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Research Article

The Structure of Lexical-Semantic Networks at Global and Local Levels: A Comparison between L1 and L2

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This article applies quantitative methods from complex network analysis to investigate and compare the organization of L1 and L2 lexical-semantic networks. Forty-eight English learners with Chinese as their native language completed a semantic fluency task, first in English and then in Chinese, based on which two lexical-semantic networks were constructed. Comparison at the global level found that the L1 lexical-semantic network displays more prominent small-world and scale-free features and a clearer modular structure in comparison with its L2 counterpart. Locally, although the two lexical-semantic networks share most of their central words, they differ remarkably in their composition and the connection pattern of their peripheral words. Specifically, L1 peripheral words are likely to connect with each other to form local modules while L2 peripheral words tend to connect with central words. Moreover, word centrality was found to be closely related to time of generation, generation frequency, and accuracy in fluency tasks, and such tendency is more obvious in L1 than in L2. The findings demonstrate the advantages of quantitative analysis granted by network science in the investigation of mental lexicon and provide insights for lexical representation research and classroom vocabulary instructions.

1. Introduction

The mental lexicon is typically understood as composed of two major sections of representation closely linked with each other: one is form based and reflects a word's phonological and orthographic properties; the other is semantic-based and reflects its meaning relations with other words and with the real world [1]. Diverse experiments including word association and semantic priming have provided evidence for the important role played by semantic connections in the mental lexicon. For instance, in a semantic priming experiment, a word (e.g., apple) is responded to more quickly when it is preceded by a semantically related word (e.g., pear) as compared to an unrelated word (e.g., car). An early framework known as the spreading activation model with attempts to describe the psycholinguistic process operating in a lexical-semantic network originated from the research into semantic memory and word retrieval of Collins and Quillian [2] and Collins and Loftus [3]. In the model, access or activation of individual words in the lexical-semantic network spreads to their neighboring words along semantic links. Despite the simplicity of the model, it effectively interprets the behaviors of individual words in terms of their semantic connections with other words, proving the close relation between the organization of semantic memory and behaviors of words.

Despite a large body of research on lexical representation in monolinguals, less is known about the organization of mental lexicon of bilinguals who learn a second language with a highly structured L1 lexicon already in place. Theoretically, L2 learners are assumed to apply their L1 lexical-semantic knowledge for building their L2 lexical-semantic networks and make adjustments to form connections unique to L2 as they grow more proficient [4]. The results of word association research point to the broad conclusion that patterns of lexical connections in L2 are different from those in L1, but due to methodological limitations, little is known about the nature of these differences, including whether they are quantitative or qualitative from a holistic view and how these structural differences may relate to different processes operating in lexical-semantic networks.

Although the concept of lexical-semantic network has been used almost ubiquitously in lexical research literature, it nevertheless remains intrinsically a metaphor and an idealized theoretical construct. The advent of network science in recent years affords us the opportunity to probe the organizational characteristics of lexical-semantic networks at both macro and micro levels and the retrieving processes happening within these complicated systems. For example, the features of being small-world and scale-free, two major topological properties of previously investigated lexical-semantic networks, can tell that the nodes in the concerned networks are easily accessible to each other and newly added nodes are more likely to be connected to a small number of central nodes. It is these structural features that render the networks highly efficient in the activation of nodes. However, the limitation of most previous structural analyses is that they are isolated from microscopic studies and do not take a further step to ask about the underlying causes of these topological features in terms of the connectivity between individual words and their position within the network. Far less is known about the structural differences between L1 and L2 lexical-semantic networks in a microscopic perspective. In order to fill the gap, this study constructed lexical-semantic networks by collecting data from semantic fluency tasks and applied a tool of network analysis to quantitatively analyze the structure of the L1 and L2 lexical-semantic networks at both the global and local levels. The findings would increase our understanding of the mental mechanism underlying semantic fluency tasks.

2. Literature Review

2.1. L2 Lexical-Semantic Representation. Bilingual lexical-semantic representation has long been a topic of interest to language researchers. Existing research on bilingual mental lexicon assumes that the mental representation of vocabulary is mainly composed of two parts: word form and word meaning [5, 6]. A major controversy in L2 lexical representation is about how word forms of two languages are linked to the semantic (conceptual) systems. Different answers to this question have led to the distinction of separate and shared representations. In the view of the shared representation, the word forms of the two languages correspond to a common semantic system, whereas for separate representation, the word form of one language is connected with its own semantic system [7, 8]. Although the notion of separate representation was once very popular, much subsequent research has revealed that it is applicable only to certain types of words like abstract and noncognate words, hence the existence of the word-type effect [9–11]. For example, Kolers [9] found that words referring to concrete and tangible objects more often have similar associations across languages than words referring to abstract states or emotions. Therefore, they concluded that experiences and memories unique to one culture are stored separately from those of another culture in the mind, but common concepts shared by people of different cultures are represented identically. Thus, it is reasonable to say that L1 and L2 semantic representations overlap with each other, sharing some semantic components and differentiated in others. A major challenge is then how to identify the words (or concepts) in which they overlap and the ones in which they differ from each other. In order to address this problem, researchers employed various methods including word associations, stroop-type tasks, priming, word translation, and picture/word naming to collect data and observe how L1 and L2 interact with each other [5]. Previous research largely focuses on the mental representation of several targeted words, and thus fails to provide a global picture of the lexical-semantic network of a semantic category by telling how it is organized, how words interact with each other to affect the structure of their network, and how the position of individual words may differ within networks across languages. Thanks to the development of network science, these questions can now be addressed conveniently and their solution can shed light on how words are represented and retrieved in bilingual lexicon.

2.2. Network Science. Networks are composed of nodes and edges (or links), with the former representing entities and the latter indicating connections between them. The development in mathematics and computer science has provided an infrastructure for modeling complex constructs of the natural world and human activity as networks, which allows for the investigation of relationships between entities at multidimensional levels [12]. Based on a wide array of well-defined and quantified parameters, the network approach can unfold structural features of complex systems decided by the connection patterns of nodes within the systems [13, 14]. The major concepts and parameters frequently used in network analysis include the following:

Size (n) of a network refers to the number of nodes a network has. Neighbors of a node are nodes directly linked to the node, and neighborhood size refers to the number of neighbors a node has.

Average shortest path length (l) is the average minimum number of steps that must be traversed from one node to other nodes in the network. In a network with a small l, nodes are close to each other because it takes fewer steps to go from one node to reach other nodes. Therefore, the network is considered to be more compact.

Clustering coefficient (C) calculates the probability that neighbors of a node are also neighbors of each other, describing the tendency of forming cohesive clusters in a network.

Centrality measures the importance of individual nodes in networks. A frequently used centrality measure is d*egree*, which denotes the number of connections a node possesses, and weighted degree calculates the sum of connections multiplied by their weight, which takes into account the varying degree of importance of each connection in a network. *Average weighted degree* calculates the average sum of weighted degree of all nodes in a network, which can reflect the connectivity of a weighted network. Another centrality measure is *eigenvector centrality*, which describes a node's importance as well as the influence of its neighbors.

A network is considered to be small world if it has a short path length ($l < l_{\mathrm{rnd}}$) and a high local clustering ($C > C_{rnd}$) when compared to a random network. It is quantitatively measured by the parameter, small-worldness(S):

$$S = \frac{C/C_{\mathrm{rnd}}}{L/L_{\mathrm{rnd}}}, \quad (1)$$

where l_{rnd} and $\mathrm{C}_{\mathrm{rnd}}$ represent the path length and the clustering coefficient of a random network with the same number of nodes and edges, in which the edges are randomly distributed across the nodes. A value greater than 1 would mean that the concerned network is a small-world network;

In a scale-free network, its degree distribution follows a power-law pattern, which means that the majority of nodes are poorly connected and a few nodes have a large number of connections.

Modularity indicates the presence of dense clusters/communities of related nodes embedded within the network. In a modular network, connections are not evenly distributed because connections within communities are denser than connections between communities [15, 16].

2.3. The Global Structure of Lexical-Semantic Networks. The existing studies in L1 consistently confirm that semantic networks have small-world features with evidence from different languages using different sources of semantic connections [17–23]. For example, Steyvers and Tenenbaum [19] built three large-scale semantic networks with data from three sources: word associations, Wordnet, and Roget's Thesaurus to find that the three networks all possess small-world and scale-free features. As small-world networks have a short global distance and a strong local clustering, it takes only a few steps to traverse the distance between any two words and the words more semantically related to each other are closer in position within the network and form clusters more easily. Therefore, the small-world structure results in maximization of processing efficiency since the high clustering of semantically related words facilitates the activation of the connected words, and the short distance entails fast search and retrieval of targeted words [24].

Small-world properties were also reported in the organization of L2 lexical-semantic networks, by Borodkin et al. [25] and Li et al. [26]. Borodkin et al. [25] built L2 lexical-semantic networks of Hebrew from semantic fluency tasks to find that similar to L1 lexical-semantic networks, L2 lexical-semantic networks are also small-world networks. Li et al. [26] investigated the development of the English lexical-semantic network of Chinese learners as the size of the network increases from 660 to 2002 based on an associative mechanism. They found that the lexical-semantic network retains its small-world properties even on the initial scale of 660 words. This provided further evidence for small-world features of L2 lexical-semantic networks.

In scale-free networks, only a few nodes are connected to a large number of nodes while most words are poorly connected. Therefore, in an associative semantic network with scale-free features, only a minority of words is central and can semantically trigger the activation of many other words, while most words are quite isolated and only elicit a small number of other words [27]. More importantly, researchers suggest that central nodes play a fundamental role in the growth of networks, a process known as preferential attachment, which contributes to power-law degree distribution [19]. According to this principle, preexisting well-connected nodes in the network stand a higher chance of acquiring new links with the expanse of the network [19]. The scale-free property was reported in a large number of L1 lexical-semantic network studies where the degree of word nodes fits the power-law distribution [17–19, 21–23, 28, 29]. However, to the best of our knowledge, only one study by Li et al. [26] examined and confirmed the scale-free property of L2 lexical-semantic networks.

Modular structure is another property closely related to small-world and scale-free features. It has been noted that modular networks tend to have small-world features but small-world networks are not necessarily modular [30]. There is evidence that L1 semantic networks consistently show thematic structure [27], with words occurring in the same semantic setting being grouped together. Borodkin et al. [25] investigated the structure of L2 Hebrew lexical-semantic networks and found that the L2 lexical-semantic networks are characterized by greater local connectivity and reduced modularity as compared to their L1 equivalents, so words in L2 are not easily clustered to form semantic subgroups despite rich connections between them, which is not favorable for the interaction between nodes in the scope of the whole network.

The general belief is that the global structure of lexical networks is language-specific and can be influenced by language proficiency [12]. This notion has been verified by an array of empirical studies in L1 [21–23, 31]. However, evidence from L2 research still lacks. Borodkin et al. [25] investigated the global structure of L2 Hebrew lexical-semantic networks with 51 participants based on the data of semantic fluency tests. We constructed lexical-semantic networks of similar scale in the same semantic category to explore the structure of the L2 English lexical-semantic network of a group of less proficient learners.

2.4. Centrality of Words in Lexical-Semantic Networks. Centrality defines the position of an individual word in the network and its influence on other words. Central nodes were reported to be more likely to receive new links, so they serve as the foundation for the development of the network [19]. One important way to define centrality is to look at the number of connections that a node possesses, known as degree centrality. According to the spreading activation theory, when a node is activated, activation first spreads to all the nodes linked to this initial node and then further to their related nodes in a decreasing gradient [32–34]. It is believed that the size of a word's neighborhood and the number of connections it possesses can determine its accessibility [35]; [13]. There is evidence that words with more connections are responded to more accurately and quickly in lexical tasks such as word decision, categorization, and visual word recognition [36, 37], but these studies were conducted in L1 and it remains unknown whether central words in L2 lexical-semantic networks exhibit similar processing advantages relative to their L1 counterparts.

In summary, the review above reveals that the application of network science in the investigation of lexical representation and processing needs to be further expanded. On the one hand, it is unclear whether small-world and scale-free features are the general organizational principles of L2 lexical-semantic networks or only typological features pertaining to certain language types. On the other hand, existing L2 network analyses mainly concentrate on global properties while investigation from microscopic perspective is lacking, though actually the latter is more relevant to L2 vocabulary learning and teaching. Moreover, less is known about the differences between L1 and L2 lexical-semantic networks at both global and local levels.

In order to enrich the research of this line, this study conducted semantic fluency task experiments in the semantic category of vegetables and fruits among Chinese students who study English as their second language. We aim to compare L1 and L2 lexical-semantic networks at both the global and local levels with a network analysis tool Ucinet 6 [38]. In so doing, we intend to answer the following questions:

(1) How are L1 and L2 lexical-semantic networks different in global structure in terms of small-world, scale-free, and modular features?
(2) How are L1 and L2 lexical-semantic networks different in local structure in terms of central and peripheral words?
(3) How is centrality of words in L1 and L2 lexical-semantic networks related to time of generation, frequency, and accuracy in fluency tasks?

3. Materials and Methods

This research addresses the global and local structure of L1 and L2 lexical-semantic networks. Macroscopic analyses involve the measurement and comparison of small-world and scale-free properties of the two networks. Microscopic analyses identify the central and peripheral words in the two lexical-semantic networks and investigate to what an extent the central words demonstrate retrieval advantages in L1 and L2 as reflected by their generation position, frequency, and written accuracy. The generation position of a word demonstrates the time of activation in word associations [20]. As for corpus frequency, the frequency of L1 words was obtained from the dialogue sub-corpus of BCC (Beijing Language and Culture University Corpus Center), a Chinese corpus containing more than 15 billion words. The frequency of L2 words was obtained from the spoken corpus of BNC (British National Corpus), a large, well-balanced corpus of British English that is freely available online. The reason for choosing the two corpora is that Chinese dialogues and spoken English are supposed to be closely related to everyday life and then are likely to contain high proportion of fruit and vegetable words. We expect to observe the retrieval advantages of the central words in L1 and L2 lexical-semantic networks reported by Goldstein and Vitevitch [39] and Siew [40] in spoken and visual recognition based on phonological and orthographic networks, respectively. With these aims, we administered a fluency task experiment in a group of Chinese learners of English and two lexical-semantic networks were established by taking the steps to be introduced in 3.3.

3.1. Participants. A total of 49 students participated in the English semantic fluency test but one student dropped out of the corresponding Chinese test due to a sick-leave, resulting in 48 valid Chinese responses. All the students were freshman undergraduates majoring in engineering in a university in central China with an average age of 19.6 years. They all had Chinese as their native language and learned English as a second language, and had no experience of living in an English-speaking country for over a year. Like most Chinese EFL learners, they learned English mainly in classroom contexts. Their English learning started at grade three (around 9 years old) in primary schools, lasting 6 years in middle and high schools. At university, English is a compulsory course for undergraduates in the first two semesters. At the time of the experiment, the participants were taking College English Course twice a week (90 min each). They all chose to attend the experiments on their own will and oral consent was obtained from each of them. They rated themselves as intermediately proficient (on a scale ranging from 0 = none to 10 = perfect) in speaking ($M = 4.81$, $SD = 1.63$), reading ($M = 6.55$, $SD = 1.59$), and listening ($M = 4.59$, $SD = 1.25$) in English, generally above average in the national college entrance examination of China.

3.2. Semantic Fluency Test. In semantic fluency tests, participants were asked to produce as many words as they could that belonged to a given semantic category (e.g., animal, country, and food) in a limited time. In this study, the categories of fruits and vegetables were selected because the students were familiar with them and could be less influenced by their vocabulary limit. The two categories were actually treated as a single category so as to avoid possible confusion caused by botanical definition and common use [25]. The test was conducted twice, first in English (L2) and then in Chinese (L1) with an interval of three weeks to avoid possible priming effects between the two languages. The order of the English test before the Chinese test was for the reduction of language order effects observed in previous studies [25, 41]. Because of administrative and practical considerations, the tests were conducted in writing and the participants were required to write down all the fruit and vegetable words that they could come up with within 1 min.

3.3. Building Lexical-Semantic Networks. All the data were carefully examined to eliminate responses that did not meet our criteria. First, responses that did not belong to the category of either fruits or vegetables were excluded. This procedure removed four English responses, namely, *jerry*, *jelly*, *pine*, and *photo* and one Chinese response, *huasheng* (*peanut*). Second, wrongly spelled words that could not be confidently identified were deleted. For example, the word *been* could be a wrong spelling of either *bean* or *beet*, and it is hard to tell which is the intended one. Misspelled words like *bananna* were corrected and kept, because it is an obvious misspelling and we assumed the participant had established the semantic relation between *banana* and *fruit*. In doing so, we removed three English responses: *bean*, *pumpling,* and *gabbage* and preserved 99.85% and 98.42% responses in L1 and L2, respectively.

In our lexical-semantic networks, nodes represent generated nouns and edges represent semantic connections between words. One most important step in building lexical-semantic networks is to define semantic connection. In the current study, we placed an edge between two words if one followed the other with a minimum frequency of 2. The rationale is that adjacent items are typically closer in semantics than nonadjacent items and a threshold of two times of co-occurrence is to prune some spurious edges which are not semantically close but only co-occur by chance or because they span a cluster switch boundary. This method of network construction was used and proved to be valid by Wulff et al. [42]. All adjacent word pairs and their co-occurrence frequency were extracted and saved in an CSV file via Python coding, where the first two columns are source words (they point to others) and target words (they are pointed to), and the third column represents weight, which is the number of times that the two words co-occur as adjacent pairs in fluency lists. In this research, the networks were treated as undirected given that estimating directionality could result in a rather sparse network. Moreover, the networks were weighted because the strength of semantic connections is very informative in analyzing semantic network structure. Table 1 exemplifies the co-occurrence data, which were input into network analysis tools *Gephi* and *Ucinet* to do further network analysis.

Table 1: An example of co-occurrence data.

Source	Target	Weight
Apple	Banana	20
Potato	Tomato	20
Strawberry	Watermelon	11
Peach	Pear	10
Apple	Pear	8
Banana	Peach	7
Raspberry	Strawberry	7

4. Results

The participants generated a total of 665 responses in L1 and 435 responses in L2. Paired-sample t-test confirmed that significantly more responses were produced in the participants' L1 than in L2 ($t = 8.088$, $p = 0.000$). The combination of repeated responses reduced the number of unique words to 89 in L1 and 40 in L2. Using a threshold frequency of 2, we obtained 96 different word pairs in L1, with *pingguo* (apple) and *xiangjiao* (banana) being the most frequent co-occurring pair by virtue of a weight of 17, followed by *li* (pear) and *pingguo* (apple) (15 times of co-occurrence) and *li* (*pear*) and *tao* (peach) (11 times of co-occurrence). The unique network-constructing responses, or the fruit and vegetable words that are included in the L1 lexical-semantic network, was 51. Likewise, the total of 80 different word pairs were extracted in L2, with *apple-banana* and *tomato-potato* getting the highest hits of 20, followed by *strawberry-watermelon* with an co-occurrence of 11. The final number of unique responses included in the L2 lexical-semantic network diminished to 25 in L2.

The two lexical-semantic networks were visualized with Netdraw function in *Ucinet 6* and the resulting graphs are presented in Figure 1, which show the overall organization of the two lexical-semantic networks. The size of nodes in the graphs denotes their centrality so that the larger the word node, the more central and important the word node is to the network structure. The width of lines indicates the strength of connections, with wider lines indicating stronger relations. The color of nodes illustrates the distinction of communities in networks in that words belonging to the same community were drawn in the same color. As shown in Figure 1(a), the L1 lexical-semantic network is larger, consisting of two components, and it is more compartmentalized than the L2 lexical-semantic network (Figure 1(b)). Finer structure analysis was conducted for comparing the structure of the L1 and L2 lexical-semantic networks.

4.1. Global Structure. For investigating the global structure of L1 and L2 lexical-semantic networks, network parameters related to small-world and scale-free features were calculated and presented in Table 2. The major parameters include: n = number of nodes; D = network diameter; $\langle k \rangle$average weighted degree; $\langle l \rangle$average shortest path length; $\langle C \rangle$clustering coefficient; Q = modularity; S = small-world measure; γ = exponent of the power law that best fits to the degree distribution; R^2 = determination coefficient of the power law with exponent γ; parameters with a tag "rnd" denotes the value of their corresponding random networks that share the same number of nodes and edges with the target network.

4.1.1. Small-World Features. According to the model of Watts and Strogatz [43], small-world networks are characterized with strong clustering coefficient $\langle C \rangle$ and short average path length $\langle l \rangle$. Comparison of l and C of the L1 and L2 lexical-semantic networks with value of their corresponding random networks reveals that the two target networks are both small-world networks. This is because both lexical-semantic networks have short global distance, suggesting most words can reach each other via only a few intermediate words, on average two to three words in the

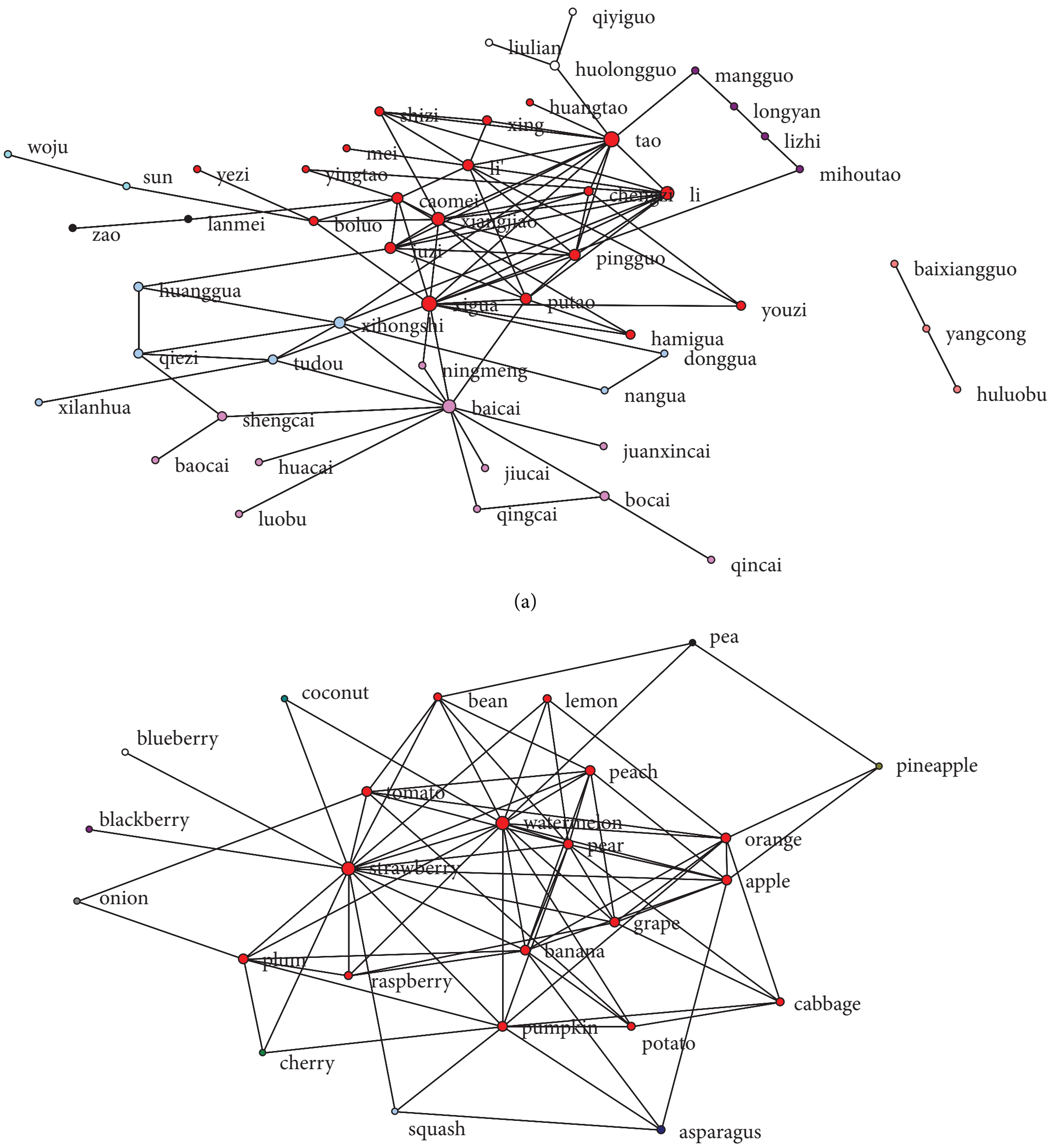


Figure 1: Overall lexical-semantic network in L1 (a). Overall lexical-semantic network in L2 (b).

Table 2: Global network structure of the two lexical-semantic networks.

	Chinese as L1	English as L2
n	51	25
D	6	3
$\langle k\rangle$	12.314	23.12
$\langle C\rangle$	0.293	0.49
$\langle C_{\mathrm{rnd}}\rangle$	0.077	0.28
$\langle l\rangle$	3.019	1.863
$\langle l_{\mathrm{rnd}}\rangle$	3.014	1.88
Q-Modularity	0.422	0.003
S (small-worldness)	3.799	1.766
γ	−0.7001	−0.456
R^2	0.97935	0.83327

L1 lexical-semantic network and one to two words in the L2 lexical-semantic network (as shown in Table 2). In addition, both networks have much higher clustering coefficient than their random network counterparts, suggesting a high probability of observing clusters in the two lexical-semantic networks. Examination of their small-worldness value further verifies the small-world nature of the two lexical-semantic networks and the small-world features are more prominent in the L1 lexical-semantic network than its L2 counterpart.

4.1.2. Scale-Free Features. In a scale-free network, only a very small number of nodes are connected with many other nodes, while the majority of nodes have weak connectivity.

As a result, the degree distribution of a scale-free network follows power-law pattern. To avoid the potential bias associated with the binning method of data in log-log plots [16], we plotted degree that resulted from cumulative distribution, with the horizontal axis representing the degree of the words, k, in the network, and the vertical axis, the probability of randomly finding a node whose degree is equal to or higher than k (illustrated in Figure 2). The graphs in Figure 2 show that it is easy to find low-degree words but the probability of finding high-degree words is quite low, as demonstrated by the tail of the distribution. In addition, the drop of the tail reveals that the probability falls sharply with the increase of degree.

The power-law function in a graph with logarithmic scales has the format of a straight line. Indeed, the distribution manifests a linear pattern in the above log-log plots. As is seen in Table 2, the curve estimation analysis yielded an $R^2 = 0.97935$ for the L1 network ($p < 0.0001$), which means that 97.935% of this distribution can be explained by a power-law structure, and the resulting scaling parameter is 0.7001. Similarly, the R^2 for the L2 network is 0.83327 ($p < 0.0001$), with a scaling parameter of 0.456. The results reveal that the degree distribution of both networks significantly fit power-law model, but the scaling parameter and determination coefficient in L1 is larger than the corresponding value in L2, indicating that the degree distribution of L1 fits power law better. As a result, we may say that the L1 lexical-semantic network has stronger scale-free features than the L2 lexical-semantic network.

4.1.3. Module Structure. Modularity reports the partitioning pattern of networks and is closely related to scale-free and small-world organization of nodes in many real world networks [44, 45]. The clustering of nodes in the same module gathers similar pieces of information, which can enhance efficiency in completing specific functions or locating information in a large network [45, 46]. Specifically, the degree of modularity reflects the differences between connections among nodes within a module and nodes across different modules. We used the popular Girvan–Newman algorithm for analyzing modularity of networks in this study. A positive modularity value means that the connections within modules are denser than connections between different modules. For example, if the modularity of a random network is 0.3, a network of the same size and the same number of connections has a modularity greater than 0.3, then this network is considered to have a clear module structure [46, 47].

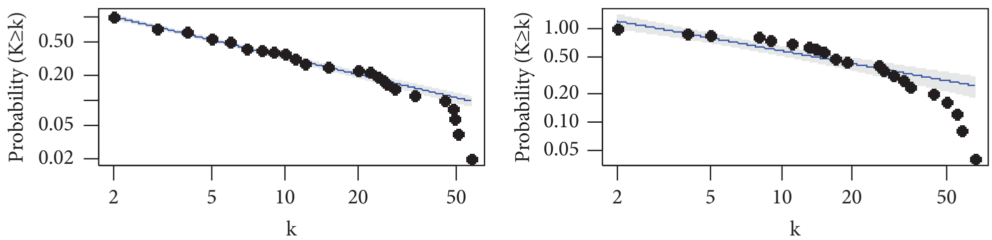
The data reveal that the words in the L1 lexical-semantic network are more likely to be partitioned into identifiable subcategories. According to Table 2, the modularity value of the L1 lexical-semantic network ($Q = 0.422$) is much higher than that of the L2 lexical-semantic network ($Q = 0.003$). As is illustrated in Figure 1, in the L1 lexical-semantic network, there are clear separations between different subgroups, with all vegetable words located at the bottom right corner and fruit words in the middle and upper left corner. Moreover, words with similar semantic features are likely to reside in the same module. For instance, the word *huolonguo* (pitaya or dragon fruit in English) is surrounded by two other tropical fruit words, *liulian* (durian in English) and *qiyiguo* (kiwi fruit in English), and is linked to other modules via a central word, tao (peach). In contrast, there is no clear distinction between different modules in L2. The general pattern in the L2 lexical-semantic network features popular fruit and vegetable words forming the core of the network, with less popular words located in the periphery and directly linked to the central words.

4.2. Central and Peripheral Words in L1 and L2 Lexical-Semantic Networks. In a network, the importance of nodes is usually defined in terms of the number of links they possess. Intuitively, the nodes that possess the largest number of connections should contribute the most to the network structure and are thus the most influential. However, it was found that the position of a node's connected nodes also contributes to the influence of this node. A node which is linked to many unimportant nodes was found to be less influential than a node which is linked to a few important nodes [48]. The measure of eigenvector centrality takes the quality of connections into consideration and proved to be effective in identifying important and relevant web pages for search engines [48, 49]. In the current research, we calculated the eigenvector centrality of the words in the two lexical-semantic networks with *Ucinet 6* and worked out the ten most and least important words in the two lexical-semantic networks, as presented in Table 3. The words are ranked based on their centrality in a descending order, and the words whose translation equivalents are also located in the corresponding central and peripheral sections are highlighted in bold.

Comparison of central words in the two networks revealed that the L1 and L2 lexical-semantic networks share a large proportion of central words but few peripheral words. According to Table 3, of the 10 central words, 9 in bold are shared by L1 and L2 lists, namely, caomei (strawberry), xigua (watermelon), li (pear), xiangjiao (banana), tao (peach), pingguo (apple), putao (grape), juzi (orange), and li'(plum), while in the periphery, only two pairs form translation equivalents, that is, *baicai-cabbage*, *yangcong-onion*. It was found that many peripheral words in one language are not present in the lexical-semantic network of another language, as in the case of *longyan* (longan), zao (date), and qincai (celery) in L1, and coconut and blackberry in L2. This means that these words are specific to certain individuals or a particular language and are not prominent enough to enter the lexical-semantic network of another language.

A more microscopic perspective is to look at the connection pattern of the central and peripheral words, respectively, in the networks. Figure 3 presents ego-networks of some words in the two networks, in which only words that are directly linked to the target words are included.

Comparison of connection patterns of words in the center of the networks revealed differences in both the number of connections and the connection pattern. First, the L1 central words tend to have sparser neighborhood than



(a) (b)

Figure 2: Log-log plot of the cumulative degree distribution of the lexical-semantic network of L1 (a). Log-log plot of the cumulative degree distribution of the lexical-semantic network of L2 (b).

Table 3: Central and peripheral words in L1 and L2 lexical-semantic networks.

L1		L2	
Central	Peripheral	Central	Peripheral
Xigua (watermelon)	Longyan (longan)	Strawberry	Cabbage
Tao (peach)	Liulian (durian)	Watermelon	Asparagus
Xiangjiao (banana)	Qiyiguo (kiwi fruit)	Pear	Cherry
Li (pear)	Baocai (cabbage)	Banana	Coconut
Pingguo (apple)	Qincai (celery)	Apple	Squash
Putao (grape)	Zao (date)	Peach	Pea
Juzi (orange)	Woju (asparagus lettuce)	Grape	Pineapple
Li'(plum)	Yangcong (onion)	Pumpkin	Blueberry
Caomei (strawberry)	Baixiangguo (passion fruit)	Orange	Blackberry
Shizi (kaki)	Huluobu (carrot)	Plum	Onion

their L2 counterparts, though the density value is quite close. The average density for the nine ego networks of the nine shared central words in L1 and L2 is 0.496 and 0.551, respectively. This could be seen from Figure 3(a) and 3(b), where fewer connections exist in the ego network of *xigua* than *watermelon*.

In comparison with the central words, peripheral words in the two networks displayed more noticeable differences in their connection pattern, as seen from Figure 3(c) and 3(d). For one, the gap in the size of neighborhoods possessed by the peripheral words in L1 and L2 is further widened on the basis of the central words. The average neighborhood size for L1 peripheral words is 1.2, suggesting that most words are directly linked to only one word, and the corresponding average value is 2.7 in L2, meaning that L2 peripheral words are linked to two to three words on average. Furthermore, a closer observation of these connections showed that peripheral words in L1 tend to have other peripheral words as neighbors while the peripheral words in L2 tend to have central words as neighbors, such as strawberry, watermelon, pumpkin, and plum.

4.3. Retrieval Advantages of Central Words. The generation position of a word in semantic fluency tasks refers to its occurrence order and measures how quickly the word is retrieved. It was obtained by averaging its position value among all cases of its production. For example, the word raspberry was produced by three participants, and it occurred as the 3rd, 12th, and 15th word, respectively, which resulted in an average position of 10. As is shown in Tables 4 and 5, word centrality is negatively correlated to the average generation position of words in both L1 ($r = -0.649$, $p = 0.000$) and L2 ($r = -0.581$ $p = 0.002$), suggesting that central words are generally retrieved more easily and earlier in the given semantic category. A comparison between L1 and L2 showed that the correlation coefficient is higher in L1 than in L2, pointing to stronger relevance between word centrality and time of retrieval in L1.

Generation frequency reflects how many times words were produced in the semantic fluency tasks while corpus frequency indicates how often a word is generally used in a language. Statistics analysis showed that word centrality is positively correlated to generation frequency in the two languages. Tables 4 and 5 reveal that the correlation is particularly strong between centrality and generation frequency with a correlation coefficient of 0.897 ($p = 0.000$) in L1 and 0.832 ($p = 0.000$) in L2. This finding indicates that centrality is a good predictor of generation frequency. However, although centrality is significantly related to frequency to a large extent, centrality is a more integrated measure, which can tell much more than simple frequency about the features of words. For instance, the two words *tomato* and *potato* are highly frequent in both L1 and L2, but they emerge as central words in neither network. The reason is that the two words tend to co-occur with each other with a rather high frequency and are seldom linked to other words. For habitually co-occurring words of this type, the activation of one word has a larger chance of activating the other, so in some way we can say that the two words are

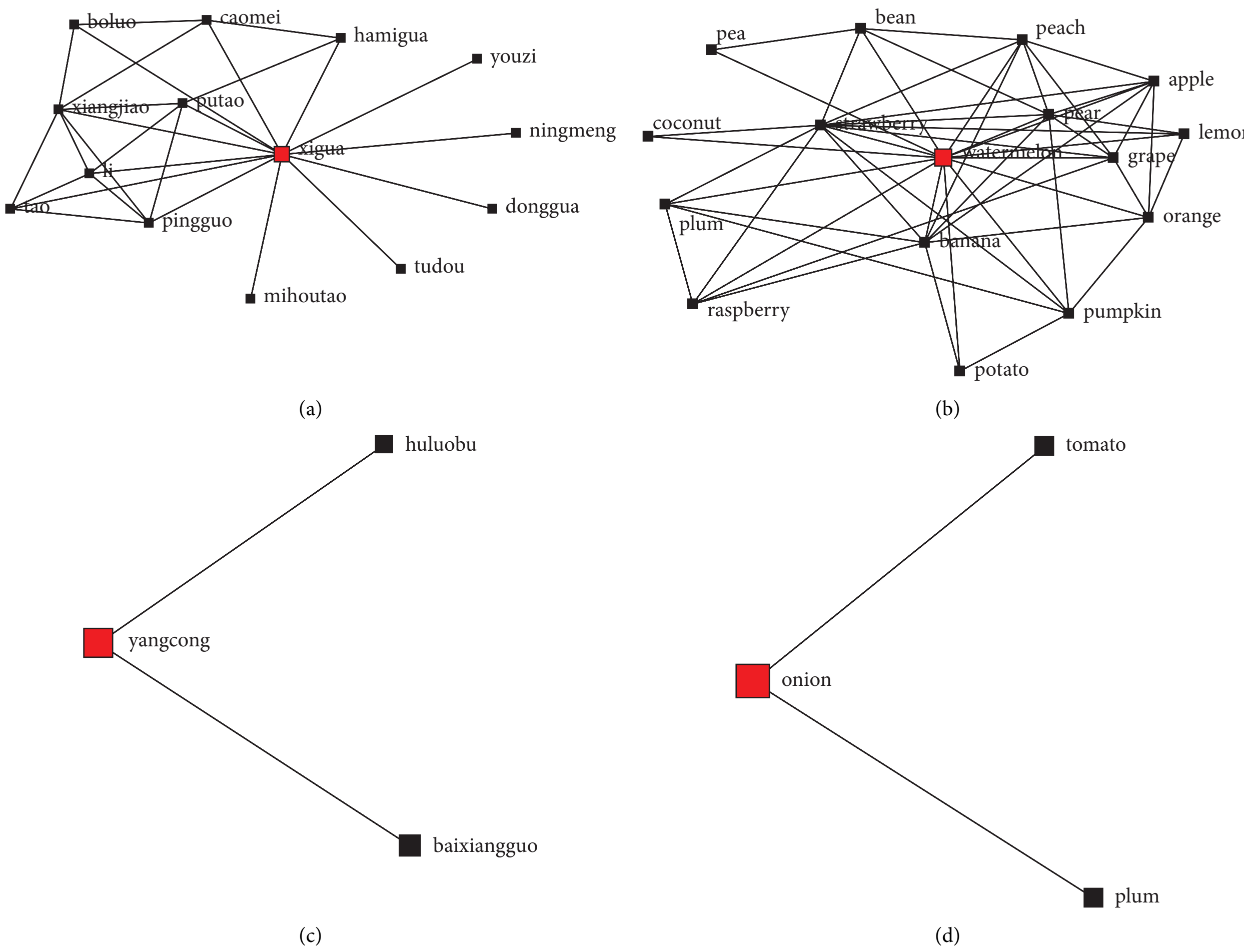


Figure 3: Ego network of central word xigua (a), ego network of central word watermelon (b), ego network of peripheral word yangcong (c), and ego network of peripheral word onion (d).

Table 4: The correlation between word degree and generation position, generation frequency, and corpus frequency in L1.

		Position	Frequency 1	Frequency 2
	Pearson correlation	−0.649**	0.897**	0.494**
Centrality	Sig. (2-Tailed)	0.000	0.000	0.000
	N	51	51	51

**correlation is significant at the 0.01 level (two-tailed); frequency 1 = generation frequency; frequency 2 = corpus frequency.

Table 5: The correlation between word degree and generation position, generation frequency, and corpus frequency in L2.

		Position	Frequency 1	Frequency 2
	Pearson correlation	−0.581**	0.832**	0.172
Centrality	Sig. (two-Tailed)	0.002	0.000	0.412
	N	25	25	25

**correlation is significant at the 0.01 level (two-tailed); frequency 1 = generation frequency; frequency 2 = corpus frequency.

important to each other but have less influence on other words in the whole network and thus are categorized out of central words in the lexical-semantic network. In addition, centrality is found to be significantly related to general frequency in L1 ($r = 0.494$, $\rho = 0.000$), again verifying the idea that central fruit and vegetable words are generally more frequently talked about in everyday communications. No such correlation was found in L2 ($r = 0.172$, $\rho = 0.412$), but this does not necessarily mean that the central L2 words are not frequently used by L2 learners in their talk, for the language learning environment for L2 learners is different from that in L1, and the data from the native language corpus could not represent the actual amount of language exposure of L2 learners.

The written accuracy was also examined, particularly for L2 where students' lexical proficiency differs to a larger extent. We found few spelling errors for the central words like apple, banana, peach, and grape but many errors for more peripheral words like raspberry (e.g., ruspberry, raspeberry, aspeberry, and rapaberry), asparagus (e.g., asparagas), carrot (e.g., carrat, parrot), bean (e.g., pean), and cucumber (e.g., cucober). This finding implies that words in the center are better consolidated in learners' lexicon and have a better chance of being retrieved accurately while words in the periphery are less assimilated into the lexicon and are at a higher risk of being erroneously retrieved. However, there are also exceptions. Many participants also made errors on two central words strawberry (straberry) and watermelon (watermellon), but the difference lies in that in these two cases, they made mistakes because letters *w* and *l* are not pronounced in accordance with general phonological rules. In other words, the concerned participants successfully activated the words' pronunciations but only failed to spell them out because of the irregular match between the pronunciation and spelling of those words. However, the errors in the peripheral words display different types. Students even mixed one word with another. For example, parrot was mistaken for carrot, pean for bean, indicating a failed retrieval of the correct pronunciation. In a word, even though the learners sometimes indeed made mistakes on central words, these mistakes were usually caused by irregularity of the words' pronunciation, while errors for the peripheral words were more varied, indicating a weaker command of the peripheral words.

5. Discussion

Data analyses above show that at the global level, the L1 lexical-semantic network possesses a larger scale as indicated by more word nodes and a larger diameter but is globally less connected compared with its L2 counterpart. Both the L1 and L2 lexical-semantic networks demonstrate small-world and scale-free features, but such features are more prominent in L1 than L2. Words in the L1 lexical-semantic network tend to form cohesive semantic subgroups while words in L2 are less likely to be partitioned into semantic subgroups. At the local level, L1 and L2 lexical-semantic networks share a large proportion of central words but few peripheral words. Word centrality is related to generation time, generation frequency, and accuracy, but to different extent in L1 and L2. In a more microscopic perspective, it was found that central and peripheral words differ in such important aspects as neighborhood size, strength of connections, and centrality of neighbors. In this section, the research findings are further discussed to present their theoretical, methodological, and pedagogical implications.

5.1. Small-World and Scale-Free Features of Lexical-Semantic Networks. The research results reconfirm the small-world and scale-free properties of L2 lexical-semantic networks, but the smaller S value and a less satisfying power-law fitting for the L2 lexical-semantic network suggest lower efficiency of word retrieval in L2 than in L1. This discrepancy between L2 and L1 points to the close relation between the structure of lexical-semantic networks and lexical proficiency. Li et al. [26] have found that with the increase of L2 vocabulary size, small-world and scale-free properties of a lexical-semantic network also increase. The present research contributes to the existing literature by demonstrating that the impacts of the organization of lexical-semantic networks on language proficiency hold true across two languages: English and Chinese. This adds to the findings made by Borodkin et al. [25] who based their conclusion on the comparison between L1 English and L2 Hebrew lexical-semantic networks. The scale-free features of L1 and L2 lexical-semantic networks reveal that the majority of words in them have a small number of connections while a few words have a large number of connections in the networks. This organizational model of lexical-semantic networks is in line with "the principle of least cognitive efforts" in lexical processing. As the central words are in small number and the peripheral words are used in restricted contexts due to low frequency, the cognitive efforts of language users can be greatly reduced. The prominent scale-free features in L1 lexical-semantic networks imply that the participants exert less effort in vocabulary processing in L1 so that they can deal with the increased difficulty in lexical search imposed by a much larger lexical-network. In order to increase the small-world and scale-free properties of L2 lexical-semantic networks, instructors need to combine learners' vocabulary growth with word connection strengthening. It is advisable for teachers to prioritize words with rich semantic connections and make these words the foundation of lexical-semantic network expansion.

5.2. Modular Structure in Lexical-Semantic Networks. The modular structure of a network can inform the dynamics of information transmission within a network [15]. Correspondingly, the modular structure of lexical-semantic networks may reveal the dynamics of activation spreading among words in the mind in language use. In a lexical-semantic network with clear modular structure, words within modules are more densely connected with each other than with words from other modules. As such, when a word is activated, chances are that activation is contained within a module rather than widely dispersed to the rest of the network. Therefore, the modularity of a lexical-semantic network may facilitate word retrieval in that it helps narrow down the search space for a word from the entire network to a small module, and thus saves search time when the network is large. Hence, the suboptimal modular organization of the L2 lexical-semantic network as compared to L1 indicates that the L2 lexical-semantic network is less well-organized than its L1 equivalent, which replicates the results of Borodkin et al. [25]. It is worthy to note that the modularity of our L2 lexical-semantic network is extremely low, probably because of the small network size. In other words, the students are not proficient to know enough members in subcategories. Therefore, this calls for the need to enlarge vocabulary size of the students. Particularly, it is advisable to teach vocabulary by enriching semantic subcategories to foster the formation of word communities.

5.3. Central and Peripheral Words in L1 and L2 Lexical-Semantic Networks. Comparison of central and peripheral words in L1 and L2 lexical-semantic networks reveals that most of the central words, but a small number of peripheral words, are shared by the two networks. This is possibly because the central words are typical fruit and vegetable words and humans of different cultural backgrounds share common knowledge about the central members of a category. This result illustrates how different languages are similar in the central section of semantic representation. In contrast, the peripheral words are nontypical and pertain to individual experiences and highlight the differences of the two languages. These peripheral words can project the unique cultural and language experiences of the learners. Another possible reason for the overlapping of the L1 and L2 lexical representations is that the learners build their L2 lexical-semantic networks based on their existing L1 networks [4, 50, 51]. If this is the case, then the process of borrowing from L1 into L2 seems to start from the center and gradually reduce to the periphery. This pattern of L2 borrowing from L1 is at least partly due to the fact that the central words are learned better while the peripheral words are not well integrated into the network yet. Whatever the causes of the discrepancy in L2 and L1 lexical-semantic networks, the results of the current research can provide evidence for the overlapping of the semantic representations of L1 and L2 vocabulary. What's more, the distinguishing of the central words from the peripheral ones can provide timely information for classroom vocabulary instructions.

5.4. Word Centrality and Processing Advantages in Word Production. Data analyses of the present study reveal that the central words tend to be produced earlier and more frequently in word production. The correlation between centrality and generation time and frequency is probably because the words with high centrality can receive significant partial activation via their links to their neighbors. This result is in agreement with other studies with L1 which found that the central words are more easily accessed in lexical processing [52]. Duñabeitia et al. [37] observed the effect of centrality on four different tasks: lexical decision, reading aloud, progressive demasking, and online sentence reading. Griffiths et al. [36] found that centrality effect on memory search is similar to what happens to information search on the Internet. In short, in both L1 and L2, the central words are essential for lexical processing in the lexical-semantic networks. In addition, compared with its L1 counterpart, the L2 lexical semantic network tends to follow a more obvious central-periphery sequence in word retrieval. This demonstrates a weaker peripheral section which needs to be strengthened in order to enhance the function of the whole network. Thus, for L2 learners, it is the peripheral words that require more endeavors to get connected with each other and integrated in form and meaning.

6. Conclusion

The current research demonstrates the structural discrepancies in L1 and L2 lexical-semantic networks at not only the global but also the local level. The prominent global features of the L1 lexical-semantic network correspond to the higher proficiency of L1 in comparison with L2. The different connection patterns of central words and peripheral words relate to their special behavior in lexical processing and their distinctive roles in the development of the mental lexicon. These findings deepened our understanding of lexical representation and processing. For example, the small-world and scale-free features identified in both L1 and L2 lexical-semantic networks point to the possibility that the differences between L1 and L2 mental lexicons are quantitative rather than qualitative. Both lexicons are structured favorably for network efficiency despite their differences in density and modularity. In addition, the discrepancy of central and peripheral words in L1 and L2 lexical representations implies a process gradually transiting from shared to separate representation. Central members in a category are more stable and shared by both languages while peripheral members are more flexible and differentiate L1 and L2.

Moreover, the high degree of correlation between network structure measures and lexical performance indicates the network approach to be effective in the investigation of the mental lexicon. The strength of this approach lies in its capability in quantifying the structure of the mental lexicon with well-defined parameters on different resolutions. The interpretation of lexical behavior from the structure of the lexical-semantic networks and the processes happening within the systems can hardly be realized with other linear methods.

Our study has the following limitations. First, we adopted a small sample size, and the participants we recruited were at approximately the same proficiency level. Research on a larger scale featuring heterogeneity of participants is expected in future research. Second, this study focuses on the lexical-semantic networks of L2 learners without separating lexical representation from semantic representation strictly for the consideration that the two systems are closely related to each other and tightly integrated in language use including semantic fluency experiment. As a result, the influence of lexical, cultural, and language experience factors could not be discerned clearly and could only be discussed generally. In order to distinguish the effects of different factors on the structure of the mental lexicon, different types of networks will have to be established based on corresponding experiments, such as word naming for lexical network and semantic priming for semantic network. These various types of networks deserve new endeavors in the future. Third, as the semantic fluency data were given in the written form, the different orthography features of English and Mandarin may have influenced the fluency responses to some extent, so a replication study which conducts the semantic fluency experiments in oral form in the future can be valuable in the verification of the conclusions drawn in the current research.

Data Availability

The semantic fluency data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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