Deep Learning Models for Analyzing Social Construction of Knowledge Online

Charlotte N. Gunawardena
University of New Mexico, USA

Yan Chen
University of Nevada, Las Vegas, USA

Nick Flor
Damien Sánchez
University of New Mexico, USA

Abstract
Gunawardena et al.'s (1997) Interaction Analysis Model (IAM) is one of the most frequently employed frameworks to guide the qualitative analysis of social construction of knowledge online. However, qualitative analysis is time consuming, and precludes immediate feedback to revise online courses while being delivered. To expedite analysis with a large dataset, this study explores how two neural network architectures—a feed-forward network (Doc2Vec) and a large language model transformer (BERT)—could automatically predict phases of knowledge construction using IAM. The methods interrogated the extent to which the artificial neural networks' predictions of IAM Phases approximated a human coder's qualitative analysis. Key results indicate an accuracy of 21.55% for Doc2Vec phases I-V, 43% for fine-tuning a pre-trained large language model (LLM), and 52.79% for prompt-engineering an LLM. Future studies for improving accuracy should consider either training the models with larger datasets or focusing on the design of prompts to improve classification accuracy. Grounded on social constructivism and IAM, this study has implications for designing and supporting online collaborative learning where the goal is social construction of knowledge. Moreover, it has teaching implications for guiding the design of AI tools that provide beneficial feedback for both students and course designers.

Keywords: social construction of knowledge online, interaction analysis model, neural networks

Gunawardena, C., Chen, Y., Flor, N., & Sánchez, D. (2023). Deep learning models for analyzing social construction of knowledge online. *Online Learning*, *27*(4), 69-92.
DOI: https://doi.org/10.24059/olj.v27i4.4055

The exponential growth of online learning during the pandemic added impetus to the exploration of how people learn together online (Ba et al., 2023; Guo et al. 2022; Lee et al., 2023; Lehtinen et al., 2023). Learning together (Dillenbourg, 1999) is grounded in principles of social constructivism (Pea, 1993; Vygotsky, 1978), where knowledge is co-constructed by members of an interacting group through a process of negotiation of meaning and validation of newly constructed knowledge. Traditionally, the co-construction of knowledge manifested in varied online discussion structures has been analyzed by qualitative content analysis examining the meaning of interactions between participants (Rourke et al., 2001). However, given a large dataset, qualitative content analysis becomes a time-consuming task (Silverio et al., 2020) and requires human coders to be experienced in both qualitative coding methods as well as have a good understanding of the conceptual frameworks used to perform the coding tasks (Hu et al., 2020; Megli et al., 2023a; 2023b). These realities mean that while transcripts of online discussions and collaborations could be analyzed weekly, it is not realistic or practical. Further, it makes it difficult to effectively research online knowledge co-construction while a course is in session, so instructors can provide feedback to participants as well as revise courses as they are being delivered.

Perhaps one solution to this issue may lie in exploring alternative techniques for analyzing knowledge construction online, employing methods used in social learning analytics (Kaliisa et al., 2022), machine learning (Ouyang et al., 2023) and the sub-field of Neural Networks (NNs) which can map patterns of interactions (Schmidhuber, 2015) and reveal how a learning algorithm can come close to matching a human coder's qualitative analysis. Of particular interest when trying to match a qualitative coder's analysis of social construction of knowledge are deep learning models based on the large language models (LLMs). "Deep learning is a subset of machine learning in which multilayered neural networks learn from vast amounts of data...Deep learning uses multi-layered structures of algorithms called neural networks to draw similar conclusions as humans would" (Oppermann, 2022, pp. 1–2). We define a LLM as a deep learning model trained on a large corpus of text which then allows it to do classifications, translations, problem solving, create documents and images, etc. Examples of LLMs are BERT, ChatGPT, and LLaMA (see Appendix A).

This paper explored how a basic feed-forward, NN classifier (doc2vec) and a deep learning model (BERT, a transformer and LLM) can predict a qualitative analyst's coding of the Phases of social construction of knowledge in online discussions when the predication is based on the theoretical foundation of social construction of knowledge as specified by the Interaction Analysis Model (IAM) (Gunawardena et al., 1997). The aim was to situate the deep learning model on a sound theoretical base that can explain how people learn in collaboration with each other. The need for grounding analytics on a sound learning theory base that accounts for collaborative interaction and social construction of knowledge between participants in an online environment is highlighted in the review of 36 social learning analytic studies conducted by Kaliisa and colleagues (2022). This study used the IAM as it stipulates the process of social construction of knowledge to predict a qualitative analyst's coding of discussion transcripts. The study will also use the same coded transcripts found in Megli et al.'s study (2023a; 2023b), and demonstrate how a feed-forward NN classifier and a deep learning model could predict the Phases of knowledge construction coded according to the IAM. This study will therefore extend the research completed by our larger research team (Megli et al., 2023a; 2023b) where a detailed description of the methods used in the qualitative coding of online transcripts can be found.

We want readers to be aware that this paper focuses on using artificial intelligence (AI) models to predict qualitative coders' analysis of online discussions. Therefore, the terminology and descriptors associated with AI models will be technical in nature. We have provided a glossary at the end of this paper to help the reader understand the unfamiliar terms.

The Development of Neural Networks (NNs)

The history of neural networks (NNs) began with McCulloch and Pitts (1943), who described a mathematical model for an artificial neuron and provided mathematical proof that a network of artificial neurons, hereafter "nodes," could perform any logical operation and, therefore, theoretically any computation. Their work laid the foundation for later research in artificial NNs.

The first implementation of a NN is credited to Rosenblatt (1958). Rosenblatt named his network a "perceptron," and it consisted of two layers: an input layer and an output layer. Each node in the input layer was connected to every node in the output layer. The output nodes took the inputs, weighted them, summed the weighted inputs, and produced a result if the weighted sum exceeded a threshold. Essentially, each output node performed a task similar to linear regression, with the weights analogous to the coefficients in a regression equation. A perceptron could learn by adjusting the weights of the output nodes, akin to how one fits a regression model by modifying coefficients. Applications of perceptrons include pattern recognition tasks, such as image recognition, and learning linear functions. However, the perceptron's major drawback is its inability to handle non-linear input-output mappings, which many real-world tasks require. As a result, it cannot solve non-linear classification and regression tasks.

The inability to learn non-linear classification tasks, along with the difficulty of programming perceptrons to learn, slowed research in NNs until the mid-1980s. It was then when the Parallel Distributed Processing (PDP) group at the University of California introduced a three-layer network―consisting of an input layer, a hidden layer, and an output layer―and a learning algorithm known as backpropagation (Rumelhart et al., 1986). The inclusion of a hidden layer, combined with the backpropagation learning algorithm, enabled artificial networks to solve non-linear classification problems. This network architecture is commonly known as a *basic feed-forward network*. Applications of 3-layer NNs include image recognition, e.g., classifying images into faces or objects, speech recognition, e.g., converting spoken language to text, natural language processing, e.g., language translation, and machine learning from data, e.g., predictive models. However, there were several drawbacks to three-layer networks: lengthy training times, inadequate availability of big data for training, and the fact that classification algorithms like support vector machines and decision trees were more accurate.

Deep learning networks, also known as *deep learning models*, were introduced to overcome the limitations of 3-layer networks. Characterized by multiple hidden layers, these networks have demonstrated performance and accuracy often surpassing those of traditional machine learning algorithms. This is largely attributed to a combination of big data availability, improvements in computational power―notably, GPUs capable of training numerous artificial neurons in parallel u2015, enhanced learning algorithms, and the capability to effectively train multiple-layered networks. The evolution of deep learning was significantly advanced by the work of Hinton et al. (2006). Their approach centered on a two-phase training strategy for deep learning networks. The first phase, *unsupervised pre-training*, had the NN independently learning statistical relationships between input patterns. The second phase, *supervised fine-tuning*, trained the network to link specific inputs with their respective labels. Specifically, Hinton et al. (2006) used this approach to train a network to associate images of numbers with their correct labels, ranging from 0 to 9. Their innovations have since fueled many advancements in the field of deep learning.

Undoubtedly, one of the most significant advancements in the field of NNs was the *large language model* (LLM), a type of deep learning model predominantly implemented using the transformer architecture (Vaswani et al., 2017). In an approach similar to Hinton's (2006) deep learning network, these LLMs also undergo a two-stage training process. However, rather than being trained on image data to discern patterns in pixels, an LLM is pre-trained unsupervised on a massive corpus of text data, which includes webpages, books, and social media posts. This enables the model to learn the relationships and statistical patterns between words and phrases. Following this, the model is fine-tuned in a supervised manner for specific language tasks. Through this process, LLMs are capable of achieving state-of-the-art performance in various natural language processing tasks, such as classification, question answering, summarization, translation, and more. This combination of unsupervised pre-training and supervised fine-tuning has yielded significant advances in natural language processing tasks. LLMs are a powerful new tool that have the potential to revolutionize the way we interact with computers and how we learn with computers. As LLMs continue to improve, they will be able to perform even more complex tasks.

Theoretical Framework for this Study: Social Construction of Knowledge

Social construction of knowledge explains how learners learn together while dialoguing and collaborating with each other (Chen et al., 2018; Dillenbourg et al., 1996; Resta & Laferrière, 2007; Stahl, 2006). This view of learning has roots in both sociocultural theory and social constructivism (Duffy & Jonassen, 1992; Koschmann, 1996). Sociocultural theory predominantly attributed to Vygotsky (1978) focuses on how culture, context, and social interaction shape and influence learning (Kumpulainen & Wray, 2002), and emphasizes the significance of cultural and historical contexts, social interaction, peer collaboration, and the construction of new knowledge with the guidance of adults and peers. Unlike the cognitive perspective (Piaget, 1971), which emphasizes the individual's mental processes and relationship to a social context, the sociocultural perspective emphasizes the social nature of learning and places the learner within a social context. The sociocultural approach centers on the interdependence of social and individual processes in the co-construction of knowledge (John-Steiner & Mahn, 1996). From a sociocultural perspective, learning takes place within cultural contexts, through sharing and interaction, and via language, signs, and systems.

Piaget and his collaborators' research on cognitive development (Piaget, 1971) propelled the development of constructivism as a learning theory. Constructivism emphasizes the individual's mental processes in the construction of knowledge; the active character of the learner, interacting with the environment either alone or with others, and constructing knowledge. Constructivists with a growing interest in the social nature of learning and the social context within which learning happens, propelled the development of social constructivist views on learning. Social constructivists subscribed to the constructivist's views of knowledge as constructed, but unlike other hardcore Piagetian constructivists, considered construction of knowledge to be a social process. Social constructivists also focus on the collaborative nature of learning (Koschmann, 1996). Therefore, both sociocultural and socioconstructivist views of learning emphasize the social context in which the individual is acting and in which knowledge is constructed (Kumpulainen & Wray, 2002).

Grounded in sociocultural and socioconstructivist theories of learning, social construction of knowledge online is about a social process contingent on learners' interactions and collaborations with each other in varied online spaces (Gunawardena et al., 1997; Lee et al. 2023; Sammons, 2007). In this social process, learners are actively engaged in learning collaboratively, share information based on their existing knowledge, encourage discourses and dissonance through real-life problem-solving processes, and solidify learning through reflection on co-constructed ideas. This negotiated learning perspective is important to learning online. On one hand, such a learning environment enables the co-existence of multiple realities, and presents new opportunities for individuals to develop higher-order cognition and knowledge co-construction (Rannikmäe et al., 2020). On the other hand, the nuanced dynamics in online collaboration indicate the transformation of learner's identity and engender a new culture for learning (Goodfellow & Hewling, 2005).

Social Construction of Knowledge Online

Research has extensively investigated the process of the learners' social interaction and construction of knowledge in various online contexts (Ahmad et al., 2022; Gunawardena et al., 1997; 2001; Lucas et al., 2014; Tao et al. 2022; Tirado et al., 2015). One of the most frequently used data sources for this investigation is the text-based transcript extracted from asynchronous online discussion forums (Ahmad et al., 2022; Floriasti et al., 2023). The emerging patterns of social construction of knowledge can reveal the effectiveness of social interaction and learning behaviors providing insight for instructor feedback and remediation. Findings from Lin et al.'s (2016) study examining social construction of knowledge in a team-based activity of a group of 78 high school students in Taiwan who engaged in a discussion on "Serving Fisherman Village" for two days on the Moodle platform, indicated that social interaction played an important role in shaping social construction of knowledge through online collaborations for different groups. Students from the high-performing teams showed more adaptive motivation and were more engaged in higher cognitive level practice (e.g., applying constructed meaning and resolving inconsistency). However, students from the low-performing teams showed less motivation and more distractions, (e.g., inadequate online searching skills and interactions with off-topic behaviors). In another study, using a Mann Whitney T-test and GSEQ 5.1, Tao et al. (2022) assessed a group of Chinese college students' social construction of knowledge during a collaborative writing task to develop English writing skills which was supported by the instant messaging application Tencent QQ. Tao et al. found that the cognitive development and conflicts of student groups from different backgrounds, such as high and low performers, exerted an impact on the development of their social construction of knowledge online. To promote students' engagement in higher-level social construction of knowledge in online collaborations, research suggests that instructors structure the activity by considering group size and strategies, discussion duration, instructional prompts, peer mediation, and incorporating appropriate tools provided through digital applications or online learning platforms (Duvall et al., 2020; Guo & Chen, 2022; Hew and Cheung, 2011; Howell et al., 2014).

Analyzing Social Construction of Knowledge Using the Interaction Analysis Model (IAM)

The Interaction Analysis Model (IAM, see Table 1), developed by Gunawardena and colleagues (1997), has been used as a research method by over 50 researchers nationally and internationally with over 2,551 citing it as a viable framework for analyzing social construction of knowledge in both formal and informal learning environments (Buraphadeja & Dawson, 2008; Megli et al., 2023b; Nguyen & Diederich, 2023; Sanchez, 2019; Valtonen et al., 2022; Lehtinen et al., 2023). Social construction of knowledge as discussed earlier, draws from sociocultural and social constructivist theories that establish the vital role socialization plays in the learning process (Pea, 1993; Vygotsky, 1978). The IAM describes five phases of co-constructing knowledge that correlate with Vygotsky's (1978) concept of a learner's movement from lower to higher mental functions. The model begins with participants working at the lower levels of sharing and comparing information, moving through dissonance (Phase II) to higher mental functions of co- construction of new knowledge (Phase III). It is in Phase III that evidence of socially constructed knowledge appears. Phase IV and V represent validation of the knowledge constructed, the testing, and the adoption of new knowledge into the learner's framework and schema.

Table 1
The Interaction Analysis Model Developed by Gunawardena et al. (1997), adapted from the Original

PHASE I: SHARING/COMPARING OF INFORMATION	
A. A statement of observation or opinion	[PhI/A]
B. A statement of agreement from one or more other participants	[PhI/B]
C. Corroborating examples provided by one or more participants	[PhI/C]
D. Asking and answering questions to clarify details of statements	[PhI/D]
E. Definition, description, or identification of a problem	[PhI/E]
PHASE II: THE DISCOVERY AND EXPLORATION OF DISSONANCE OR INCONSISTENCY AMONG IDEAS, CONCEPTS OR STATEMENTS. (This is the operation at the group level of what Festinger [20] calls cognitive dissonance, defined as an inconsistency between a new observation and the learner's existing framework of knowledge and thinking skills.)	
A. Identifying and stating areas of disagreement	[PhII/A]
B. Asking and answering questions to clarify the source and extent of disagreement	[PhII/B]
C. Restating the participant's position, and possibly advancing arguments or considerations in its support by references to the participant's experience, literature, formal data collected, or proposal of relevant metaphor or analogy to illustrate point of view	[PhII/C]

PHASE III: NEGOTIATION OF MEANING/CO-CONSTRUCTION OF KNOWLEDGE	
A. Negotiation or clarification of the meaning of terms	[PhIII/A]
B. Negotiation of the relative weight to be assigned to types of argument	[PhIII/B]
C. Identification of areas of agreement or overlap among conflicting concepts	[PhIII/C]
D. Proposal and negotiation of new statements embodying compromise, co-construction	[PhIII/D]
E. Proposal of integrating or accommodating metaphors or analogies	[PhIII/E]
PHASE IV: TESTING AND MODIFICATION OF PROPOSED SYNTHESIS OR CO-CONSTRUCTION	
A. Testing the proposed synthesis against "received fact" as shared by the participants and/or their culture	[PhIV/A]
B. Testing against existing cognitive schema	[PhIV/B]
C. Testing against personal experience	[PhIV/C]
D. Testing against formal data collected	[PhIV/D]
E. Testing against contradictory testimony in the literature	[PhIV/E]
PHASE V: AGREEMENT STATEMENT(S)/APPLICATIONS OF NEWLY-CONSTRUCTED MEANING	
A. Summarization of agreement(s)	[PhV/A]
B. Applications of new knowledge	[PhV/B]
C. Metacognitive statements by the participants illustrating their understanding that their knowledge or ways of thinking (cognitive schema) have changed as a result of the conference interaction	[PhV/C]

Analyzing Social Construction of Knowledge with Social Learning Analytic Methods (SLAMs)

Social Learning Analytics, a subfield of learning analytics that is informed by social, cultural, and contextual perspectives on learning (Kaliisa et al. 2022) and focuses on learning in an online participatory culture (Buckingham Shum & Ferguson, 2012), provide a set of tools to automate the analysis of interactions in online environments as well as research how a group of people engage, collaborate, and co-construct knowledge. Buckingham Shum and Ferguson (2012) point out that if we view learning analytics from a social perspective, it will highlight the types of analytics that can be employed to make sense of learner activity in a social setting. "As groups engage in joint activities, their success is related to a combination of individual knowledge and skills, environment, use of tools, and ability to work together. Understanding learning in these settings requires us to pay attention to group processes of knowledge construction—how sets of people learn together using tools in different settings. The focus must be not only on learners, but also on their tools and contexts" (Buckingham Shum & Ferguson, 2012, p. 5). NNs, LLMs, and deep learning models fall within the larger umbrella of social learning analytic methods (SLAMs). They are applications generated by developments in artificial intelligence (AI) and machine learning.

Studies (Ba et al., 2023; Hu et al., 2020) have used machine learning algorithms to analyze collaborative constructivist learning based on the Community of Inquiry (COI) model developed by Garrison et al. (2001), which incorporates three types of presences; social, cognitive, and teaching. Hu et al. (2020) trained automated classifiers for different phases of cognitive presence in asynchronous discussions from an archived course of the Logical and Critical Thinking MOOC at the Open University in the United Kingdom. The trained automated cognitive classifiers indicated a 95.4% agreement with a weighted Cohen Kappa of 0.94. This study verified the possibility of machine learning as a method for automated analysis of online discussions. In a similar study, using Garrison's et al.'s (2006) COI coding framework, Ba et al. (2023) investigated cognitive presence and cognitive development from three online courses delivered in a public university in the Midwest United States. Ba et al. (2023) implemented text classification using the emerging LLM Bidirectional Encoder Representations from Transformers (BERT) and applied epistemic network analysis (ENA) to further "track learners' learning progressions" (p. 262) for learning assessment. Findings of this study showed that the integrated approach of the BERT-based text classifier along with ENA enhanced the accuracy of the prediction as well as illuminated new patterns of the learners' cognitive presence where learners "would summarize and build on each other's comments" in advancing further cognitive development (p. 260).

SLAMs have been employed by researchers to study social construction of knowledge online as stipulated by the IAM. By combining interaction analysis with learning analytics and Social Network Analysis, Gunawardena et al. (2016) were able to conceptualize the process by which knowledge construction takes place in online platforms. They suggest that learning analytics be used by IAM analysts to inform the results of qualitative transcript coding. For example, data scraping, sentiment and social presence analyses, are useful techniques for: (a) highlighting areas that a qualitative researcher should focus on in the data, (b) indicating the socio-emotional context that accompanies knowledge construction, and (c) suggesting hypotheses for future research. Subsequent studies have built on this initial study and used

SLAMs for analyzing social construction of knowledge according to IAM in the Black Lives Matter Twitter platform (Sanchez et al., 2020), and asynchronous discussion forums in nursing (Schaaf, 2020), the learning sciences and nursing (Megli et al., 2023a; 2023b), and provided insights on how SLAMs and IAM based content analysis of transcripts complement one another.

Given the theoretical base of social constructivism on which the IAM is grounded, NNs, and deep learning models, subfields of AI can quantitatively map the process of social construction of knowledge as stipulated by IAM in an online discussion dataset or transcript. Conceptually, machine-learning algorithms can be viewed as searching through a large space of candidate programs, guided by training experience, to find a program that optimizes the performance metric (Jordan & Mitchell, 2015). Many algorithms focus on function approximation problems, where the task is embodied in a function (such as determining social construction of knowledge according to IAM). The learning problem is to improve the accuracy of that function, with experience consisting of a sample of known input-output pairs of the function. NNs, a subset of machine learning, mimic the human brain through a set of algorithms (Kavlakoglu, 2020). This study explored if a basic feed-forward NN classifier and a deep learning model built on multi-layered NNs could predict the Phases of social construction of knowledge as stipulated by IAM.

Research Questions

We hypothesize that deep learning algorithms should indicate a consistent, similar pattern to classify online posts if human coders "use specific words and phrases within the posting to classify the IAM Phases of a post" (Megli et al., 2023b, p. 7). Therefore, the purpose of this study was to test if a basic feed-forward NN classifier and a LLM (Ahmad et al., 2022; Ba et al., 2023) could accurately predict the IAM Phases of social construction of knowledge, thereby advancing Megli's et al. (2023a; 2023b) study. We address the following research questions in this study:

1. Can a basic feed-forward NN classifier predict the phases of social construction of knowledge in online discussions according to the IAM?
2. Can a more advanced NN classifier, such as a LLM, improve on the prediction accuracy of the IAM phases?
   2a. Can fine-tuning a pretrained LLM improve on the prediction accuracy of the IAM phases over a basic feed-forward NN classifier like Doc2Vec?
   2b. Can using prompt engineering on an LLM improve on the prediction accuracy of the IAM phases over a basic feed-forward NN classifier like Doc2Vec?
3. To what extent do the predicted phases match a human coder's qualitative analysis of social construction of knowledge according to IAM?

Research question 2 has two subquestions that explain the two different ways in which a LLM can be trained to perform categorization on a dataset: (a) Fine-tuning a pre-trained model and (b) using prompt engineering on a pre-trained model. In the fine-tuning approach one takes a language model that was pre-trained on a large corpus of documents, such as Wikipedia, and then trains it on a task-specific, labeled dataset—such as discussion board posts coded according to IAM phases. In the prompt engineering approach, we give the LLM examples of the categories, then give it a new dataset and have it pick the closest matching category.

Methods

We selected an exploratory sequential mixed-method study design (Creswell et al. 2018) because we are exploring the possibility of predicting qualitative coding using an NN and because the qualitative baseline must be established before the automated quantitative analysis using an NN. This procedure involved three steps. The first step was the qualitative coding of the Phases of social construction of knowledge (according to IAM) in three online discussions that served as the basis for comparison with subsequent quantitative results from NN and LLM analysis. Next, a basic feed-forward NN classifier was used to predict the Phases of social construction of knowledge. This text classification task required choosing an architecture for the NN and providing the NN a training dataset and a testing dataset. The third step was designed to improve on the results of the basic feed-forward NN classifier by using a LLM, which is a more advanced NN classifier. After the three steps were concluded, we compared the basic feed-forward NN predictions and the LLM predictions with the qualitative coding of social construction of knowledge by researchers. The details of the qualitative coding, datasets, and the code used to train and test the NN and LLM are described in the following sections. For this exploratory study, we calculate prediction accuracy by dividing the number of correct NN predictions by the total number of predictions.

Qualitative Coding of Social Construction of Knowledge

Our dataset consisted of transcripts from two-semester long graduate-level online courses from the learning sciences and nursing in a public Research I university in the Southwestern United States. These transcripts were selected because the discussion prompts directed the students to construct knowledge. The discussion activities were initiated by differing instructor prompts. For the Learning Sciences discussion prompt, the faculty asked the students to build on the first posting on definitions of culture and eLearning. The goal was to come to a consensus on a definition and discuss how the definitions are related. The learning activities included collaborative problem-solving, negotiating, researching, and building consensus. The nursing discussion prompt asked students to post one question that came to mind regarding the topic and to research other sources to answer the question.

Six doctoral-level student researchers manually coded the three transcripts in pairs using the IAM coding spreadsheet to identify the Phases of knowledge construction. Each discussion post was one unit of analysis. The doctoral-level student researchers initially coded the transcripts individually, and then in pairs. Once the transcripts were coded, the pairs met to discuss their codes and check for agreement in their coding. Areas of disagreement were reviewed and resolved. We did not conduct a statistical intercoder calculation as it contradicts the interpretative nature of qualitative content analysis. We were able to reach a consensual interpretation of the data working within the common coding framework of the IAM (O'Connor & Joffe, 2020).

We used the three datasets for training the NN: Culture e-Learning 1 (2022a), Culture e-Learning 2 (2022b), Culture e-Learning 3 (2022c). For the text classification task, we chose an architecture for the NN, and provided the NN a training dataset and a testing dataset. For testing the dataset, we used the dataset Culture e-Learning B (2022d). All datasets are available for download at https://github.com/professorf/IAM-Data-Code. All three datasets combined had a total of 307 postings.

Neural Network (NN) Analysis

The quantitative methods included two studies using NNs that are described below as Study 1 and 2.

Study Design 1: Basic Feed-Forward NN Classifier (Doc2Vec)

Apparatus

We used the R programming language for data wrangling, RStudio as our integrated development environment, and the Doc2Vec package to train and test our NN. Finally, we used the lsa package, for its cosine similarity function, to determine the similarity or, how close the test postings were to the NN's representations (embeddings) of the five IAM Phases.

Procedure (NN Model: Doc2Vec)

The following procedure was followed:

1. Read in training datasets and combined them into a single dataset.
2. Collapsed the IAM subphases in the dataset into just the five main IAM Phases.
3. Formatted the dataset for the Doc2Vec function paragraph2vec.
4. Trained the Doc2Vec model.
5. Tested the accuracy of the Doc2Vec model.

We performed this procedure on all five IAM Phases, and on just Phases I-III, which signal the process of knowledge construction. We ran the above procedure in the following four conditions:

1. Trained using all five IAM Phases, each post labeled with the highest IAM Phase score.
2. Trained using all five IAM Phases, each post labeled with all non-zero phase scores. For example, if a post contained Phase I, III, and V elements, the post would have three labels.
3. Trained using just Phases I-III, each post labeled with highest phase score.
4. Trained using just Phases I-III, each post labeled with all non-zero phase scores.

The code can be downloaded at: https://github.com/professorf/IAM-Data-Code and is resident in the Culture-eLearning folder.

Study Design 2: LLM

Apparatus

We used the Python programming language for data wrangling, Visual Studio Code as our integrated development environment, and the PyTorch and HuggingFace transformer packages to train and test our NN. The hardware used to train the NNs was a Windows PC with an AMD Ryzen 7 5700X CPU and an Nvidia 3070 GPU.

Study Design 2a Procedure (Fine-tuning a pre-trained LLM):

We trained and tested our NN using five main steps:

1. Read in training datasets and combined them into a single dataset.
2. Collapsed the IAM subphases in the dataset into just the five main IAM Phases.
3. Formatted the dataset for general use by the transformers package.
4. Fine-tuned the pre-trained BERT model: *distilbert-base-uncased*.

5. Plotted the accuracy of the BERT model using a confusion matrix.

Study Design 2b Procedure (Prompt engineering using an LLM):

We tested three kinds of prompts:

1. The full five descriptions of the IAM Phases from Gunawardena et al (1997; see Table 1).
2. Just the five title descriptions of the IAM Phases from Gunawardena et al (1997; see Table 1 Phase titles).
3. Five short custom sentences that serve as a typical example of the five IAM Phases:
    3.1. "I define the concept this way. Or I believe the concept is that."
    3.2. "I disagree with how you have defined the concept."
    3.3. "I want to modify your definition of the concept."
    3.4. "I want to test your definition of the concept."
    3.5. "Let us now apply your definition of the concept."

Results

Results of Study 1 using the basic feed-forward NN classifier Doc2Vec is reported first, followed by the results of the two conditions in Study 2 using a more advanced NN classifier, the LLM.

Study 1: Basic Feed-Forward NN Classifier (Doc2Vec)

Each condition was trained and tested for accuracy twenty times to get an average accuracy score. The NN trained on all five IAM Phases had better accuracy (M = 21.55%, SD = 3.95) when each posting was labeled with multiple scores instead of labeled with a single score denoting the highest IAM Phase detected in the posting, $t(36) = 3.65$, $p < .001$. However, there was no significant difference in accuracy when the network was trained on just IAM Phases I-III, between postings labeled with a single versus multiple labels. Finally, the NN had better accuracy when trained on just Phases I-III (M = 34.39, SD = 4.13) versus training on all five Phases, $t(74) = 14.85$, $p < .001$. To summarize, for predicting all five phases, the highest prediction accuracy achieved was 21.55%.

Table 2
NN Classification Results

		IAM Phases Trained	
		I-III	I-V
Post Label	Single High-Score	34.12%	16.42%
	Multiple Scores	34.66%	21.55%

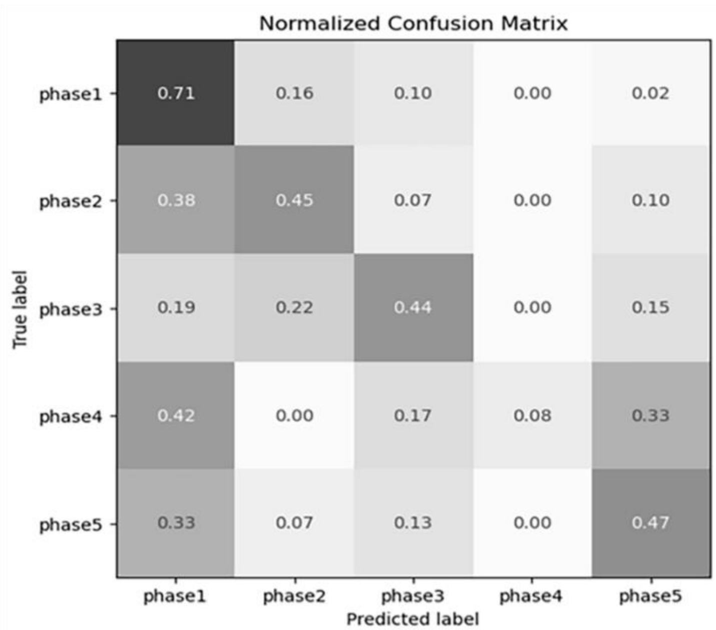
Table 2 shows the prediction accuracy of the basic feed-forward NN. The first row labeled "Single High-Score" indicates the results when only the highest IAM Phase was considered in the analysis in a post that was coded with several IAM Phases. The second row labeled "Multiple Scores" indicates the results when multiple IAM Phase codings for a single post was considered in the analysis.

Study 2a: Fine-tuning a Pre-trained BERT Model

The confusion matrix in Figure 1 depicts the accuracy of the model's predictions ("Predicted label") compared to the human coders' labels ("True label") in the matrix diagonal.

For example, 0.71 in the upper left corner indicates that the NN was 71% accurate predicting posts that the human coders had labeled as IAM Phase I. The NN's lowest accuracy was for Phase IV, at 0.08, i.e., only 8% of its posts labeled as IAM Phase IV matched the human coders' labels. The row values for any IAM Phase in the confusion matrix show what the NN mistook as the correct answer. For example, for Phase IV, the NN mistakenly labeled 42% as Phase 1 and 33% as Phase V. The mean of the diagonal values suggests a 43% prediction accuracy.

Figure 1
A Confusion Matrix for the BERT Model Trained on IAM Data. The Diagonal of the Matrix Depicts the "True Label" (Labeled by IAM coders), and the Model's "Predicted Label").



Study 2b: Prompt Engineering Using an LLM

There are two ways in which we can ask an LLM to categorize a post. One can give the LLM the entire post to categorize, or give the LLM one sentence of the post at a time to categorize, and assign the highest sentence category as the post category. This is similar to what some human IAM analysts do—code the individual sentences in a post, then assign a Phase to the entire post based on the highest sentence Phase. Table 3 shows the results of having an LLM categorize posts based on prompt engineering. The highest prediction accuracy achieved was 52.79%, by prompting the LLM using custom short examples.

Table 3
Categorization of Posts by an LLM based on Prompt Engineering

Prompt	Accuracy: Post Categorizing	Accuracy: Sentence Categorizing
Full IAM description	16.75%	12.69%
1-sentence IAM description	17.77%	38.01%
Custom short examples	52.79%	24.87%

In Table 3, Row 1 includes all operations in the five Phases of IAM. The results in Row 1 do not indicate high accuracy for the model. Row 2 is in a similar position with results indicating low accuracy. Row 3 instead is far more accurate when the LLM was fed custom short examples as they work best for the model. Just as students seek examples to understand complex phenomena, the LLM did best when it was given examples of IAM Phases. Therefore, mining key examples of IAM Phases and operations from a coded dataset and feeding them into a LLM that will learn with these examples may guarantee more accuracy when trying to match a human coder's analysis.

Discussion

The two studies demonstrated the viability of using machine learning and deep learning methods employing NNs and LLMs to analyze online social construction of knowledge according to the IAM. The study explained the research procedures for using both a basic feed-forward NN and a more sophisticated LLM for predicting a qualitative coder's analysis of social construction of knowledge. The results of the two studies showed that NNs have a promising ability to predict a human analyst's qualitative coding of the five Phases of IAM—which describes the process of social construction of knowledge online. The two studies demonstrated that when based on a sound theoretical foundation of learning such as social construction of knowledge, the underlying theory in IAM, NNs can quickly analyze Big Data, which is not viable with qualitative approaches alone. While the two studies demonstrated that NNs can predict a human coder's qualitative analysis of the IAM Phases (research question 3), the extent to which a NN can predict differed in the two studies. Therefore, further research with larger datasets is needed to increase the NN prediction accuracy.

More specifically, in Study 1, the low accuracy in all conditions is likely due to (1) an insufficient amount of training data and (2) multiple codes being assigned to single postings. For example, the original Doc2Vec authors (Le & Mikolov, 2014) used a dataset of 25,000 Internet Movie Database (IMDB) postings to train their NN. Much more data is required to train the NN for future studies since our entire study used only 307 postings. An additional challenge in training the NN was the low number of IAM Phase IV and V postings, which signal the higher levels of knowledge construction. The improved accuracy when phase IV and V scores were removed from the training data provides evidence that an insufficient volume of data was used to train the NN on these Phases. Historically, studies using the IAM have found many more occurrences of Phases I-III when compared to Phases IV and V (Kanuka & Anderson, 1998; Lucas et al.2014; Luebeck & Bice, 2005). This is because IAM Phases IV and V indicate validation of newly constructed knowledge compared to the earlier stages (Phases I-III) of co-construction of knowledge. IAM Phase III needs to occur for Phases IV and V to follow. Therefore, employing a NN when there were fewer frequency of occurrences of Phase IV and V in a dataset was problematic.

In their study, Le and Mikolov (2014) used just two labels: positive sentiment and negative sentiment. When using IAM, a post could represent more than one IAM Phase and/or operation (Commander et al., 2016). This known feature of the IAM increases the complexity for a NN, which must transform text into a high dimensional numerical vector known as an *embedding*, and makes it more difficult for the NN to discriminate between IAM Phases as compared to binary outputs. However, the insignificant results between postings with single versus multiple labels suggest that giving posts multiple Phase labels may not be necessary if there is enough training data. We had hoped that the basic feed-forward NN would predict IAM Phases with at least 70% accuracy, and are still hopeful that with more data, especially in Phases IV and V, it will be possible for a basic feed-forward NN to automatically predict all IAM Phases.

Given the shortcomings of using a basic feed-forward NN classifier to predict the qualitative analyst's coding of IAM Phases, in Study 2 we used a more advanced NN classifier, a LLM, to improve on the prediction accuracy of the IAM Phases. As the results of Study 2 demonstrate, the LLM did better than the basic feed-forward NN classifier in the prediction of the coding of IAM Phases. Of the two different methods reported in the second study, Study 2a, fine-tuning a pre-trained BERT model did the best. Our findings are similar to other studies that have used BERT. Sebbaq and Faddouli (2022) compared three neural network architecture on the task of classifying MOOC posts according to BLOOMs taxonomy: LSTM, Bi-LSTM, and BERT. They found BERT had the highest accuracy among the three architectures. Wulff et al (2022) also compared BERT's performance to two other deep learning models (FFNN, LSTM) on the task of classifying physics teachers' blog reflections along five categories. BERT once again outperformed the other deep learning models. Our study builds on these initial approaches by applying BERT to classifying discussion posts into the five phases of IAM.

In Study 2b (see Table 3) we found that the LLM did best when it was trained on custom short examples. This corroborates with our experience training students on coding IAM phases. In particular, providing students with specific examples of statements representing the five IAM phases helps them understand how to code the five Phases. Therefore, a table of examples of each of the IAM Phases and the subphases should be created to help both the human coder and AI based NNs and LLMs.

The results of the two NN studies also indicated the need to improve the IAM and better clarify the distinction between the five Phases, specifically Phases IV and V. Further refinement of the IAM may result in distinct embeddings of the text in hyperdimensional space, which may increase the accuracy of the NN predictions of social construction of knowledge. There are several ways to go about improving the IAM. One is to clearly delineate the function of Phases I-III as describing the process of knowledge construction, and the function of Phases IV and V as describing the process of knowledge validation. The sub-Phases of IAM could clarify this distinction. Further, when providing directions for online discussions with the aim of reaching social construction of knowledge, the directions should ask participants to reference the newly constructed meaning when considering its testing and application (Phase IV and Phase V). This way, the LLMs could pick up the cues to newly constructed knowledge when assigning a post to Phase IV and V. In the results of Study 2 we found that the LLM was confusing Phases IV and V with the earlier phases. Therefore, prefacing statements with signaling phrases such as "based on your new proposition," or "given our new understanding" may help the LLM as well as human coders classify the IAM Phases more accurately.

This study has implications for designing and supporting online collaborative learning where the goal is social construction of knowledge. When groups collaborate online whether in academic settings or workplaces, one challenge has been the difficulty of determining the extent to which group members negotiate meaning by sharing and comparing ideas, discovering and exploring differences, synthesizing ideas, creating new knowledge and then validating the newly constructed meaning. This is the process of knowledge co-construction that is described in the five Phases of IAM. Sammons (2007) has noted that IAM describes the process of collaborative learning, which also parallels studies of collaboration in face-to-face settings. By developing a NN based on IAM, this study has shown that it is possible to get a snapshot of the process of knowledge construction as group members engage with each other. Traditionally, such a snapshot of collaboration would not be possible without analyzing the interactions qualitatively after the collaboration has ended. The availability of such a snapshot through a NN based on the IAM, enables a group to fine tune its goals and objectives and determine its trajectory during the process of knowledge construction, while also helping instructors provide the necessary prompts and scaffolding to support a group's construction of knowledge. Since group discussions are an important part of the teaching and learning process of an online course, this study is a first step in using NN's to automatically gauge the degree to which social construction of knowledge is taking place in a collaborative group. This enables an online instructor to observe a group's co-construction of knowledge as it unfolds during collaboration, providing additional insight into how one group's collaboration maybe different from another's and how one group's strategies may have reached a higher level of knowledge construction. These insights provide a broader view of collaborative learning rather than merely assessing individual contributions to group collaboration often measured using rubrics of participation.

Limitations

Here, we reflect on the limitations of our study, some of which we pointed out in our earlier discussion. First, we emphasize that the purpose of using machine learning and deep learning algorithms in this study context was to predict a qualitative coder's analysis of social construction of knowledge among a group of interacting online participants. The aim was to determine if these algorithms could match a qualitative human coder's analysis. Therefore, the results of these predictions should not be used for purposes for which they were not intended, such as grading the performance of a group of students.

Second, while this research presents a novel perspective, we acknowledge that its predictive accuracy leaves room for refinement. However, based on the findings, we made suggestions for improving the prediction of IAM Phases using NNs and LLMs. We wish to emphasize that these findings are exploratory in nature, and should be viewed as a baseline for improvement by further research in this domain. Our study can thus serve as a foundational resource for other researchers aiming to enhance the accuracy and efficiency of such models applied to analyzing social construction of knowledge. It also provides a comparison point for other NN architectures and machine learning algorithms to improve upon.

Third, this particular AI model was trained on data from graduate students in a Research I university in the disciplines of LS and nursing. The model might not be applicable in every context. Since the model enables the determination of the level of social construction of knowledge in online collaborations, it may work well with disciplines that focus on collaboration specifically, education and the social sciences. However, researchers and instructors, need to interpret the results of the AI model based on their own contexts, including discussion prompts that give directions for discussions.

Conclusion

We were able to demonstrate through two separate studies that NNs and LLMs can predict a human analyst's qualitative coding of social construction of knowledge according to the five Phases of IAM, while the extent to which they could make the prediction differed. This approach can guide researchers to analyze large datasets and provide feedback to instructors to improve online learning as it unfolds. This study emphasized the necessity for a sound learning theory base such as social construction of knowledge on which to make predictions using deep learning algorithms. Without a learning theory foundation, the outcome of deep learning algorithms would not be useful for online learning. Future directions should focus on increasing the accuracy of the NN model's predictions and explore social construction of knowledge among diverse groups of learners in diverse disciplines, and contexts.

As a concluding note, we advocate the ethical use of findings from machine learning and deep learning algorithms as they may not be 100 percent accurate nor provide a reasonable picture when devoid of context and learner characteristics. As Garrison (2023) cautions, we must constantly question the educational value of adopting powerful AI tools as powerful technologies also bring severe risks. In their work on ethics in technology-based learning environments, Moore & Tillberg-Webb (2023) recommend that we engage in reflective practice and a critical and theoretically informed analysis of technology use.

Declarations

All the authors have no conflicts of interest to declare.
The authors declare that no approval from an IRB or Ethics Board was needed.

Appendix A

Glossary

Algorithm: A set of step-by-step instructions for solving a particular problem or performing a specific task. Computers use algorithms, transformed into code by programmers, to process data and transform it into useful information. Algorithms can differ in terms of memory needed, speed of execution, and quality of solutions. They are the backbone of machine learning and neural network applications (see also *machine learning* and *neural networks*).

Artificial Intelligence (AI): The capability of machines or software to solve problems and perform tasks that are traditionally thought to require human intelligence. It encompasses many different methods and technologies designed to replicate or mimic human-like problem-solving capabilities. In the context of learning sciences, AI can be employed to enhance personalized learning experiences, assist educators in assessing student progress, and provide insights into the efficiency of instructional methods.

BERT: A type of deep-learning model, based on the transformer architecture, designed by Google to understand the context of words in a sentence. BERT stands for "Bidirectional Encoder Representations from Transformers." It's widely used in tasks that require a deep understanding of context, such as search engines or question-answering systems. In learning sciences, BERT can assist in comprehending student inputs, facilitating language-based assessments, or enhancing educational tools that work with text.

ChatGPT: An LLM developed by OpenAI. The GPT is short for Generative Pre-trained Transformer architecture. ChatGPT was trained to generate human-like text responses to the input it receives, making it suitable for chatbots, virtual assistants, and other interactive applications. In the context of learning sciences, ChatGPT can be used to simulate educational dialogues, assist students with questions, or provide interactive learning experiences.

Deep Learning: An advanced kind of machine learning that uses multi-layer neural networks, which are commonly referred to as “deep neural networks” or “deep learning networks.” The term "deep" refers to the depth of the network, as these models can have many layers of interconnected nodes. These deep structures enable the system to create and relate multiple levels of abstraction from data, which has resulted in state-of-the-art solutions for complex tasks like image & speech recognition, language translation, natural language processing, and creating content. In the context of learning sciences, deep learning can be applied to automatically analyze and understand student responses, to classify student learning styles, and to help instructors find patterns in group work. (see also *machine learning*, *neural network*).

Deep Learning Model: A computing system that uses deep learning to solve problems and perform tasks.

LLaMA: A large language model (LLM) developed by Meta, Facebook’s parent organization. It is an acronym for Large Language Model Meta AI. Like many LLMs, LLaMA was trained on a massive corpus of text documents, and can generate text, translate languages, write different kinds of creative content, and answer your questions in an informative way.

Large Language Model (LLM): A type of artificial intelligence system designed to understand and generate human-like text based on vast amounts of data. These models are “large” because they consist of billions or more of parameters, enabling them to discover nuanced word and phrase relationships and to produce coherent, contextually relevant responses. They are also large because they have been trained on a vast corpus of documents including web pages, social media posts, books, and software repositories. In the context of learning sciences, a large language model can be used for tasks such as auto-grading essays, providing feedback on writing, generating educational content, or even facilitating interactive learning through simulated dialogue.

Machine Learning: A subset of artificial intelligence focused on creating computer applications that are designed to learn from and take actions based on data. By identifying patterns in data, these systems improve and refine their operations over time. In the context of learning sciences, machine learning can help instructors discern students' learning strategies, tailor educational content to individual needs, and offer predictive insights to educators about potential challenges students might encounter (see also *artificial intelligence*).

Neural Network: A computing system inspired by the structure of the human brain that is designed to process information in a way that emulates human cognitive processes. Neural networks consist of interconnected nodes, which are analogous to neurons in the brain, that can be trained to recognize relationships and patterns in data. In the context of learning sciences, neural networks can be used to analyze and understand student behaviors, predict learning outcomes, and to develop personalized learning strategies. Neural networks are one approach to designing AI and machine learning systems (see also *artificial intelligence*).

Pre-trained Language Model (PLM): A type of artificial intelligence system that has been previously trained (pre-trained) on vast amounts of text data, allowing it to understand and generate language. The "pre-training" means it has already learned from general text data and is available for fine-tuning for specific tasks. In the context of learning sciences, a pre-trained language model can be further tailored for educational applications, such as understanding student responses from a specific class, generating content for a specific class, or assisting in coding transcripts using a particular codebook.

Transformer: A specific collection of algorithms, or architecture, commonly used in large language models. The transformer architecture revolutionized the field of natural language processing due to its effectiveness in learning from vast amounts of text data. The name derives from its ability to “transform” input data—from sentences to entire documents—into meaningful outputs like translations or summaries. In the context of learning sciences, transformers can assist in building instructors and learners powerful capabilities that aid in language translation, content summarization, and other tasks that involve understanding or generating text (see also *large language models*).

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