Received 28 July 2022, accepted 7 September 2022, date of publication 12 September 2022, date of current version 15 September 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3206028

RESEARCH ARTICLE

Teaching Method for Entity–Relationship Models Based on Semantic Network Theory

SHIN-SHING SHIN
Department of Information Science and Management Systems, National Taitung University, Taitung 950, Taiwan
e-mail: shinshing@gmail.com

This work was supported by the Ministry of Science and Technology of Taiwan under Grant 110-2511-H-143-003.

ABSTRACT Students in database courses often have difficulty learning entity–relationship (ER) modeling. According to semantic network theory, learning to construct an ER diagram for a database problem requires complex semantic transformations between the problem and the diagram. Such complex transformation may require excessive mental effort by learners, jeopardizing their learning outcomes. A concept map is a learning tool that incorporates elements of both learning theory and semantic network theory. In this study, concept maps were used to describe the semantic transformation process to increase learner understanding of ER modeling. An empirical experiment was conducted on two database courses (one concept-map-based and one conventional course) to examine the effect of using concept maps on understanding ER modeling according to cognitive load theory. The experimental results revealed that the concept-map-based teaching method was superior to the conventional teaching method because it improved mental efficiency by reducing extraneous load while increasing germane load. Moreover, concept maps can be used as a medium to facilitate communication regarding ER modeling problems between learners and instructors, thereby improving learning efficiency. The results can help educators and researchers understand the effectiveness of concept maps for ER model learning, motivate them to resolve learning difficulties, and encourage them to develop improved teaching methods by using semantic network theory.

INDEX TERMS Entity-relationship models, semantic network theory, concept maps, cognitive load theory, learning.

I. INTRODUCTION

Students in database courses often find learning entity–relationship (ER) modeling to be difficult [1], [2], [3], [4], [5]. Unlike the transformation from an ER model to a relational model, which can be conducted in accordance with mapping rules, the transformation from a database problem to an ER model is open-ended [6]. In ER modeling, a vast gap exists between the problem space and the solution space [7]. The vagueness of this transformation relationship increases the difficulty of learning ER modeling [8]. A better method of presenting this transformation relationship may help bridge this gap and may further serve as a communication tool between learners and instructors and thus increase learning efficiency. Studies have reported that concept maps are a useful tool for graphically representing the cognitive structure of an individual within a problem domain [9], [10], [11]. These considerations raise the question: *Can concept maps be used as a learning tool to enhance learner understanding of ER modeling?*

Many researchers have observed that learning how to describe the data requirements of database problems with ER models is not trivial [12], [13], [14] because the modeling process itself is a complex activity [15], [16], [17], despite the simplicity of the concepts foundational to ER models. Numerous studies have investigated the learning difficulties and the causes of errors committed by learners attempting ER modeling tasks. Topi and Ramesh [18] noted that users, especially novices, frequently commit errors when constructing ER diagrams for database problems. Hall and Gordon [17]

The associate editor coordinating the review of this manuscript and approving it for publication was Meriel Huggard.

indicated that novices find ER modeling tasks difficult and their ER models often have systematic errors. For example, novice designers often confuse entities with attributes [19], seemingly refuting Weber's [20] memory recall experiment that demonstrated that humans view entities and attributes as distinct constructs.

Batra *et al.* [12] noted that novices do not find modeling entities to be challenging but nevertheless have considerable difficulty modeling relationships. Learners often create derived relationships that result in redundant relationship errors [19], [21], eventually leading to unnormalized relational models [22]. Batra and Antony [16] reported that learners typically encounter difficulties when modeling not only unary and ternary relationships but even binary relationships. The difficulty of modeling increases with the degree of relationship [1]. Batra and Davis [23] examined the difficulties encountered by novices by exploring the differences between experts and novices. They observed that novices are hindered by the amount of information used in ER modeling tasks. Database experts can integrate multiple information elements into a cognitive schema and treat them as a single element to reduce intrinsic cognitive load by reducing element interactivity. By contrast, novices cannot fully think through the myriad elements in a textual description of a database problem. Students have difficulty learning if the received information load exceeds the inherent limitations of human cognition [7]. Thus, novices are more susceptible to information overload. A strategy for managing mental effort, such as using concept maps, is required to reduce the load on learner memory.

Numerous tools have been proposed for reducing the difficulty of learning ER modeling, such as EER-Tutor [8], TOOL [13], ERM-VLE [17], COLER [24], ER-Converter [25], ADbC (Animated Database Courseware) [14], CODASYS (COnceptual modeling tool for DAtabase SYStems) [21], ACME (Adaptive Caching with Multiple Experts)-DB [26], OpenMark [27], LabDER [4], LearnER [28], ADVICE [29], and MonstER Park [5]. These tools improve learner understanding of ER modeling by leveraging various features, including immediate feedback during the learning process (e.g., ERM-VLE), student modules that record learning status and provide personalized exercises (e.g., EER-Tutor), correction modules that grade learner answers (e.g., ACME-DB), collaborative learning environments (e.g., COLER), or gamification that motivates learners to engage in learning activities (e.g., MonstER Park). In addition to these features, some tools focus on analyzing the ER modeling process to develop better tools for learning ER modeling (e.g., TOOL) instead of directly evaluating the ER diagrams of or providing feedback to learners. Some tools focus on developing automatic ER diagram generators that can be used in intelligent ER model tutoring systems (e.g., ER-Converter). Some tools force learners to construct the ideal solution for an ER modeling task (e.g., ERM-VLE), whereas others allow learners to submit alternative correct solutions with the same semantics (e.g., EER-Tutor).

A variety of techniques have been used to develop these features, such as natural language processing (NLP) techniques (e.g., TOOL), a heuristics-based approach (e.g., ER-Converter), compiler theory (e.g., LabDER), a knowledge-based approach (e.g., CODASYS), supervised machine learning (e.g., LabDER), and a constraint-based approach (e.g., EER-Tutor). To achieve the usefulness of intelligent tutoring systems for ER modeling, it is necessary to invest a significant amount of time and money in defining heuristic rules, constraints, or knowledge. Artificial intelligence techniques (e.g., data mining [30], [31]) can be used to automatically generate this information.

These studies have promoted research regarding ER model learning. However, learning ER modeling is still difficult for students [1], [2], [3], [4], [5]. These difficulties must be examined and resolved from a broader perspective, such as with semantic network theory. From the perspective of semantic network theory, ER modeling can be considered to be the process of transforming the data semantics of a database problem into an ER model [16], [20], [23]. A complex cognitive process underlies this semantic transformation [16]. For teaching methods for ER models, further emphasizing the semantic transformation process by integrating materials that can represent the process may be necessary. Graphical organizers [32] (e.g., concept maps) based on Ausubel's advance organizer [33] have been recognized as effective for activating previous knowledge and illustrating the semantic relationship between previous knowledge and newly acquired knowledge. Concept maps are widely used in science education [34]. Explicitly representing a semantic transformation by using concept maps may assist learners in diagnosing errors and thus aid them in developing a superior understanding of ER modeling.

The difficulties of learning ER modeling, the lack of methods for expressing the semantic transformation from database problems to ER models, and the characteristics of concept map techniques were the motivating factors for the development of a concept-map-based teaching method for learning ER modeling in this study. Two groups of students, one learning ER modeling in a conventional database course and one in a concept-map-based database course, were compared. At the end of the courses, the learners were asked to perform an ER modeling task. Their mental effort and problem-solving ability were measured to assess the utility of concept maps for increasing student understanding of ER modeling. The factors affecting learner understanding of ER modeling were then analyzed from the perspectives of semantic network theory, cognitive load theory, and communication theory.

This paper is organized as follows. Section 2 presents a brief overview of the difficulties in and tools for learning ER modeling. Section 3 presents relevant theories and hypotheses. Section 4 describes the research methodology. Section 5 reports the results of data analysis. Section 6 discusses the findings and their implications. Section 7 addresses possible threats to validity. Section 8 presents the conclusion.

II. LITERATURE REVIEW OF ER MODEL LEARNING

In this section, previous research on the difficulties of and tools for learning ER modeling is reviewed.

A. DIFFICULTIES OF LEARNING ER MODELING

This section presents a survey of the difficulties in learning ER modeling, errors that novice ER modelers frequently commit, and the leading causes of the errors.

Numerous studies have reported that novices often commit systematic errors in ER modeling tasks. These errors are categorized as syntactical or semantic errors [35]. Syntactical errors violate the notation rules for ER model construction and can be detected and avoided with ER modeling tools. For a semantic error, the ER model is syntactically correct but it does not correctly represent the intended data semantics. Topi and Ramesh [18] reported that the seemingly simple task of modeling identifiers is difficult for novices. Weber [20] conducted a memory recall experiment; the results revealed that humans view entities and attributes as distinct constructs. However, Fessakis *et al.* [19] reported that novice designers often confuse entities and attributes.

Rashkovits and Lavy [1] discussed the difficulty of learning relationship types and indicated that the identification of relationships between entities is a major challenge for novice modelers. Herzberg [36] indicated that the most common semantic errors are related to cardinality constraints. Fessakis *et al.* [19] reported that learners are prone to errors in redundant relationships (relationships that can be derived from other relationships). Batra and Antony [16] observed novices have difficulty determining the degree of a relationship (e.g., binary or ternary) and entity types (e.g., weak or strong entity types) participating in a relationship. Furthermore, these difficulties increase as the degree of relationship increases [16]. Topi and Ramesh [18] reported that identifying and modeling ternary and unary relationships correctly is difficult for novices. Batra and Antony [16] indicated that novices have difficulty modeling not only unary and ternary but also binary relationships. Batra and Davis [23] observed that experts and novices exhibited modeling behavior that was similar for entities, identifiers, descriptors, and binary relationships; somewhat different for ternary relationships; and quite different for modeling unary relationships and categories.

Studies have investigated the underlying causes of novice errors. Batra and Antony [16] demonstrated that the causes of errors include the misapplication of heuristics, the complexity of the modeling task, incomplete knowledge of database design, and a lack of feedback about solutions. Rashkovits and Lavy [1] indicated that reasons for errors include insufficient experience, failure to reflect on solutions, and a lack of immediate feedback. Feedback is key for developing learning motivation and for improving learning outcomes [37]. Batra and Sein [38] reported that feedback can help ER model learners avoid errors when modeling ternary relationships.

Antony and Batra [21] indicated that the most common error in ER modeling is literal translation, where novices literally translate the textual description of a database problem into the ER model but do not reflect on the underlying structure or attempt to propose alternative solutions [16]. The misapplication of heuristics can cause these literal translation errors. For example, a heuristic rule commonly used in ER modeling is as follows: if two entities are related by a transitive verb, then the verb can be transformed into a relationship between the entities. However, indiscriminate use of this heuristic rule can lead to errors. For example, for the requirement "customers buy products," the above heuristic rule suggests that a relationship should be constructed between the "customer" and "product" entity types. However, the correct solution entails creating an entity type "order" and subsequently defining one relationship between the entity types "customer" and "order" and another between the entity types "order" and "product."

Cognitive complexity can lead to ER modeling errors [7]. Information overload is a major source of cognitive complexity [7]. Studies have demonstrated that human cognition can process only seven plus or minus two chunks of information at a time before cognitive overload occurs [39]. In the context of ER modeling, information load is related to the number of entity types and attributes, the interrelations between entity types, and the degree of relationship types. If the information exceeds the limitations of student memory, this information overload increases cognitive complexity and jeopardizes learning outcomes. Cognitive load theory [40] suggests that a material with high element interactivity have a high intrinsic load that inhibits comprehension of the material. Batra and Davis [23] examined the effect of cognitive complexity on ER modeling by exploring the differences between experts and novices engaged in ER modeling tasks. They observed that experts can achieve a holistic understanding of a database problem before developing the ER model. By contrast, novices cannot integrate the information in the problem description and map it into an ER knowledge structure before beginning to develop the ER model. As a result, novices are more susceptible to cognitive complexity, and errors appear in their solutions more frequently. Therefore, this study proposes to reduce cognitive load through concept maps to improve learner understanding of ER modeling.

B. ER MODEL LEARNING TOOLS

Researchers have developed a number of learning tools for ER modeling that use various techniques to improve learner understanding of ER models. This section summarizes 13 ER model learning tools (Table 1). The summary table presents the main features of these tools and their techniques and theories.

These learning tools are superior to conventional pen-and-paper instruction methods. However, learning ER models is still challenging [1], [2], [3], [4], [5]. These learning tools focused on improving ER model learning by developing various features (e.g., immediate feedback, student modules,

TABLE 1. A review of ER model learning tools.

Learning Tool	Main features, techniques, and theories
LearnER [28]	• LearnER uses gamification and feedback to improve learning motivation. • Points are awarded for solving exercises but are deducted when feedback is requested. • Each exercise has a leaderboard showing student rankings.
TOOL [13]	• A multimodal observation approach was developed to identify learning difficulties in ER modelling, commonalities among these difficulties, and methods of overcoming them. • NLP techniques are used to implement process-oriented feedback.
MonstER Park [5]	• MonstER Park makes ER model learning entertaining by incorporating a theme park story. The full story comprises 33 levels and 19 tasks. Each level has a unique storyline.
LabDER [4]	• LabDER can automatically grade learner answers to ER model exercises and provide instant feedback. • Supervised machine learning techniques are used to grade learner answers. • Feedback is provided by comparing learner ER diagrams with the correct solution by using compiler theory and software engineering metrics.
EER-Tutor (i.e. KERMIT) [8]	• EER-Tutor analyzes student answers, highlights incorrect parts, provides error feedback, and collects student learning status during the learning process. • Constraint-based techniques are used to intelligently evaluate learner solutions. • Semantic constraints are used to identify alternative solutions with the same semantics by searching for equivalent ER notation.
OpenMark [27]	• OpenMark can automatically evaluate the correctness of ER diagrams drawn by students. • The marking tool uses NLP techniques to measure the similarity between learner solutions and the correct solution. • NLP techniques are used to identify the minimal meaningful units (MMUs) of learner ER diagrams and combines these MMUs into useful meaningful units to interpret the meaning of the diagrams.
ADVICE [29]	• ADVICE can automatically evaluate student answers and provide feedback. • A verification algorithm was developed to identify which entities or attributes are missing in student answers by comparing the following: 1) the number and name of entity types in an ER diagram; 2) the number, type, and name of attributes in an entity type; and 3) the primary keys, foreign keys, and candidate keys in an entity type.
ADbC [14]	• ADbC uses animations and visualization techniques to support the learning of database concepts, including ER models, mapping ER models to tables, normalization, and denormalization.
ACME-DB [26]	• ACME-DB includes a correction module for assessing student answers and providing feedback. • The tool collects learning information and automatically creates a personalized workbook for each student.
ER-Converter [25]	• ER-Converter uses syntactic and semantic heuristics to semi-automatically transform a database problem into an ER diagram. • Heuristics are used to parse the description of database problems, assign an appropriate part of speech to each word in the description, and finally determine the applicable data modelling elements (such as entities or attributes)
CODASYS [21]	• CODASYS uses procedural data modeling knowledge to prevent knowledge- and rule-based errors occurring in ER modelling by utilizing question dialogues and warning messages. • The knowledge incorporated into CODASYS is based on textbooks, journal articles, and heuristics.
COLER [24]	• COLER is a collaborative learning environment based on sociocognitive conflict theory. • Learners learn to build ER diagrams collaboratively through a chat window; an opinion panel displays teammates' opinions on a problem. • A virtual personal coach is constructed for each student. The coach analyzes their interactions and recommends possible actions for improving these interactions.
ERM-VLE [17]	• Learners learn to build ER diagrams by interacting with rooms in a virtual world through text-based commands. ER diagrams are automatically generated in accordance with the commands. • ERM-VLE provides a collaborative learning environment in which learners can share solutions with each other and ask questions using an internet chat system.

correction modules, collaborative learning environments, and gamification). By contrast, this study focuses on the challenge of cognitive complexity in ER learning. Batra [7] stated that mental aids and visual feedback are two key elements that can reduce the complexity of ER modeling for learners. This study employs concept maps as a mental aid for reducing cognitive complexity and as a visual feedback tool for improving the efficiency of communication between instructors and learners.

III. THEORY AND HYPOTHESIS DEVELOPMENT

A. COGNITIVE LOAD THEORY

Cognitive load theory offers instructional designers a tool for designing teaching methods. Cognitive load theory divides the cognitive load imposed on learners into three types: intrinsic, extraneous, and germane cognitive loads [40], [41], [42]. Intrinsic load refers to the load placed on working memory due to the complexity (element interactivity) of the learning material [43]. If learning materials have high levels of element interactivity, a high intrinsic load is placed on learners [44]. Furthermore, learner intrinsic load is affected by their previous knowledge about the learning material. Intrinsic load is lower for learners with more previous knowledge about the material because these learners can integrate multiple informational elements into a cognitive schema and treat them as a single element. This reduction of the number of elements in the learning material decreases element interactivity and intrinsic load.

Extraneous cognitive load is the load placed on working memory due to the instructional design itself [45]. Teaching methods that require learners to engage in activities irrelevant to schema acquisition have greater extraneous load, and students have more difficulty understanding the material [9], [46]. For example, learners use working memory to search for the information required for learning. If the extraneous load is reduced, learners can devote the freed cognitive capacity to activities that can induce a germane load.

Germane load is the load caused by mental activities relevant to schema acquisition, such as organizing learning materials and relating them to previous knowledge [47]; thus, this load facilitates learning. Instructors can increase germane load by directing students to devote mental resources to learning-related activities [44]. Accordingly, extraneous load and germane load are affected by teaching methods, while intrinsic load is inherent to the learning material. Teaching methods should be designed in accordance with cognitive load theory; specifically, extraneous load should be minimized and germane load should be maximized. In this study, extraneous load and germane load were compared between the groups in the conventional and concept-map-based courses to determine whether concept maps facilitate learning ER modeling.

B. CONCEPT MAPS FOR LEARNING ER MODELS

Semantic network theory proposes that cognitive structures are stored in semantic memory in the form of networks [48]. A concept is stored independently in semantic memory as a node. A semantic relationship between concepts is stored as a link between the nodes [49]. From this perspective, ''meaningful learning'' means that learners can create nodes for newly learned concepts and connect them with known concepts in semantic memory through links [49]. For example, suppose a student is to meaningfully learn the following ER modeling semantic relation: ''A verb in the textual description of database problems can be represented by using a relationship type of ER models.'' Learners must be able to create a node for the ''relationship type'' (newly learned concept) and connect it with the ''verb'' (known concept); thus, the semantic relationship between these concepts is learned. Therefore, from the perspective of semantic network theory, the process of learning ER modeling involves a series of semantic relation constructions. Learning ER modeling can be considered a process of establishing semantic transformation relationships between database problems and ER models in semantic memory. In this context, network representations (e.g., concept maps) are useful for displaying the semantic transformation relationships.

Concept maps were developed by Novak [10] to represent the human cognitive structure. A concept map is a semantic network representation comprising nodes and links. Nodes are labeled with descriptive text (a word or short phrase) to represent the data semantics of concepts. Links are used to specify semantic relationships between nodes, and labels on links are used to describe the meaning of these semantic relationships. Concepts can be linked to express a propositional statement about an object or event in a problem domain (called a semantic unit) [50]. Concept maps comprise interacting semantic units [11]. Research has demonstrated that concept maps improve learning outcomes [34], [51], [52]. Concept maps offer a framework for interpreting information and have been widely applied in different contexts, such as aiding learning by explicitly integrating new and old knowledge [34]; assessing understanding or diagnosing misunderstanding [53]; representing and analyzing decision-making processes [54], [55]; communicating complex ideas [49]; producing mental models of humans [56]; and supporting knowledge elicitation, acquisition, and sharing [10], [57].

Accordingly, this study proposed to integrate concept maps into ER model learning to facilitate learning the process of semantic mapping from a database problem to an ER model. Constructing an ER diagram for a database problem comprises two steps: 1) Learners study the text description of the database problem to form a mental model of the data semantics, and 2) learners create a representation of the mental model by using ER model syntax. Learners iterate between these two steps until the ER diagram for the database problem is completed. The following introduces the integration of concept maps into the ER model learning process.

In Step 1, concept maps are used to represent learners' mental models regarding data semantics. Learners identify objects, associations between these objects, and their features from the textual description of a database problem. They then use concept maps to describe their mental models of the problem semantics. Objects and object features are represented by nodes, whereas associations between objects are represented by links. Features of associations are also represented by nodes. Fig. 1 presents an example of a database problem. To construct an ER diagram (e.g., Fig. 2) for this database problem, the student uses a concept map (e.g., Fig. 3) to represent their mental model about the data semantics. For example, for the requirement ''Members can refund ordered products. Each refund must include a unique refund number, a member, refund time (mm/dd/yyyy hh:mm), the returned products, the returned quantities, the order number to which the returned products belong, and the refund amount,'' the concept map reveals that the learner identifies the node ''Refund'' and its three features (''Refund_Number,'' ''Refund_Time,'' and ''Refund_Amount'') from the database problem. The feature ''Refund_Number'' is conceptualized as a key feature, and the feature ''Refund_Amount'' is the total refunded amount for the returned products. Two links (''must be submitted by only one'' and ''can submit many'') are identified to describe the semantic relationship between the node ''Member'' and the node ''Refund.'' In addition, the node ''Item'' is used to describe the returned products and is related to the node ''Order'' and the node ''Product'' through four links to record the order number of the returned products. The concept map represents the learner's understanding of the data semantics of the database problem.

In Step 2, concept maps are used to represent the semantic mapping relationship from database problems to ER diagrams. Learners map the concept map constructed in Step 1 into an ER diagram. For example, a node of concept maps can be mapped to an entity type or an attribute of ER models. A link of concept maps can be mapped to a relationship type of ER models, and use the (min, max) notation to specify the structural constraints. These numbers mean that each instance of an entity type in a relationship type must participate in at least *min* and at most *max* relationship instances in the relationship type. $Min = 0$ indicates partial participation, whereas $min > 0$ indicates total participation. The semantic mapping can be expressed by adding dotted lines marked as ''be mapped to'' on the concept map constructed in Step 1. For the concept map in Fig. 3, suppose that Fig. 4 was constructed by a learner to represent the semantic mapping from Fig. 3 to the ER diagram (Fig. 2). Fig. 4 reveals that the learner uses the entity type ''Member'' and its six attributes to represent the seven nodes (''Member,'' ''SSN,'' ''Member_ID,'' ''Name,'' ''Address,'' ''Phone_Number,'' and ''Credit_Rating'') of the concept map, where the link ''has key feature'' from the node ''Member'' to the node ''SSN'' is mapped to the key attribute (SSN) of the entity type ''Member.'' The link ''must place at least one or many'' from the node ''Member'' to the node ''Order'' is mapped to the structural constraints (1, N) on the member side of the relationship type ''Places''; thus, each member must place at least one order but can place many orders. Fig. 4 presents how a learner could map his/her understanding of the database problem into ER model notation.

The presentation of learning material has a strong influence on learner understanding of the material. Studies have indicated that graphical organizers (such as concept maps) are an effective technique for representing an individual's cognitive structure for a problem domain [10], [33], [58], [59]. Constructing and studying concept maps can help learners correlate new concepts with their prior knowledge to retain new knowledge [53]. Furthermore, concept maps are useful for communicating complex concepts and diagnosing misunderstandings [49], [53]. Based on the literature review and these arguments, concept maps may be an effective teaching method for learning ER modeling. Therefore, the following hypothesis was proposed in this study:

Hypothesis: Learners who receive concept-map-based teaching gain a clearer understanding of ER models compared with those who receive conventional teaching.

Design an ER diagram to record the details of a product sales system that tracks orders and refunds. After analyzing user needs, the requirements for this database were determined to be as follows:

Each member must be invited by another member to place an order and become a member. Each member can invite many people to become a member. Each member has a unique Social Security number, member identifier, name, phone number, address, and credit rating (coded as 1 for classic level, 2 for gold level, and 3 for platinum level). Each member can place multiple orders with different salespersons to purchase products, and each salesperson can sell products to different members. Each salesperson has a unique employee identifier, name, and gender. Each salesperson can handle a number of orders. Each order has a unique order number (coded as a three-digit serial number 1, 2, 3, … with the date of purchase—for example, 20200505-001), order time (mm/dd/yyyy hh:mm), credit card information (coded as a combination of bank name, card type, card number, and expiry date), and a number of products. Each order is related to a single member who placed the order and to a single salesperson who handled the order. A product has a unique product number, name, and category. Members can refund ordered products. Each refund must include a unique refund number, a member, refund time (mm/dd/yyyy hh:mm), the returned products, the returned quantities, the order number to which the returned products belong, and the refund amount.

FIGURE 1. Example of a database problem.

IV. RESEARCH METHODOLOGY

An empirical experiment was conducted to evaluate the effect of concept maps on learner understanding of ER models. Control and experimental groups participated in courses with a conventional and a concept-map-based teaching method, respectively. The two database courses lasted for 18 weeks, including 1 week each for mid-term and final exams (total 2 weeks), with 3 h of class time per week. Both courses began with an introduction to databases (1 week) and then introduced ER models (2 weeks), relational models (1 week), and ER-to-relational model mapping (1 week). Learners then studied structured query language (4 weeks), relational algebra (1 week), normalization (1 week), storage architectures and indexing structure (1.5 weeks), query optimization (2 weeks), and transaction control and database recovery (1.5 weeks). The concepts taught for ER modeling included entity types, single-valued attributes, multivalued attributes, simple attributes, composite attributes, complex attributes, derived attributes, key attributes, relationship types, recursive relationship types, roles, participation constraints, cardinality ratios, weak entity types, partial keys, relationship types with degree higher than two, and naming conventions.

The two courses were structured such that identical material was taught at an identical pace by the same instructor.

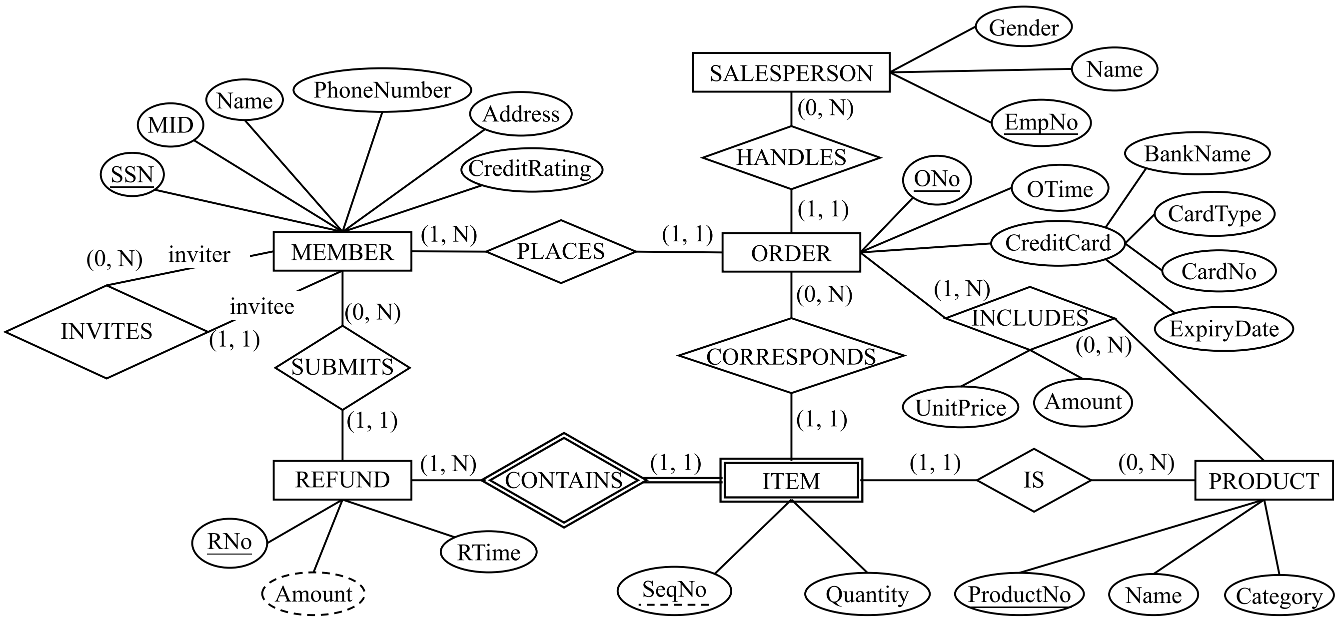

FIGURE 2. ER diagram for the database problem in Fig. 1.

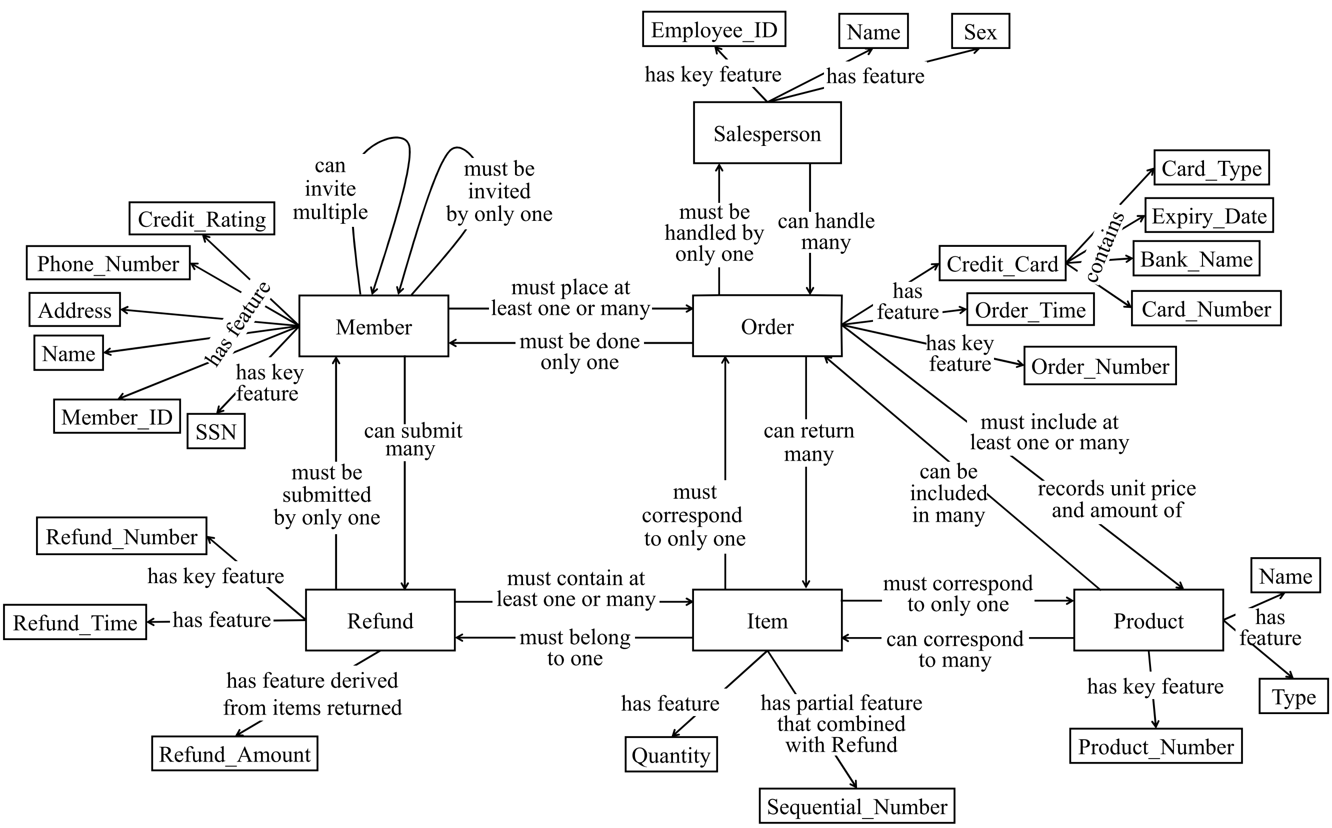

FIGURE 3. Example of a concept map describing the data semantics of the database problem of Fig. 1.

Management information system (MIS) undergraduate students were recruited as participants; 40 students participated in the conventional course, and 45 students participated in the concept-map-based course. The students were all in the same year at the same university. Before the courses began, a pilot test was conducted to investigate the participants' level of prior knowledge of ER models. The results revealed that the two groups were comparable; students in both groups

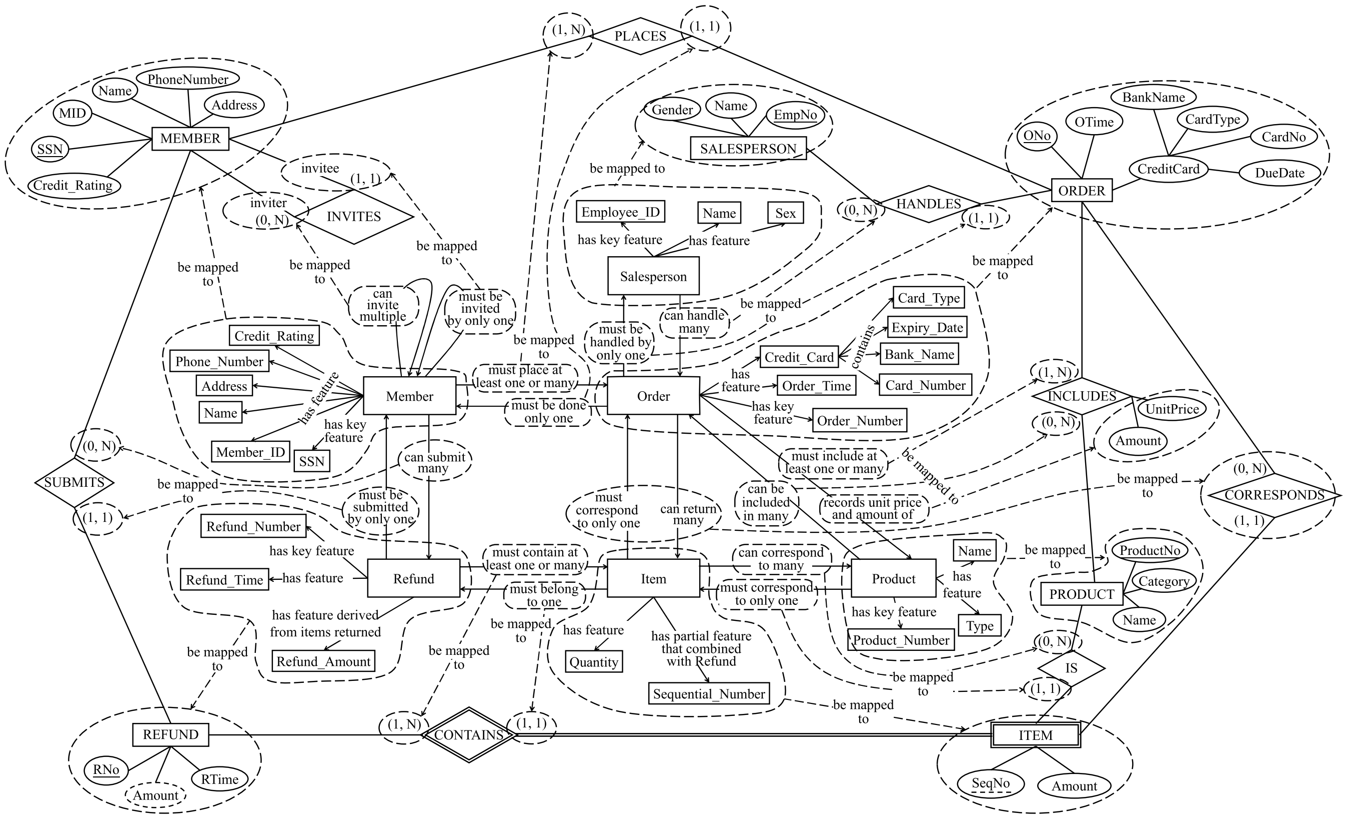

FIGURE 4. A concept map with semantic mapping information.

had no ER modeling knowledge. At the end of both courses, student understanding of ER modeling was measured in and compared between the two groups to assess the effectiveness of using concept maps for learning ER modeling.

A. CONCEPT-MAP-BASED AND CONVENTIONAL TEACHING METHODS

Students in both courses learned the same material; the courses only differed in the teaching method used to learn ER models. The conventional and concept-map-based teaching methods for ER modeling are briefly introduced as follows.

Concept-map-based teaching method: The instructor first taught concept maps and trained learners to use concept maps to express their cognitive structure. After completing the training, the instructor taught ER modeling by instructing learners to construct concept maps for database problems in three phases: 1) The instructor guided learners to analyze database problems and asked them to construct concept maps to describe their understanding of the data semantics of the database problems. The learners then represented the semantic mapping of the database problems to ER diagrams by adding dotted lines marked as "be mapped to" on the concept map. 2) The instructor guided learners to study the instructor's concept map to clarify their misconceptions about ER modeling. 3) If learners had questions about the solutions, the instructor answered the questions by using the concept maps constructed by the learners and instructor.

Conventional teaching method: Instructors verbally explained ER models without using concept maps. For the example database problem (Fig. 1), instructors first introduced the problem and then used its ER diagram (Fig. 2) to explain how each requirement was represented by using ER model notations as follows:

> To construct an ER model for this database problem, we must identify the required entity types, their attributes, and the relationship types between the entity types. The ER diagram of this database problem is presented in Fig. 2.
>
> For the data requirement that each member has a unique Social Security number, member identifier, name, phone number, address, and credit rating (coded as 1 for classic level, 2 for gold level, and 3 for platinum level), we can describe this requirement by using the entity type "Member," which contains six attributes: SSN, MID, Name, PhoneNumber, Address, and CreditRating; here, "SSN" is the key attribute.
>
> Now, we attempt to determine the relationship types between the entity types. The database problem indicates that each salesperson can handle multiple orders. Thus, the relationship type "Handles" is created and marked (0, N) on the salesperson side, assuming that salespeople are allowed to not handle any orders.

The instructor used the same method to explain the other entity types, attributes, and relationship types latent in the database problem in Fig. 2.

B. MEASUREMENTS

Understanding is often used as a dependent variable in research on learning ER modeling [12], [18]. A literature review revealed that understanding is typically measured with the following metrics: recall accuracy, response latency, problem-solving ability, and mental efficiency [44], [45], [60], [61]. Response latency is the time required for processing information before answering a question [60]. Recall accuracy is the percentage of desired information correctly recalled from semantic memory [61]. Problem-solving ability is the ability to apply learned knowledge to solve relevant problems in a new context [45]. Mental efficiency is the efficiency of accessing the cognitive schemas required for problem solving [44]. Recall accuracy and response latency are suitable for measuring surface-level understanding; by contrast, problem-solving ability and mental efficiency are suitable for measuring understanding at a deep level [44], [62].

The author's long-term observations of ER model learning have revealed that most learners can clearly understand the meaning of each ER model notation; however, they find the application of these notations to perform an ER modeling task to be complex and difficult. Learners must gain a deep understanding of the semantic translations from database problems to ER models rather than only a superficial understanding of the meaning of ER model notation. Therefore, measures of mental efficiency and problem-solving ability were used to examine the hypothesis of this study.

Modeling correctness has frequently been used to measure problem-solving ability in research on ER model learning [12], [18]. In most studies, the correctness of a model is defined as the degree to which the model corresponds to a predefined "correct" solution. Batra *et al.* [12] refined the concept of correctness by measuring the correctness of various facets or structural elements of ER models [e.g., entities, identifiers, descriptors, categories, and types of relationships (unary, binary, and ternary)]. The same facet structure was used later by Lee and Choi [63] and by Liao and Palvia [64]. Extending these studies, problem-solving ability was measured in this study by using modeling correctness, which was defined as the extent to which an ER diagram correctly describes the data semantics of a database problem and was expressed as a percentage. Any solution could be correct if it expressed the correct semantics. Modeling correctness was scored using the facet structure developed by Batra *et al.* At the end of the two courses, the participants were asked to perform an ER modeling test to measure their problem-solving ability. The participants' solutions were scored by an MIS professor and a database expert through discussion and review.

This study used Paas and van Merriënboer's [65] computational method (equation 1) to measure mental efficiency; this method has been used in numerous education studies [65]. Problem-solving ability and the mental effort invested to achieve the problem-solving ability are used to measure mental efficiency; the scores for problem-solving ability and mental effort were transformed into standardized z-scores based on the grand mean across teaching methods. A positive efficiency score represents efficient learning because the problem-solving ability is higher than the invested mental effort. Conversely, a negative efficiency score indicates inefficient learning. Mental effort was measured using a 7-point Likert-type subjective rating scale developed by Paas and van Merriënboer [65]; scores ranged from extremely low mental effort (1) to extremely high mental effort (7). Studies have indicated that subjective measures and the index of task difficulty are highly correlated [67]. Furthermore, subjective measures used to assess task difficulty are closely related to objective measures [68]. Subjective measures are considered reliable, valid, and sensitive to small differences in invested mental effort [69].

$$\begin{aligned} &\textit{Mental Efficiency Score} \\ &\quad = \frac{Z_{\textit{Problem-solving Performance}} - Z_{\textit{Mental Effort}}}{\sqrt{2}} \end{aligned} \qquad (1)$$

The mental effort of participants was measured in the learning and testing stages of the courses. In the learning stage, mental effort was measured after the participants had learned ER models in the conventional course; for the concept-map-based course, mental effort was measured twice, once after the participants had built concept maps and once after they had studied the instructor's concept maps. In the test stage, the measurement was performed after the test had been completed. Finally, independent sample t tests on problem-solving ability, mental effort, and mental efficiency were performed to examine the hypothesis.

C. ER MODELING TASK

The ER modeling task is presented in Fig. 1. The participants performed the modeling task at the end of the courses. Participants had 1 h to study the textual description of the database problem and to construct an ER diagram with paper and pencil. To validate the task and the test procedure, two database experts and two MIS professors were recruited. They suggested some modifications to the task material. Ten undergraduates majoring in MIS and who had previously completed the same database course taught by the same instructor were recruited for a pilot test. They were asked to construct an ER diagram for the database task and share their opinions. The results of the pilot test indicated that the task material and test procedure were appropriate for the goals of the study.

V. DATA ANALYSIS AND RESULTS

Table 2 presents independent sample t test results for problem-solving ability and mental effort. In the learning stage, the participants in the concept-map-based course invested higher mental effort when constructing concept maps and lower mental effort when studying the instructor's concept maps than did participants in the conventional course when learning ER modeling. Moreover, the participants in the concept-map-based course had higher problem-solving ability than those in the conventional course. The participants who received the concept-map-based teaching method invested less mental effort in the test stage than those who received the conventional teaching method.

The relative mental efficiency scores of the participants were calculated by using the standardized values (z-scores) of mental effort and problem-solving ability based on the grand mean across teaching methods. Table 3 shows the examination results of the independent sample t test for mental efficiency. The participants in the concept-map-based course had significantly higher mental efficiency than did those in the conventional course; thus, learners receiving concept-map-based teaching understood ER modeling better than did learners receiving conventional teaching.

TABLE 2. **Problem-solving ability and mental effort scores: Mean Scores (Standard deviations) and independent sample *t* test (*p*).**

Dependent Variable	Conventional Teaching Method (n = 40)	Concept-Map-Based Teaching Method (n = 45)		Independent Sample *t* Test (*p*)	
Problem-Solving Ability	0.778 (0.071)	0.867 (0.089)		−5.114*** (0.000)	
Mental Effort		Building concept maps	Studying concept maps	Building concept maps	Studying concept maps
● *Learning stage*	5.225 (1.143)	5.822 (1.154)	3.222 (1.185)	−2.392** (0.019)	7.907*** (0.000)
● *Test stage*	5.325 (1.047)	4.556 (1.391)		2.9** (0.005)	

$^{***}p < .001$

TABLE 3. **Relative mental efficiency: mean scores (Standard deviations) and independent sample *t* test (*p*).**

Conventional Teaching Method (n = 40)	Concept-Map-Based Teaching Method (n = 45)	Independent Sample *t* Test (*p*)
−0.584 (0.277)	0.519 (0.245)	−19.503*** (0.000)

$^{***}p < .001$

VI. DISCUSSION AND IMPLICATIONS

In the following section, the advantages of the concept-map-based teaching method are analyzed in terms of cognitive load theory, semantic network theory, and communication theory.

A. COGNITIVE LOAD THEORY

This section analyzes the advantages of concept maps for ER model learning in terms of two aspects: learning by constructing concept maps and learning by studying concept maps created by an instructor.

1) LEARNING BY CONSTRUCTING CONCEPT MAPS

Cognitive load theory suggests that teaching methods that motivate learners to engage in learning activities can increase germane cognitive load, thereby facilitating learning. In this study, constructing concept maps compels learners to externalize the cognitive process of the semantic transformation from a database problem to an ER model. This motivates learners to participate in ER modeling learning activities and thereby induces a germane load. This argument is consistent with the result in Table 2 that during the learning stage, students exerted more mental effort when building concept maps than did students in the conventional course when learning ER modeling.

Mental effort represents total cognitive load. Changes in intrinsic, extraneous, and germane load can be determined by keeping intrinsic load constant and examining the relationship between mental effort and problem-solving performance [44], [70]. When learners have the same level of previous knowledge about a material, the material imposes the same level of intrinsic load on the learners [44]. The pretest revealed that all participants had the same level of prior knowledge of ER models; thus, they had the same intrinsic load. Therefore, changes in the germane and extrinsic loads of these participants could be determined by examining the relationship between their mental effort and problem-solving ability. Accordingly, the increased mental effort used to construct concept maps should be classified as germane load because the participants in the concept-map-based course performed better on the test task than did those in the conventional course; by contrast, if this mental effort was extraneous load it would have reduced the learners' test performance. That is to say, compared with the conventional teaching method, the concept-map-based teaching method significantly induced a higher germane load and thus enhanced learner understanding of ER models.

For example, suppose that the concept map in Fig 4. was constructed by a learner for learning to construct an ER diagram of the database problem (Fig. 1). This concept map externalizes the learner's cognitive process. The learner identifies a semantic unit that connects the concept "Member" and the concept "Order" and maps this semantic unit into the relationship type "Places" with structural constraints (1, N) and (1, 1). While constructing the concept map, the learner must actively seek relevant information to describe the semantic transformation of the semantic unit to the relationship type "Places." Kao *et al.* [71] reported that learning by externalizing knowledge structures can prompt learners to reflect on their knowledge and learning experiences. Concept maps have been recognized as being an effective tool for externalizing learner knowledge structures [72], [73]. Accordingly, the concept-map-based teaching method may trigger higher ER model learning motivation and increase learner willingness to learn ER modeling, thereby improving learning outcomes.

2) LEARNING BY STUDYING INSTRUCTOR CONCEPT MAPS

Semantic transformations from database problems to ER models were verbally presented in the conventional course, whereas this information was presented diagrammatically in the concept-map-based course. Studies have reported that information that is processed sequentially can be relayed verbally, whereas diagrams are more suitable for displaying information that is processed in parallel [82]. Considering that ER modeling often needs to consider multiple detailed semantic elements simultaneously, sequential reasoning is not useful in ER model learning because sequentially indexed verbal representations require an additional extraneous cognitive load to retain multiple data semantic constraints in working memory. The limited cognitive capacity of learners may be consumed by processes that are not directly relevant to the learning material [83].

For example, when learning the relationship type "Invites" in the ER diagram in Fig. 2, in the conventional teaching method, learners received the instructor's oral explanations and sequentially related them to the elements of the ER diagram and the sentences of the database problem description (Fig. 1). Learners first identified the relationship type "Invites" from the ER diagram, brought the information into working memory, and invested mental resources to maintain the cognitive elements in working memory. They then identified the sentences that described this requirement from the database problem and brought them into working memory. Finally, they mentally established a semantic relationship between the relationship type "Invites" and the description of the requirement in working memory and transferred the newly learned semantic relation to semantic memory for storage. The sequential presentation of information in the conventional teaching method required that learners devote additional memory resources to keep the received information in working memory and wait for subsequent information to develop the understanding of ER modeling. In this context, their attention shifts with sequential processing, which distracts them and causes excessive extraneous load [45].

On the contrary, the concept-map-based teaching method taught the relationship type "Invites" by guiding learners to study the instructor's concept map. Suppose that the concept map in Fig 4. was constructed by the instructor for the database problem in Fig. 1. The map simultaneously displays the data requirement "Each member must be invited by another member to place an order and become a member," the relationship type "Invites," and the semantic relation between them. The concept map represents the instructor's cognitive process of semantic transformation in an integrated manner. Learners do not need to keep track of this information in working memory, thereby reducing their extraneous load [83]. This is supported by the data in Table 1, which reveals that, compared with the conventional teaching method, the concept-map-based teaching method required less mental effort when learners studied the instructor's concept maps. Their reduced mental effort was due to a reduction in extraneous load, not germane load, as evidenced by the superior test performance of the students in the concept-map-based course. Therefore, learning ER modeling by studying instructor concept maps can reduce extraneous load. Furthermore, freed student memory resources could be further invested in germane load to improve their understanding of ER modeling. This logic is consistent with cognitive load theory, which holds that reducing extraneous load can improve student learning performance.

B. SEMANTIC NETWORK THEORY

From the perspective of semantic network theory, the term "meaningful learning" is the assimilation of knowledge into semantic memory during learning [49]. The concept-map-based teaching method accords with semantic network theory because it emphasizes the relationship between ER modeling and a learner's existing knowledge to facilitate meaningful learning. A learner constructing an ER diagram for the database problem (Fig. 1) who first constructs the concept map in Fig. 4 must make decisions about the semantic relationships that are latent in ER modeling. For example, the learner must identify the semantic relation from the seven concepts "Member," "SSN," "Member_ID," "Name," "Address," "Phone_Number," and "Credit_Rating" to the entity type "Member" and its six attributes. In this process, the learner is compelled to relate the newly learned concepts (entity type "Member" and its six attributes) and the already-known concepts (the seven concepts). This process helps learners clarify contradictions or misconceptions in their knowledge structure; correcting misconceptions leads to better understanding [51].

Studies have found that learning through concept maps can facilitate meaningful learning [49], [74], [75] because the network representation of concept maps helps reveal and integrate the semantic relationships between old and new knowledge [76]. Furthermore, concept maps can trigger memory and focus learner attention on the semantic relationship between known and new knowledge [51]. Hence, from the perspective of semantic network theory, the concept-map-based teaching method may assist learners in assimilating novel ER model knowledge into existing knowledge structures and form so-called meaningful learning, thereby enhancing learners' understanding of ER models.

C. COMMUNICATION THEORY

After an instructor presents the answer to a database question, some learners may still be confused as to why their ER diagram is wrong or think that their ER diagram may also be correct. In this case, further explanation is required. In general, instructors first identify learner errors and then determine why the errors occurred; finally, they explain how to correctly construct an ER diagram. However, long-term observation of teaching ER modeling has revealed that this communication is difficult and often results in information overload for learners.

Successful learning is directly related to effective communication between learners and instructors [77]. Mayer [45] indicated that modeling can facilitate communication between instructors and learners because key information is highlighted. Communication theory indicates that a model can be conceptualized as a message that is processed cognitively by readers to develop an understanding of the material [78]. The concept-map-based teaching method uses conceptual models, namely concept maps, to present the ER modeling process. According to communication theory, concept maps can be used as a communication medium between learners and instructors to improve communication efficiency.

For example, the ER diagram in Fig. 5 was constructed by a learner for the database problem (Fig. 1). This ER diagram violates the data requirement that each order can only be related to one member who placed the order. In the concept-map-based teaching method, the concept map (Fig. 6) constructed by the learner can serve as a communication medium to explain this error. The instructor can explain the cause of the error by guiding the learner to examine the two semantic units of the concept map: 1) "Order" and "Salesperson" (an order must be handled by only one salesperson) and 2) "Salesperson" and "Member" (a salesperson can sell to many members). The combination of these two semantic units produces a new semantic unit that violates the data requirement: an order can be related to many members. Concept maps can help instructors explain why learner errors occurred and help learners understand the cause of their errors through their own concept maps. After examining the learner's concept map, the instructor's concept map can be used to explain how the instructor constructs a correct ER diagram. By contrast, in the conventional teaching method, communication is based on the ER diagrams of instructors and learners. Instructors must invest additional mental resources to imagine the cognitive processes that caused learners to commit errors. This communication process is expected to impose additional cognitive load on both learners and instructors.

Another advantage of the concept-map-based teaching method is that instructors can explain learner errors in data semantics and ER model syntax separately without interference because the data semantics of database problems and their mapping relations to ER model syntax are presented separately in concept maps. For example, the instructor may explain the semantic error in Fig. 5 by using Fig. 6 without requiring the use of ER model syntax. Avoiding the use of ER model syntax may reduce learner information load and increase communication efficiency.

By contrast, in the conventional teaching method, the instructor explains the error by examining the learner's ER diagram and referring to the instructor's correct ER diagram. The instructor will inevitably use ER model notation to explain the semantic error; however, the notation is unrelated to this semantic error. Cognitive load theory indicates that investing mental resources in activities unrelated to learning reduces learning outcomes. Thus, the conventional teaching method may impose a higher extraneous load and increase the difficulty of understanding this semantic error. The results in Table 3 support this finding; participants in the conventional course had significantly lower mental efficiency than did those in the concept-map-based course, suggesting that the concept-map-based teaching method facilitates the understanding of ER models more than the conventional teaching method does. Table 4 summarizes the advantages of concept maps for learning ER modeling.

VII. THREATS TO VALIDITY

In this section, possible sources of bias and threats to the validity of this study are explored. Conclusion, internal, construct, and external validity are discussed [79].

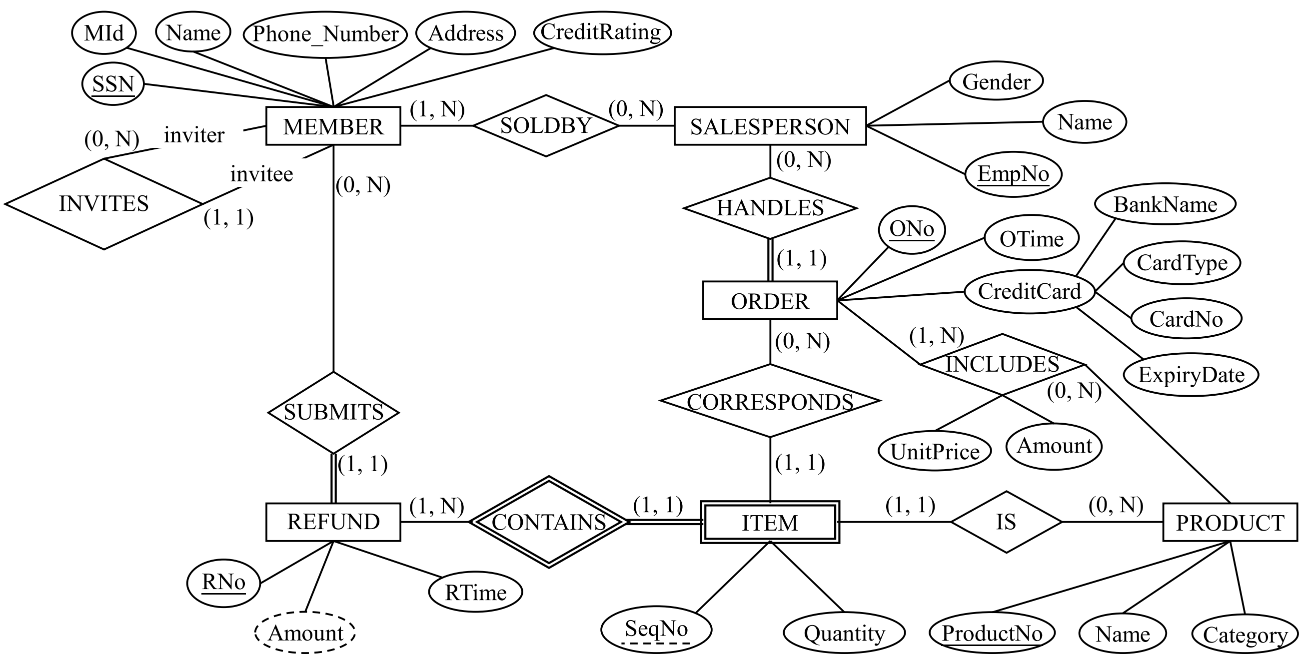

FIGURE 5. ER diagram constructed by a learner for the database problem in Fig. 1.

Conclusion validity aims to ensure the relationship between the treatment and experimental results [79]. The following possible influences on conclusion validity were addressed: Reliability of measures, sample size, and the random heterogeneity of subjects. During the development of the measurements, the reliability of measures was addressed by adopting widely used measures to evaluate learner understanding of ER modeling. Modeling correctness has been used in numerous studies on ER model learning [80], [81] to measure problem-solving ability. Relative mental efficiency was measured using the computational approach of Paas and van Merriënboer, which has been widely used to measure the efficiency of instructional conditions [65]. Mental effort was measured by using Paas and van Merriënboer's [65] rating scale; mental effort is often measured using rating scales and psychophysiological techniques [66]. Although a limited number of subjects participated in the experiment, the sample size was sufficient to achieve conclusion validity in an independent sample t test. Random heterogeneity of the subjects was addressed when recruiting participants. To ensure that all participants had the same prior level of knowledge about ER modeling, they took a pretest before the course; the results revealed that they did not have expertise in ER modeling, confirming that random heterogeneity was not a problem.

Internal validity is the reliability of the results within a given setting [79]. The following internal validity threats were addressed: history, testing, and mortality. If different treatments are applied to a participant at different times, this treatment history may affect the experimental results. Only one treatment was applied in this study; thus, history was not a concern. Second, if tests in an experiment are repeated, unintended learning may occur because the participants learn the study procedures. Because only one query-writing test was conducted at the end of the course, the testing threat was avoided. Finally, participants leaving a study is referred to as mortality and may affect internal validity. None of the participants left the experiment; thus, mortality did not affect the results.

Construct validity aims to ensure that the experimental setting accurately reflects the constructs to be studied [79]. For better reflecting ER model learning outcomes, mental efficiency and problem-solving ability were used in this study to measure learner understanding of ER models instead of recall accuracy and response latency because learners must develop a deep understanding of the semantic transformations involved in ER models, and mental efficiency and problem-solving ability are suitable for measuring the deep understanding of materials [44], [62]. Two other threats: interaction

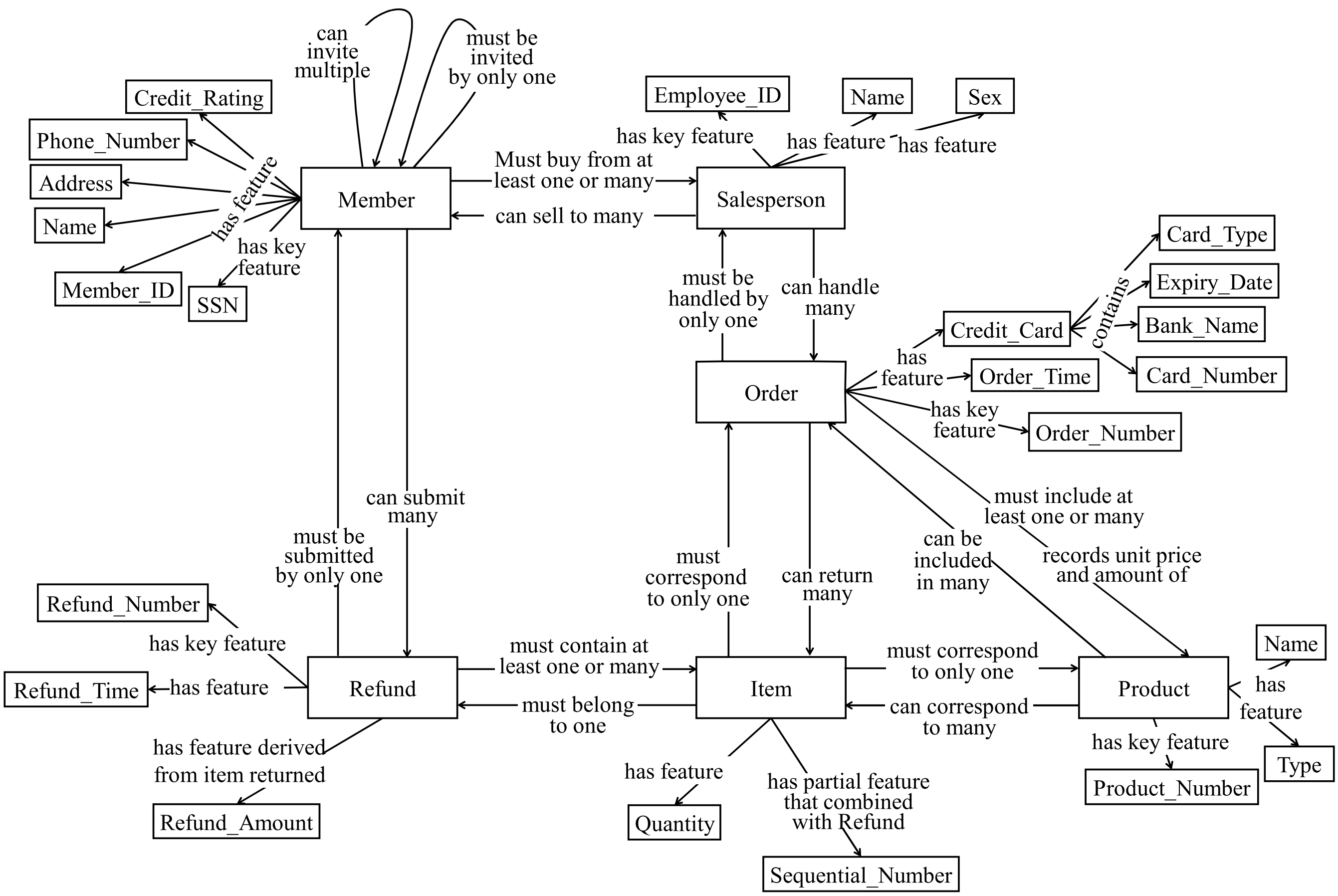

FIGURE 6. Concept map constructed by a learner for the database problem in Fig. 1.

TABLE 4. Advantages of concept maps for learning ER modeling.

Cognitive Load Theory
- Learning by constructing concept maps compels learners to externalize the cognitive process of the semantic transformation, which engages the learners in learning activities related to ER modeling, thus inducing a germane load.
- Learning by studying the instructor's concept maps can reduce the extraneous load required to hold learning information in the working memory.
Semantic Network Theory
- Concept maps explicitly present the semantic relationship between ER model notation and learner knowledge and can thus focus learners' attention on the semantic relationship, thereby helping them assimilate ER model knowledge into their existing knowledge structures, resulting in so-called meaningful learning.
Communication Theory
- Concept maps can be used as a communication medium between learners and instructors for improving communication efficiency.
- Learner concept maps can be used by instructors to explain why learners made errors and to help learners understand the cause of their errors with their own concept maps.
- The instructor's concept map can be used to explain how the instructor constructs a correct ER diagram.
- Learner errors in data semantics and ER model syntax can be explained separately without interfering each other, which can reduce the information load placed on learners and increase communication efficiency.

of different treatments, and experimenter expectancies. Interaction of different treatments is to ensure that the results of an experiment may be affected by other experimental treatments. The participants did not participate in other studies; hence, treatment interactions did not affect the validity. Moreover, experimenter expectancy was avoided because the participants were not aware of the experimental hypothesis.

External validity is the generalizability of the results of a study outside the experimental setting [79]. A study is generalizable if its subjects and settings are representative of other settings and populations; both the generalizability of the setting and participants were considered. For the setting, this experiment was conducted in a database course at a university. The instructor was a database professional. Thus, the results of this study are likely valid for learners studying ER modeling at universities. Whether the results are valid for other environments in which ER models are studied could be investigated in a future study. With respect to the participants, MIS undergraduate students were enrolled as participants to clarify the difficulties associated with learning ER models. Because the ability to design databases using ER models is a core competency for MIS undergraduate students, the participants were representative of ER model learners. Thus, the results of this study were determined to have good external validity.

VIII. CONCLUSION

Learners in database courses frequently have difficulty learning ER modeling. From the perspective of semantic network theory, the complex semantic transformation from database problems to ER diagrams and the large amount of data semantic information result in an excessive cognitive load for learners and consequently jeopardizes their learning outcome. To mitigate their cognitive load, the concept-map-based teaching method was proposed. The method integrates concept mapping into conventional ER model education by representing the ER modeling process using concept maps. The results revealed that the concept-map-based teaching method is superior to the conventional teaching method. In the test stage, learners who received the concept-map-based teaching method achieved higher problem-solving ability with less mental effort for the test task. In the learning stage, constructing concept maps for learning ER modeling forced learners to engage in learning activities related to ER modeling. Learners were required to relate what they were learning about ER models to their existing knowledge structures to represent the semantic transformation process, thereby promoting meaningful learning. Studying instructor concept maps enables learners to understand the cognitive structures that instructors use for ER modeling; thus, learners can more easily perceive the semantic transformations because the information that must be mentally integrated to understand ER modeling is integrated and highlighted in the concept maps. Furthermore, these concept maps can be used as a communication medium for answering learner questions, thus improving learning efficiency.

This research provides empirical insight into the effect of concept maps on learner understanding of ER modeling. However, this research is only an initial step in fully understanding the cognitive process of ER model learners. More in-depth follow-up research from the perspective of semantic network theory is needed concerning topics such as the semantic distance between database problems and ER models. Insight into the influence of semantic distance on learner understanding of ER modeling may help researchers identify the root causes of the difficulties in learning ER modeling, and other teaching methods could be developed accordingly.

REFERENCES

[1] R. Rashkovits and I. Lavy, "Students' difficulties in identifying the use of ternary relationships in data modeling," *Int. J. Inf. Commun. Technol. Educ.*, vol. 16, no. 2, pp. 47–58, Apr. 2020.
[2] M. Omar and A. Abdulla, "The entities extraction for entity relationship models from natural language text via machine learning algorithms," in *Proc. 4th Int. Conf. Basic Sci. Their Appl.*, Elbeida, Libya, 2020, pp. 1–4.
[3] A. Del Pino Lino and A. Rocha, "Automatic evaluation of ERD in e-learning environments," in *Proc. 13th Iberian Conf. Inf. Syst. Technol. (CISTI)*, Caceres, Spain, Jun. 2018, pp. 1–5.
[4] A. Lino, A. Rocha, L. Macedo, and A. Sizo, "LabDER-relational database virtual learning environment," in *Proc. 38th Int. Conf. Conceptual Modeling*, Salvador, Brazil, 2019, pp. 42–55.
[5] J. Schildgen, "MonstER park-the entity-relationship-diagram learning game," in *Proc. 39th Int. Conf. Conceptual Modeling*, Vienna, Austria, 2020, pp. 150–157.
[6] A. Weerasinghe and A. Mitrovic, "Studying human tutors to facilitate self-explanation," in *Proc. ITS*, Berlin, Heidelberg, 2006, pp. 713–715.
[7] D. Batra, "Cognitive complexity in data modeling: Causes and recommendations," *Requirements Eng.*, vol. 12, no. 4, pp. 231–244, Oct. 2007.
[8] A. Mitrovic and P. Suraweera, "Teaching database design with constraint-based tutors," *Int. J. Artif. Intell. Educ.*, vol. 26, no. 1, pp. 448–456, Mar. 2016.

[9] N. Marcus, M. Cooper, and J. Sweller, "Understanding instructions," *J. Educ. Psychol.*, vol. 88, no. 1, pp. 49–63, Mar. 1996.

[10] J. D. Novak and D. B. Gowin, *Learning How to Learn*. Cambridge, U.K.: Cambridge Univ. Press, 1984.

[11] J. D. Novak and A. J. Cañas, "The theory underlying concept maps and how to construct and use them," Florida Inst. Hum. Mach. Cognition, Pensacola, FL, USA, Tech. Rep. IHMC CmapTools 2006-01 Rev 01-2008, 2008.

[12] D. Batra, J. A. Hoffler, and R. P. Bostrom, "Comparing representations with relational and EER models," *Commun. ACM*, vol. 33, no. 2, pp. 126–139, Feb. 1990.

[13] K. Rosenthal, B. Ternes, and S. Strecker, "Understanding individual processes of conceptual modeling: A multi-modal observation and data generation approach," in *Proc. Modellierung*, Bonn, German, 2020, pp. 77–92.

[14] M. Coffin Murray and M. Guimaraes, "Animated courseware support for teaching database design," *Issues Informing Sci. Inf. Technol.*, vol. 6, pp. 201–211, 2009.

[15] P. Suraweera and A. Mitrovic, "An intelligent tutoring system for entity relationship modelling," *Int. J. Artif. Intell. Educ.*, vol. 14, nos. 3–4, pp. 375–417, 2004.

[16] D. Batra and S. R. Antony, "Novice errors in conceptual database design," *Eur. J. Inf. Syst.*, vol. 3, no. 1, pp. 57–69, Jan. 1994.

[17] L. Hall and A. Gordon, "A virtual learning environment for entity relationship modelling," in *Proc. SIGCSE*, New York, NY, USA, 1998, pp. 345–349.

[18] H. Topi and V. Ramesh, "Human factors research on data modeling: A review of prior research, an extended framework and future research directions," *J. Database Manage.*, vol. 13, no. 2, pp. 3–19, 2002.

[19] G. Fessakis, A. Dimitracopoulou, and V. Komis, "Improving database design teaching in secondary education: Action research implementation for documentation of didactic requirements and strategies," *Comput. Hum. Behav.*, vol. 21, no. 2, pp. 159–194, 2005.

[20] R. Weber, "Are attributes entities? A study of database Designers' memory structures," *Inf. Syst. Res.*, vol. 7, no. 2, pp. 137–162, Jun. 1996.

[21] S. R. Antony and D. Batra, "CODASYS: A consulting tool for novice database designers," *ACM SIGMIS Database: DATABASE Adv. Inf. Syst.*, vol. 33, no. 3, pp. 54–68, 2002.

[22] T. J. Teorey, *Database Modeling and Design*, San Mateo, CA, USA: Morgan Kaufmann, 1994.

[23] D. Batra and J. G. Davis, "Conceptual data modelling in database design: Similarities and differences between expert and novice designers," *Int. J. Man-Mach. Stud.*, vol. 37, no. 1, pp. 83–101, Jul. 1992.

[24] M. de los Angeles Constantino-González and D. D. Suthers, "A coached collaborative learning environment for entity-relationship modeling," in *Intelligent Tutoring Systems* (Lecture Notes in Computer Science), vol. 1839. Berlin, Germany: Springer, 2000, pp. 324–333.

[25] N. Omar, J. R. P. Hanna, and P. McKevitt, "Heuristic-based entity-relationship modelling through natural language processing," in *Proc. AICS*, Dublin, Ireland, 2004, pp. 302–313.

[26] F. Prados, I. Boada, J. Soler, and J. Poch, "An automatic correction tool for relational database schemas," in *Proc. 6th Int. Conf. Inf. Technol. Based Higher Educ. Training*, Santo Domingo, Dominican, 2005, p. S3C-9.

[27] P. Thomas, "Online automatic marking of diagrams," *Systemic Pract. Action Res.*, vol. 26, no. 4, pp. 349–359, Aug. 2013.

[28] O. Dæhli, B. Kristoffersen, and T. Sandnes, "Lessons learned from developing and evaluating an educational database modeling tool," in *Proc. Eur. Conf. e-Learn.*, Berlin, Germany, 2020, p. 129.

[29] M. Cvetanovic, Z. Radivojevic, V. Blagojevic, and M. Bojovic, "ADVICE—Educational system for teaching database courses," *IEEE Trans. Educ.*, vol. 54, no. 3, pp. 398–409, Aug. 2011.

[30] D. Fossati, B. Di Eugenio, S. Ohlsson, C. Brown, and L. Chen, "Data driven automatic feedback generation in the iList intelligent tutoring system," *Technol., Instruct., Cognition Learn.*, vol. 10, no. 1, pp. 5–26, 2015.

[31] V. Aleven, B. M. McLaren, J. Sewall, and K. R. Koedinger, "A new paradigm for intelligent tutoring systems: Example-tracing tutors," *Int. J. Artif. Intell. Educ.*, vol. 19, no. 2, pp. 105–154, 2009.

[32] R. F. Barron, "The use of vocabulary as an advance organizer," in *Research in Reading in the Content Areas: First Year Report*. Syracuse, NY, USA: Syracuse University Reading and Language Arts Center, 1969.

[33] D. P. Ausubel, J. D. Novak, and H. Hanesian, *Educational Psychology: A Cognitive View*, 2nd ed. New York, NY, USA: Holt, Rinehart & Winston, 1968.

[34] G.-J. Hwang, P.-H. Wu, and H.-R. Ke, "An interactive concept map approach to supporting mobile learning activities for natural science courses," *Comput. Educ.*, vol. 57, no. 4, pp. 2272–2280, Dec. 2011.

[35] V. Dimitrieski, M. Čeliković, S. Aleksić, S. Ristić, A. Alargt, and I. Luković, "Concepts and evaluation of the extended entity-relationship approach to database design in a multi-paradigm information system modeling tool," *Comput. Lang., Syst. Struct.*, vol. 44, pp. 299–318, Dec. 2015.

[36] M. Herzberg, "Errors in entity-relationship-diagrams: Classification and statistical data," in *Proc. TLAD*, Antrim, Northern Ireland, 2010, pp. 72–76.

[37] S. I. Mehta and N. W. Schlecht, "Computerized assessment technique for large classes," *J. Eng. Educ.*, vol. 87, no. 2, pp. 167–172, Apr. 1998.

[38] D. Batra and M. K. Sein, "Improving conceptual database design through feedback," *Int. J. Hum.-Comput. Stud.*, vol. 40, no. 4, pp. 653–676, Apr. 1994.

[39] G. A. Miller, "The magical number seven, plus or minus two: Some limits on our capacity for processing information," *Psychol. Rev.*, vol. 63, no. 2, pp. 81–97, 1956.

[40] J. Sweller, "Cognitive load theory, learning difficulty, and instructional design," *Learn. Instruct.*, vol. 4, no. 4, pp. 295–312, Jan. 1994.

[41] P. A. Kirschner, "Cognitive load theory: Implications of cognitive load theory on the design of learning," *Learn. Instruct.*, vol. 12, no. 1, pp. 1–10, Feb. 2002.

[42] N. Refat, M. A. Rahman, A. T. Asyhari, I. F. Kurniawan, M. Z. A. Bhuiyan, and H. Kassim, "Interactive learning experience-driven smart communications networks for cognitive load management in grammar learning context," *IEEE Access*, vol. 7, pp. 64545–64557, 2019.

[43] P. Weichbroth, "Usability of mobile applications: A systematic literature study," *IEEE Access*, vol. 8, pp. 55563–55577, 2020.

[44] T. van Gog and F. Paas, "Instructional efficiency: Revisiting the original construct in educational research," *Educ. Psychol.*, vol. 43, no. 1, pp. 16–26, Jan. 2008.

[45] R. E. Mayer, "Models for understanding," *Rev. Educ. Res.*, vol. 59, no. 1, pp. 43–64, Mar. 1989.

[46] J. Sweller, J. J. G. van Merrienboer, and F. G. W. C. Pass, "Cognitive architecture and instructional design," *Educ. Psychol. Rev.*, vol. 10, no. 3, pp. 251–296, 1998.

[47] F. Paas, J. E. Tuovinen, H. Tabbers, and P. W. V. Gerven, "Cognitive load measurement as a means to advance cognitive load theory," *Educ. Psychol.*, vol. 38, no. 1, pp. 63–71, Mar. 2003.

[48] A. M. Collins and M. R. Quillian, "Retrieval time from semantic memory," *J. Verbal Learn. Verbal Behav.*, vol. 8, no. 2, pp. 240–247, Apr. 1969.

[49] H.-H. Chen, Y.-J. Chen, and K.-J. Chen, "The design and effect of a scaffolded concept mapping strategy on learning performance in an undergraduate database course," *IEEE Trans. Educ.*, vol. 56, no. 3, pp. 300–307, Aug. 2013.

[50] C. Soderston, N. Kleid, and T. Crandell, "Concept mapping: A job-performance aid for hypertext developers," in *Proc. SIGDOC*, New York, NY, USA, 1996, pp. 179–186.

[51] P.-H. Wu, G.-J. Hwang, M. Milrad, H.-R. Ke, and Y.-M. Huang, "An innovative concept map approach for improving students' learning performance with an instant feedback mechanism," *Brit. J. Educ. Technol.*, vol. 43, no. 2, pp. 217–232, Mar. 2012.

[52] G.-J. Hwang, Y.-R. Shi, and H.-C. Chu, "A concept map approach to developing collaborative mindtools for context-aware ubiquitous learning," *Brit. J. Educ. Technol.*, vol. 42, no. 5, pp. 778–789, Sep. 2011.

[53] Y. Erdogan, "Paper-based and computer-based concept mappings: The effects on computer achievement, computer anxiety and computer attitude," *Brit. J. Educ. Technol.*, vol. 40, no. 5, pp. 821–836, Sep. 2009.

[54] R. Axelrod, *Structure of Decision*, Princeton, NJ, USA: Princeton Univ. Press, 1976.

[55] C. Eden, S. Jones, and D. Sims, *Thinking in Organizations*, London, U.K.: Macmillan, 1979.

[56] R. McAleese, "Concepts as hypertext nodes: The ability to learn while navigating through hypertext nets," in *Designing Hypermedia for Learning*, Berlin, Germany: Springer, 1990, pp. 97–115.

[57] C. van Boxtel, J. van der Linden, E. Roelofs, and G. Erkens, "Collaborative concept mapping: Provoking and supporting meaningful discourse," *Theory Pract.*, vol. 41, no. 1, pp. 40–46, Feb. 2002.

[58] D. B. Gowin, *Educating*, Ithaca, NY, USA: Cornell Univ. Press, 1981.

[59] J. D. Novak, *A Theory of Education*, Ithaca, NY, USA: Cornell Univ. Press, 1977.

[60] G. L. Bradshaw and J. R. Anderson, ''Elaborative encoding as an explanation of levels of processing,'' *J. Verbal Learn. Verbal Behav.*, vol. 21, no. 2, pp. 165–174, Apr. 1982.

[61] R. Ratcliff, ''A theory of memory retrieval,'' *Psychol. Rev.*, vol. 85, no. 2, pp. 59–108, Mar. 1978.

[62] F. Bodart, A. Patel, M. Sim, and R. Weber, ''Should optional properties be used in conceptual modelling? A theory and three empirical tests,'' *Inf. Syst. Res.*, vol. 12, no. 4, pp. 384–405, Dec. 2001.

[63] H. Lee and B. G. Choi, ''A comparative study of conceptual data modeling techniques,'' *J. Database Manage.*, vol. 9, no. 2, pp. 26–35, Apr. 1998.

[64] C. Liao and P. C. Palvia, ''The impact of data models and task complexity on end-user performance: An experimental investigation,'' *Int. J. Hum.-Comput. Stud.*, vol. 52, no. 5, pp. 831–845, May 2000.

[65] F. G. W. C. Paas and J. J. G. Van Merriënboer, ''The efficiency of instructional conditions: An approach to combine mental effort and performance measures,'' *Human Factors*, vol. 35, no. 4, pp. 737–743, 1993.

[66] N. Moray, *Mental Workload: Its Theory and application*. Boston, MA, USA: Springer, 1979.

[67] D. Gopher and R. Braune, ''On the psychophysics of workload: Why bother with subjective measures?'' *Hum. Factors*, vol. 26, no. 5, pp. 519–532, Oct. 1984.

[68] R. D. O'Donnell and F. T. Eggemeier, ''Workload assessment methodology,'' in *Handbook of Perception and Human Performance*. New York, NY, USA: Wiley, 1986, pp. 1–49.

[69] F. Paas, J. J. G. van Merriënboer, and J. J. Adam, ''Measurement of cognitive load in instructional research,'' *Perceptual Motor Skills*, vol. 79, no. 1, pp. 419–430, Aug. 1994.

[70] P. Ayres, ''Using subjective measures to detect variations of intrinsic cognitive load within problems,'' *Learn. Instruct.*, vol. 16, no. 5, pp. 389–400, Oct. 2006.

[71] G. Kao, S. Lin, and C. Sun, ''Breaking concept boundaries to enhance creative potential: Using integrated concept maps for conceptual self-awareness,'' *Comput. Educ.*, vol. 51, no. 4, pp. 1718–1728, Dec. 2008.

[72] L. Anderson-Inman and L. Ditson, ''Computer-based concept mapping: A tool for negotiating meaning,'' *Learn. Lead. Technol.*, vol. 26, no. 8, pp. 6–13, 1999.

[73] H. Y. Peng, Y. J. Su, C. Chou, and C. C. Tsai, ''Ubiquitous knowledge construction: Mobile learning re-defined and a conceptual framework,'' *Innov. Educ. Teach. Int.*, vol. 46, no. 2, pp. 171–183, May 2009.

[74] C. C. Liu, P. H. Don, and C. M. Tsai, ''Assessment based on linkage patterns in concept maps,'' *J. Inf. Sci. Eng.*, vol. 21, no. 5, pp. 873–890, Sep. 2005.

[75] J. C. Nesbit and O. O. Adesope, ''Learning with concept and knowledge maps: A meta-analysis,'' *Rev. Educ. Res.*, vol. 76, no. 3, pp. 413–448, Sep. 2006.

[76] J. Turns, C. J. Atman, and R. Adams, ''Concept maps for engineering education: A cognitively motivated tool supporting varied assessment functions,'' *IEEE Trans. Educ.*, vol. 43, no. 2, pp. 164–173, May 2000.

[77] A. Khan, S. Khan, S. Zia-Ul-Islam, and M. Khan, ''Communication skills of a teacher and its role in the development of the students' Academic success,'' *J. Educ. Pract.*, vol. 8, no. 1, pp. 18–21, 2017.

[78] K. Kellermann and T. Lim, ''Inference-generating knowledge structures in message processing,'' in *Message Effects in Communication Science*. Newbury Park, CA, USA: Sage, 1989, pp. 102–128.

[79] C. Wohlin, P. Runeson, M. Höst, M. C. Ohlsson, B. Regnell, and A. Wesslén, *Experimentation in Software Engineering*. Berlin, Germany: Springer, 2012.

[80] H. C. Chan, K. K. Wei, and K. L. Siau, ''User-database interface: The effect of abstraction levels on query performance,'' *MIS Quart.*, vol. 17, no. 4, pp. 441–464, Dec. 1993.

[81] K. L. Siau, H. C. Chan, and K. K. Wei, ''Effects of query complexity and learning on novice user query performance with conceptual and logical database interfaces,'' *IEEE Trans. Syst., Man, Cybern., A, Syst. Humans*, vol. 34, no. 2, pp. 276–281, Mar. 2004.

[82] A. Paivio and K. Csapo, ''Concrete image and verbal memory codes,'' *J. Exp. Psychol.*, vol. 80, no. 2, pp. 279–285, May 1969.

[83] J. H. Larkin and H. A. Simon, ''Why a diagram is (Sometimes) worth ten thousand words,'' *Cogn. Sci.*, vol. 11, no. 1, pp. 65–100, Jan. 1987.