

Application of Knowledge Chain in the Construction of Online Tourism Education Resources

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Abstract—Online tourism education occupies an important position in tourism education. Building a knowledge chain can clearly demonstrate the logical relationship between knowledge points of the entire discipline of tourism education, and enable the students to better grasp and understand the relationship between relevant knowledge points through online tourism education. This paper explores the application of knowledge chain in the construction of online tourism education resources (OTERs). Specifically, the associations between knowledge units in OTERs were modeled, the associations between knowledge units were computed, the structure of knowledge chain was optimized, and the OTER knowledge chain was analyzed in details. Through experiments, an example knowledge chain was constructed, and the students' satisfaction with the application of OTER knowledge chain was evaluated thoroughly.

Keywords—knowledge chain, tourism education, construction of online tourism education resources (OTERs)

1 Introduction

In recent years, tourism has been developing rapidly, and occupied an important position in the tertiary industry, making significant contributions to politics, economy, culture, and ecology [1-5]. The demand for high-quality tourism talents continues to grow, owing to the structural adjustment and upgrading of tourism, and the integration between culture and tourism [6-15]. Online tourism education plays a pivotal role in tourism education. With the surging amount of data on the Internet, online tourism education resources (OTERs) become increasingly diverse and colorful [16]. Building a knowledge chain can clearly demonstrate the logical relationship between knowledge points of the entire discipline, and enable the students to better grasp and understand the relationship between relevant knowledge points through online tourism education.

With the aim to develop a teaching model based on mobile technology and e-learning environment, Vuojärvi et al. [17] introduced the theoretical bases for the model design, and tried to build a work-based teaching model for mobile learning in tourism education. Perez-Valle and Sagasti [18] summarized the previous research

into the value of virtual reality (VR) in education and tourism, and clarified the potential of VR as a protective tool in tourism education and experience generation. Eriksson [19] surveyed the cognition of smartphones among vocational tourism students before and after using smartphones, and provided these highly mobile students with smartphones, in hope of reflecting their learning possibility, and improving their communication with tutors during the apprenticeship. Lee et al. [20] proposed a novel approach that can be used to build immersive VR applications specifically for training tourism English skills, and demonstrated the feasibility of the approach through a simple case with three scenes of English usage of leaders, which includes the planning 360-degree panoramic scenes, building virtual characters of dialogue partners, and designing related dialogue scenes and teaching tips.

Some scholars have discussed the management and application of OTER knowledge chain from many aspects. It is generally agreed that the management of OTER knowledge chain can improve learning resource recommendation of online education platforms. However, very few researchers have studied the specific direction of modeling knowledge chain associations. Therefore, this paper explores the application of knowledge chain in the construction of OTERs. Firstly, Section 2 models the associations between knowledge units in OTERs, computes the associations between knowledge units, and optimizes the structure of knowledge chain. Section 3 analyzes OTER knowledge chain, constructs an example knowledge chain, and evaluates the students' satisfaction with the application of OTER knowledge chain.

2 Construction of OTER knowledge chain

2.1 Knowledge unit association modeling

One knowledge unit in OTERs may depend on, fall on the same level, or be superior/inferior to the other knowledge unit. This association can be represented by a vector space model based on knowledge units. Table 1 illustrates the structure of knowledge chain. Let $P(L_i, L_j)$ be the association between two knowledge units L_i and L_j . Then, the associations E_p between knowledge units can be expressed as:

$$E_p = \begin{bmatrix} P(L_1, L_1) & \cdots & P(L_1, L_j) \\ \vdots & \ddots & \vdots \\ P(L_i, L_1) & \cdots & P(L_i, L_j) \end{bmatrix} \quad (1)$$

Table 1. Structure of knowledge chain

Attribute	Meaning
<i>Title</i>	Name of knowledge unit
<i>Root Node</i>	Root node of knowledge unit
<i>Common Node</i>	Public node of knowledge unit
<i>Description</i>	Description of knowledge unit
...	...

By the improved term frequency-inverse document frequency (IF-IDF) algorithm, this paper determines the weights of word vectors of knowledge units, and those of knowledge chain, in OTER text set. The attributes of OTERs are illustrated in Table 2. The improved algorithm can select OTER text features based on the thesaurus of synonyms. Let Q_l , WF_l , and IFF_l be the feature weight, number of occurrences in OTER text set E , and IDF of word vector l , respectively; SF_l , and SFF_l be the number of occurrences in OTER text set E , and IDF of synonyms of word vector l , respectively; M be the number of texts in E ; m_l be the number of texts containing word vector l . Then, we have:

$$Q_l = \frac{WF_l * IFF_l + SF_l * SFF_l}{\sqrt{\sum_{l=1}^M m_l * IFF_l * SFF_l}} \tag{2}$$

$$IFF_l = \log \frac{M}{m_l + 1} \tag{3}$$

Table 2. Attributes of OTERs

Attribute	Meaning
<i>Toe_Title</i>	Title of resource
<i>Toe_Name</i>	Name of resource
<i>Toe_Key</i>	Label of resource
<i>Toe_Description</i>	Description of resource
<i>Toe_Key Word</i>	Keywords of resource
.....

To facilitate the similarity computing between knowledge units and our knowledge chain, this paper vectorizes the OTERs corresponding to each knowledge unit and the knowledge chain. Let N_1 and N_2 be the knowledge unit information and knowledge chain information to be matched, respectively; L_{mi} and Q_{mi} be the word vector and feature weight of word vector i in N_1 , respectively; L_{nj} and Q_{nj} be the word vector and feature weight of word vector of N_2 , respectively. Then, we have:

$$N_1 = \left[\{ (L_{m1}, Q_{m1}), (L_{m2}, Q_{m2}), \dots, (L_{mi}, Q_{mi}) \} \right] \tag{4}$$

$$N_2 = \left[\{ (L_{n1}, Q_{n1}), (L_{n2}, Q_{n2}), \dots, (L_{nj}, Q_{nj}) \} \right] \tag{5}$$

After N_1 and N_2 are extracted, the similarity $Sim(N_1, N_2)$ between them can be solved by cosine similarity:

$$Sim(N_1, N_2) = \cos \frac{\sum_{j=1}^m (Q_{mj} * Q_{nj})}{\sqrt{\sum_{j=1}^m Q_{mj}^2 * \sum_{j=1}^m Q_{nj}^2}} \tag{6}$$

Based on the results of formula (6), the M knowledge units with relatively high association weights are selected as the OTER knowledge units for association generation. The similarity calculation flow is given in Figure 1.

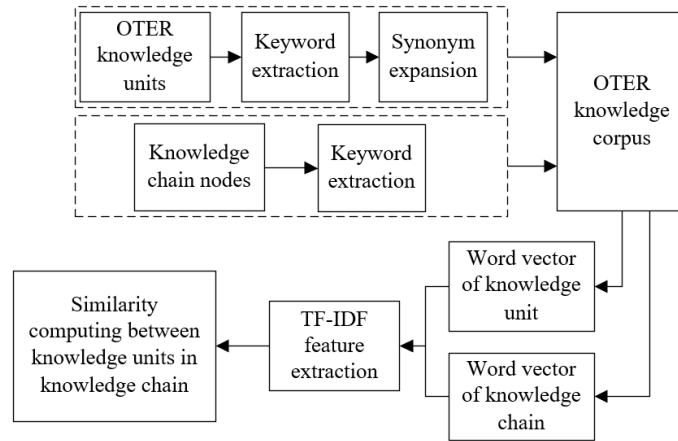


Fig. 1. Flow of similarity calculation

2.2 Calculation of associations between OTER knowledge units

The associations between OTER knowledge units are calculated based on path and depth. The similarity between two knowledge units depends on the commonality and individuality of these two units. Let $\log(COM(X, Y))$ be the volume of commonality information between X and Y ; $\log(IND(X, Y))$ be the denominator representing the information volume required by X and Y . From the angle of information theory, the similarity between any two knowledge units can be calculated by:

$$sim(X, Y) = \frac{\log(COM(X, Y))}{\log(IND(X, Y))} \quad (7)$$

The association between two knowledge units can be obtained by:

$$Q(X, Y) = \frac{COM(X, Y)}{COM(X, Y) + DIF(X, Y)} \quad (8)$$

Let $COM(X, Y)$ and $DIF(X, Y)$ be the commonality and difference between knowledge units X and Y in the knowledge chain, respectively; RD be the root node of the knowledge chain; CN be the common node between X and Y ; RX and RY be the distance from X and Y to the nearest common node, respectively; SJ be the depth from RD to the nearest common node; $R(A, B) = RX + RY$ be the shortest path between X and Y ; β be the depth adjustment parameter; $SJ(CN(X, Y))$ be the depth of the nearest common node CN of X and Y . In the OTER knowledge chain, the commonality and

difference between any two knowledge units X and Y can be respectively calculated by:

$$COM(X, Y) = \beta + SJ(CN(X, Y)) \quad (9)$$

$$DIF(X, Y) = \alpha + R(X, Y) \quad (10)$$

The association weight between any two knowledge units X and Y can be given by:

$$Q(X, Y) = \frac{\beta + SJ(CN(X, Y))}{\beta + SJ(CN(X, Y)) + \alpha + R(X, Y)} \quad (11)$$

Let N_{SN} be the direct secondary nodes of the nearest main public node of two knowledge units; BS be the branch spacing of two knowledge units in the nearest main public node. Then, the spacing between two knowledge units in the branch layer can be defined as a path adjustment parameter α :

$$\alpha = \frac{BS}{N_{SN}} \quad (12)$$

Let $Q(BS_X, BS_Y)$ be the association weight between knowledge units X and Y . Then, the association weight set E_q between knowledge units can be established as:

$$E_q = \begin{bmatrix} Q(BS_1, BS_1) & \cdots & Q(BS_1, BS_Y) \\ \vdots & \ddots & \vdots \\ Q(BS_X, BS_1) & \cdots & Q(BS_X, BS_Y) \end{bmatrix} \quad (13)$$

The next is to compute the associations between hierarchical knowledge chains. The formation flow of such a chain is given in Figure 2. Suppose knowledge chain LO_1 contains m knowledge units $\{BS_{11}, BS_{12}, \dots, BS_{1m}\}$, and knowledge chain LO_2 contains n knowledge units $\{BS_{21}, BS_{22}, \dots, BS_{2n}\}$. The associations between knowledge units of the two chains can be calculated by:

$$E_p = \begin{bmatrix} P(BS_{21}, BS_{11}) & \cdots & P(BS_{21}, BS_{1m}) \\ \vdots & \ddots & \vdots \\ P(BS_{2n}, BS_{11}) & \cdots & P(BS_{2n}, BS_{1m}) \end{bmatrix} \quad (14)$$

The proportionality coefficient, association weight relationship, and association weight between knowledge units of LO_1 and LO_2 can be respectively calculated by:

$$\psi = \begin{bmatrix} \psi(BS_{21}, BS_{11}) & \cdots & \psi(BS_{21}, BS_{1m}) \\ \vdots & \ddots & \vdots \\ \psi(BS_{2n}, BS_{11}) & \cdots & \psi(BS_{2n}, BS_{1m}) \end{bmatrix} \quad (15)$$

$$E_q = \begin{bmatrix} P(BS_{21}, BS_{11}) & \cdots & P(BS_{21}, BS_{1m}) \\ \vdots & \ddots & \vdots \\ P(BS_{2n}, BS_{11}) & \cdots & P(BS_{2n}, BS_{1m}) \end{bmatrix} \quad (16)$$

$$Q_{LO_1, LO_2} = \frac{\sum_{j=1}^n \sum_{i=1}^m \psi(BS_{2j}, BS_{1i}) * Q(BS_{2j}, BS_{1i})}{n * m} \quad (17)$$

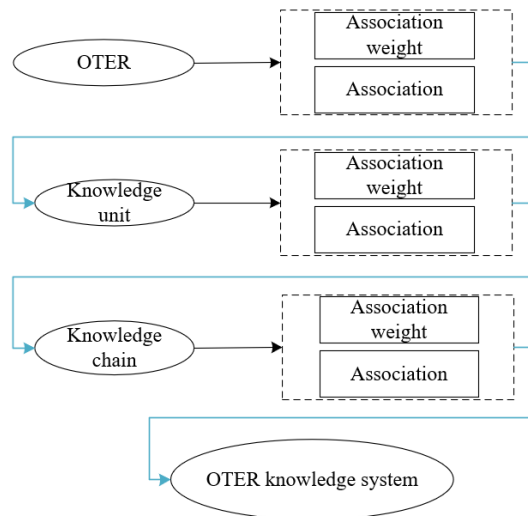


Fig. 2. Formation of hierarchical knowledge chain

Figure 3 provides the flow of computing the associations between knowledge units in OTER knowledge chains.

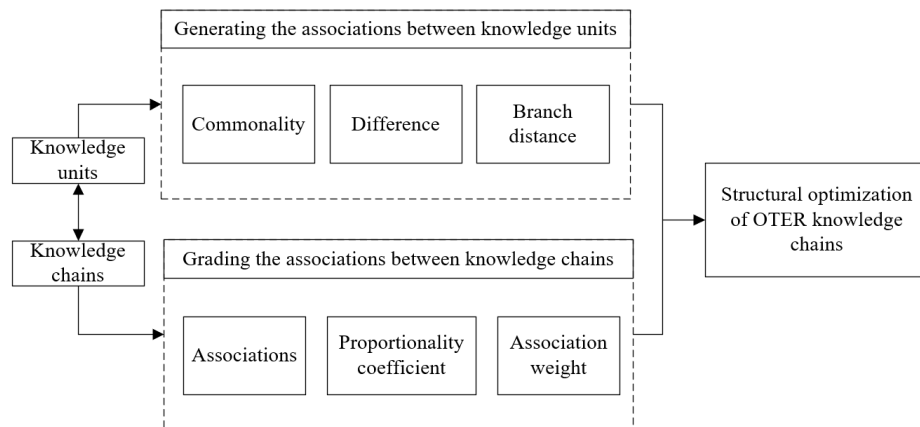


Fig. 3. Calculation flow of the associations between knowledge units

2.3 Structural optimization of OTER knowledge chain

In each OTER knowledge chain, every knowledge unit is associated to a number of OTERs, which have association weights between them. The association weight between OTERs P_1 and P_2 can be calculated by:

$$AW_{P_1, P_3} = \cos \frac{\overline{P_1} \times \overline{P_3}}{|P_1| |P_3|} \quad (18)$$

Similarly, the association weights between P_1 and P_4 , P_3 and P_2 , as well as P_4 and P_2 can be obtained as AW_{P_1, P_4} , AW_{P_2, P_3} , and AW_{P_2, P_4} , respectively. Let $i(i=0, 1, \dots, I)$ and $(j=0, 1, \dots, J)$ be the resources associated with knowledge chains LO_1 and LO_2 , respectively. Then, the association weight of the OTERs between LO_1 and LO_2 can be calculated by:

$$AW_{p1, p2} = \frac{\sum_j \sum_i AW_{i, j}}{I * J} \quad (19)$$

Let $Q(X, Y)$ be the association weight between knowledge units X and Y ; $Q_i(X, Y)$ be the associations between the OTERs correlated with knowledge units X and Y If the association structure between the knowledge points in two knowledge chains is correct, the positive correlation between $Q(X, Y)$ and $Q_i(X, Y)$ can be expressed as:

$$\frac{Q(x, y)}{Q_i(x, y)} \approx \Omega \quad (20)$$

Based on the positive correlation Ω of association distribution, $Q(X, Y)$ and $Q_i(X, Y)$ can be analyzed by:

$$\beta = \left| \frac{Q_i(n, m)}{Q_p(n, m)} - \Psi \right| \quad (21)$$

If threshold λ is greater than β , then the associated knowledge units X and Y are reasonable; if threshold λ is smaller than β , then at least one of the associated knowledge units X and Y is reasonable. Figure 4 shows the structural optimization of knowledge chain.

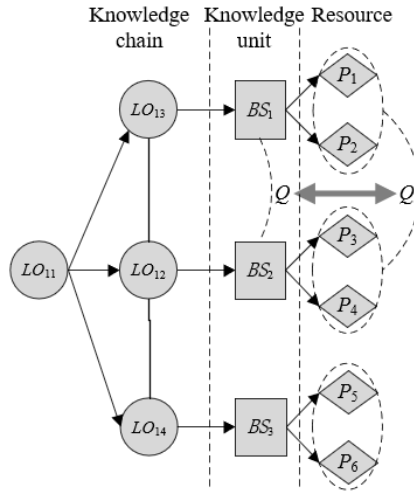


Fig. 4. Structural optimization of knowledge chain

3 Analysis of OTER knowledge chain

In each OTER knowledge chain, the learners realize knowledge activities by learning OTERs. This paper visualizes the dependence between learners, knowledge activities, and learning resources. Let L_ACH be a knowledge activity; CAR be the combination of learner-activity-resource; γ_x and γ be the dependences of learners' knowledge activities on knowledge unit X , and on knowledge unit Y , respectively; $L_ACH(l_x, l_y)$ be the degree of influence of the variation in knowledge activity l_x in L_ACH . Then, the dependence $I_ACHI(X, Y)$ between knowledge units X and Y can be calculated based on L_ACH and CAR :

$$I_ACH_1(X, Y) = CAR(X, \gamma_x, 0) \times CAR(Y, \gamma_y, 0) \times L_ACH(l_x, l_y) \quad (22)$$

From OTER P_ACH and learner-activity-resource combination CAR , it is possible to derive the dependence $I_ACH_2(X, Y)$ between knowledge units X and Y :

$$I_ACH_2(X, Y) = CAR(X, 0, \alpha_x) \times CAR(Y, 0, \alpha_y) \times P_ACH(p_x, p_y) \quad (23)$$

Let α_x and α_y be the dependences of knowledge units X and Y on OTERs, respectively; $P_ACH(p_x, p_y)$ be the degree of influence of resource p_y over resource p_x in P_ACH .

From knowledge activity L_ACH , OTER P_ACH , and learner-activity-resource combination CAR , the dependence between knowledge units X and Y can be calculated by:

$$I_ACH(X, Y) = I_ACH_1(X, Y) + I_ACH_2(X, Y) \quad (24)$$

Then, the knowledge units of each OTER knowledge chain are classified by a clustering algorithm. Let θ_1 and θ_2 be two weights satisfying $\theta_1 + \theta_2 = 1$; $I_ACH(X, Y)$ be the dependence between knowledge units X and Y ; l be the class of the selected OTER knowledge unit; v_l and μ_l be the first and last knowledge units in class l , respectively; M_{KE} be the total number of knowledge units; $\sum^{v_l}_{X=v_l} I_ACH(X, v_l)$ and $\sum^{\mu_l}_{Y=v_l} I_ACH(v_l, Y)$ be the sum of nonzero influencing factors in the row and column of the newly added knowledge unit v_l in a class, respectively; $\sum^{M_{KE}}_{X=1} I_ACH(X, v_l)$ and $\sum^{M_{KE}}_{j=1} I_ACH(v_l, Y)$ be the total influence of the selected OTER knowledge unit over all the other knowledge units in the knowledge chain, and the total influence of all the other knowledge units in the knowledge chain over the selected OTER knowledge unit, respectively. Then, the additional ratio of intra-class dependence to between-class dependence can be calculated by:

$$\max QUP(cluster_i) = \frac{\theta_1 \cdot \sum_{i=ml}^{n_i} I_ACH(T_i, n_i) + \theta_2 \cdot \sum_{j=ml}^{n_i} I_ACH(n_i, T_j)}{\sum_{i=1}^M I_ACH(T_i, n_i) + \sum_{j=1}^M I_ACH(n_i, T_j)} \quad (25)$$

4 Experiments and results analysis

Figure 5 exemplifies the construction of knowledge system-knowledge chain for online tourism education. The example mainly involves OTERs like hotel management, tourism management, cooking skills and nutrition, western food skills, exhibition planning and management, catering management, leisure service and management, wine marketing and management, as well as Chinese and western pastry skills; travel English, travel Japanese, applied Korean, as well as applied Spanish; financial management, accounting, e-commerce, media marketing, as well as flight attendance. The effectiveness and scientific nature of the knowledge chain were empirically analyzed based on the core courses of information analysis in library and information discipline. The experimental results were demonstrated and analyzed with examples.

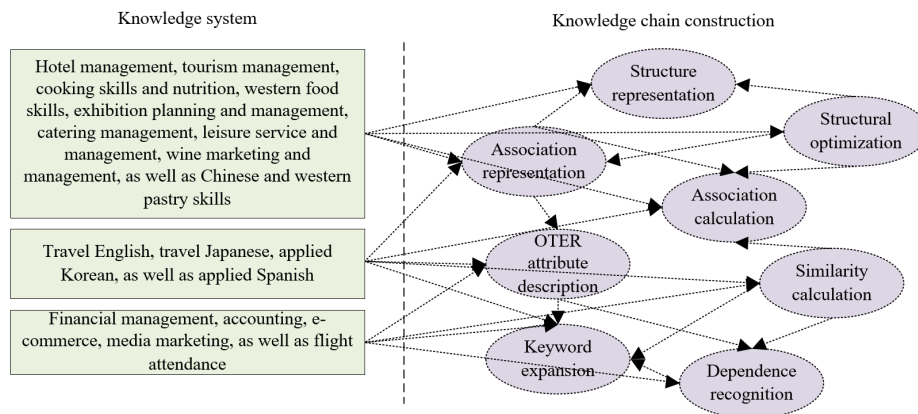


Fig. 5. Construction of knowledge system-knowledge chain for online tourism education

Figures 6 and 7 exemplify the construction of knowledge chains for core online courses and teaching units, respectively. It can be observed that the same knowledge unit may appear in multiple courses or teaching units. The OTERs focus on different issues, because different courses and teaching units vary in emphasis. For example, Introduction to Tourism talks more about tourism dealers, and distribution strategies, while Tourism Management focuses on operational management.

According to the sequence of courses, the relevant OTERs need to be adjusted according to the contents of the earlier courses, making the education more in-depth. If a student notices any interesting knowledge unit or educational resource, he/she could quickly find the associated courses and teaching units via the knowledge chain. Figure 8 provides a complete knowledge chain for Tourism Psychology.

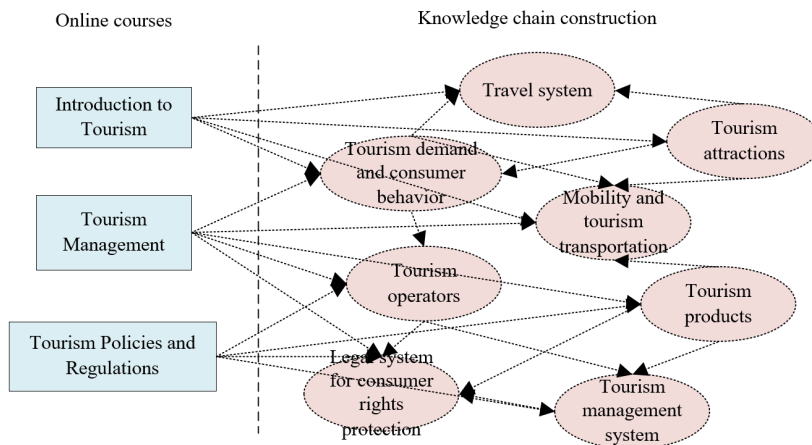


Fig. 6. Construction of core online courses-knowledge chain

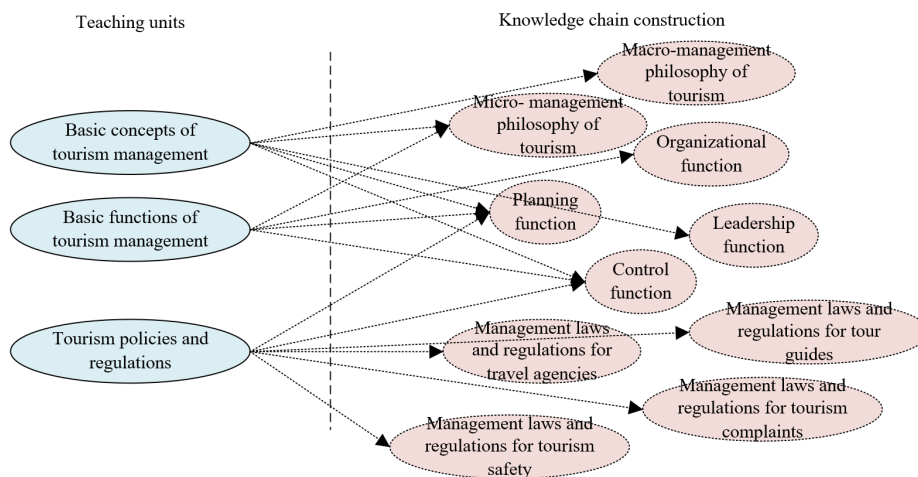


Fig. 7. Construction of teaching units-knowledge chain

The Independent Samples T-Test was employed to verify whether there are significant differences in the knowledge chains of different courses and teaching units. The test results are displayed visually as a P-P plot in Figure 9. It can be seen that the sample points were all close to the diagonal of the first quadrant, and approximate the normal distribution. This means the application of knowledge chain to online tourism education greatly facilitates the construction of the knowledge logic system for relevant courses and teaching units.



Fig. 8. Knowledge chain of tourism psychology

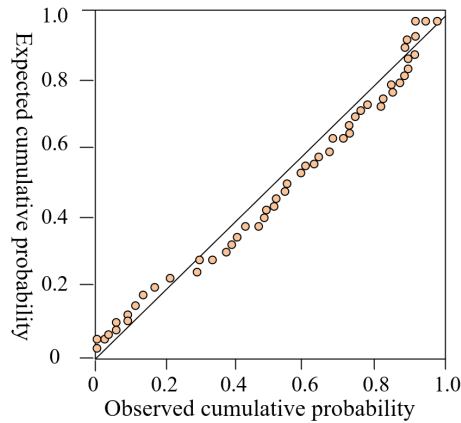


Fig. 9. Probability-probability (P-P) plot of knowledge chain verification

Table 3 provides the statistics on student satisfaction with the proposed knowledge chain of online tourism education. The overall satisfaction was measured by three indices: the satisfaction with knowledge system, that with the implementation of courses or teaching units, and that with resource recommendation. The total mean stood at 3.62, suggesting that the students are satisfied with the learning or query of learning resources, using the proposed knowledge chain of online tourism education. Except for the overall satisfaction with resource recommendation, Groups I and II differed in the mean satisfaction with knowledge system and that with the implementation of courses or teaching units. The overall satisfaction of Group I was slightly higher than that of Group II. In addition, although the overall satisfactions of the two groups with resource recommendation were not very different, the two groups had a certain difference in the dispersion of satisfaction scores on resource recommendation. The slightly lower dispersion of Group I indicates that the students in that group have less consistent views of resource recommendation.

Table 3. Statistics on student satisfaction

	Overall satisfaction with knowledge system			Overall satisfaction with the implementation of courses or teaching units			Overall satisfaction with resource recommendation			Total mean
	Group I	Group II	Total	Group I	Group II	Total	Group I	Group II	Total	
No. of people	21	18	36	22	17	38	23	20	41	3.57
Mean	3.85	3.62	3.74	3.82	3.69	3.48	3.81	3.29	3.48	
Dispersion	0.86	1.12	0.95	0.785	0.72	0.763	0.75	0.82	0.74	

5 Conclusions

This paper explores the application of knowledge chain in OTERs. After modeling the associations between knowledge units in OTERs, the authors computed these associations, optimized the structure of knowledge chain, and analyzed OTER

knowledge chain. The relevant experimental results were demonstrated and analyzed with examples. Through experiments, the following issues of online tourism education were exemplified: the construction of knowledge system-knowledge chain, the construction of core online courses-knowledge chain, the construction of teaching units-knowledge chain, and the construction of the knowledge chain of Tourism Psychology. The Independent Samples T-Test was employed to verify whether there are significant differences in the knowledge chains of different courses and teaching units. The test results are displayed visually as a P-P plot, which demonstrates that the application of knowledge chain to online tourism education greatly facilitates the construction of the knowledge logic system for relevant courses and teaching units. Finally, the students' satisfaction with the application of OTER knowledge chain was obtained.

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