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Research article

The value co-creation behavior in learning communities: Comparing conventional learning and e-learning

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Abstract: With the rapid development of ICT, the present world is experiencing rapid changes in the field of education. Implementation of e-learning and ICT in the education system could allow teachers to upgrade and improve their lectures. However, from the perspective of value co-creation behavior in learning communities, conventional learning and e-learning classrooms may encounter different opportunities and challenges. Thus, a more in-depth investigation would be needed. Based on the S-O-R framework, this study identifies self-directed learning as a stimulus, perceived benefits as the organism, and value co-creation behavior as the response. By applying the multi-criteria decision-making techniques of DEMATEL, ANP, and VIKOR, this study explores the causal effects, influential weights, and performance ranking of the primary constructs in the framework as criteria. This study's theoretical and practical implications are discussed, and ways of improving learning performance are suggested.

Keywords: self-directed learning; value co-creation; S-O-R framework; U & G theory; VIKOR

1. Introduction

The current field of education is experiencing rapid changes. Some of the changes are pushed by the rapid development of information and communication technology (ICT). Sharing information has become more convenient with the emergence of computers, mobiles, and the Internet [1]. Implementation of e-learning and ICT in the educational system could allow teachers to upgrade or improve their lectures [2]. According to Corbett and Trask [3], e-learning is the development of a computer program or a series of programs with the explicit aim of replacing the current methods of instruction. This incorporation of technology was also called computer-based instruction.

E-learning is encouraging student-oriented online studies. The creation of online learning programs was under the influence of constructivism [4]. Under the control of constructivism, it was believed that new knowledge could be acquired on the foundation of previous knowledge. E-learning could provide a flexible method to revisit the issues in the learning process to gain the benefits of knowledge management. Learners played an active role in their learning process [5]. Learners' starting level had become less significant comparing to the conventional learning environment [6]. Thus learners have better opportunities to explore and exploit the knowledge cumulated in e-learning platforms [7,8]. According to [9], there are three primary reasons for introducing and adopting e-learning by educational institutions: enhancing the quality of learning, maintaining competitive advantage, and improving access to education and training.

In the viewpoint of cooperative learning, learning could be seen as a value co-creation behavior of two parties: instructors and students, which was especially true in the context of online learning context. Both instructors and learners were facing a new challenge. Instructors needed to make efforts and digitalize traditional teaching materials. Learners must be willing to engage in the learning process, relying on a strong desire and autonomy. All the teaching and learning was conducted in the virtual environment, and the online interaction could be considered as a value co-creation behavior. In this way, learning and knowledge management complement each other efficiently and effectively.

Since online learning has become highly popular in education, many researchers have focused on the development and the impact of online learning. It was essential to compare the value co-creation behavior in conventional learning and e-learning contexts to identify the most effective learning environments for learning and knowledge management.

In the ambidexterity processes of value co-creation, the mutual impact of learning and knowledge management is complicated and dynamic. Multiple criteria decision making (MCDM) techniques with features without prior hypotheses of decision elements are applied to the relationship among self-directed learning, perceived learning benefits, and value co-creation behavior. Questionnaires were designed to gauge these factors. The results of this study could become helpful to the instructors responsible for planning and management courses.

The research purposes of this study are:

(1) Understanding the dynamic nature between self-directed learning and value co-creation behavior.

(2) Identifying the norms to compare conventional learning and online learning.

(3) Suggesting strategies to improve learning environments and enhance the quality of learning.

2. Literature review

In this section, we first introduce the S-O-R framework as the foundation to build the research model. Then under the context of e-learning, for the knowledge exploration and exploitation purpose, self-directed learning and perceived benefits from the learner's side, and value co-creation behavior from both learners and instructors are essential elements. Therefore, these constructs are introduced in turn.

2.1. S-O-R framework

The S-O-R framework assumed that various environmental factors acted as stimuli that jointly affected people's internal states, triggering their behavioral responses [10]. The whole process involved different attitudinal and behavioral activities [11]. S-O-R framework divided this process into stimulus, organism, and response. In this study, the learner's self-directed learning motivation was considered the stimulus, their perceived benefits of the e-learning system as the organism, and the desired value co-creation behavior as the response. However, these constructs had a dynamic nature in social science.

2.2. Self-directed learning

Self-directed learning (SDL) was a concept widely used in learner autonomy [12]. Most of the fundamental principles underlying self-directed learning indicated that individuals would empower themselves and took responsibility for various decisions related to their learning [13]. In other words, self-directed learners could fill charge of their learning processes.

In self-directed learning, the learners needed to exchange ideas with other learners to receive a wide range of information to meet their learning needs [14,15]. The use of technology might have a direct impact on self-directed learning. For instance, Andersen and Heilesen [14] reported that Web 2.0 could facilitate self-directed learning. Still, some researchers found that learners might have poor time management and organizational skills. They could be inadequate managers of their online learning [15]. Therefore, to become a successful online learner, the person had to make wise decisions to reach the learning goals at one's own pace [16]. Since a disciplined learner tended to be zealous in online learning, this person would be more likely to become a successful self-directed learner.

In the virtual environment, students took a more active role in their learning. Having a solid discipline to do self-directed learning was critical to the effectiveness of online learning activities. Students had to take responsibility and decide what they wanted to learn [17,18]. Researchers had identified the character traits of effective self-directed learners. These learners tended to be motivated and goal-oriented. They usually had a strong locus of control and self-efficacy [19–21]. Moreover, these learners also needed to have the abilities to set their own goals, implement plans, conduct interpersonal communication, and self-monitor the learning process [22,23]. So, in this study, four factors are considered: learning motivation, planning and implementing, self-monitoring, and interpersonal communication.

2.2.1. Perspectives of self-directed learning

Self-directed learning has been examined from several different perspectives. Some researchers considered self-directed learning as a process; others suggested it as a personal attribute. Knowles [13] defined self-directed learning as a process in which individuals take the initiative, with or without help from others. They would diagnose their learning needs, formulate goals, identify human and material resources, implement appropriate learning strategies, and evaluate their learning outcomes. In accord with Guglielmino’s [24] suggestion, highly self-directed learners accepted responsibility for their learning and viewed problems as challenges. They would have self-discipline, a strong desire to learn, and necessary study skills. They would know how to manage time and develop a plan to complete the tasks. This kind of learner tended to be goal-oriented and enjoy learning. Under Brookfield [25], self-directed learning was a process of learning in which the learners controlled their learning by setting goals, finding resources, selecting appropriate methods to learn, and evaluating the learning progress.

According to Stiller and Ryan [26], self-directed learning is a people-oriented activity. They also claimed that self-directed learners should have the ability to collaborate with peers and saw peers as learning resources. Based on Gibbons [27], self-directed learning accumulated knowledge, skill, or personal development that individuals accomplished by their efforts. Following Smedley [28], self-directed learning is an approach that relied on flexibility in time and place of learning. The responsibility of learning was entrusted to the learner. In pursuance of Teo et al. [29], a self-directed learner would take the initiative to plan and manage their workload and time without the supervision of teachers or other adults. This learning approach would teach the learner how to cope with multiple tasks and a vital life skill.

Moreover, Gibbons [27] suggested that learners who practiced self-directed learning would find new challenging topics to learn. They would also develop personal knowledge and skills in the process. The learner could continue applying the acquired knowledge and skills in other areas in life [30].

2.2.2. Dimensions of self-directed learning

This study followed Cheng et al.'s [31] proposition regarding major dimensions of SDL, which are described as follows.

2.2.2.1. Learning motivation

Motivation is an influential factor in learners' attitudes and learning behaviors in educational research and practice [32,33]. It was the encouragement that came from the needs and desires to achieve something. This attribute could determine the success or the failure in any undertaken effort [34]. Therefore, motivation could be defined as an inner drive of the learner and an external stimulus that drove the desire to learn and take responsibility for one's learning [31].

The motivation was often categorized into intrinsic and extrinsic motivations that represented different causes of human activity [35,36]. Intrinsic motivation was a series of factors that influenced users' behaviors for their reason, such as feeling interested or engaged [37]. In the context of learning, intrinsic motivation had been identified as one of the critical factors affecting the learning process [26]. Unlike intrinsic motivation, extrinsic motivation was characterized by its tool orientation and the dependence on external rewards and pressures [38]. Both intrinsic and extrinsic motivation are key factors influencing the learning process.

2.2.2.2. Planning and implementing

Planning and implementing were two of the major components in the learning process. Planning was a process of assessing current needs and resources, articulating measurable goals, and selecting best practices to implement. Implementing referred to the actual delivery of the chosen methods [39]. Cheng et al. [31] defined planning and implementing as the ability to independently set learning objectives and use appropriate learning strategies and resources to achieve the learning goals effectively.

2.2.2.3. *Self-monitoring*

Self-monitoring was defined as evaluating one's learning process and outcomes and making progress [31]. This process was critical for learners to identify the advantages and disadvantages of their learning. With self-monitoring, learners would be able to refine their learning activities and goals based on their current performance [40]. Also, it helps the learner to monitor their learning progress to understand what to do in the next step.

2.2.2.4. *Interpersonal communication*

According to Cheng et al. [31], interpersonal communication refers to the ability of learners to interact with others in the learning process. The ability to conduct interpersonal communication was a foundation in an interpersonal relationship, especially in online learning environments. Using communication tools was necessary for online communication. Online learners could use Skype, for example, to receive instant messages, ask questions, and exchange ideas online [18]. It was an excellent opportunity for students to communicate and interact with instructors and peers while learning something new.

2.3. *Perceived benefits*

Uses and gratifications (U & G) theory could reasonably interpret the perceived benefits in SDL. This theory described how and why people seek out specific media [41]. Since users' needs were considered essential in personal psychology depicting how people use media [42], many scholars have started to recognize the importance of applying the U & G theory to new media and technology [43–46]. Therefore, U & G theory has become a primary tool to interpret people's motivations and behaviors in media and technology usage.

The U & G theory proposed by Blumler and Katz [47] identifies four types of benefits that individuals could obtain when using the media, which is also appropriate in the learning process: (1) cognitive benefits, (2) social integrative benefits, (3) personal integrative benefits, and (4) hedonic benefits. Cognitive (or learning) benefits referred to the accessibility of information and a better understanding of the environment. Social integrative benefits related to strengthening emotional bonds with other community members. Personal integrative benefits represented the returns of enhancing the sense of self-efficacy and identity or reputation. And the hedonic benefits denoted the experience related to the concept of flow [47].

According to Nambisan and Baron [48], a common issue with U & G theory-related research is consumer interaction with the media and others in specific contexts. It explores how these interactions gratify the different needs and create opportunities for gratification [49]. The recent application of U & G theory in the context of virtual communities suggested that those four types of benefits could be found while specific benefits might vary from context to context [48]. Therefore, the U & G theory could be applied to the setting of value co-creation behavior in learning communities.

2.4. *Value co-creation behavior*

Cooperative learning was defined as small group activities that students strived for themselves and their peers to reach the highest levels of learning [50]. Cooperative learning, therefore, had a nature of value co-creation.

Value co-creation behavior included customer participation behavior and customer citizenship behavior [51–53]. The in-role nature of customer participation behavior was a necessary component to reach a successful value co-creation. In contrast, the extra-role nature of customer citizenship behavior was voluntary, and it made an extraordinary contribution to value co-creation. Empirical studies identified different antecedents and consequences in customer participation and citizenship behavior [51–53].

According to Yi and Gong [52], information seeking, information sharing, responsible behavior, and personal interaction were significant components in customer participation behavior. Feedback, advocacy, helping, and tolerance were essential in customer citizenship behavior. The researchers also developed and validated a scale for these constructs. Since the scale was developed in the context of physical service encounters, this study modifies the relevant constructs to suit the learning background and is described below.

2.4.1. Participation behavior

The first dimension of customer participation behavior is information seeking, defined by Johnson [54] as the purposeful access to information from selected information carriers. In pursuance of Yi and Gong [52], information seeking had two primary purposes. First, it would reduce customer uncertainty and better understand and control the co-creation environment. Second, it enhanced the ability of customers to play an adequate role in the value co-creation process. Customers could seek information by directly asking or observing the behaviors of other knowledgeable or experienced stakeholders.

The responsible behavior, identified by Ennew and Binks [55], was the second dimension of customer participation behavior. This dimension reflected the core nature of the value co-creation process, where all parties had their duties and responsibilities.

The third dimension of customer participation behavior was personal interaction [55]. It referred to the interpersonal relationship between the customer and the service employees [52].

2.4.2. Citizenship behavior

The first dimension of customer citizenship behavior was knowledge sharing, including experience, values, contextual information, and insights acquired through experience [56]. Because knowledge created personal differentiated advantage, it was against human nature to share it with others. Therefore, knowledge sharing was considered as a silent citizenship behavior.

The second dimension of customer citizenship behavior was advocacy. Advocacy, also called word-of-mouth, referred to the oral or written recommendation of the goods or service offered by satisfied customers to their friends or relatives the good or service [57]. Advocacy was extra-role in nature because it was a spontaneous behavior. Any external force or solicitation did not guide it.

The third dimension of customer citizenship behavior was helping. Helping was voluntary, and it was the behavior purposed to support other customers [52]. Following Rosenbaum and Massiah [58], customers would extend their empathy to other customers in the process of helping.

The fourth dimension of customer citizenship behavior was continuance intention. Since most people established virtual communities spontaneously and voluntarily, the continuance intention of the virtual community member was extra-role and voluntary. These voluntary virtual members were often willing to maintain the emotional bond to the virtual community, like holding the membership [59].

3. Methodology

3.1. Research model

The research model in this study is based on the S-O-R framework, which relates to the system viewpoint of Input-Process-Output. First, because e-learning includes both synchronous and asynchronous studies, learner's self-directed learning is essential for learning performance. Consequently, the motivation of SDL plays the role of a stimulus. Second, in Nambisan and Baron's [48] study on the value co-creation activities in voluntary virtual customer environments, they recognized that perceived benefits mediate the relationship between customer interaction characteristics and customer participation in value co-creation. Next, in line with Nambisan and Baron's [46] findings, this study regards perceived benefits from U & G theory as an organism. The desired value co-creation behavior, including both participation behavior and citizenship behavior, is considered a response. The current research framework is illustrated in Figure 1.

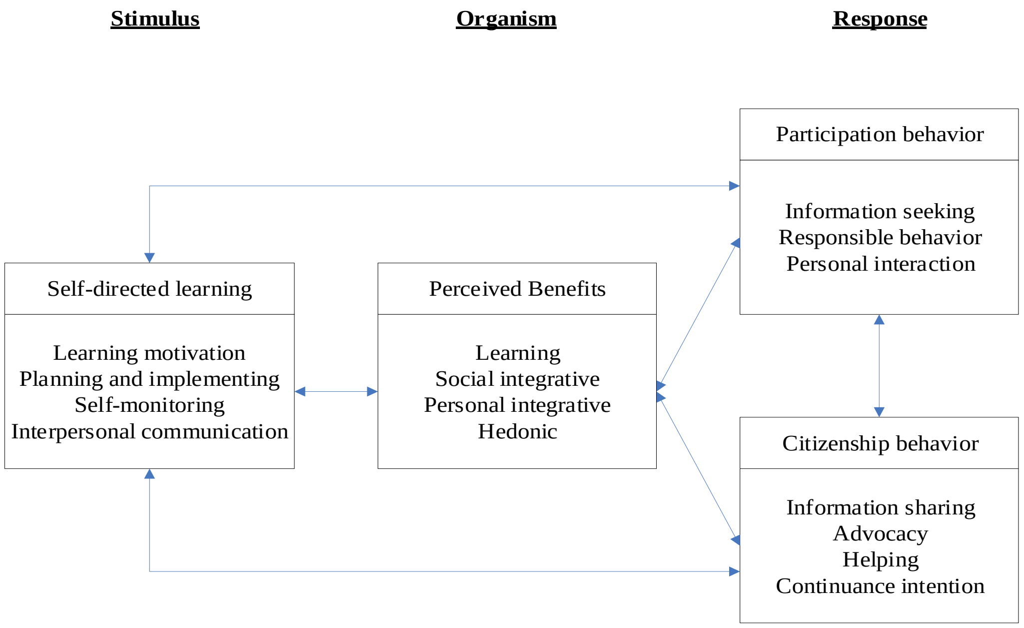

Figure 1. Research framework.

The MCDM technique was adopted to explore the dynamic interrelationships among all the factors in this framework without prior hypotheses. Therefore, double-headed arrows are used in the current research procedure as in Figure 2.

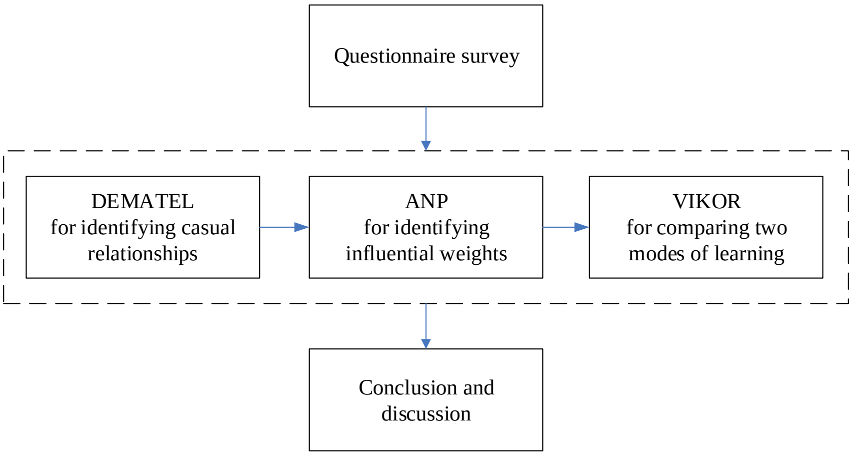

Figure 2. Research procedure.

3.2. Measurement

3.2.1. Survey dimensions and criteria

Based on the established research framework, this study presented explanatory items in the questionnaire referenced from the extant literature review to ensure respondents understand the exact meaning of survey constructs. Descriptive items of primary criteria are summarized as follows Table 1, Table 2 and Table 3.

Table 1. Criteria and explanatory items of (A) self-directed learning.

(a1) Learning motivation 1. I know what I need to learn. 2. Regardless of the performance of my learning, I still like learning. 3. I strongly desire to improve and excel in my learning constantly. 4. Whether successful or not, I am inspired to continue learning. 5. I enjoy finding solutions to problems. 6. I will not give up learning even I face some difficulties.
(a2) Planning and implementing 1. I can actively establish my learning goals. 2. I know what learning strategies are appropriate for me in reaching my learning goals. 3. I set the priorities of my learning. 4. Whether in practice, lecture, or self-study, I can follow my learning plan. 5. I am good at arranging and controlling my learning schedule. 6. I know how to find resources for my learning.

(a3) Self-monitoring 1. I can apply new knowledge to my personal experiences. 2. I understand the strengths and weaknesses of my learning. 3. I can monitor my learning progress. 4. I can evaluate my learning outcomes.
(a4) Interpersonal communication 1. My interaction with others helps me plan for further learning. 2. I would like to know better those with whom I frequently interact. 3. I can express messages effectively in oral presentations. 4. I can communicate messages effectively in writing.

Source: [31]

Table 2. Criteria and explanatory items of (B) Perceived Benefits.

(b1) Learning 1. Participating in the learning community enhances my knowledge of the subject. 2. Participating in the learning community solves my problems in the learning domain. 3. Participating in the learning community enhances my knowledge about advanced issues in the learning domain.
(b2) Social integrative 1. Participating in the learning community expands my social network. 2. Participating in the learning community enhances the strength of my affiliation with the community. 3. Participating in the learning community enhance my sense of belongingness with the community.
(b3) Personal integrative 1. Participating in the learning community enhances my reputation as an expert in the learning domain. 2. Participating in the learning community reinforce my credibility/authority in the learning domain. 3. Participating in the learning community derives satisfaction from influencing others in the community. 4. Participating in the learning community derive satisfaction from influencing learning progress.
(b4) Hedonic 1. Participating in the learning community spends some enjoyable and relaxing time. 2. Participating in the learning community derives fun and pleasure. 3. Participating in the learning community entertains and stimulates my mind. 4. Participating in the learning community derives enjoyment from problem solving, idea generation, etc.

Source: [46]

Table 3. Criteria and explanatory items of (C) Participation Behavior and (D) Citizenship Behavior.

(c1) Information seeking 1. I have asked others for information on the knowledge of the learning field. 2. I have searched for information on the knowledge of the learning field. 3. I have paid attention to how others behave in this community.
(c2) Responsible behavior 1. I performed all the required tasks in this community. 2. I adequately completed all the expected behaviors in this community. 3. I fulfilled responsibilities to this community. 4. I followed the directives of this community.
(c3) Personal interaction 1. I was friendly to members of this community. 2. I was kind to members of this community. 3. I was polite to members of this community. 4. I was courteous to members of this community. 5. I didn't act rudely to members of this community.
(d1) Knowledge sharing 1. I will share my knowledge of the learning field with other members more frequently in the future. 2. I intend to share my knowledge of the learning field with other members more frequently in the future. 3. I try to share my expertise in the learning field with other members more effectively.
(d2) Advocacy 1. I said positive things about this community to others. 2. I recommended this community to others. 3. I encouraged others to participate in this community.
(d3) Helping 1. I assist other members if they need my help. 2. I help other members if they seem to have problems. 3. I teach other members knowledge of the learning field. 4. I advise other members.
(d4) Continuance intention 1. It would be tough for me to leave this community. 2. I am willing to pay more time and effort to this community than to other communities. 3. I intend to stay on a member of this community.

Source: [53, 60]

3.2.2. Research sample

The sample of this study is the master's students at a university in the central part of Taiwan. They are the students in the course of Strategic Information Systems (SIS). SIS is a capstone course in management information systems, which emphasizes ICT applications to create sustainable competitiveness. In this course, extensive discussion of scenario-orientated cases of ICT application is a significant feature. Team-based practices and presentations are conducted every week so that students have to join the teams and do the tasks.

The instructor adopts the same course materials in two successive semesters. The teaching model in the first semester was majorly conventional. In contrast, the teaching model in the second semester was e-learning in essence. The e-learning activities include two hours of asynchronous online studying and one hour of synchronous case presentation and discussion. In these two different teaching scenarios, different dynamics of value co-creation can be observed, which is why the students in this course are recruited for research purposes.

3.2.3. Questionnaire design

The survey questionnaire is divided into three parts. The first part is to collect the demographic information of the respondents. The second part explains the major constructs of this questionnaire. The third part is a comprehensive pairwise comparison of the constructs. Table 4 is an example of the questionnaire. The first step is to decide the relationship of the constructs; the second step is to determine the degree of influence, which has five levels, from 0 to 4. The level of 0 represents no impact at all. Level 1 and 2 represents a low and medium impact. Level 3 and 4 stands for high and very high impact. The questionnaire is given to the respondents by the researcher in person. The researcher would like to ensure that all the respondents understand the constructs and the questionnaire's content.

Table 4. Questionnaire response example.

Construct 1	Construct 2	Relationship of the constructs	→ Degree of influence	← Degree of influence
X1	Y1	× → ← ↔	1 2 3 4	1 2 3 4
	Y2	× → ← ↔	1 2 3 4	1 2 3 4

Table 4 indicates that construct X1 is affected by construct Y1, and the degree of influence is 2; X1 and Y2 affect each other, X1 has a level-3 effect on Y2, and Y2 also has a level-4 effect on X1.

3.3. Data analysis method

Under the context of cooperative learning, the required ambidexterity processes of value co-creation among participating members are complicated and dynamic for exploring and exploiting knowledge. Consequently, applying multiple criteria decision-making (MCDM) techniques with features without prior hypotheses of decision elements is appropriate. Specifically, DEMATEL identifies the cause-effect relationships among major dimensions and criteria, represented as impact relationship maps (IRM). Besides, ANP investigates the influential weights of all criteria. Last, VIKOR compares criteria performance under different learning contexts. The specific procedure of these tools is shown in the Figure 3.

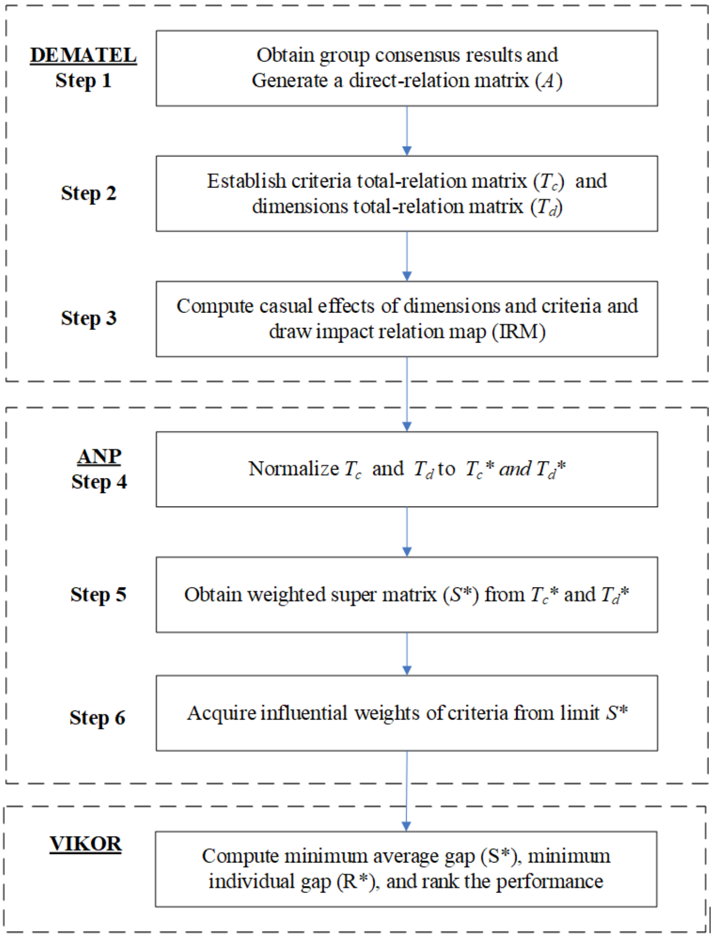

Figure 3. Procedure of MCDM techniques.

3.3.1. Determining the causal effects by DEMATEL

The steps for determining a causal effect using the DEMATEL technique (steps 1–3) are provided as follows.

Step 1: Generate the initial direct-relation matrix.

Assess the direct influence between pairs of elements from a committee of domain experts. The pairwise comparisons specify five levels, from 0 to 4: no influence, very low influence, low influence, strong influence, and very strong influence, respectively. The initial direct-relation matrix A is a $n \times n$ matrix, in which a_{ij} is denoted as the degree to which the element i affects the element j, i.e., $A = [a_{ij}]_{n \times n}$.

Step 2: Normalized the initial relation matrix to obtain total-relation matrixes.

The normalized direct-relation matrix $X = [x_{ij}]$ can be obtained through Eq. (1).and (2).

$$s = max_{ij}\left[\max_{1\le i\le n}\sum_{j=1}^{n} a_{ij}, \max_{1\le j\le n}\sum_{i=1}^{n} a_{ij}\right] \tag{1}$$

$$X = \frac{1}{s}A \tag{2}$$

Where Eq. (1) represents the maximum values out of the sums of all the rows and columns. Eq. (2) illustrates the normalized initial direct-relation matrix. All elements in matrix X comply with $0 \le x_{ij} \le 1$, and all principal diagonal elements are equal to 0. The total relation matrix, T, can be obtained by using the following calculation:

$$T = X + X^2 + \cdots + X^p = X \times (I - X)^{-1} = \left[X_{ij}\right]_{n\times n}, p \to \infty \tag{3}$$

$$T = \left[t_{ij}\right]_{n\times n}, i, j = 1,2, \dots, n \tag{4}$$

I is the identity matrix, and p represents the power. Hence when p is close to infinity, the matrix X will converge. The total relation matrix produced through the DEMATEL approach is based on the comparisons among criteria; therefore, it can be renamed as criteria total relation matrix $\left(T_c = [T_c^{ij}]_{n\times n}\right)$, as shown in Eq. (5), with m dimensions and $n_1\ to\ n_m$ criteria each. D_m refers to the m_{th} dimension; C_{nm} represents the m_{th} criteria in the n_{th} dimension; and T_c^{ij} is the principal eigenvector of the influences of the elements in the i_{th} dimension, as compared to the i_{th} dimension.

$$T_c = \begin{array}{ccc} & & \begin{array}{ccccc} D_1 & \cdots & D_j & \cdots & D_m \\ C_{11}\cdots C_{1n_1} & & C_{j1}\cdots C_{jn_j} & & C_{m1}\cdots C_{mn_m} \end{array} \\ \begin{array}{c} D_1 \\ \vdots \\ D_i \\ \vdots \\ D_m \end{array} & \begin{array}{c} C_{11}\\ C_{12}\\ \vdots \\ C_{1n_1} \\ \vdots \\ C_{i1}\\ C_{i2}\\ \vdots\\ C_{im_i}\\ \vdots\\ C_{m1}\\ C_{m2}\\ \vdots\\ C_{mn_m}\end{array} & \begin{bmatrix} T_c^{11} & \cdots & T_c^{1j} & \cdots & T_c^{1m} \\ \vdots & & \vdots & & \vdots \\ T_c^{i1} & \cdots & T_c^{ij} & \cdots & T_c^{im} \\ \vdots & & \vdots & & \vdots \\ T_c^{m1} & \cdots & T_c^{mj} & \cdots & T_c^{mm} \end{bmatrix} \end{array} \tag{5}$$

Based on T_c, the dimensions total relation matrix T_d can be generated from the total criteria matrix by Eq. (6), where t_d^{ij} is the average of elements of the matrix T_c^{ij}.

$$T_d = \begin{bmatrix} t_d^{11} & \cdots & t_d^{1j} & \cdots & t_d^{1m} \\ \vdots & & \vdots & & \vdots \\ t_d^{i1} & \cdots & t_d^{ij} & \cdots & t_d^{im} \\ \vdots & & \vdots & & \vdots \\ t_d^{m1} & \cdots & t_d^{mj} & \cdots & t_d^{mm} \end{bmatrix} \tag{6}$$

Step 3: Produce the impact relation map.

The impact relation map (IRM) of T_c and T_d is established via the vectors r, s, and the sums in rows and in columns, respectively. It is calculated in Eq. (7):

$$r = [r_i]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \tag{7}$$

$$s = [s_j]_{n\times 1} = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1\times n} \tag{8}$$

where r_i stands for the sum of the i_{th} row and it represents the entire influence of criteria/dimensions on other criteria/dimensions. Besides, s_j refers to the sum of the i_{th} column of the matrix Tc / Td, which is the total impact that criteria/dimension j receives from another criteria/dimensions.

The impact relation map (IRM) can be constructed by mapping the dataset of the $(r_i + s_j, r_i - s_j)$. The horizontal axis vector $(r_i + s_j)$ named "Prominence" is made by adding r_i to s_j, which shows the importance of the element. Similarly, the vertical axis $(r_i - s_j)$ named "Relation" is made by subtracting r_i from s_j. Generally, when $(r_i - s_j)$ is positive, the element belongs to the cause group, otherwise, the element belongs to the effect group [61].

3.3.2. Identifying influential weights by ANP

The Analytic Network Process (ANP) established by Saaty [62], was a generalization of the Analytic Hierarchy Process (AHP) to interpret complicated feedback structure that was evaluating the dependence between the elements of the hierarchy, which involves the interaction and dependence between higher-level and lower-level elements in the hierarchy. Therefore, ANP was usually represented by a network rather than a hierarchy.

Based on the criteria total relation matrix and dimensions total relation matrix generated by DEMATEL, the steps to identify influential weights using the ANP technique (steps 4–6) are summarized as follows.

Step 4: Normalize the criteria total relation matrix.

Total criteria relation matrix T_c can be normalized by total degrees of effect and influence of the dimensions to obtain T_c^* as shown in Eq. (9).

$d_{ci}^{11} = \sum_{j=1}^{m_1} t_{ij}^{11}, \quad i = 1.2. \ldots, m_1,$

$$T_{c*}^{11} = \begin{bmatrix} t_{c11}^{11}/d_{c1}^{11} & \cdots & t_{c1j}^{11}/d_{c1}^{11} & \cdots & t_{c1n_1}^{11}/d_{c1}^{11} \\ \vdots & & & & \vdots \\ t_{ci1}^{11}/d_{ci}^{11} & \cdots & t_{cij}^{11}/d_{ci}^{11} & \cdots & t_{cin_1}^{11}/d_{ci}^{11} \\ \vdots & & & & \vdots \\ t_{cn_11}^{11}/d_{cn_1}^{11} & \cdots & t_{cn_1j}^{11}/d_{cn_1}^{11} & \cdots & t_{cn_1n_1}^{11}/d_{cn_1}^{11} \end{bmatrix} =$$

$$\begin{bmatrix} t_{c11*}^{11} & \cdots & t_{c1j*}^{11} & \cdots & t_{c1n_1*}^{11} \\ \vdots & & & & \vdots \\ t_{ci1*}^{11} & \cdots & t_{cij*}^{11} & \cdots & t_{cin_1*}^{11} \\ \vdots & & & & \vdots \\ t_{cn_11*}^{11} & \cdots & t_{cn_11*}^{11} & \cdots & t_{cn_1n_1*}^{11} \end{bmatrix}$$

and

$$T_c^* = \begin{bmatrix} T_{c*}^{11} & \cdots & T_{c*}^{1j} & \cdots & T_{c*}^{1m} \\ \vdots & & \vdots & & \vdots \\ T_{c*}^{i1} & \cdots & T_{c*}^{ij} & \cdots & T_{c*}^{im} \\ \vdots & & \vdots & & \vdots \\ T_{c*}^{m1} & \cdots & T_{c*}^{mj} & \cdots & T_{c*}^{mm} \end{bmatrix} \tag{9}$$

Step 5: Normalize the dimensions total relation matrix.

The dimensions total relation matrix T_d can be normalized by Eq. (10) to obtain T_d^* representing the weights of dimensions.

$t_d^i = \sum_{j=1}^{m} t_d^{ij}$,

$$T_d^* = \begin{bmatrix} t_d^{11}/t_d^1 & \cdots & t_d^{1j}/t_d^1 & \cdots & t_d^{1m}/t_d^1 \\ \vdots & & \vdots & & \vdots \\ t_d^{i1}/t_d^i & \cdots & t_d^{ij}/t_d^i & \cdots & t_d^{im}/t_d^i \\ \vdots & & \vdots & & \vdots \\ t_d^{m1}/t_d^m & \cdots & t_d^{mj}/t_d^m & \cdots & t_d^{mm}/t_d^m \end{bmatrix} = \begin{bmatrix} T_{d*}^{11} & \cdots & T_{d*}^{1j} & \cdots & T_{d*}^{1m} \\ \vdots & & \vdots & & \vdots \\ T_{d*}^{i1} & \cdots & T_{d*}^{ij} & \cdots & T_{d*}^{im} \\ \vdots & & \vdots & & \vdots \\ T_{d*}^{m1} & \cdots & T_{d*}^{mj} & \cdots & T_{d*}^{mm} \end{bmatrix} \tag{10}$$

Step 6: Build the weighted super-matrix and obtain influential weights of elements.

Multiplying normalized total criteria relation matrix (T_{c*}) with normalized total dimensions relation matrix (T_{d*}) will make the original weighted super-matrix S as shown in Eq. (11).

$$S = \begin{bmatrix} T_{c*}^{11} \times T_{d*}^{11} & \cdots & T_{c*}^{1j} \times T_{d*}^{1j} & \cdots & T_{c*}^{1m} \times T_{d*}^{1m} \\ \vdots & & \vdots & & \vdots \\ T_{c*}^{i1} \times T_{d*}^{i1} & \cdots & T_{c*}^{ij} \times T_{d}^{ij} & \cdots & T_{c*}^{im} \times T_{d*}^{im} \\ \vdots & & \vdots & & \vdots \\ T_{c*}^{m1} \times T_{d*}^{m1} & \cdots & T_{c*}^{mj} \times T_{d*}^{mj} & \cdots & T_{c*}^{mm} \times T_{d*}^{mm} \end{bmatrix} \tag{11}$$

S is further transposed to a column-stochastic super-matrix S^*, as shown in Eq. (12).

$$S^* = \begin{bmatrix} T_{c*}^{11} \times T_{d*}^{11} & \cdots & T_{c*}^{i1} \times T_{d*}^{i1} & \cdots & T_{c*}^{m1} \times T_{d*}^{m1} \\ \vdots & & \vdots & & \vdots \\ T_{c*}^{1j} \times T_{d*}^{1j} & \cdots & T_{c*}^{ij} \times T_{d}^{ij} & \cdots & T_{c*}^{mj} \times T_{d*}^{mj} \\ \vdots & & \vdots & & \vdots \\ T_{c*}^{1m} \times T_{d*}^{1m} & \cdots & T_{c*}^{im} \times T_{d*}^{im} & \cdots & T_{c*}^{mm} \times T_{d*}^{mm} \end{bmatrix} \tag{12}$$

Limit the weighted super-matrix S^* by raising it to a sufficiently large power φ (i.e., $\lim_{\varphi\to\infty} (S^*)^{\varphi}$) until it converges, and it becomes a permanent, stable super-matrix. Then the final global priority matrix (i.e.,$W = [W_1, \cdots W_j, \cdots W_n]$) will define the influential weights among criteria.

3.3.3. Comparing performance by VIKOR method

The VIKOR method was a decision-making method where compromises between conflicting criteria were evaluated using the Lp-metric form [63,64]. VIKOR was further developed into a multi-criteria decision-making tool. It was capable of compromising ranking to maximize group utility and minimize individual regret of the objection.

The VIKOR method was conducted in the following steps:

Step 1. Find the normalized gap by determining the best value (X^*) and worst value (X^-) of all criteria. The following equations can be used to do the calculation.

$$X_j^* = \left\{ \left(\max_i x_{ij} \middle| j \in B \right), \ \left(\min_i x_{ij} \middle| j \in C \right), \ \ j = 1,2, \ldots, n \right\} \tag{13}$$

$$X_j^- = \left\{ \left(\min_i x_{ij} \middle| j \in B \right), \ \left(\max_i x_{ij} \middle| j \in C \right), \ \ j = 1,2, \ldots, n \right\} \tag{14}$$

B and C represent benefit and cost criteria, respectively. Then the normalized gap to the best value can be computed in Eq. (15).

$$Y_j = \frac{(X_j^* - x_{ij})}{(X_j^* - X_j^-)} \tag{15}$$

Step 2. Compute the distance to the best values S_i and R_i using the relations

$$S_i = \sum_{j=1}^{m} w_j \frac{(X_j^* - x_{ij})}{(X_j^* - X_j^-)} \tag{16}$$

$$R_i = \max_j \left[w_j \frac{(x_j^* - x_{ij})}{(x_j^* - x_j^-)} \right] \quad (17)$$

Step 3. Compute the index values Q_i using the relation

$$Q_i = \nu \frac{(S_i - S^*)}{(S^- - S^*)} + (1 - \nu) \frac{(R_i - R^*)}{(R^- - R^*)} \quad (18)$$

where $S^* = \min_i S_i$, $S^- = \max_i S_i$, $R^* = \min_i R_i$, $R^- = \max_i R_i$. Additionally, ν is a weight value for the strategy of maximum group utility, whereas $1-\nu$ is the weight of an individual regret. Thus, if $\nu < 0.5$, group utility is emphasized; generally, ν will be set to 0.5, representing a balanced view.

Step 4. Rearrange the alternatives by their Q values; generally, the lower the Q, the better the alternative will be. Nevertheless, to have the best compromise solution the following two conditions should be fulfilled: suppose A(1) is the best, and A(2) is second best in the ranking list according to Q. Then the first condition (C1) will be "acceptable advantage": Q(A(2)) – Q(A(1)) >= DQ where DQ = 1/(J-1), J is the number of alternatives. The second condition (C2) is "acceptable stability in decision making," in which the alternative A(1) must also have the highest ranking by S or/and R. If one of the conditions is not satisfied, then a set of compromise solutions will be proposed. It will consist of Alternatives A(1) and A(2), if only the condition C2 is not satisfied, or - Alternatives A(1), A(2),..., A(M) if the condition C1 is not satisfied; A(M) is determined by the relation Q(A(M)) – Q(A(1)) < DQ for maximum M.

4. Results

4.1. Sample size and group consensus

This study took the suggestions of Chiu, Tzeng, and Li [66] and selected the appropriate sample size in the following. Errors of gap ratio (EGR) = $\frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{i=1}^{n} \frac{\left| a_{ij}^{p} - a_{ij}^{p-1} \right|}{a_{ij}^{p}} \times 100\%$, where p denotes the number of samples and a_{ij}^{p} is the average influence of i criteria on j; the number of gap ratio elements is n (n-1). When EGR is α, the significant confidence will be $(1-\alpha)$. In general, when α is less than 5%, we will have a confidence level of more than 95% to claim that there is no significant difference between the evaluation of sample size p and p-1. Therefore, it is reasonable to assume that the sample size p is significantly close to information saturation, and it is qualified to be an appropriate size.

This study recruited 19 students (with EGR = 4.76%) in the conventional learning context and 18 students (with EGR = 4.29%) in the e-learning context by applying the saturation principle. The demographics of the sample profile is summarized in Table 5.

Table 5. Demographics of participants.

Measure	Item	Conventional learning context		E-learning context	
		Count	%	Count	%
Gender	Male	14	73.68	13	72.22
	Female	5	26.32	5	27.78
Age	Less than 20	1	5.26	0	0.00
	20 to 30	18	94.74	18	100.00
Average time spent in learning communities daily	30 minutes and less	9	47.37	6	33.33
	Around 1 hour	5	26.32	7	38.89
	Around 2 hours	2	10.53	1	5.56
	3 hours and greater	3	15.79	4	22.22

4.2. Results of causal effects

This study summarized r_i and s_j and related these two values to two different learning contexts to determine the causal effects of dimensions and criteria. The calculation of the DEMATEL matrix was applied. The results of the calculation were shown in Table 6.

Table 6. Causal effects of different learning contexts.

	Conventional learning context				E-learning context			
	r_i	s_j	r_i+s_j	r_i-s_j	r_i	s_j	r_i+s_j	r_i-s_j
(A) Self-directed learning	0.586	0.408	0.994	0.178	0.731	0.531	1.262	0.200
(a1) Learning motivation	0.520	0.414	0.935	0.106	0.671	0.565	1.236	0.106
(a2) Planning and implementing	0.420	0.483	0.903	-0.064	0.573	0.659	1.232	-0.086
(a3) Self-monitoring	0.392	0.464	0.856	-0.072	0.506	0.508	1.014	-0.003
(a4) Interpersonal communication	0.493	0.464	0.957	0.030	0.545	0.563	1.107	-0.018
(B) Perceived benefits	0.542	0.562	1.104	-0.020	0.679	0.737	1.416	-0.057
(b1) Learning	0.555	0.615	1.169	-0.060	0.851	0.744	1.595	0.107
(b2) Social integrative	0.583	0.507	1.090	0.076	0.738	0.759	1.497	-0.021
(b3) Personal integrative	0.525	0.575	1.100	-0.050	0.669	0.759	1.428	-0.089
(b4) Hedonic	0.587	0.554	1.141	0.033	0.747	0.743	1.490	0.004
(C) Participation behavior	0.445	0.442	0.887	0.003	0.552	0.532	1.084	0.019
(c1) Information seeking	0.230	0.286	0.516	-0.056	0.293	0.293	0.586	0.000
(c2) Responsible behavior	0.245	0.252	0.498	-0.007	0.309	0.297	0.606	0.012
(c3) Personal interaction	0.294	0.231	0.525	0.063	0.309	0.320	0.629	-0.012
(D) Citizenship behavior	0.464	0.624	1.088	-0.160	0.603	0.766	1.369	-0.163
(d1) Knowledge sharing	0.658	0.585	1.243	0.073	0.800	0.711	1.511	0.089
(d2) Advocacy	0.422	0.373	0.795	0.049	0.587	0.466	1.053	0.121
(d3) Helping	0.640	0.560	1.200	0.079	0.749	0.767	1.516	-0.017
(d4) Continuance intention	0.473	0.674	1.146	-0.201	0.638	0.831	1.469	-0.193

The value of r_i-s_j in DEMATEL computation determined the causal effects. Self-directed learning had the highest value of r_i-s_j value than other dimensions. This result could be represented by Self-directed learning (A) → (Participation behavior (C), Perceived benefits (B), Citizenship behavior (D)). It means that A would affect C, B, and D. This relationship would also imply: C → (B, D) and B → (D). However, for the streamlined presentation, this study only listed the primary relationship of different teaching contexts in Table 7.

Table 7. Causal effects of dimensions and criteria.

Dimensions/Criteria	Conventional learning context	E-learning context
S-O-R dimensions	Self-directed learning → (Participation behavior, Perceived benefits, Citizenship behavior)	Self-directed learning → (Participation behavior, Perceived benefits, Citizenship behavior)
Self-directed learning	Learning motivation → (Interpersonal communication, Planning and implementing, Self-monitoring)	Learning motivation → (Self-motoring, Interpersonal communication, Planning and implementing)
Perceived benefits	Social integrative → (Hedonic, Personal integrative, Learning)	Learning → (Hedonic, Social integrative, Personal integrative)
Participation behavior	Personal interaction → (Responsible behavior, Information seeking)	Responsible behavior → (Information seeking, Personal interaction)
Citizenship behavior	Helping → (Knowledge sharing, Advocacy, Continuance intention)	Advocacy → (Knowledge sharing, Helping, Continuance intention)

Two IRMs of dimensions in two different teaching styles were shown in Figure 4 and Figure 5.

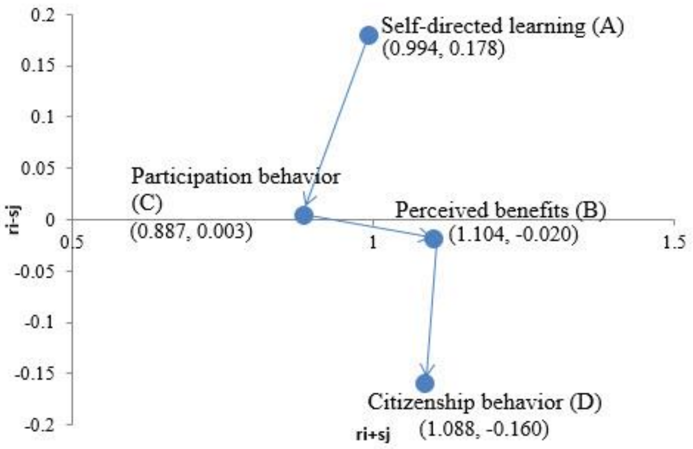

Figure 4. IRM of conventional learning context.

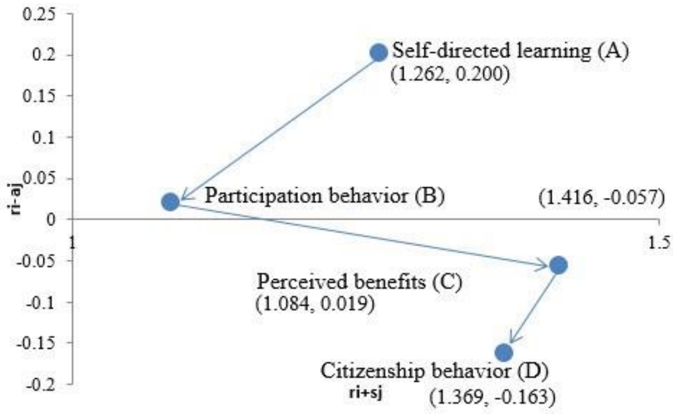

Figure 5. IRM of e-learning context.

4.3. Results of influential weights

After considering the dynamic dependence between a network of criteria as system elements, DANP identified influential weights of criteria in the feedback structure in Table 8.

Table 8. Influential weights of dimensions/criteria.

Dimensions/Criteria	Conventional learning context	E-learning context
(A) Self-directed learning	0.240	0.213
(a1) Learning motivation	0.083	0.052
(a2) Planning and implementing	0.056	0.053
(a3) Self-monitoring	0.046	0.047
(a4) Interpersonal communication	0.055	0.061
(B) Perceived benefits	0.265	0.290
(b1) Learning	0.064	0.082
(b2) Social integrative	0.067	0.068
(b3) Personal integrative	0.061	0.070
(b4) Hedonic	0.073	0.070
(C) Participation behavior	0.167	0.173
(c1) Information seeking	0.055	0.068
(c2) Responsible behavior	0.053	0.056
(c3) Personal interaction	0.059	0.049
(D) Citizenship behavior	0.328	0.323
(d1) Knowledge sharing	0.084	0.087
(d2) Advocacy	0.068	0.053
(d3) Helping	0.083	0.083
(d4) Continuance intention	0.094	0.099

The influential weights of dimensions showed the same pattern for both conventional learning and e-learning contexts. This result could be formulated as (Citizenship behavior → Perceived benefits

→ Self-directed learning → Participation behavior). Moreover, the top 3 weights for conventional learning context could be formulated as (Personal interaction → Learning motivation → Information seeking) and the top three weights for e-learning context could be formulated as (Information seeking → Responsible behavior → Continuance intention.).

4.4. Synthesis of causal effects and influential weights

The results of criteria causal effects and influential weights could be synthesized to delve deeper insights of the relationships among all the criteria. One of the novel ways to do so is to draw causal effects on the Y-axis and influential weights on the X-axis. Then identify the influential patterns of criteria. The influential weights determined by ANP range from 0 to 1. Nevertheless, it was not so for the causal effects. Therefore, this study rescaled and normalized values of r_i-s_j to create a reasonable comparison standard. This study could categorize criteria in the first quadrant as primary driving factors, second as secondary driving factors, third as secondary received factors, and fourth as primary received factors. The influential patterns of conventional learning context and e-learning context were summarized in Table 9 and Table 10.

Table 9. Driving and received factors of conventional learning context.

	Secondary	**Primary**
Driving	(a4) Interpersonal communication	(a1) Learning motivation
	(c3) Personal interaction	(b2) Social integrative
		(b4) Hedonic
		(d1) Knowledge sharing
		(d2) Advocacy
		(d3) Helping
Received	(a2) Planning and implementing	(d4) Continuance intention
	(a3) Self-monitoring	
	(b1) Learning	
	(b3) Personal integrative	
	(c1) Information seeking	
	(c2) Responsible behavior	

4.5. Results of performance ranking

This study used the influential weights measured by the DANP technique. First, through Eq. (13) and Eq. (14), the maximum value was found to be 0.099, and the minimum value was found to be 0.049, respectively. Second, normalized gaps in the influential weights of criteria were computed in Eq. (15). Third, Third, Si and Ri were computed in Eq. (16) and Eq. (17). The results were shown in Table 11.

Table 10. Driving and received factors of e-learning context.

	Secondary	Primary
Driving	(a1) Learning motivation (c2) Responsible behavior (d2) Advocacy	(b1) Learning (b4) Hedonic (c1) Information seeking (d1) Knowledge sharing
Received	(a2) Planning and implementing (a3) Self-monitoring (a4) Interpersonal communication (c3) Personal interaction	(b2) Social integrative (b3) Personal integrative (d3) Helping (d4) Continuance intention

Table 11. Normalized gaps of criteria.

Dimensions	Criteria	Conventional learning context		E-learning context	
		Weights	Gap	Weights	Gap
Self-directed learning	Learning motivation	0.083	0.302	0.052	0.887
	Planning and implementing	0.056	0.811	0.053	0.868
	Self-monitoring	0.046-	1.000	0.047	0.981
	Interpersonal communication	0.055	0.830	0.061	0.717
Perceived benefits	Learning	0.064	0.660	0.082	0.321
	Social integrative	0.067	0.604	0.068	0.585
	Personal integrative	0.061	0.717	0.070	0.547
	Hedonic	0.073	0.491	0.070	0.547
Participation behavior	Information seeking	0.055	0.830	0.068	0.585
	Responsible behavior	0.053	0.868	0.056	0.811
	Personal interaction	0.059	0.755	0.049	0.943
Citizenship behavior	Knowledge sharing	0.084	0.283	0.087	0.226
	Advocacy	0.068	0.585	0.053	0.868
	Helping	0.083	0.302	0.083	0.302
	Continuance intention	0.094	0.094	0.099*	0.000
S			9.132		9.189
R			1.000		0.981
S*=Min Sj	9.132	0.057			
S-=Max Sj	9.189				
R*=Min Sj	0.981	0.019			
R-=Max Sj	1.000				

Next, by identifying the best (minimum) value of S and R and the worst (maximum) value of S and R, the index value Qi could be computed, and the ranking of alternatives could be determined. The results were shown in Table 12.

Table 12. Ranking solutions of conventional learning and e-learning.

	Conventional learning context	E-learning context
Sj	9.132	9.189
Rj	1.000	0.981
Qj	0.500	0.500
Ranking	1	1

The results of performance ranking of conventional learning and e-learning reveal that from the perspective of gaps (or regrets), conventional learning performs better in minimizing average gap (Sj), while e-learning performs better in minimizing individual gap (Rj). Because two kinds of gaps are combined by the parameter ν that is the weight for a minimum average gap, whereas $1-\nu$ is the weight of an individual gap. Generally, ν is set to 0.5, representing a balanced view; therefore, two teaching contexts are evenly matched. Otherwise, if $\nu > 0.5$, it means that group utility (or minimum average gap) is emphasized, and conventional learning is therefore better. In contrast, if $\nu < 0.5$, the minimum individual gap is preferred, and e-learning is consequently leading.

5. Conclusions and discussion

5.1. Theoretical implications

The field of education was currently experiencing rapid changes accompanying the rapid development of ICT. Implementation of e-learning and ICT in the educational setting could allow teachers to upgrade their teaching, creating a new challenge for teachers. In response to this trend, the findings of this study can be described as follows.

5.1.1. Features and contributions of the methodology

This study applies the MCDM techniques: DEMATEL, ANP, and VIKOR to investigate the dynamic causal effects, influential weights, and performance ranking in conventional learning and e-learning. This novel application of methodology offered a valuable complement to the traditional SEM approach. For instance, ANP treated all the criteria as a feedback network structure and explored the causal effects and the influential weights through pairwise comparisons. This method was different from the approach of hypotheses testing, which assumed linear and independent influences. Therefore, this study obtains deeper insights into the issues.

This study also refined the popular MCDM technique in significant ways. First, this study used the saturation principle in qualitative research [65, 66] to ensure the participants' appropriate sample size and group consensus. Second, the results from the MCDM analysis were generally too complicated to interpret. This study creatively applied Northcutt and McCoy's [67] suggestion to establish an uncluttered IRM as a transparent and interpretable theoretical model. Third, this study advanced findings from DEMATEL and ANP by VIKOR [68,69]. Last, this study demonstrated that causal effects and influential weights could be synthesized to provide more helpful decision support by correct data rescale.

From the methodology perspective, this study diverges from similar studies. Nevertheless, the findings of this study converge with similar studies, as illustrated below.

5.1.2. Effects of self-directed learning

Most SDL-related studies focused on developing scales and the relationship between SDL and other important dependent constructs, such as learning performance or satisfaction. For instance, Cheng et al. [31] developed and conducted a preliminary test of a self-rating instrument to measure the self-directed learning ability of nursing students; Hung et al. [18] developed an instrument to measure learners' readiness for online learning and their perceptions; Teo et al. [29] developed and validated a self-directed learning with technology scale (SDLTS) for young students; and Cadorin et al. [70] developed a Self-Rating Scale of Self-Directed Learning (SRSSDL).

In terms of the impact of SDL, Kim et al. [71] leveraged learning analytics to study self-regulated learning (SRL) in asynchronous online courses and concluded that SRL would affect instructional strategies. Besides, Li [72] established a research model to illustrate how self-regulated strategies would affect MOOC learners' perception of learning and satisfaction. Furthermore, Lung-Guang [73] incorporated the theory of planned behavior and the self-regulated plan model and found a significant positive relationship between SRL and TPB in the MOOCs online learning. Last, Song and Hill [74] proposed a conceptual model to interpret the learning activities and learners' satisfaction in an online SDL.

This study was conceptualized according to the S-O-R framework with SDL as a stimulus. It was confirmed that SDL would affect other dimensions. If viewing criteria as a feedback network structure, some criteria in SDL, such as planning and implementing (a2) and self-monitoring (c3) would play the role of received instead of driving factors. This condition would imply that teaching strategies would be required to produce perceived benefits among learners. This finding was consistent with the conclusions of Song and Hill's [74] conceptual model of SDL.

5.1.3. Comparison of causal effects

The overall causal effects in conventional learning and e-learning contexts could be interpreted as Self-directed learning → (Participation behavior, Perceived benefits, Citizenship behavior). This interpretation was different from the original hypothesized research framework. Moreover, the research results showed that learning motivation was the primary driving factor in both the conventional and e-learning contexts for the SDL dimension. For the perceived benefits dimension, the major driving factor of conventional learning context is social integrative compared to learning for e-learning context. Furthermore, the participation behavior in the conventional learning context would start from personal interaction comparing to the responsible behavior in the e-learning context. Finally, the driving factor of citizenship behavior was helping in the conventional learning context, whereas advocacy was the driving factor in the e-learning context. These findings would make sense considering the different nature of conventional learning and e-learning contexts.

5.1.4. Comparison of influential weights

The influential weights of dimensions in conventional learning and e-learning were identified by examining the criteria in the feedback network structure. These results could be interpreted as (Citizenship behavior → Perceived benefits → Self-directed learning → Participation behavior). Citizenship behavior was the influential driving factor among learners. Also, there exist differences in the top 3 influential weights, in the conventional learning context as (Personal interaction → Learning motivation → Information seeking), and the e-learning context as (Information seeking → Responsible behavior → Continuance intention.). These differences were reasonable and reflected the unique nature of two distinct learning contexts.

By synthesizing causal effects and the influential weights, this study also identified some similar features between conventional learning and e-learning context: (1) Hedonic and Knowledge sharing were both the primary driving factors, (2) Planning and implementing, as well as self-monitoring were the secondary received factors, and (3) Continuance intention was the primary received factor.

5.1.5. Comparison of value co-creation performance

Researches on the comparison of conventional learning and e-learning were scant. Therefore, this study utilized VIKOR to investigate the differences between conventional learning and e-learning contexts from value co-creation performance. VIKOR technique was based on the concept of gaps to the ideal value. This technique has two kinds of gaps: minimum average gap (often referred to as group utility) and minimum individual gap. Then a weight (v) is set to decide the preference toward the ends. In general, decision-makers set v to 0.5, representing a balanced view. This study found that conventional learning context performed better in the minimum average gap, and e-learning context performed better in the minimum individual gap. Therefore, both learning contexts were found to be helpful to the learners. However, the conventional learning context would benefit the learners if the minimum average gap was considered the priority. Otherwise, an e-learning context would be more helpful.

5.2. Managerial implications

5.2.1. Promoting self-directed learning

Research findings in this study revealed that SDL would affect value co-creation behavior. It was essential to develop learners' ability to conduct SDL in conventional learning and e-learning. Therefore, instructors should monitor learners' learning motivation, planning and implementing, self-monitoring, and interpersonal communication.

After examining the driving and received factors, some other suggestions could be provided in this study. As learning motivation (a1) was found to be the primary driving factor in the conventional learning context as well as the secondary driving factor in the e-learning context, instructors could emphasize the vision and the different advantages of the course over other alternatives so that learners could maintain their motivation. Furthermore, since interpersonal communication (a4) was found to be the secondary driving factor in the conventional learning context, supplemental tasks, such as group assignments could be used to enhance teamwork and interpersonal communication.

Furthermore, planning and implementing (a2) and self-monitoring (a3) were found to be the secondary received factors in both learning contexts. Having more personal interaction in the conventional learning context could increase the opportunities for learners to use their skills of planning and implementing, as well as self-monitoring. In contrast, in the e-learning context, responsible behavior (c2) and advocacy (d2) were found to be the driving factors for improving these abilities. More emphasis on self-regulated rules could be offered, and learners' responsible behavior would be reinforced.

5.2.2. Emphasizing common primary driving factors

In the context of conventional learning and e-learning, two common primary driving factors were found. It was suggested that instructors pay more attention to them. First, learners tended to prefer lots of hedonic elements in the course., Therefore, instructors could apply some software of learning games, such as Kahoot, and interacting with learners. Through gamification, more hedonic elements would be provided in the learning environment.

Second, knowledge sharing was another important driving factor. Because knowledge was the power for innovation and competitiveness, it was against human nature to share one's knowledge with others. It could be difficult for learners to share their knowledge with their peers. This issue could be discussed from the perspective of social capital to overcome this difficulty. The structural, relational, and cognitive dimensions of social capital should be considered [75]. Therefore, teamwork, benchmarking, and knowledge sharing could be included in the learning environment to foster citizenship behavior.

5.2.3. Customizing efforts in the different learning contexts

In terms of performance ranking in VIKOR, two different learning contexts were equally effective if a balanced view was adopted, but the conclusion could be different if the evaluation were biased. In general, learners in the conventional learning context were found to perform better in all aspects compared with the counterpart. In contrast, e-learning performs slightly better in the exact worst performance of criteria (self-monitoring) of both learning contexts. Since both learning contexts could be effective settings for learners, customized efforts can be offered to enhance final learning performance. For example, the benefits of social integration could be stressed in the conventional learning context, and cognitive benefit could be emphasized in the e-learning context. In addition, self-monitoring was weak and had room for significant improvement; instructors could regularly arrange modular study plans with checkpoints and enhance the self-monitoring abilities of learners.

5.3. Limitations

Although this study has offered some valuable insights, some research limitations still need notice. First, the participants of this study were master's students majoring in Management Information Systems. Thus, the generalizability of this study might be limited. Future research may consider exploring different samples to improve the robustness of current conclusions. Second, e-learning has different contexts, such as web-facilitated and hybrid online learning, which may create different dynamics in the value co-creation behavior. Future research may examine and compare the effects of value co-creation behavior in different learning contexts. Third, though the consensus expert opinions worked well in this study, future research could apply different methodologies, such as a quantitative study with a large sample, in-depth qualitative research, or a longitudinal survey. Last, future research could investigate other aspects of value co-creation behavior, such as social capital, knowledge management, role ambiguity, and so on.

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Conflict of interest

No conflict of interest has been declared by the authors.

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