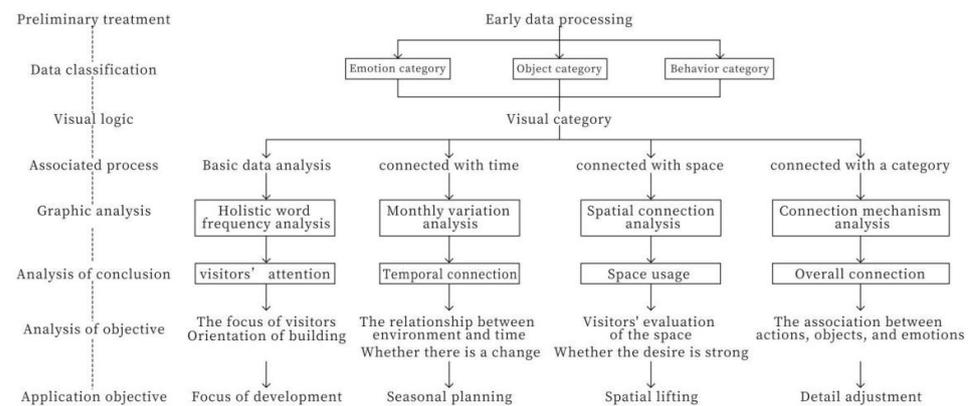


Figure 17. System of Analytical Methods for the Architecture Environment.

In terms of the pertinence of questions and the uniqueness of perspectives, the evaluation core of the traditional evaluation method has changed from the objective environment of buildings and preset questions of investigators to the spontaneous experience of visitors who have actually been to buildings. At the same time, it uses the rich diversity of big data to introduce a complex “multi-cause and multi-effect” investigation mechanism, which is different from the traditional evaluation method, which is dominated by accurate single evaluation. A mechanism is studied with the following characteristics: it has a change from structural to open and from top–down to bottom–top; it makes up for the shortcomings of soft experience and the spontaneity of visitors in traditional evaluation methods. It plays a specific role from a variety of design contents (objects) to a variety of design evaluation indexes (behavior and emotion) in massive data.

In terms of the scientificity of the method and the applicability of the object, the data source based on the subjective text evaluation on the network is more real and cumulative in both time and space [34]. It can cross geographical and time barriers and improve the efficiency of data collection and analysis. As computer technology can reduce labor time and speed up the research process, it can be applied to the built environment assessment of any public buildings with big data accumulation, especially libraries, shopping malls, exhibition centers, railway stations, etc., which have high exposure. Buildings such as the Kimbell Art Museum are public structures with inherent functionality, indoor spaces, and outdoor vistas. Visitor assessments pinpoint the connection between visitor activities and these components, enabling precise modifications. In different types of spaces, researchers can adjust the subitems in a macro category to form a new evaluation system to focus on spatial pain points and find usage problems to obtain systematic evaluation and design strategies.

By establishing the connection and continuous logic between the complex network data and the actual space use phenomenon, the semantic network technology quantitative analysis text, which has the advantages of large data volume, good accumulation, strong diversity, and high spontaneity, can be systematically applied to the post-occupancy

evaluation of public buildings. It can improve the comprehensiveness and accuracy of the evaluation system and make the evaluation scope wider and deeper. The method of identifying problems from data and transforming them into design guidance is applied to provide more objective, detailed, and in-depth guiding value and theoretical support for the current demand analysis of public buildings and the future development trend.

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