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RESEARCH ARTICLE

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A personal social knowledge network (PSKN) facilitates learners' wayfinding and its differences in behavior patterns between high and low performers in connectivist learning

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Abstract

Wayfinding, which is a part of learning in connectivist learning, involves consolidating a wide variety of resources and information and building connections among them. However, learners often encounter difficulties in wayfinding, and are lost without technological support in connectivist learning. This study examined the wayfinding processes occurring within a network of learners in a personal social knowledge network (PSKN), explored differences in behavior patterns between high and low performers in PSKN. The results reveal the diversity and complexity of wayfinding in a PSKN, including finding and connecting nodes, forming cognitive maps, finding and filtering information, and creating new nodes. Moreover, the characteristics of wayfinding in the PSKN differed across participants, and high- and low-performing participants demonstrated different and unique wayfinding behavioral patterns, which provided a basis for comprehensive analyses of wayfinding. These findings can be used to provide instructional support and network navigation in connectivist learning for learners at various performance levels. The proposed PSKN shows promise in facilitate wayfinding including finding nodes and connecting nodes, as well as relations between knowledge nodes and the course base demonstrated by PSKN, providing great convenience for learners to form cognitive maps based on the node sequence. Compared with current studies, this research focuses on diversified interaction data and resource behavior rather than teaching videos and quizzes or exercises as the main resources and considering that course and technological factors influence the ways in which learners access resources in connectivist learning.

Keywords: Wayfinding, Behavioral patterns, Distributed learning environments, Personal social knowledge network, Connectivist learning

Introduction

Connectivist learning has attracted increasing attention (Corbett & Spinello, 2020) and has shown great potential for supporting online learning (Dziubaniuk et al., 2023). Connectivist learning is typically structured as weekly activities with videos or filmed lectures, supported by supplementary readings and assignments (Kaplan & Haenlein, 2016). Rather than transmitting knowledge, teachers in connectivist learning focus on facilitating learners' interactions with learning materials or other learners. They, offer course materials that can be used, repurposed, and extended as necessary (Kaplan & Haenlein, 2016). Learners can access courses and resources based on personal goals and common interests (Fidalgo-Blanco et al., 2016; McAuley et al., 2010) and construct their learning processes through connective interactions (Downes, 2020; Siemens, 2012) such as sharing, collecting, co-editing, and creating knowledge with peers or friends, structure, and manage their own learning at their own pace (Sunar et al., 2020).

From a pedagogical perspective, connectivist learning based on the Connectivism learning theory, and argued that learning is less dependent on teachers and relies more on establishing connections and nodes between learners and content (Mackness et al., 2013). It argues that learning is achieved through node connections and network formation and emphasizes developing and maintaining human and knowledge nodes (Siemens, 2005). It also connects learners to quality resources and learning partners (Mackness et al., 2013; Saadatmand & Kumpulainen, 2014). Therefore, finding nodes and building connections are key to connectivist learning (Siemens, 2007), wherein wayfinding is fundamental (Li et al., 2016; Wang et al., 2014).

Wayfinding refers to the ability to navigate a network and find resources in complex online environments (Li et al., 2016; Siemens, 2012; Wang et al., 2017). Learners "learn how to navigate the networking terrain by identifying the reliable resource nodes (people or information)" (Kizito, 2016, p. 23). However, learners often encounter difficulties in wayfinding and are lost in connectivist spaces that lack connections (Dron & Anderson, 2009; Li et al., 2022b). This is especially true for learners without direction and technological support (Dziubaniuk et al., 2023; Kop, 2011; Mackness et al., 2013); thus, providing technology support is necessary. Considering that technological factors influence the ways in which learners access resources in connectivist learning (Duan et al., 2019; Dziubaniuk et al., 2023; Yang et al., 2017), how learners' wayfinding occurs and accessing materials in technology enhanced learning environment needs deeper understanding (Corbett & Spinello, 2020; Dziubaniuk et al., 2023).

This study proposes and evaluates a new approach developed based on technological support to support the wayfinding process, a personal social knowledge network (PSKN) environment. The PSKN emphasized the dynamic visualization of individual and group connective interactions and oriented the navigation, formation, and transfer of knowledge and connections between learners. This PSKN offers the new possibility of wayfinding in cconnectivist learning. Considering PSKN is dynamically generated and expanded, its complexity places high demands on learners' wayfinding. At the same time, resources are distributed across the network, and learners follow their own learning paths, create networks, evaluate information, and make principal decisions in cconnectivist learning (Kop, 2011).

Consequently, an in-depth empirical exploration of wayfinding behaviors in PSKN, particularly learners' learning network navigation, orientation, and connection formation, is necessary. Our previous studies have provided empirical evidence of its effectiveness as an assessment and prediction tool for learner interaction and performance (Duan et al., 2019) and compared this environment with knowledge networks (KN) and social networks (SN), confirming a positive effect on knowledge construction and learning performance (Duan et al., 2023). However, there is a lack of in-depth empirical exploration of wayfinding behaviors in a PSKN, especially regarding how and why learners navigate learning networks in the way they do and how they find and form connections. To evaluate the efficacy of PSKN-based wayfinding and its features, the present study investigated learners' wayfinding characteristics and how wayfinding strategies differ across high and low performers. Our study provides an in-depth understanding of the navigation process and the process of building connections in the connectivist learning context facilitated by PSKN. The following research questions (RQs) guided this study.

1. What types of wayfinding behaviors do learners demonstrate?
2. What types of behavioral patterns do learners demonstrate in wayfinding?
3. What are the differences in wayfinding behavioral patterns between high- and low-performing learners?

Literature review

Wayfinding and wayfinding difficulties in connectivist learning

Wayfinding involves spatial orientation using environmental cues (Allen, 1997). It describes how individuals orient themselves in new settings for information seeking and learning (Siemens, 2012), including developing an understanding of space, search, and orienting cues (Darken & Sibert, 1996). In connectivism, information is a node, knowledge is a connection, and wayfinding involves social and environmental cues for navigating information, wayfinding services guide connection formation and network navigation (Siemens, 2012) by identifying the reliable nodes (Kizito, 2016; Li et al., 2016; Siemens, 2012; Wang et al., 2017). Wherein understanding space and searching refer to identifying the reliable resource nodes (Kizito, 2016) by evaluating relationships between them (Kop, 2011; Li et al., 2016; Mackness et al., 2010); orienting cues indicates not getting lost on the route linked to a task (Rangel & Mont'Alvão, 2020).

In related work, AlDahdouh (2018) proposed a connection-forming model and argued that the process includes three stages: planning, cognitive processing, and evaluation. First, learners plan paths and eliminate and sort nodes based on their perception, forming a cognitive map. Second, they interact with and connect the selected nodes. Third, learners monitor the value of the interactions to evaluate and filter information. Two basic methods exist for learners to orient themselves: direct and indirect wayfinding (Wang et al., 2017). Direct wayfinding refers to individual learners finding paths and orienting themselves. In contrast, indirect wayfinding refers to helping others with wayfinding, such as creating new network nodes to which others can connect (Duan et al., 2019).

Therefore, finding nodes (Kizito, 2016), forming cognitive maps (AlDahdouh, 2018), connecting nodes, and finding and filtering information (Kop, 2011; Li et al., 2016; Mackness et al., 2010) are categorized as direct wayfinding, whereas creating nodes is an indirect wayfinding. The definitions and measurement sources of wayfinding derived from the existing literature are presented in Table 1.

As a basis of connectivist learning, wayfinding has been the focus of access paths of diverse resources. It is a fundamental way for learners to expand their social networks

Table 1 Categories of wayfinding

Category		Definition	Source(s)
Direct wayfinding	Finding nodes	Finding nodes refers to searching, evaluating, and orienting nodes, aiming to identify the right resource nodes	Kizito (2016); Li et al. (2016); Kop (2011)
	Forming a cognitive map	Forming cognitive maps refers to the learning process in which learners actively establish relationships between nodes or concepts during network navigation	AlDahdouh (2018); Wan &Yu (2020); Chen et al., (2017); Eden (2004);
	Connecting nodes	Connecting nodes refers to interactions with the selected nodes and making connections with and between nodes	Li et al. (2016), AlDahdouh, 2018; Wang et al. (2017)
	Evaluating and filtering information	Evaluating and filtering information emphasizes monitoring the value of the interaction with the nodes by interacting with the selected nodes	Siemens (2012), Li et al. (2016); Zhou (2018); AlDahdouh (2018)
Indirect wayfinding	Create nodes	Creating nodes refers to when learners act as teachers by creating new knowledge nodes for others to connect with	Griesbaum (2014); Yu et al. (2019); Duan et al., (2019)

and join the learning community. However, studies also found that most learners are exposed to wayfinding difficulties, such as information overload and technical difficulties (Kammerer et al., 2013; Kiili et al., 2020; Kop, 2011; Li et al., 2016, 2022b). Li et al. (2016) found that learners in connectivist learning could not discover and filter information, establish effective cognitive maps, and find and connect important nodes. Therefore, wayfinding support is necessary.

PSKN supporting wayfinding for connectivist learning

A connective Massive Open Online Course (cMOOC) platform named LCS[1] was chosen as a case study to develop PSKN and facilitate wayfinding in connectivist learning. The PSKN integrates various types of social software and resources into one learning network (Duan et al., 2019, 2023), such as QQ, WeChat, Wiki pages, discussion forums, or groups (Mackness et al., 2013; Saadatmand & Kumpulainen, 2014), which facilitates learners' identification of resources and network navigation. Theoretically, the PSKN provides wayfinding references for learners to find resources and offers options to alleviate difficulties by integrating knowledge and social networks (KNs/SNs) into a structured and networked environment (Yu et al., 2015, 2019). KNs provide structured concepts as knowledge nodes and connections that learners navigate. SNs organize learners' personal profiles and social connections to encourage interaction and support

[1] http://lcell.bnu.edu.cn.

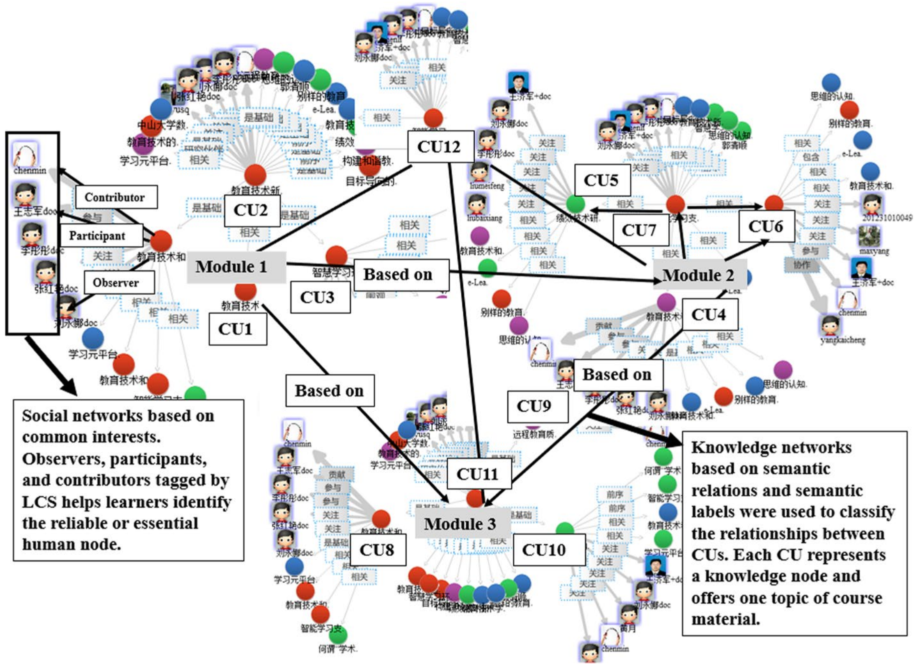

Fig. 1 Overview the PSKN from the perspective of course series from Duan et al. (2019). CU = knowledge node

learning. By integrating KN and SN features, learners in the PSKN orient knowledge and human nodes to engage in connectivist learning (see Fig. 1).

In the PSKN, each CU represents a knowledge node and offers one topic of course material, including content, resources, and activities. Conceptually, CU is a topic of learning content, but technically, it is a collaborative page such as the Wiki page. Relevant learning content, resources, and activities are added to the page/CU. learners in LCS can comment, modify, or create knowledge or CU and participate in activities based on a single collaborative page; it is also possible to connect and interact with peers through social media such as QQ and WeChat (see *the Technology Environment and Pedagogy section*). Thus, by making connections, learners can access various courses and resources based on their personal goals and common interests (Mcauley et al., 2010).

Furthermore, the PSKN evolves and displays learners' connectivity process dynamics. Learners navigate the PSKN and contribute to or create nodes; their contributions and social links are incorporated into the PSKN. Thus, the PSKN dynamically demonstrates connection formation between humans and knowledge nodes in one social space and gradually expands as learning proceeds (Duan et al., 2019; Yu et al., 2019). In PSKN, nodes have prerequisite, inclusion, causal, and progressive relationships (Pian et al., 2019). Relationships between knowledge nodes are provided by the lecturer before learning or by the system based on semantic labels. Semantic labels were used to classify the relationship between knowledge nodes or CU, and this classification is automatic in the LCS. Real-time use of the PSKN labels indicates backward-and-forward and affiliate relationships between knowledge nodes based on semantic ontology technology (Yu et al., 2015). This facilitates learning by determining how related CU or knowledge nodes should be connected and make connections (Vas et al., 2018). If knowledge node A is

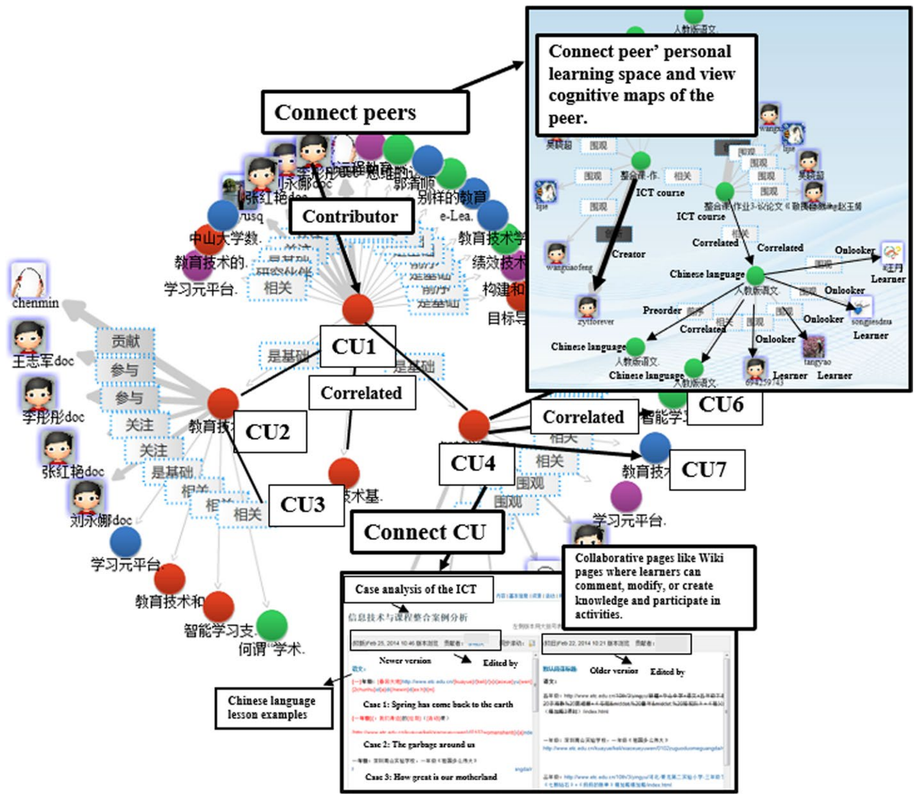

Fig. 2 Wayfinding in a PSKN connectivist learning environment

the basis of knowledge node B, learners must first build connections with knowledge node A. Learners and teachers can observe the PSKN throughout the learning process and adjust their wayfinding strategies to ensure the desired nodes are met. Each learner's PSKN varies based on their connections. Moreover, the knowledge nodes color indicates wayfinding progress (Duan et al., 2019; Pian et al., 2019).

The features of wayfinding in PSKN are shown in Fig. 2.

Finding nodes

During the wayfinding phase, learners learn to find reliable resource nodes (Kizito, 2016) and important nodes (Li et al., 2016), which are the basic behaviors that contribute to spatial orientation and place recognition (Golledge, 1992). The PSKN contributes to finding reliable and important nodes in the connectivist learning context, which also supports orienting nodes in both human and knowledge nodes (Duan et al., 2019; Yu et al., 2019). For example, the PSKN can provide a knowledge node contribution score for learners to define the importance of human nodes using tags, such as observers, participants, and contributors, with different tags marking the interaction relationships between learners and nodes based on the contribution of the node. The LCS has five types of contribution behavior: knowledge acceptance, knowledge sharing, refinement and reflection, knowledge collaboration, and knowledge innovation. When learners participate in various activities, the LCS automatically calculates the contribution values and compares them to the values of each label type. If the correlation value is higher than the specified value, relevant labels are obtained. For each individual, the degree of interaction was calculated using the following weighted rate (Duan et al., 2019):

$$\text{Connectivist interaction degree} = \text{Con (A)} = \sum_{i=1}^{10} ti * wi$$

where A represents each CU, Con (A) represents the contribution value of the learner to each CU, ti represents the frequency of the learner's content contribution, and wi represents the different weighting rates of each CU. The LCS records interactions and calculates them automatically. Thus, learners can distinguish the "reliable" or "important" nodes pertinent to their learning purposes.

Forming a cognitive map. A cognitive map is an external representation of cognitive structures and processes (Jonassen, 2005), in which learners categorize knowledge into several dimensions based on the subject or relationship (McDonald et al., 2004; Pian et al., 2019). Although cognitive map shares graphical similarity with a mind map or concept map, the cognitive map serving as a "advance organizer" to assist individual actively establishes connections based on the semantic relationships between topics, and contribute to meaningful learning (Ausubel, 1960). The concept map or mind map refers to the deep understanding of relevant concepts by creators or the divergent expression of individual viewpoints, which is created by individuals and externalizes their understanding or viewpoints. Furthermore, cognitive map presented in the PSKN interfaces were dynamic, structure initiated with only primary topics, and developed throughout the course by system, the concept map or mind map is used to evaluate one's understanding, or viewpoint, were summative in nature, created by individuals.

In PSKN, the cognitive map is based on knowledge nodes, which is a topic set based on cMOOC features; therefore, a course will consist of multiple knowledge nodes, and the semantic relationships between knowledge nodes indicate the correlation between node topics, forming a cognitive map for learners to navigate in the network. In PSKN, forming cognitive maps refers to the learning process in which learners actively establish relationships between subject knowledge, such as identifying key concepts and their relationships and classifying knowledge nodes according to the topic in the connectivist context (Li et al., 2016; Wan & Yu, 2020). This is believed to promote meaningful learning and cultivate learning efficacy in complex situations (Chen et al., 2017; Jonassen, 2005). In the PSKN, once learners have identified important knowledge nodes, they can form a cognitive map based on the semantic relationships of these knowledge nodes.

Consequently, they can identify the central knowledge nodes to be learned in the future and the sequence among them based on their own needs (Duan et al., 2019). The PSKN provides relationships between knowledge nodes (Duan et al., 2023). These relationships may not be appropriate for all learners; therefore, each sequence provides only a wayfinding reference, so, learners do not need to follow them strictly. Moreover, learners can plan their own learning path at the beginning with all the knowledge nodes in the PSKN; that is, they can reconstruct the relationships between knowledge nodes to form a cognitive map based on the node sequence (Zheng, et al., 2023). For example, when facing several closely related nodes A, B, and C in a certain course in a PSKN, learners can learn nodes A, B, and C in order, or they can learn nodes B, D, F, etc. according to their own needs, and reconstruct the relationship between nodes B, D, and F to form their own cognitive map. Among them, PSKN serve as "advance organizers" to help individuals actively establish connections and build knowledge based on their own experiences (Kandel, 2006; Kandel et al. 2012).

Connecting nodes

In connectivism, knowledge exists as a network, and learning is a process of network formation; thus, connecting important and reliable nodes is crucial in realizing that “the pipe is more important than the content within the pipe (simply because content changes rapidly)” (Siemens, 2006, p. 32). “The more a student is capable of connecting to specialized nodes, the better his/her position will be in the learning networks” (AlDahdouh, 2018, p. 3). Therefore, establishing connections between important nodes is a key step in the wayfinding process. In a PSKN, a node can be a content unit (CU) related to a certain topic (this study describes it as a knowledge node) or a course knowledge base that aggregates many CUs (many knowledge nodes on the same subject). A node can also be a human (peers or experts) correlated with the knowledge node or course knowledge base; therefore, learners can connect with related nodes by learning a single knowledge node or taking a course. Furthermore, learners can join learning communities to connect with their peers or experts by accessing learner profiles and sending direct messages based on their shared interests (Duan et al., 2019). Once a learner is connected to a knowledge node or human node, this new connection is demonstrated in the PSKN, and the learner becomes a new node in the PSKN to which others can connect (Duan et al., 2023).

Evaluating and filtering information

In connectivism, evaluating and filtering information is a basic activity for orienting reliable nodes (Goldie, 2016; Siemens, 2012). Through information evaluation and filtering, learners can search for and locate the required information from complicated information resources (Zhou, 2018). In the PSKN, learners can find and filter information by accessing the titles, tags, categories, and summaries of the knowledge or course nodes, or they can find and filter information by the score of each CU; the evaluation automatically by the LCS system is based on trust evaluation model from perspectives of resource trustworthiness and user trustworthiness (Yang et al., 2014). Thus, the quality and reliability of CU are becoming relatively reliable. In addition, learners can evaluate and filter information according to their understanding by commenting (on the content, structure, or specifications) or inviting collaborators (the creator invites other users to become collaborators of the knowledge node/shared course knowledge base to edit titles, tags, or categories). For example, learners can edit the basic information of a knowledge node, such as correcting its label, so that other learners can complete the tasks of searching for and filtering information more quickly for efficient wayfinding (Krasny et al., 2018).

Creating nodes

In the connectivist learning context, learners can provide connections to assist others' wayfinding by creating nodes (Griesbaum, 2014; Yu et al., 2019), facilitating learners to act as teachers (Duan et al., 2019; Yu et al., 2019). When a learner creates a node, others can follow up and connect. In the PSKN, how learners create nodes include creating learning communities, knowledge nodes, or knowledge bases (containing many knowledge nodes related to the course). The created knowledge node or base is not an alternative or substitute for existing courses; it is an additional open knowledge base directed at self-motivated learners. Other learners can add relevant content to it and generate knowledge (Griesbaum, 2014). Once a learner has created a node, other nodes related to that node are displayed in the PSKN (Duan et al., 2019, 2023). Therefore, learners can navigate more quickly and easily. As such, creating nodes supports indirect wayfinding for individuals and others.

Material and methods

To answer our research questions, we examined wayfinding behaviors and patterns to understand the differences across various learning efficacies. Lag sequence analysis (LSA) was used. LSA detects the statistical significance of a certain behavior followed by another (Bakeman & Gottman, 1997) and has been widely used to explore how interactive behaviors and behavioral patterns contribute to learning success (Hou & Wu, 2011; Yang et al., 2018) and identify differences in behavioral sequences of learners with varying learning performances (Hou & Wu, 2011; Li et al., 2021; Yang et al., 2018). Moreover, LSA has been applied to analyze resource access paths of learners in Massive Open Online Courses (MOOCs), extract sequences of behaviors or resource objects, and reveal paths and time characteristics. Li et al., (2022a, 2023) used LSA to examine behavior sequence patterns related to teaching videos, quizzes, and exercises. In the connectivist learning context, resource access paths are complex, and resources are diverse; thus, LSA can provide a comprehensive understanding of wayfinding.

Background and participants

We collected data from the learners of a cMOOC. The course has attracted increasing attention; many teachers have turned to online education to improve themselves. Although connectivist learning is generally limited to 6–8 weeks and initially intended for large groups of learners, previous research has shown that developing task-oriented, small-scale courses can better serve teaching and learning (Costello et al., 2018; Mackness et al., 2013). Therefore, the selected course is a small-scale, task-based connectivist course, called Information and Communications Technology (ICT). This ICT course has been open to public since it was developed, and there has been an annual round of online courses aimed at helping teachers build a comprehensive understanding of IT integration in classrooms.

The course has three modules and a total of seven topics. As the learning progresses, the course topics will be continuously updated and learning resources will be supplemented; teaching quizzes, and video courseware will be provided to encourage students to deepen their understanding of the course content through topic discussions and artifact creation. After the course ends, all learning resources, activities, and content for that period will still be open to learners. Each course round lasted 12 weeks based on the learning characteristics and course requirements (Xu & Du, 2021). The course was developed by a team of experts from a university in China, combining ICT experts who have teaching experience and other experts with practical skills. The expert team developed the course based on its objectives. The researcher participated in the relevant activities as a course-learning assistant and evaluator.

Since opening up, it has continuously attracted a large number of learners, a total of 3119 participants, and we have chosen the period with the most active users and the most concentrated number of learners for analysis, which is also one of the commonly used methods for cMOOC learner data extraction (Duan et al., 2019, 2023; Wang et al., 2018). The initial sample comprised 298 participants; after excluding repeat enrollees, unconnected floaters, and connected lurkers (Wang et al., 2018), the final sample comprised 285 in-service teachers (31 men and 254 women; average age: 27.5 years, the youngest is 22 years old, and the oldest is 35 years old) with diverse backgrounds in academic subjects and ICT skills. Their teaching subjects included Chinese languages, design and technology, computer applications, English, mathematics, science, and the arts. Their teaching experience ranged from zero to five years. They are participating in this form of learning for the first time and do not have the corresponding cMOOC learning experience. Therefore, in the week before the start of the course, they first received operational training on the platform and course tasks to ensure that they did not have technical difficulties and obstacles in the learning process. They were specially trained in using PSKN navigation to learn topics and resources, helping them to quickly and efficiently lock in tasks and engage in learning. Also, the participants had no difficulty using computers. At the beginning of the study, the participants did not know each other.

It should be pointed out that the research data was provided by one cMOOC platform of a particular university only used for academic research. To avoid any negative impact of data information on learners and teachers, the research blurred specific course round and teacher information. Additionally, to ensure the quality of the study, the informed consent form was waived for the participants, and the scientific office approved the study at our university.

Technology environment and pedagogy

The LCS developed by Beijing Normal University facilitated learning by providing learners with dynamic learning content, activities, resources as well as a PSKN (Yu et al., 2015, 2019) to facilitate wayfinding and access materials. Figure 3 illustrates an example of a PSKN that facilitates wayfinding in the connectivist learning context.

The connectivist course was designed from the scenario, environment, activity and role level perspective according to the cORPS (cMOOC-ORiented Pedagogical Scenario) model (Bakki et al., 2017, 2020).

The design of "scenarios" was based on three levels: course module, content unit (CU), and activity. The ICT course had three modules with seven CUs (one CU in Module 1, three CUs in Module 2, and three CUs in Module 3). CUs were topic-oriented and designed by the teacher at the beginning of the course. CUs integrated learning activities and evaluation, which could be oriented by name, topic, and relationships with other CUs. The course has set up a series of learning activities and

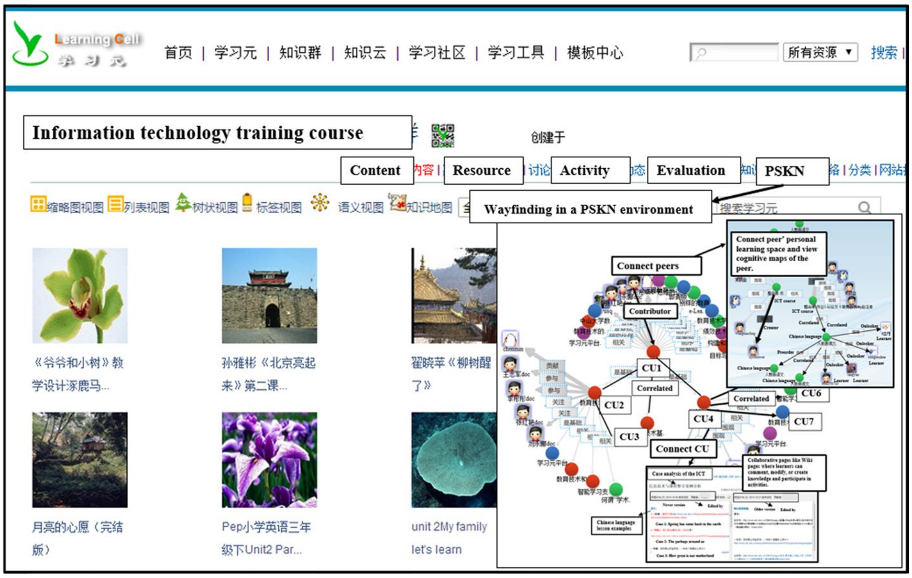

Fig. 3 PSKN facilitates wayfinding in the connectivist learning context

tasks, and the degree of participation in course learning is evaluated by the number of learning CUs, participation in each learning activity related to CU, and the completion status of tasks. The system actively displays the participation status of each learner; as learning progresses, PSKN will also display active users who contribute more to the current topic knowledge.

The "activity" level included aggregation, remixing, repurposing, and feed forwarding (Bakki et al., 2020; Kop, 2011; Kop et al., 2011). Aggregation activities aimed to facilitate learners in finding and orienting CUs to meet their needs (Downes, 2020). Based on interpretingthe information collected during the aggregation phase, and network navigating related CUs, remixing activities aimed to facilitate learners connecting all CUs and information during the aggregation phase. Learners were encouraged to express their understanding of a topic through comments, annotations, or WeChat. They could also use tools provided by the LCS to exchange ideas with others. Repurposing activities aimed to encourage learners and support individuals or groups' production process (Bakki et al., 2020). Feedforward activities aimed to encourage learners to share their work online and distribute the knowledge nodes and new resources created by participants (Siemens, 2005).

The "role" level indicated that learners played different roles, such as teacher, facilitator, and evaluator, in connectionism (Bakki et al., 2020). As teachers, they created nodes or published contents for others to learn. As evaluators, they evaluated and filtered node information. As facilitators, they created knowledge, resources, and nodes to allow others to form connections.

The "environment" level included the resources and tools to facilitate pedagogical activities (Bakki et al., 2020) and resources to navigate the PSKN. Learners navigated the learning network and oriented nodes, assessed relationships between nodes, formed cognitive maps, and scored, edited, and created nodes. In PSKN, the course content is presented in the form of a collaborative page where everyone can share, collect, and create knowledge with peers or friends (Sunar et al., 2020). When they made contributions to the collaborative page, their contributions were processed and displayed on the PSKN graph, illustrating the relationship between their contributions and the entire knowledge network (Duan et al., 2023). Simultaneously, new social links were added to peers who also contributed to the same collaborative page (Duan et al., 2023). Learners can participate in diverse activities on the collaborative page, which links activities such as discussions in forums, publishing artifacts, comments, or votes (Duan et al., 2019). In addition, the collaborative page provides diverse resources such as videos, lectures, literature, and teaching lessons, and learners have access to various resources based on personal goals and common interests (Mcauley et al., 2010). In addition, the collaborative page also integrates learning tools, such as subject calculation tools and screen recording software. Thus, learners can learn at their own pace (Kaplan & Haenlein, 2016) in one knowledge node, or jump from one node to another by making connections.

Procedures

In the beginning, learners were given a pretest about the primary knowledge and skills of the course. They were then introduced to the online learning requirements and provided guidance that included course objectives, course schedule, learning activities, learning strategies, and the principal operation of the LCS. Then, the learners studied for 12 weeks assisted by the PSKN, which helped them with wayfinding. A PSKN provides learners with a default learning sequence of knowledge nodes to guide their learning, and learners can observe their real-time PSKN throughout the learning process. The PSKN helps them observe the learning process and adjust their wayfinding strategies accordingly. In addition, the instructor checked each learner's PSKN during the learning process. At the end of the course, they were asked to create a 10–15-min microteaching demo video as the final test.

Instruments

Wayfinding behavior code scheme

During wayfinding, various learner behaviors occurred and were recorded in the LCS. This study focused on finding and connecting important nodes, forming cognitive maps, finding and filtering information, and creating nodes. Twelve specific behaviors were selected for analysis (Table 2).

After gathering the behavior log, we performed LSA using the GSEQ 5.1 software. The main steps (Yang et al., 2018) include: defining behavior code, accessing behavior logs, coding all behaviors records in the logs, running kappa to test encoding consistency, and putting code into GSEQ to draw behavior transition diagrams.

This study's log behavior data used in LSA was directly extracted through LCS according to the coding scheme of wayfinding behaviors. All behavioral categories were automatically identified and did not require manual coding. Therefore, the coding of behavioral sequences was objective and did not require consideration of coding reliability (Yang et al., 2016). We defined the behavioral sequences based on release times. For instance, if the first wayfinding behavior of a learner was coded as FK, and

Table 2 Coding scheme of wayfinding behaviors

Dimensions	Log behavior	Code	Explanation
Creating nodes	Create a learning community Create knowledge nodes Create knowledge bases	CC CK CB	Learners create a community Learners create a CU Learners create a course
Finding nodes	Find knowledge nodes and plan to learn Find knowledge bases and plan to learn	FK FB	Orient CU created by others and add to personal schedule Orient course created by others and add to personal schedule
Forming a cognitive map	Establish relationships between nodes or concepts of CU Establish relationships between nodes or concepts of course knowledge bases	EK EB	Edit the topic, structure, and essential information of the CU Edit the topic, structure, and essential information of course knowledge bases
Connecting nodes	Connect the learning community Connect knowledge nodes Connect knowledge bases	JC LK LB	Join a community created by others Access a CU created by others Access a course created by others
Evaluating and filtering information	Evaluate and filter information of knowledge nodes Evaluate and filter information of knowledge bases	RK RB	Evaluate and score a CU created by others Evaluate and score a course created by others

CU = course unit (knowledge node in the PSKN)

the next was coded as LK, a sequential code of FK → LK was generated. Each learner had an ordered set of codes that represented their wayfinding sequence over time. Finally, behavioral transition diagrams were drawn, and behavioral patterns were detected (Hou & Wu, 2011) by examining the statistical significance of one specific behavior followed by another (Bakeman & Gottman, 1997).

Test tools for learning efficacy

To compare the learning efficacy, a previous study defined high- and low-performing learners as those in the top and bottom 50th percentiles, respectively (Duan et al., 2019). Another study ranked high- and low-performing learners above the 75th and below the 25th percentiles, respectively (Casquero et al., 2015). As this study aimed to differentiate wayfinding behavior that could enrich the analysis for various learners, we classified learners who ranked in the top and bottom 27% as high- and low-performing, respectively (Yang et al., 2018). We assessed whether learning performance can be influenced by wayfinding behavior and patterns. Thus, 77 high- and low-performing learners in each category were identified.

Prior to administering the course, we conducted a pretest to train participants to use the technology and assess their existing ICT knowledge. The pretest consisted of ten yes or no questions, ten multiple-choice questions, and six fill-in-the-blank questions, totaling 100 points. Moreover, the effectiveness of the course contents was evaluated by other educators.

After the course, learners' performances were measured using microteaching demo videos. To determine skills and competencies for mastering new pedagogies, to facilitate changes in knowledge and practice in the workplace (Chen et al., 2020).

Table 3 Wayfinding behavior frequencies (N = 285)

	Create nodes			Find nodes		Form cognitive map		Connect nodes			Find and filter information	
	CC	CK	CB	FK	FB	EK	EB	JC	LK	LB	RK	RB
Sum	1	485	3	4450	704	74	7	7	6989	805	1924	178
Mean	0.004	1.702	0.011	15.614	2.470	0.260	0.025	0.025	24.523	2.825	6.751	0.625
SD	0.059	2.834	0.102	7.917	1.593	1.745	0.176	0.307	4.236	1.238	6.475	0.858
Max	1	30	1	69	16	20	2	5	46	9	40	4
Min	0	0	0	0	0	0	0	0	17	1	0	0

CC Create a learning community, *CK* Create knowledge nodes, *CB* Create course knowledge bases (including one or more related knowledge nodes), *FK* Find knowledge node; *FB* Find course knowledge base, *EK* Establish relationships between knowledge nodes and form a cognitive map, *EB* Establish relationships between course knowledge base and form a cognitive maps, *JC* Join the learning community, *LK* Connect knowledge nodes, *LB* Connect course knowledge bases, *RK* Evaluate and filter information of knowledge nodes, *RB* Evaluate and filter information of knowledge bases

Learning efficacy was assessed by experts (two teachers with at least ten years of professional ICT teaching experience) who developed the assessment criteria. To produce high-quality microteaching demos, learners had to browse the course units and actively navigate additional knowledge nodes or course knowledge bases to gain. Three principles based on course objectives were followed to evaluate the demos: substitutability, integration, and creativity. Substitutability indicates that there was no improvement in instructional performance despite the use of new theoretical and cognitive tools. Integration indicates that the teaching improved significantly and functions well. Creativity means that the entire instruction structure improved significantly, and the entire procedure was innovative (characterized by flexibility and multiple technical skills). After the evaluation, a kappa congruence test (Cohen, 1960) was performed on the demo scores. A consistency test was conducted to measure the fit between the two experts. The results revealed good consistency (k = 0.765 > 0.75).

Data collection and analysis

Behavioral data were obtained from the interaction log recorded in the LCS during the course. When learners logged in and started learning, their wayfinding behavior was recorded, and all product and activity logs were obtained through the LCS (Yang et al., 2016). All the interaction data generated during the wayfinding process were exported to an Excel file for further analysis. Each log included behavioral data, such as the number, categories, and timestamps of wayfinding behaviors.

Results

RQ1: What types of wayfinding behaviors do learners demonstrate in PSKN?

The participants conducted various learning activities and generated various wayfinding behaviors (Table 3). The frequency of wayfinding behavior was relatively high for finding nodes (5154, 33%) and connecting nodes (7801, 50%), followed by creating nodes (489, 3%) and filtering information (2183, 14%). However, the proportion of forming cognitive maps was relatively low (81, 0.01%).

Creating knowledge nodes (CKs) was more common than creating communities (CCs) or course knowledge bases (CBs). Moreover, the participants identified reliable resource nodes and planned to learn more from knowledge nodes (FK) than from the course nodes (FB), as the course initially provided seven knowledge nodes based on the one course knowledge base. Additionally, the participants established relationships between knowledge nodes (EK) and the course knowledge base (EB) to actively form cognitive maps.

The course had three modules and seven CUs. However, the results indicated that learners connected more than 7 CUs, with a mean of 15.614. The maximum is 69; In addition, the participants connected various types of nodes. They identified important knowledge nodes and the course knowledge base and connected knowledge nodes (LK) more than connecting course knowledge bases (LB) or joining learning communities (JC). They connected more to the course knowledge bases than joining learning communities.

Furthermore, the participants found and filtered information and commented on the content, structure, specifications, titles, tags, categories, and summaries of knowledge nodes and course knowledge bases. The behavioral frequency of evaluating knowledge nodes (RK) was higher than that of evaluating knowledge bases (RB), indicating that the participants rated nodes based on their comprehensive evaluation during the learning process.

RQ2: What types of behavioral patterns do learners demonstrate in wayfinding?

Table 4 shows the frequencies of wayfinding behaviors during learning.

A sequence reaches statistical significance if its Z value exceeds 1.96 (Bakeman & Gottman, 1997). We drew behavioral transition diagrams to visualize significant behavioral sequences. All sequences that reached statistical significance are shown in Fig. 4. Nodes represent behavioral categories, values represent the Z value of that sequence, arrows represent the direction of transition, and thicknesses represent significance levels.

The behavioral sequence CK → CK indicated that the participants spent time creating knowledge nodes and then discovering other related knowledge bases (CK → FB), which lasted for some time (FB → FB). Subsequently, they connected course knowledge bases (CK → LB) or joined learning communities (CK → JC). In addition, the participants created knowledge nodes, followed by creating related course knowledge bases (CK → CB). Subsequently, they connected related knowledge bases (CB → LB). After this, they found related knowledge bases (CB → FB), which lasted for some time (FB → FB).

After orienting a course knowledge base, the participants created learning communities (FB → CC), followed by recommending knowledge nodes to the learning community and editing knowledge node information (EK → EK). They then edited information on the course knowledge base associated with that knowledge node (EK → EB). After finding a new course knowledge base, they rated it based on their overall evaluation (FB → RB), commented on the content, structure, or specifications of knowledge nodes in the base (RB → RK), and then oriented important nodes (RK → FK). The orienting behavior lasted for some time. The participants spent time evaluating a one-course knowledge base (RB → RB) or node (RK → RK) or planning to learn one knowledge node (FK → FK).

The participants did not always follow the behavioral path patterns of finding a course knowledge base (FB → RB), filtering information (RB → RK), and finding

Table 4 Learners' adjusted residuals (Z scores; N = 285)

	CC	CK	CB	FK	FB	EK	EB	JC	LK	LB	RK	RB
CC	− 0.01	− 0.18	− 0.01	− 0.64	− 0.19	14.46*	− 0.02	− 0.02	− 0.91	− 0.23	− 0.38	− 0.11
CK	− 0.18	50.59*	9.59*	− 7.2	5.47*	− 0.21	− 0.48	3.84*	− 14.39	2.25*	− 0.5	1.51
CB	− 0.01	− 0.31	− 0.02	− 1.1	5.82*	− 0.12	− 0.04	− 0.04	− 1.58	2.3*	− 0.65	− 0.19
FK	− 0.64	− 2.87	− 1.1	49.21*	− 4.24	− 1.05	− 0.85	− 0.01	− 47.48	− 10.41	15.19*	− 0.24
FB	4.56*	0.75	− 0.38	0.6	34.35*	− 1.88	− 0.58	1.22	− 19.14	6.43*	0.35	11.97*
EK	− 0.07	1.23	− 0.12	− 3.84	0.86	62.93*	5.35*	− 0.18	− 6.57	− 0.82	0.72	1.31
EB	− 0.02	− 0.47	− 0.04	− 0.85	− 0.52	− 0.18	17.65*	− 0.06	1.38	− 0.6	− 1	− 0.28
JC	− 0.02	− 0.47	− 0.04	− 0.85	− 0.52	− 0.18	− 0.06	17.65*	− 0.9	1.16	0.14	3.28*
LK	− 0.91	− 14.55	− 1.57	− 48.26	− 18.62	− 7.07	− 1.64	− 2.4	83.99*	− 1.59	− 36.19	− 9.94
LB	− 0.2	0.78	− 0.35	− 4.09	15.32*	0.06	3.33*	1.39	− 12.31	29.29*	− 4.41	0.4
RK	− 0.38	− 2.55	− 0.66	11.62*	− 1.73	0.3	− 1	− 1	− 29.97	− 5.47	33.94*	3.92*
RB	− 0.11	1.55	− 0.19	1.29	4.62*	− 0.93	3.24*	− 0.29	− 9.06	− 1.27	7.02*	7.08*

*Z > 1.96 and p < 0.05

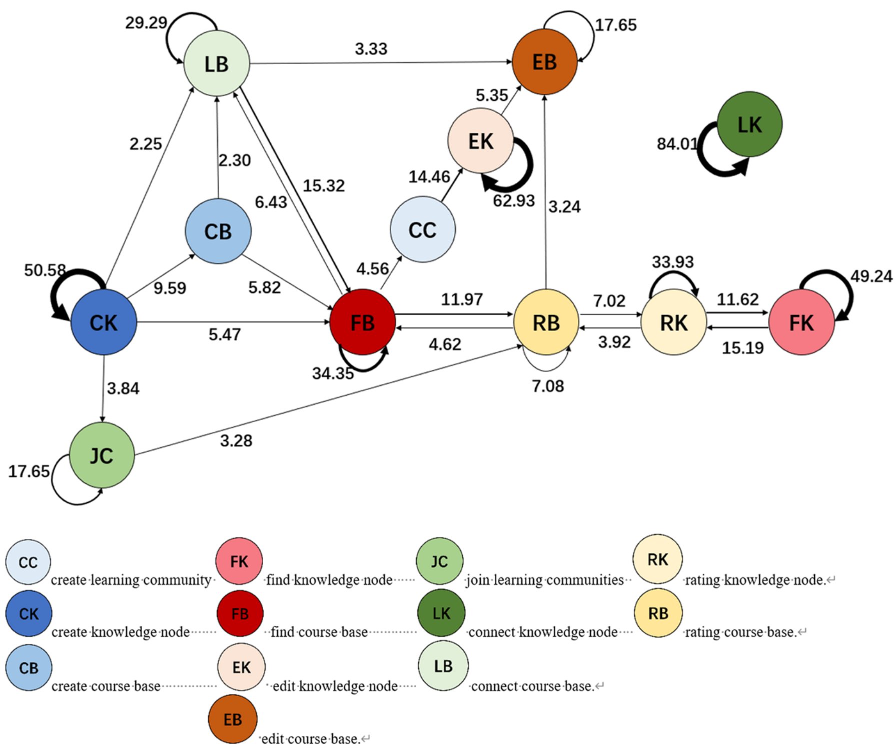

Fig. 4 Significant wayfinding behavioral sequences (N = 285)

Table 5 Wayfinding behavior frequencies for high- and low-performing (H/L) learners

	Create nodes			Find nodes		Form cognitive map		Connect nodes			Find and filter information	
	CC	CK	CB	FK	FB	EK	EB	JC	LK	LB	RK	RB
H learners	1	140	1	1386	234	34	1	0	2043	219	650	50
L learners	0	33	1	1116	123	2	2	0	1715	230	407	42
Total	1	173	2	2502	357	36	3	0	3758	449	1057	92

CC Create a learning community, *CK* Create knowledge nodes, *CB* Create course knowledge bases (including one or more related knowledge nodes), *FK* Find knowledge node, *FB* Find course knowledge base, *EK* Establish relationships between knowledge nodes and form a cognitive map, *EB* Establish relationships between course knowledge base and form a cognitive maps; *JC* Join the learning community, *LK* Connect knowledge nodes, *LB* Connect course knowledge bases, *RK* Evaluate and filter information of knowledge nodes, *RB* Evaluate and filter information of knowledge bases

knowledge nodes (RK → FK). Occasionally, the opposite was true. For instance, when they found a knowledge node, they evaluated it (FK → RK) and its associated knowledge base (RK → RB). Sometimes, they joined a learning community (JC → JC) and then filtered the information (including the evaluation of knowledge nodes and course knowledge bases) to connect important nodes.

Moreover, the participants connected course knowledge bases (LB → LB) and oriented related knowledge bases (LB → FB). They also edited information about the knowledge base. They formed a cognitive map (LB → EB), such as titles, tags, categories, and summaries, and categorized the concept of the knowledge node, which

Table 6 Adjusted residuals (Z scores) of high-performing learners (N = 77)

	CC	CK	CB	FK	FB	EK	EB	JC	LK	LB	RK	RB
CC	−0.01	−0.17	−0.01	−0.65	−0.2	11.87*	−0.01	0	−0.88	−0.22	−0.4	−0.1
CK	−0.18	20.74*	5.7*	−3.43	2.89*	0.01	−0.18	0	−6.21	−0.57	1.64	0.48
CB	−0.01	−0.17	−0.01	−0.65	4.96*	−0.08	−0.01	0	−0.88	−0.22	−0.4	−0.1
FK	−0.65	0.27	−0.65	25.92*	−2.78	0.11	−0.65	0	−26.17	−5.21	8.27*	−0.99
FB	4.37*	−0.74	−0.23	−0.53	20.08*	−1.32	−0.23	0	−10.07	3.01*	−0.64	11.08*
EK	−0.08	0.06	−0.08	−2.89	0.69	35.57*	−0.08	0	−4.26	−0.39	1.32	−0.58
EB	−0.01	−0.17	−0.01	−0.65	−0.2	−0.08	−0.01	0	1.14	−0.22	−0.4	−0.1
JC	0	0	0	0	0	0	0	0	0	0	0	0
LK	−0.87	−7.11	−0.87	−25.97	−9.93	−5.04	−0.87	0	46.44*	−1.09	−19.81	−5.21
LB	−0.19	0.01	−0.19	−2.88	5.01*	0.76	5.17*	0	−5.29	18.86*	−3.27	0.21
RK	−0.4	−0.29	−0.4	7.1*	−1.18	−1.3	−0.4	0	−17.18	−2.98	17.97*	0.98
RB	−0.1	1.28	−0.1	1.02	6.64*	−0.6	−0.1	0	−5.37	−0.88	2.09*	2.1*

* $Z > 1.96$ and $p < 0.05$

Table 7 Adjusted residuals (Z scores) of low-performing learners (N = 77)

	CC	CK	CB	FK	FB	EK	EB	JC	LK	LB	RK	RB
CC	0	0	0	0	0	0	0	0	0	0	0	0
CK	0	23.36*	10.39*	−1.97	3.28*	−0.14	−0.14	0	−3.39	1.74	−1.5	−0.63
CB	0	−0.09	−0.02	−0.67	−0.17	−0.02	−0.02	0	−0.95	4.21*	−0.36	−0.11
FK	0	−0.69	−0.67	26.73*	−1.76	−0.95	−0.95	0	−25.14	−7.63	7.11*	0.66
FB	0	2.13*	−0.19	0.18	8.13*	−0.27	−0.27	0	−8.54	8.34*	−0.25	8.16*
EK	0	−0.13	−0.02	0.58	−0.24	−0.03	−0.03	0	−1.35	−0.34	1.73	−0.15
EB	0	−0.13	−0.02	−0.95	−0.24	−0.03	29.96*	0	0.07	−0.34	−0.5	−0.15
JC	0	0	0	0	0	0	0	0	0	0	0	0
LK	0	−3.9	−0.95	−26.35	−9.02	−1.34	0.07	0	40.72*	−0.75	−17.54	−5.26
LB	0	−0.26	−0.22	−2.6	15.71*	−0.31	−0.31	0	−9.49	16.01*	−1.41	2.28*
RK	0	−0.7	−0.36	4.66*	0.22	3.96*	−0.51	0	−13.76	−3.69	17*	1.1
RB	0	−0.58	−0.11	0.33	1.73	−0.15	−0.15	0	−4.03	−0.17	5.04*	0.74

* $Z > 1.96$ and $p < 0.05$

usually continued for some time (EB → EB). The participants also exhibited isolated wayfinding behaviors, such as connecting a single knowledge node (LK → LK).

In summary, there were several typical wayfinding paths in the PSKN. In addition, some wayfinding behaviors were more critical than others.

RQ3: What are the differences in wayfinding behavioral patterns between high- and low-performing learners?

As shown in Table 5, CK behavior frequency was significantly higher for the high-performing than for the low-performing participants. The high performers created knowledge nodes nearly four times as often as the low performers. Moreover, high performers exhibited more frequent FB behaviors than low performers. The behavioral frequencies of FK, LK, EK, and RK were higher among high performers. This indicated that high performers were more proactive and engaged in the wayfinding process.

Tables 6 and 7 show the results of the adjusted residuals for the high- and low-performing groups, respectively. The results indicated that 21 and 19 behavioral

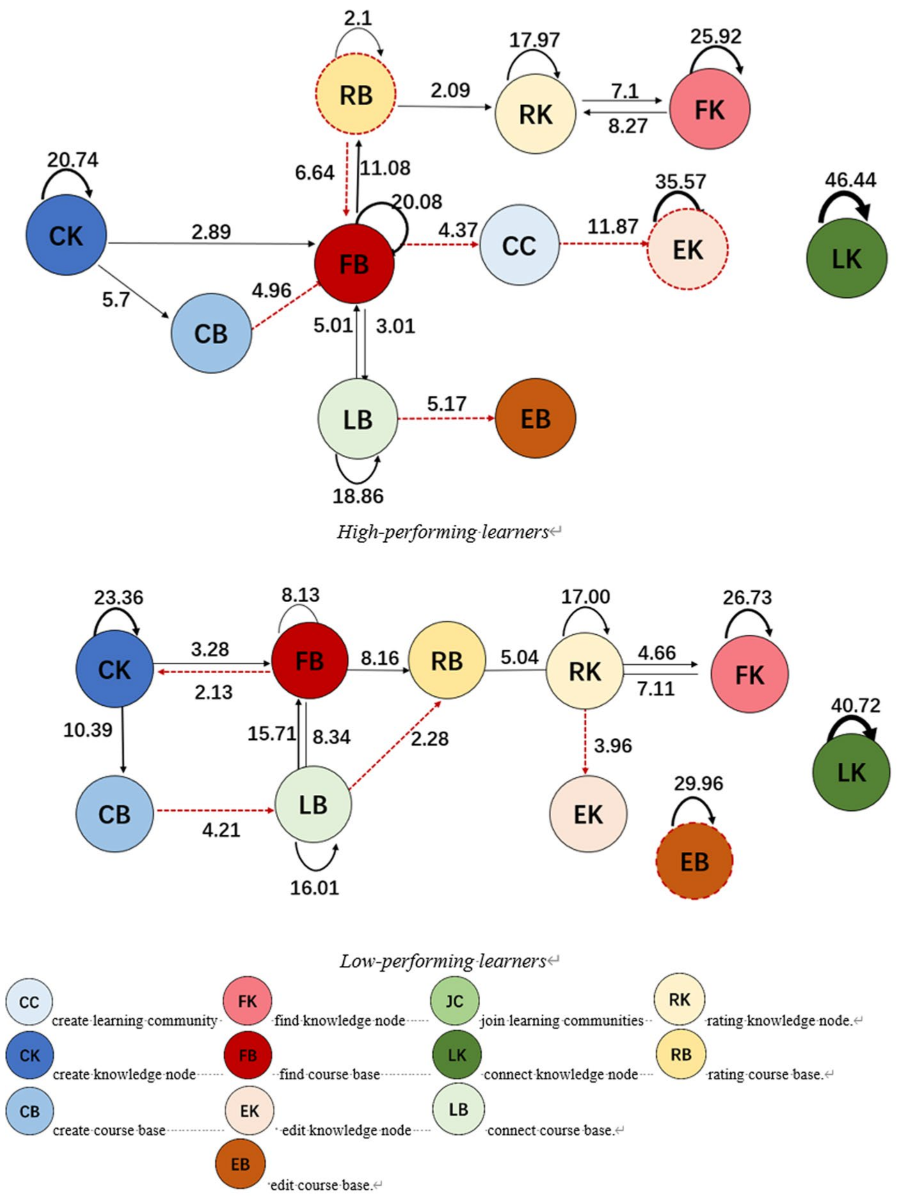

Fig. 5 Significant wayfinding behavioral sequences of high- and low-performing learners

sequences were statistically significant for the high and low performers, respectively. Furthermore, behavioral transition diagrams were plotted to visualize significant behavioral sequences. The black line represents significant sequences that coincided between the high- and low-performing groups, whereas the red line represents significant sequences that existed only in the high- or low-performing groups (Li et al., 2021).

As indicated by the red line in Fig. 5, after creating knowledge nodes and course knowledge bases (CK → CB), high performers found related course knowledge bases (CB → FB), whereas low performers directly built connections (CK → LB). The behavioral LB → EB path implies that high performers connected essential course knowledge bases, identified the relationships between course nodes, and formed cognitive maps. Low performers rated and filtered information about course knowledge bases (LB → RB).

Furthermore, high performers edited important nodes and formed cognitive maps based on knowledge nodes (EK → EK), whereas low performers had more EB → EB behaviors.

The RB → RB and RB → FB behavioral paths occurred in the high-performing group, indicating that the participants rated the course knowledge base and then found important nodes. The participants continued to find and filter information for a certain period; they filtered relevant information before serious learning, and this filtering behavior lasted for some time. The FB → CC and CC → EK behavioral paths demonstrated that high performers found course knowledge bases, followed by creating related learning communities. Subsequently, they edited knowledge nodes, formed cognitive maps, and maintained this behavior for some time. High performers found essential course knowledge bases, created communities, and edited and filtered community knowledge nodes (FB → CC → EK). However, after finding it, low performers created knowledge nodes only within the course knowledge base (FB → CK). In addition, the CB → LB and LB → RB behavioral sequences were found in the low-performing group, indicating that they first created course knowledge bases and then focused on connecting and rating them. The RK → EK path revealed that low performers first evaluated knowledge nodes and then edited them; however, they did not spend more than half hours editing information and forming cognitive maps of knowledge nodes as high performers did.

Discussions and implications

Discussion main findings

This study proposed and examined wayfinding in the PSKN, provided a comprehensive understanding of wayfinding in the PSKN and analyzed learners' wayfinding behaviors and patterns to investigate differences across different learning efficacies.

Five types of wayfinding behaviors exist in PSKN

This study identified five types of wayfinding behaviors in PSKN for learners: creating nodes, finding important nodes and forming cognitive maps, connecting important nodes, and finding and filtering information. Our findings verified the diversity of wayfinding in the PSKN. Previous studies have focused on wayfinding difficulties, such as information evaluation (Kammerer et al., 2013; Kiili et al., 2020), resource disorientation (Wang et al., 2022) and technical difficulties (Kop, 2011; Li et al., 2016). However, few studies have examined technological factors influence the ways learners access resources in connectivist learning, such as the PSKN. Four wayfinding behaviors were defined in this study based on a connection-forming model (AlDahdouh, 2018). We further defined a new wayfinding behavior, creating nodes, in the PSKN, with three types of creating behavior: learning communities, knowledge nodes, and course knowledge bases. Consistent with previous studies, the results demonstrated that generating knowledge nodes facilitated learners acting as teachers or content producers (Griesbaum, 2014), contributing to more connections (Duan et al., 2019; Yu et al., 2019).

Furthermore, we revealed creation of behavior-supported indirect wayfinding for individuals, through which learners can navigate the network and identify diversity nodes effectively (Kizito, 2016). Our results indicated that all learners navigated the PSKN and oriented additional nodes. Compared with previous studies, this study found that creating nodes was an essential wayfinding feature in the PSKN. This may be because, with the increase in network connectivity, resource navigation moved from relying on preexisting nodes to wayfinding by creating nodes to identify more important nodes and make connections. This reflects a change in the role of learners during the wayfinding process, that is, a gradual move from finding to creating nodes. This also means that indirect wayfinding was a crucial wayfinding feature, and creating nodes was a critical behavior in the PSKN. Moreover, as the connection proceeds, the learner becomes like a teacher, and creating nodes becomes a critical wayfinding behavior in connectivist learning.

Wayfinding patterns show complexity and flexibility in PSKN

This study indicated wayfinding complexity (Farr et al., 2012) and flexibility (Courbois et al., 2013) in the PSKN. The participants found a single knowledge node and then a course knowledge base related to this knowledge node after evaluating and filtering it before planning their learning. Moreover, they oriented course knowledge bases created by others and added them to their schedule; then, after evaluating and filtering information, they found the reliable nodes to connect. This indicates that they consolidated various resources and information and built connections to form cognitive maps and carefully filtered information before deciding which nodes to learn. Thus, we identified two typical behavioral patterns: one starts by searching for knowledge nodes and the other starts by searching for course nodes. “Efficient wayfinding behavior can take different forms” (Courbois et al., 2013, p. 1826). However, participants sometimes exhibited isolated wayfinding behaviors, probably because the nodes were significant, such as a lecture provided by an expert in the field or a typical course example. Therefore, the learners remained connected to the node and did not perform other wayfinding behaviors. Thus, this study showed that learners in the PSKN could navigate networks and create flexible wayfinding patterns.

Forming cognitive maps and creating nodes contribute to learning efficacy

A previous study argued that how students navigate learning networks from one node to another is governed by cognitive processes (AlDahdouh, 2018), thus forming a cognitive map that enables learners to actively establish relationships between knowledge nodes, concepts, or information of the course (Li et al., 2016; Wan & Yu, 2020). This study confirmed the role of the PSKN in helping learners form cognitive maps. After oriented course knowledge bases, they tended to establish relationships between nodes or concepts of course knowledge bases and form cognitive maps. The relationships between knowledge nodes and course bases demonstrated by the PSKN (Duan et al., 2019, 2023) facilitate the forming of cognitive maps based on the node sequence. Correspondingly, learners created their cognitive maps according to their reconstruction of the node relationship based on their understanding.

Furthermore, node creation facilitates learning performance. By comparing the behaviors of different performing groups, we found that the high-performing group created more knowledge nodes and course knowledge bases and more often found and connected important nodes based on the nodes they created. Therefore, node creation was an important wayfinding method for the high-performing group, and learners who were highly involved in creating nodes achieved better learning performance than those who created fewer nodes. In addition, the high-performing group integrated information (i.e., reconstructing the relations of knowledge or nodes and forming cognitive maps); thus, previous findings that forming cognitive maps cultivates learning efficacy in complex situations (Chen et al., 2017; Jonassen, 2005) were confirmed in this study.

Patterns of wayfinding behavior differed by groups

The results demonstrated that wayfinding behavioral patterns differed for learners with different efficacies. The high-performing group exhibited behavioral wayfinding through creating communities, indicating that they took advantage of social relationships in wayfinding. These results were consistent with the findings of Oztok et al. (2015) and Duan et al. (2019) but further revealed that in-depth wayfinding between human nodes facilitated access to more diverse nodes and promoted learning performance. Moreover, the results indicated that the pattern of wayfinding behavior differed by group, with the high-performing group preferring to carefully filter information about nodes before connecting them and then reconstructing the relationships of nodes on a large scale. This helped them form cognitive maps.

Conversely, the low-performing group edited isolated node and connected nodes before selecting and evaluating information about them. This could be because the new learning environment requires learners to be active in the wayfinding process, find and connect nodes in various ways, form cognitive maps, filter relevant information, and connect to other nodes in new ways. They must be able to find important nodes, understand the relationships between nodes in the PSKN, and construct connections between nodes and related topics. Learners must be able to explore and adapt to new ways of wayfinding and find their own strategies in the PSKN. A significant limitation is that, because they need to find nodes and aggregate and filter relevant information resources autonomously, they need high level of critical analysis skills to do so effectively (Kop, 2011). However, low performers may lack the necessary knowledge and skills (Li et al., 2016) and be overwhelmed by resources (Waite et al., 2013). Besides, we found that high-achieving learners spent more time editing the topic, structure, and essential information of the knowledge nodes than the course knowledge base to form cognitive maps, thereby establishing refined relations between knowledge nodes.

Further, the low-achieving group formed cognitive map behaviors by editing the relationships of the course knowledge base. However, this behavioral path was isolated, possibly because low-performers could not establish refined relations between nodes compared to high-performers. Since they lacked detailed understanding, they did not form in-depth cognitive maps of the course relationships before filtering and rating information.

In summary, high performers spent more time forming cognitive map based on knowledge nodes and filtering information based on course knowledge bases. In contrast, low performers formed cognitive maps based on course knowledge bases, likely because they could not reorganize the relationships between knowledge nodes. Low performers had difficulties consolidating resources and information and building connections;

therefore, instructors should provide them with guidance and learning sequences during wayfinding. Moreover, high performers conducted wayfinding through knowledge communities and bases they created, aiming to explore the space on a large scale. In contrast, low performers mainly limited their wayfinding to the knowledge bases they created.

Practical suggestions

The results apply to cMOOCs, similar to the course used in this study, and have teaching, technical, and practical implications.

For teachers and educators

Currently, teachers' professional development has become a critical issue in education (Chalikias et al., 2021), and teachers and educators need to master new teaching methods and deliver online teaching. However, how teachers navigate online teaching spaces remains an unresolved challenge (Barrot & Acomular, 2022). This study demonstrates the potential of utilizing the wayfinding support provided by PSKN, which can help teachers provide navigation services during the teaching process, reduce their workload and pressure, and provide practical teaching strategies based on the wayfinding behavior of students with different performance levels. For example, the results show that the pattern of wayfinding behavior is different for different learners, with high- performing learners tending to reconstruct the relationships of nodes on a large scale, which helps to form cognitive maps, and also preferring to carefully filter information about nodes before connecting them, while low-performing learners tend to edit an isolated node and tend to connect nodes before selecting and evaluating information about them. It is suggested that teachers and educators should pay attention to the wayfinding patterns and strategies of low-performing learners, guide them, help them connect nodes by creating nodes, and simultaneously guide them to carefully filter and evaluate nodes.

In addition, attention should be paid to their critical thinking skills and ability to form cognitive maps to help them form cognitive maps around relevant topics in a broad context and to improve their wayfinding efficiency. Furthermore, focusing on connecting important nodes and forming a cognitive map of the PSKN allows learners to connect with others through person-to-person knowledge interactions, promotes connectivist learning, and effectively guides wayfinding. Thus, teachers and educators could guide learners to construct personalized learning schedules that integrate and reconstruct nodal relationships to build a systematic understanding of a topic.

For social media and influencers

Lave and Wenger (1991) argued that knowledge and people are inseparable, and that knowledge is always situated and must be viewed by the person who built it (Hod & Ben-Zvi, 2018, p.611). This study demonstrates that PSKN integrate knowledge and people in one social space and how they scaffold wayfinding by developing and maintaining connections between people and between people and resources (Jones et al., 2017) during wayfinding in connectivist learning. Social media and influencers play a crucial role in wayfinding through diversified interaction media (Štreimikienė et al., 2021) and resource tag. For example, observers, participants, and contributors tagged by PSKN helps learners identify the reliable or essential node. However, the study found that wayfinding behavior between knowledge nodes and course knowledge bases occurred easily, whereas wayfinding behavior between human-to-human nodes occurred infrequently. Thus, establishing human connections help learners access more resources (Joksimović et al., 2018), resulting in more effective wayfinding. Learners should be aware of the importance of learning communities and peers in wayfinding through the PSKN by identifying relationships between learners through social tags and connections to those who follow the same or similar topics. In addition, they should be encouraged to add friends or access others' profiles when navigating the PSKN.

Pedagogical and technological implications

Revisiting connectivism and wayfinding in connectivist learning

Connectionism, as a learning theory, is controversial (Barberà, 2014; AlDahdouh, 2018). One controversy is whether it emphasizes the environment and technology while underestimating the individual's role in the learning process. According to Siemens and Tittenberger (2009), knowledge and learning can be described as a network with three levels: neural, conceptual, and external. Neural and conceptual levels refer to individuals' internal learning, focusing on the activities of neurons (AlDahdouh, 2017) and the connections of conceptual nodes, such as thoughts or concepts. The external level refers to external resources or nodes, such as a person or information source (AlDahdouh, 2017). However, owing to technological limitations, most studies have focused on external networks, such as resource navigation (AlDahdouh, 2021; Li et al., 2016), navigation methods (AlDahdouh, 2018), and behavioral patterns (Li et al., 2022b) in network environments.

Recent studies have further developed connectionism and paid more attention to the importance of nodes and connections, as well as internal learning processes. For example, Wang et al., (2017, p.683) identified connectivist learning has four interactive levels: "operation, wayfinding, sensemaking, and innovation, while operation level means connecting social media as well as establishing interaction spaces; sensemaking level is pattern recognition and information (knowledge) seeking in a collaborative process; and innovation level is the creation of artifacts". This indicates that the operation and wayfinding levels emphasize the environment and technology, such as digital networks and information flows, which focus on the role of the individual in the learning process and the importance of internal learning processes. In addition, AlDahdouh (2017) used new research methods to understand the formation and mechanisms of internal connections during connectivist learning, especially artificial neural networks to understand connectivism theory and knowledge connectivity from the perspective of internal learning processes (AlDahdouh, 2017), indicating the importance of nodes, connections, and internal learning processes. In his latest research, AlDahdouh (2018, 2021) studied how students jump from one resource to another to navigate their networks. proposed a connection-forming model, arguing that the process includes three stages: planning, cognitive processing, and evaluation. This indicates the importance of individual cognitive and situational understanding of information (Brown & Duguid, 2001; Wenger, 2000) by evaluating important nodes during the process of connectivist learning.

In line with these studies, this study found the importance of internal learning processes such as forming cognitive maps and evaluating and filtering information during wayfinding. According to Ausubel (1960) and Brown and Duguid (2001), the filtering and evaluation of information must be based on personal experience, as well as a comprehensive judgment of the current context and information. Thus, we argue that nodes and connections in PSKN assisting the internal learning process and serving as a "advance organizer" of wayfinding to assist individuals in actively establishing connections and constructing knowledge map according to their experiences (Kandel, 2006; Kandel et al., 2012), contribute to meaningful learning (Ausubel, 1960). Therefore, this study develop connectionism and argued that external resources and the PSKN environment are the "advance organizers' of the formation of connections, internal cognition and experience are the key to the formation of connections during wayfinding. Moreover, wayfinding and connectivist learning are not only linked to the digital environment but can also be used in the real world (AlDahdouh, 2018, 2021; Allen, 1997). We argue that connectivist learning may be an important perspective for examining wayfinding by focusing on the internal and external processes of learning both in the digital environment and real world (AlDahdouh, 2018, 2021).

Influence of course and technological factors on learners' wayfinding in connectivist learning

This study aims to help instructors and instructional designers better understand the process of navigation and building connections from the learning support perspective in a connectivist learning context. Examples include how to navigate their learning process (Lehmann et al., 2014), forming cognitive maps, finding important nodes, connecting important nodes, finding and filtering information (Kop, 2011; Li et al., 2016; Mackness et al., 2010), and creating nodes (Duan et al., 2019).

Results imply that the influence of course (e.g., pedagogy) and technological factors (e.g., navigation design of the PSKN) on the ways that learners access resources (Hecking et al., 2014). On the one hand, the wayfinding in this study was designed based on the connectivist pedagogical scenario (Bakki et al., 2017, 2020), which addresses scenario, environment, activity, and role level, reflecting the characteristics of the connectivist course. The course was supported by diversified interaction behaviors, such as browsing, editing, sharing, comments, and posting. On the other hand, learning in the connectivist context is scaffolded by technological factors (e.g., navigation design of the PSKN), which not only helps learners navigate networks and resources, but also has the characteristics of knowledge networks and social networks because of the dual properties of PSKN nodes, namely knowledge nodes and human nodes. Based on social networks, learners can interact with and establish connections through various types of media integrated with PSKN. Therefore, PSKN could be a learning tool to optimize connectivist learning performance by integrating diversified interaction media and resources, which demonstrates the advantages of wayfinding in PSKN.

However, wayfinding in PSKN is complex and flexible, and some learners are not able to navigate in PSKN simply by interacting with nodes, which has affected their learning performance; some others are unable to effectively form their personal cognitive maps by constructing their own understanding. One possible reason is that wayfinding is a complex process that involves literacy and skills in navigating complex and flexible networks as well as individual cognition and evaluation of node resources (AlDahdouh, 2018).

Therefore, some challenging issues such as providing wayfinding track and strategy of expert or high-performing learners to those groups dynamically and targeted; or detecting the internal learning process of learners (Kandel, 2006; Kandel et al., 2012). For example, understand connectivism theory and knowledge connectivity from perspective of artificial neural network, open the "black box" of internal learning process (AlDahdouh, 2017) and providing targeted groups with adaptive cognitive map in line with "advance organizers" (Ausubel, 1960), promoting their meaningful wayfinding and deep learning.

Conclusions

This study revealed the diversity and pattern complexity of wayfinding behavior in the PSKN and demonstrated differences in wayfinding between high- and low-performing groups. These findings can be used in future research to explore behaviors in connectivist learning, providing a basis for comprehensive wayfinding analyses. In addition, this study considered the idea that connectivist learning is the process of establishing connections and building learning networks and used connectivist nodes as the basic unit of analysis to analyze wayfinding patterns during the formation of individual learning networks. This study analyzed essential characteristics of wayfinding in discovering important nodes, creating, and connecting nodes, and finding and filtering information. Our findings can be used to provide instructional support and network navigation in connectivist learning for learners with various performance levels. We suggest that low performers should be guided to engage in more information filtering to improve their wayfinding efficiency and help them actively engage in more node-creating behaviors. This would allow them to transition from learner to teacher, create connections by creating nodes, and provide wayfinding strategies for others. Moreover, despite many course participants, we identified wayfinding interactions and teaching strategies for connectivist learning aimed at open access to quality educational experiences and resources (Yousef & Sumner, 2021). Connectivist learning provides differentiated guidance for different types of learners to help them engage in effective wayfinding and avoid being lost in social spaces and having low learning performance.

Limitations and future directions

This study had several limitations. First, it did not compare the PSKNs of learners and experts. In the future, if the system automatically provides students with an expert's PSKN when learning is ongoing, learners can compare their PSKNs with those of experts. This method motivates students to learn effectively from expert wayfinding patterns and strategies. Second, the effect of self-regulated learning skills on the wayfinding process, learning outcomes, and the depth of learners' connections to knowledge and person nodes in the PSKN need to be explored. Furthermore, the role of human nodes during the wayfinding process should be investigated to help learners, particularly low-performing learners, develop effective strategies. Third, we used 285 in-service teachers for an exploratory study; the sample size was relatively small, and the generalizability of the findings could be limited. Future research should analyze larger sample sizes to test the extent to which the PSKN influences wayfinding and further measure external access to acquire skills and competencies the learners have a strong connection with the usage scenarios (Brown & Duguid, 2001) due to the number of resources available in PSKN, although which provides diverse resources and develops over time. Finally, this study mainly focuses on connectivist learning and wayfinding in digital environments, such as cMOOC; in the future, more analysis will be conducted in non-digital environments.

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Availability of data and materials
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. To ensure the quality of the study, the informed consent form was waived for the participants, and the study was approved by the scientific office of our university, and the study design was approved by the appropriate ethics review board. We have read and understood your journal's policies, and we believe that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare.

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