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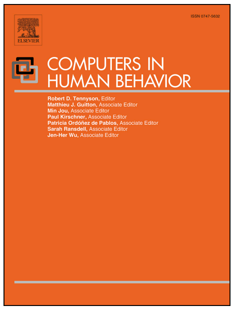

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THE EFFECT OF SUSTAINED VS. FADED SCAFFOLDING ON STUDENTS' ARGUMENTATION IN Ill-STRUCTURED PROBLEM SOLVING

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Introduction

In domain practice, experts often encounter complex, ill-structured problems that have unclear goals, multiple variables, and different perspectives (Herrington, Reeves, & Oliver, 2014; Jonassen, 1997). Given that ill-structured problems have various solution paths, expert practitioners must justify a solution in favor of a proposed resolution given the available facts, claims, and warrants of the argument. As practitioners gain expertise by solving problems, they generate complex knowledge structures and rules that allow them to generate arguments for future problems (Hmelo-Silver & Pfeffer, 2004).

Problem solving and argumentation are also important elements of deep learning. In contrast to surface-level learning, Chin and Brown (2000) summarized deep learning as the process engaged by students who are intrinsically motivated to integrate various aspects of the problems, prior knowledge, and everyday experience in the problem-solving processes. In terms of argumentation and deep learning, learners must be able to understand the initial claims, articulate alternative perspectives, and weigh the evidence presented of both sides (Jonassen & Kim, 2010; Kuhn, 1993; Kuhn & Udell, 2003). Although many educators agree that problem solving and deep learning are important pedagogical goals, this is often difficult for novice learners to master because it entails complex cognitive and metacognitive processes. Specifically, studies find that learners often approach problem solving at the surface level and often fail to engage in the deeper cognitive processes that are critical for deep learning (Dolmans, Loyens, Marcq, & Gijbels, 2016; Wang, Kirschner, & Bridges, 2016) .

To encourage students' deep learning, educational researchers have examined the role of technology to scaffold students' ill-structured problem-solving skills, such as argumentation.

Question prompts, in particular, have been embedded in a technology-supported environment as a way to internalize deep learning strategies (Hmelo-Silver, Duncan, & Chinn, 2007; Salomon, Globerson, & Guterman, 1989; Scardamalia, Bereiter, McLean, Swallow, & Woodruff, 1989). Ge and Land (2003) argued that question prompts in a technology-supported learning environment can be designed to model the types of deep learning cognitive processes that experts undergo when solving problems. Similarly, Hemberger and colleagues (2017) designed computer-based prompts to engender students' reflection on metacognitive strategies, beliefs, and domain related and task specific skills. Based on the theoretical arguments and empirical research, many extant learning environments have embedded some type question prompts as a way to engage learners in active cognitive processes and adopt deep learning strategies (Davis & Linn, 2000; Ge, Chen, & Davis, 2005; Ge, Planas, & Er, 2010; Kauffman, Ge, Xie, & Chen, 2008)

Despite the empirical support for question prompts, much of the scaffolding research has focused more on comparing types of scaffolding designs rather than how to effectively implement scaffolds during problem solving (Belland, Walker, Kim, & Lefler, 2017; Ge, Law, & Huang, 2016). One issue, in particular, is how scaffolds can be removed over time once learners have attained a skill, a process known as fading (Pea, 2004). From the theoretical perspective of cognitive load, it is imperative to understand when and how to fade scaffolds over time so that learners can engage in self-directed and problem-centered instruction (Noroozi, Kirschner, Biemans, & Mulder, 2017; van Merriënboer & Kirschner, 2012). Therefore, additional questions remain, such as *who needs to be scaffolded*, *when scaffolding needs to be provided*, and *how scaffolding should be provided*. To address this gap, this manuscript first provides a literature reviews on ill-structured problem solving and argumentation. It then introduces the theoretical constructs and related literature on scaffolding. Finally, a study is presented exploring how the the manipulation of fading scaffolds in terms of schedule and types of prompts supports students' problem-solving and argumentation skills.

Literature Review

Ill-structured Problem Solving and Deep Learning

Ill-structured problems are described as complex and ill-defined (Jonassen, 1997; Sinnott, 1989), unlike well-structured problems, which often contain a well defined initial state, a known goal state, a set of constrained operators, and prescribed solution paths (Jonassen, 2011). The goals and nature of an ill-structured problem are often vague or unclear, and many problem elements are unknown. Subsequently, there could be multiple solution paths to an ill-structured problem or there could be no solutions at all (Hung, 2015; Kitchener, 1983). Due to the inherent ambiguity of ill-structured problems, it is difficult to ascertain the explicit means or appropriate actions to remedy the solution. As such, individuals often engage in argumentation in order to reconcile their conflicting conceptualizations of the problem, identify alternative perspectives about the problem, and construct arguments as they pursue solutions (Jeong & Lee, 2008; Kuhn & Udell, 2003).

How individuals solve problem is impacted by their knowledge structures, which also include the patterns and rules they employ to solve problems and engage in argumentation (Ertmer et al., 2008; Ifenthaler, Masduki, & Seel, 2011; Kim & Clariana, 2017). Research finds that experts and novices approach ill-structured problem solving in different ways based on how they organize their content knowledge. Deep knowledge structures demonstrated by experts can be defined as a holistic, schematic organization of knowledge, in which a set of key concepts is semantically structured in a relational manner. Hmelo-Silver and colleagues (2007) further argue that a robust knowledge structure needed to solve ill-structured problems “requires mental simulation and rule-based inferences to construct a complete mental model” (p. 309). Research consistently finds that the rule-based approaches to solving problems are based on their deep knowledge of the domain principles (Chi, Feltovich, & Glaser, 1981; Ertmer et al., 2008; Ifenthaler, 2010; Larkin, Mcdermott, Simon, & Simon, 1980), and, this allows them more flexibility in the rule-based approaches they use to solve problems. In doing so, experts are able to engage in decentralized thinking that takes into accounts multiple causal paths (i.e., a gist-relational structure, (Jacobson, 2001)). Alternatively, empirical studies finds that novices knowledge structures tend to focus on perceptually visible, surface characteristics of the problem (i.e., a verbatim-linear structure) (Hmelo-Silver, Marathe, et al., 2007). When novices are not able to identify the germane variables, they are unable to construct knowledge structures or rule-based inferences needed to depict the causality of the phenomenon.

Supporting Deep Learning in PBL

Given the differences of experts and novices, the development of deep learning can be viewed as the directional changes in a learner’s knowledge structure. One approach to supporting deep learning and robust knowledge structures has been through problem-based learning (PBL), which suggests that learners be confronted with ill-structured problems in classroom contexts. In this model of learning, the instructor acts as the facilitator while students self-direct their learning (Barrows & Tamblyn, 1980). However, it is well documented that the development of robust knowledge structures that support effective argumentation in ill-structured problem solving is challenging for novices due to the complexity often embedded in these types of activities (Feltovich, Spiro, Coulson, & Feltovich, 1996). This has led to critics suggesting the problem-solving required in PBL is too complex and exacerbates cognitive load (Kirschner, Sweller, & Clark, 2006)

To support deep learning for novices in PBL, various models have attempted to outline the cognitive and metacognitive processes that are requisite for robust knowledge structures and rule-based inferences. Ge and Land (2003) identified four distinctive ill-structured problem solving processes based on a comprehensive review of previous research (Jonassen, 1997; Sinnott, 1989; Voss & Post, 1988): (a) problem representation; (b) developing solutions; (c) making justifications and constructing arguments; and (d) monitoring and evaluation. Problem representation involves understanding the problem state and goal state, as well as working through the solution path from the initial state to the goal state in the problem space. In this stage, individuals must be able to define the problems, identify factors or constraints, and prioritize the goals of problem solving. They must also be able to construct multiple problem spaces and representations to determine the appropriate solution (Hmelo-Silver, 2013; Sinnott, 1989). In addition, they also need to be able to recognize and examine divergent perspectives (Voss & Post, 1988).

The second process of the Ge and Land (2003) model included developing solutions. The generation of solutions naturally follows the elaborative problem representation process when individuals contemplate how to resolve the presented issue (Chi & Glaser, 1985). During this process, causes are identified and feasible procedures are implemented to address the problem (Eseryel, Ifenthaler, & Ge, 2013; Jeong & Lee, 2012). Additionally, various positions and different views must be identified since there are often multiple perspectives when solving an ill-structured problem. In order to make an informed decision and select the most viable solution, problem solvers must justify their solution or decision with defensible arguments against alternative solutions (Jonassen, 1997; Voss & Post, 1988). This process is identified as the process of making justifications and constructing arguments.

The fourth and final process includes the monitoring and evaluation of the entire problem solving process. This entails how learners manage the processes of problem representation, solution generation, and construction of arguments that is essential to solve an ill-structured problem (Sinnott, 1989). Given that ill-structured problem solving is an iterative process (Jonassen, 1997), the problem representation often changes throughout the problem-solving process (Stepich & Ertmer, 2009), and problem solvers often reanalyze and reexamine the problem space after they test all the possible solutions. When a solution does not work, problem solvers often have two choices: plan another solution based on their understanding of the problem or redefine the problem space. The feedback loop continues until a satisfying solution is reached (Ge & Land, 2003; Hong & Choi, 2011); (Jonassen, 1997)(Ge & Land, 2003; Hong & Choi, 2011).

Argumentation and PBL

As noted earlier, an important element of problem solving is how learners justify a solution; therefore, argumentation is one of the important evidences of deep learning. In PBL, when learners are posed with a problem that has multiple solutions, they need to generate viable solutions to solve the problem. As a learner proffers a hypothesis to solve the problem, they must be able to justify their solutions based on their rule-based inferences (Hmelo-Silver, Marathe, et al., 2007). In order to accomplish this goal, they construct, refute, and compare arguments using the available evidence gathered during the problem representation process (Hemberger et al., 2017; Kuhn, 1993). Through the process of argumentation, learners who are engaged in deep learning are also able to articulate their thoughts, use evidence to modify previous beliefs, and uncover misconceptions in reasoning (Hsu, Chiu, Lin, & Wang, 2015; Wecker & Fischer, 2014). In addition, the students who engage in deep learning often arrive at robust solutions through an iterative process of problem representation (Huang, Ge, & Law, 2017). Alternatively, students who perform at the surface level often make assertions and fail to articulate their thoughts, elaborate their argumentation, clarify the misconceptions or relationships in their reasoning, or backup their arguments with evidence. As a result, surface learning students provide solutions that are not clearly related to or aligned with their problem representations (Huang et al., 2017)

Research has focused on supporting argumentation in PBL because it is representative of the deep learnings practitioners undergo as they solve authentic problems and justify solutions. To date, empirical studies suggests that when learners engage in argumentation, they are able to gain conceptual understanding during instructional activities (Schwarz, Neuman, Gil, & Ilya, 2003; Simon, Erduran, & Osborne, 2006; Von Aufschnaiter, Erduran, Osborne, & Simon, 2008). Moreover, learners who are engaged in argumentation retain their learning outcomes longer (Asterhan & Babichenko, 2015) and transfer their learning (Crowell & Kuhn, 2014; Kuhn & Crowell, 2011). Studies have also shown increased motivation when learners are engaged in argumentation activities, possibly because students are afforded the autonomy to solve their problems (Chinn & Clark, 2013), which would lead to deeper learning.

While research has shown positive effects of argumentation, other studies have shown that learners often face additional challenges during argumentation in PBL (Wecker & Fischer, 2014). For instance, in multifaceted argumentation, students not only justify their own position, but must articulate and justify alternative perspectives beyond their initial stance. From a cognitive perspective, this form of argumentation requires individual to engage in deep learning process, including articulating the evidence for possible counterclaims and rebuttals (Jonassen &

Kim, 2010; Nussbaum & Asterhan, 2016). However, when asked to construct an alternative argument, students tend to reiterate the evidence for why their initial stance was correct (Jonassen & Cho, 2011; Kuhn & Udell, 2003). Other research has found that some students have difficulty with multi-faced arguments due to a tendency to gravitate to a "my-side bias" (Hemberger et al., 2017; Kuhn, 1993; Newell, Beach, Smith, & VanDerHeide, 2011; Voss & Means, 1991). In doing so, students opt to favor their initial stance and fail to support their positions in light of evidence-based explanations from different perspectives (Kuhn, Goh, Iordanou, & Shaenfield, 2008).

Scaffolding Argumentation with Question Prompts

One of the inherent challenges of argumentation in PBL is that learners must simultaneously learn new information and solve ill-structured problems using evidence they have obtained. As noted earlier, critics have argued that this poses an additional strain on working memory and thus precludes deep learning (Kirschner et al., 2006; van Merriënboer, 2013). Despite the concerns on working memory, other researchers have suggested that ill-structured problem-solving should still be at the center of education, but learners need to be properly supported (Belland et al., 2017; Hmelo-Silver, Duncan, et al., 2007). According to Vygotsky (1978), learning consists of cognitive development through socially mediated interactions, which become internalized within individuals' cognition over time. He further argued that within each individual exists a 'zone of proximal development', which refers to the gap between an individual's current abilities and the intended goals that would be unachievable with unassisted efforts from a more capable peer (Rosenshine & Meister, 1992). An important aspect of scaffolding is that, while the complexity of the problem is maintained, learners are able to access the support when needed. The complexity of the task is reduced so that the task becomes more manageable, aligned with the appropriate level of complexity that is within the learner's zone of proximal development (Brush & Saye, 2002).

Another important approach towards scaffolding lies in the expert-novice interactions, also known as "cognitive apprenticeship" (Brown, Collins, & Duguid, 1989). Cognitive apprenticeship is defined as sharing problem-solving experiences between an expert and a novice, with mentor being either a teacher, a more capable peer, or technology support tool. Using a cognitive apprenticeship approach, Collins and his colleagues (1991) suggest that educators can support the development of expertise using the following strategies:

- Modeling - whereby the experts perform a task that the novice can observe
- Coaching - facilitation of students as they perform a task
- Scaffolding - targeted assistance that is provided to students as they perform as task
- Articulation - encouragement of student to verbalization their thought process
- Reflection - providing opportunities for introspection of the task
- Exploration - the novice is allowed to direct their inquiry

Mentor support, such as prompts and hints, enable novices to successfully execute a problem-solving task that is beyond their current capabilities. In this cognitive apprenticeship process, the expert's knowledge structures, problem-solving strategies, self-regulation, and argumentation processes are modeled through the mentor's guidance, scaffolding, and coaching (Tawfik & Kolodner, 2016). As the mentee gains the skills needed to solve the problem, the mentor gradually fades support and encourages the mentee to perform the task independently (Lajoie & Derry, 2013). Over time, novices adopt the knowledge structures and processes of an expert, which allows them to engage in more expert-like reasoning as they construct arguments during their problem-solving.

Scaffolding and Fading

While research has explored different facets of the cognitive apprenticeship approach to support deep learning, scaffolding has generated a considerable amount of focus. In the original conceptualization, scaffolding is mostly accomplished through an adult or a more knowledgeable peer (Wood, Bruner, & Ross, 1976). However, scaffolding, as an essential component of cognitive apprenticeship modeling, can also be embedded in learning technologies to provide similar expert support to students (Ge et al., 2010) by engaging them in metacognitive activities and self-regulatory processes (Lajoie & Derry, 2013). In terms of argumentation, it is argued that providing expert-like modeling to students helps to scaffold them in developing competence in problem representation, constructing cogent arguments, constructing solutions, and monitoring and evaluating their problem-solving processes (Ge & Land, 2003; Oh & Jonassen, 2007)

An important aspect of scaffolding includes how the supports are faded over time (Pea, 2004; Puntambekar & Hubscher, 2005). For example, Lajoie (2005) defined scaffolding as “a temporary framework to support learners when assistance is needed and is removed when no longer needed” (p. 542); that is, scaffolding is “temporary and adjustable” (Palincsar, 1986, p. 75). To date, some research has begun to examine the effects of scaffold fading. For example, Lai and Law (2006) examined the effect of fading peer scaffolds in the context of computer-supported collaborative learning. In their study, Canadian students, with prior learning environment experience, worked for a month and a half with Hong Kong students with no prior learning environment experience. After the peer support from the Canadian students were faded, the researchers examined how Hong Kong students collaborated without the peer scaffold. The study revealed that (a) the more experienced students served as a peer scaffold for the less experienced students and (b) knowledge building persisted even when the peer scaffolding from the Canadian students was faded. Similarly, Bulu and Pedersen (2010) compared continuous and faded scaffolds in the context of science learning. In Week 1, three types of scaffolds, question prompts, examples, and sentence starters, were presented to the students in both groups (continuous vs. faded). Over the following three weeks, scaffolds were withdrawn gradually from the faded group, one at a time, starting from the withdrawal of examples in Week 2, then question prompts in Week 3, and finally sentence starters in Week 4. The study found that students with continuous scaffold performed better than those with faded scaffolds regarding developing solution and making justifications.

Purpose of Study and Research Questions

As discussed earlier, the concept of scaffolding and fading is central to the cognitive apprenticeship approach. While research has investigated the importance of scaffolding through question prompts, there is less research about how these scaffolds support learners' problem-solving processes over a period of time. Moreover, there is less research on fading of scaffolds on specific evidences of deep learning, such as argumentation. To address this gap, the purpose of the current study was to examine if fading of question prompts, following the initial support, would influence students' ability to reason in the form of argumentation during ill-structured problem-solving tasks. The following Research Questions (RQs) guide our effort of investigation:

1. To what degree is the quality of arguments impacted when students are supported with sustained or faded scaffolding schedules?

2. To what degree are the knowledge structures of argumentation impacted when students are supported with sustained or faded scaffolding schedules?
3. To what degree are the relationships between concepts in argumentation associated when students are supported with sustained or faded scaffolding schedules?

Methodology

Participants

Fifty-five junior business students participated in the study. They were drawn from a marketing course entitled Personal Selling, an upper division course offered in the College of Business at a large university located in the Midwest region of the United States. The course focused on how to develop and maintain customer relationships and company health in changing economic markets.

Procedure

The study was completed over a course of four weeks in the semester. In the first week, participants were randomly assigned to two conditions (sustained scaffolded vs.faded scaffolded) using the Microsoft Excel randomization function. In the ensuing weeks, participants were asked to resolve three ill-structured problems in consecutive weeks. For each of the problems, the participants were given one week to construct an argument about how they would respond to the personal selling dilemma. At the end of each problem, participants would submit a 2-3 page essay that consisted of their initial argument, counterargument, and rebuttal. The participants stayed within the same conditions for each of the three problems.

As noted earlier, the overall goal of the research was to understand how differing the presence of prompts would support problem-solving transfer as the scaffolds were adapted. To accomplish this, the prompts were presented to the participants in different ways depending on their randomly assigned condition. In the sustained condition, participants were scaffolded with the full set of Ge and Land (2003) prompts in the first two problems: problem-representation, developing solutions, making justifications, and monitoring evaluation. In the last week of the study, the scaffolds were removed so that we could investigate the impact upon transfer. Alternatively, the participants in other condition were scaffolded using a faded approach. Like the sustained condition, the participants in the faded group received the same prompts for the first problem (problem-representation, developing solutions, making justifications, and monitoring evaluation). However, the making justification and monitoring evaluation prompts were removed for the second problem. The scaffolds were completely removed for the third and final ill-structured problem, which was the same as the sustained scaffolding group. Table 1 depicts the sustained and faded conditions over the three-week study.

TABLE 1 ABOUT HERE: SCAFFOLDING CONDITIONS AND PROCEDURES

Materials

Ill-Structured Problems. The materials for the problem-solving tasks included three ill-structured problem scenarios concerning marketing principles. These similar scenarios, developed by an experienced subject matter expert with over 20 years of experience, were designed for the complexity level that was appropriate for the participants. In the first week, the students were provided with the first problem, and they were asked to individually articulate a multifaceted argument (initial argument, counterargument, rebuttal (Nussbaum, 2008)) that detailed the rationale about how they would retain an employee who was contemplating transferring to a new job market. In the second week, the participants were presented with the another problem which asked them to construct an argument about how they would improve the company by opening a new branch in a new part of the country. In this case, the participants needed to argue about how they would hire and train a new workforce as part of the move to a new market. In the third week, participants were presented with a company that had recently purchased a medical device company. This problem required participants to construct an argument about how their combined workforce would balance personal selling and technical expertise in new markets. For each problem to solve, participants were required to consider and detail how they would maintain market share, keep established clients, and expand company growth.

Scaffolds. As noted earlier, the cognitive apprenticeship model consists of the following methods: modeling, coaching, scaffolding, articulation, reflection and exploration. The provided prompts were designed to scaffold students in their problem-solving processes, articulate their reasoning (which served to elicit and assess their knowledge structure), and reflect their problem-solving processes

This study was focused on scaffolding, one of the components in the cognitive apprenticeship model, and it particularly centered on how fading of scaffolds supported deep learning. To scaffold the problem-solving process, the participants were presented with prompts below the problem scenario and embedded directly in the learning (see Figure 1). The prompts were based on Ge and Land's (2003) scaffolding framework to support problem-solving in the following areas: problem-representation, developing solutions, making justifications, monitoring evaluation. These prompts had been employed for supporting problem-solving in a variety learning designs, so the validity has been established (Bixler & Land, 2010; Chen, 2010; Hew &

Knapczyk, 2007). Within each area, subquestions were recommended which scaffolded the students as they engaged in ill-structured problem solving.

FIGURE 1 ABOUT HERE: LEARNING ENVIRONMENT WITH EMBEDDED PROMPTS ADAPTED FROM GE AND LAND (2003)

Instruments

Scoring Rubrics. Theorists argue that a key problem solving skill is the ability to generate solutions in light of alternative perspectives (Kuhn, 1991; Nussbaum, 2008). Therefore, students' argumentation artifacts were first analyzed and independently evaluated by the three researchers (Dependent Variable 1). Each argumentation was scored on measurements of initial claim, counterclaim, and rebuttal (Nussbaum, 2008). For the purposes of the experiment, the initial claim was defined as the initial stance and justification for how to solve the problem. The counterclaim was defined as a an alternative solution path and justification. Lastly, the rebuttal was defined as a way in which participants came to a final conclusion given the justification provided in the initial claim and counterclaim. Each was coded independently because the initial, counterargument, and rebuttal serve as different measures deep learning skills during problem solving.

The coding scheme for the argumentation was adapted from Jonassen and Cho (2011). However, the current study extended the rubrics to include argumentation factors such as initial argument and counterargument. Participants were scored a 0 if the argument factor (initial claim, counterclaim, and rebuttal) lacked consistency or coherence; 1 point for a position that was poorly developed; 2 points for a position that was clear, but lacked quality explanation; 3 points for an argumentation that was well developed, but only partially explained; and 4 points for an argumentation that was well developed, supported, and explained. The higher the score, the more expert-like the argument demonstrated and deeper learning it indicated. All argumentation artifacts were independently rated by two researchers.

Graphical Interface of Knowledge Structure . To further understand the impact of scaffolding on argumentation, the participant's knowledge structure reflected in their argumentation artifacts also served as a dependent variable (Dependent Variable 2). Emig (1977) asserts that "writing closely resembles thinking… and is thus a concrete artifact or manifestation of the writer's cognition (p. 44)"; that is, an external representation of internal semantic structure (Kintsch, 1994). As noted in the cognitive apprenticeship section, we assert that knowledge structure is not static, fixed property, but is gradually modified through learning and instruction toward a desired state or expert level. In this sense, learners possibly experience changes in their knowledge structures as ill-structured problems are recognized, defined, and organized (Thompson & Opfer, 2009). Thus, comparing students' knowledge structures in their argument essays with the knowledge structures in the expert argument essay would be helpful to capture the (a) qualitatively different knowledge structures as a function of the different strength of scaffolding and (b) to demonstrate depth of learning (i.e., deep vs. surface learning).

Differences between expert and students knowledge structures was measured through a computer-based text analytic system entitled *Graphical Interface of Knowledge Structure* (Kim, 2017), which is designed to capture and analyze semantic knowledge structures implicitly represented in their argument essays. The *GIKS* software selected for use in this investigation captured important key concepts in an argumentation text and then visually represent the most salient linkages among the key concepts as KS, based on the assumption that human knowledge is structured in a relational manner. Therefore, the term knowledge structure, also known as structural knowledge (Jonassen, Beissner, & Yacci, 1993) or cognitive structure (Preece, 1976), is operationally defined here as concept inter-relatedness, the pattern of relationships among concepts in memory. Note that the validity and reliability of *GIKS* system has been established in diverse domains; for example, to measure KS in an online course (Draper, 2013), to establish the text structures of narrative and expository lesson texts (Clariana, Wolfe, & Kim, 2014; Kim, 2017), to score students' essays (Kim & Clariana, 2015, 2017), to describe the knowledge structure transfer from first language to second language (Tang & Clariana, 2017), and reading comprehension (Liu, 2016).

For the purposes of this study, an expert argumentation essay was generated for comparison. The expert essay included all parts of the argumentation, including initial, counter, and rebuttal. The argumentation essay was generated by the instructor of record, who also had over 20 years of domain experience. The essay was also reviewed by another practitioner for clarity to ensure key concepts were included and alternative perspectives were represented. In total, the expert essay underwent two rounds of revisions between the subject matter experts.

The *GIKS* system automatically converted the expert and students' argumentation essays into visually represented knowledge structure network graphs to indicate specific areas of their current knowledge strengths and weaknesses in comparison with the referent KS (see for example, Figure 2). The similarity of the participants KS with the expert KS were measured as *percent overlap*, calculated as the "links in common" for two KSs divided by the average number of links in the two KSs. For example, the percent overlap of the expert and the student shown in Figure 2 is calculated as 6/((15+7)/2) = 0.55 (55% overlap), where 6 is the number of links in common (Clariana et al., 2014). Note that the *GIKS* system automatically generates the similarity value.

FIGURE 2 ABOUT HERE

Figure 2. GIKS screenshot of an example knowledge structure (KS) network graph derived from a week 1 *initial* argumentation from an expert (*left*) and a student (*right*). Student's KS consists of a highlighted network graph showing the similarity and difference Compared to the referent KS; *yellow* indicates 'missing' links/nodes and *red* indicates 'incorrect' links/nodes

This investigation also used an emerging graph-theoretical model from social network analysis, *Graph Centrality*, as a way to measure the knowledge structure form. Clariana et al. (2011) proposed graph centrality as a holistic measure of network graph visual form and quantified four typical visual layout forms using the numerical graph centrality, with 0.1 (linear), 0.4 (hierarchical), 0.6 (network), and 1.0 (star) (see for detail, Clariana et al., 2013; Kim et al., 2015, 2016).

TABLE 2 ABOUT HERE.

Graph centrality (Cgraph) calculated for network visual layout forms from Clariana et al., (2013) with Hay and Kinchin's (2006) conceptual typology

Associated Rule Mining. Similar to other argumentation research (Guo, Xing, & Lee, 2015), the current study employed association rule mining to investigate how learners associated concepts during their argumentation (Dependent Variable 3). Association rule mining is a classic algorithm in an unsupervised text mining approach to undercover the co-occurrence of important concepts and ideas in a text (Hipp, Güntzer, & Nakhaeizadeh, 2000), such as an argumentation essay. Specifically, associated rule mining is employed to "extract interesting correlations, frequent patterns, associations, or causal structures among sets of items in large datasets" (p. 2). Whereas GIKS compared students argumentation texts with an exemplar based on an expert's argument, associated rule mining describes the degree to which an individual relates two concepts with each other during argumentation. Compared with the GIKS, association rule mining is totally data driven and thus examines the more granular difference between the sustained and faded conditions. Therefore, association rule mining provides another angle to examine the influence of sustained and faded facilitation on students' argumentation ability.

The resulting format of association rule mining is a set of rules expressed as

Left Hand Side (LHS) => Right Hand Side (RHS)

where LHS and RHS represent the two set of items. Such as rule indicates that words on the LHS are likely to co-occur with the words on the RHS. This automatically discovery of co-occurrence of words is the fundamental mechanism of association rule mining (Zhang & Zhang, 2002).

Confidence Calculation. Association rule mining is usually applied in large-scale data settings. In this study, given that the number of students are relatively small, we compiled the initial, counterclaim, and rebuttal for each week in order to aggregate additional argumentation texts for association rule mining to analyze. As a result, we could compare the number of rules discovered and the rule quality difference using the confidence metric between the sustained and faded conditions. This also generated a more robust, valid, and reliable set of rules for our analysis.

The strength and quality of a rule is measured by a statistic called confidence. Confidence is a common quality measure used in association rule mining to indicate how certain the rule is found to be true (Agrawal, Imieliński, & Swami, 1993).

$$Confidence\ (LHS \Rightarrow RHS) = \frac{P(LHS \cap RHS)}{P(LHS)}$$

However, not all the words are essential for argumentation, concepts, and ideas. Therefore, stop words (e.g. "the", "a", "is", etc.) were first removed since these words are usually without substantial meaning. Then for each student, his/her argumentation artifacts were transformed to a set of words (see Table 3 below) or a “bag-of-word” representation in text mining filed (Kao & Poteet, 2007).

Table 1. Student argumentation after preprocessing example.

To generate association rules, an example of the discovery of co-occurrence of word combinations is shown in Table 2.

Table 2. Rule example.

For example, two rules:

<career> => <promote>

<top, sale, hire> => <train>

The first rule shows the co-occurrence between itemset <career> and <promote>. This rule has a confidence metric of 0.75 according to confidence formula. This indicates that when the LHS itemset <career> appears in a students’ response (Student 1, 2, 3, 4 according to Table 1), there is a 75% of probability that the RHS itemset <promote> will also appear. Similarly, the second rule represents the co-occurrence between itemset <top, sale, hire> and <train>. This rule has confidence of 0.5. This suggests that when the LHS itemset <top, sale, hire> takes place in a students’ argument (Student 3 and 4 in Table 1), there is a 50% of probability that the RHS itemset <train> will also appear (Student 3). By setting the threshold of confidence, we can identify the rules surpassing certain quality. For instance, if the threshold of confidence is set to 0.5, only the three rules, <career> => <promote>, <increase, raise> => <salary>, and <top, sale, hire> => <train>, satisfy this criterion. From this demonstration, it shows that confidence metric can indicate the rule quality and robustness.

Results

Quality of Argumentation

The first research question was to ascertain the degree to which students were able to produce quality arguments when supported with sustained or faded scaffolds. To determine this, the study adapted the rubric from Jonassen and Cho (2011) and rated students' artifacts on a scale of 1 (Argument is clear and supported by a single reason) to 4 (Argument is clear and supported by multiple reasons that are specifically explained and elaborated). Descriptives statistics of the argumentation quality are shown in Table 4.

Since the dependent variables (the quality of argumentation over three facets of argumentation) were ordinal in nature and the distributions of the variables were non-normal, we conducted General Estimating Equation (GEE) to examine the effects of fading of question prompts on three facets of students' argumentation: *initial argument*, *counterargument*, and *rebuttal argument*. GEE provided unbiased estimates for longitudinal design with non-normal data (Ballinger, 2004; Liang & Zeger, 1986) The results suggested that the main effects and the interaction effects (including the two-way interactions (time x conditions), and three-way interactions (time x conditions x facets of argumentation)) were not significant ($p > 0.05$). In other words, students argumentation quality was not significantly different between the two conditions nor the three facets of argumentations.

TABLE 4 ABOUT HERE: Descriptive statistics of students' argumentation quality

Knowledge Structure

All students' essays and expert essay were converted to KS network graphs and then the visualized students and expert KS network graphs were compared in two different ways including *similarity* of KS (as percent overlap) and *shape* of KS (as graph centrality). A two-way MANOVA was conducted with two independent variables (time and condition) and three dependent variables (initial, counter, and rebuttal argument scores) to determine if there were differences between condition over time among the three dependent variables - initial argument, counterclaim, and rebuttal scores (see Table 5). Findings suggested there was a linear relationship between the dependent variables, as assessed by scatterplot, and no evidence of multicollinearity, as assessed by Pearson correlation ($|r| < 0.9$). There were no univariate outliers in the data, as assessed by inspection of a boxplot, and no multivariate outliers in the data, as assessed by Mahalanobis distance ($p > .001$). Initial, counterclaim, and rebuttal scores were normally distributed, as assessed by Shapiro-Wilk's test ($p > .05$). There was homogeneity of covariance matrices, as assessed by Box's M test ($p = .009$), and homogeneity of variances, as assessed by Levene's Test of Homogeneity of Variance ($p > .05$).

Table 5 ABOUT HERE: KS GRAPH CENTRALITY VALUES BY CONDITION

The test identified a significant interaction effect between week and condition (sustained, faded) on the combined dependent variables, $F(4, 106) = 4.046$, $p = .004$, Wilks' $\Lambda = .753$, partial $\eta^2 = .132$. The follow-up univariate two-way ANOVAs showed a significant interaction effect between week and condition for *initial* score, $F(2, 54) = 6.406$, $p = .003$, partial $\eta^2 = .192$, for *rebuttal* score, $F(2, 54) = 12.661$, $p < .001$, partial $\eta^2 = .319$, but not for *counter* score, $F(2, 54) = 3.034$, $p = .056$, partial $\eta^2 = .101$. As such, a simple main effect analysis was conducted for initial and rebuttal scores.

As for the initial score, there was a significant difference between the two conditions for Week 2, $F(2, 54) = 17.283$, $p < .001$, partial $\eta^2 = .390$, and for week 3, $F(2, 54) = 42.55$, $p = .000$, partial $\eta^2 = .598$. This suggests that the the participants in the sustained condition performed significantly better in *initial* arguments than the participants in the faded condition over week 2 and 3. The graph centrality measure visually supported this, the sustained participants established the *hierarchical* initial KS that was more like the expert over weeks compared to the faded who had the *linear* initial KS. As for the rebuttal score, there was a significant difference between condition only for week 2, $F(2, 54) = 19.00$, $p = .01$, partial η^2 = .724; the participants in the sustained condition performed significantly better in *rebuttal* arguments than the faded condition at week 2. The graph centrality measure suggests that the sustained condition participants constructed the *linear* rebuttal KS like the expert at week 2 relative to the faded condition participants who had the *hierarchical* KS.

Figure 3 ABOUT HERE. The interaction effects of argumentation facets and weeks of Sustained (*top*), Faded (*middle*), and combined condition (sustained and faded; *bottom*) on KS similarity with the expert.

Associated Rule Mining

Association rule mining was used to examine the rules and its quality as a whole in students' argumentation. Overall, the association rule mining found that when the scaffolding faded over time, the number of rules increased. When triangulated with the results of the knowledge structure measurements, this may suggests that argumentation becomes less focused and the quality of the argumentation also decreases when scaffolds are not sustained.

Table 6 and Figure 4 shows the descriptive statistics of the number of rules generated under each condition and the related rule confidence. As shown below, the results indicate that the number of rules for sustained condition in Week 2 and Week 3 were much smaller than the corresponding weeks in the faded condition (619 < 1894 for Week2, 111 < 150 for Week3). These results show that for participants receiving full and sustained levels of scaffolding, developed rules that were much more direct. When triangulated with the KS, the sustained condition rules were less disparate and more focused.

In addition to the number of rules, the rule confidence over the two scaffolding conditions were also compared. Power analysis was first conducted to determine the number of rules needed for the two-way ANOVA analysis over condition and time. Setting the effect size as 0.25 with 0.95 power, the power analysis (Cohen, 1992) indicated that 215 was the appropriate number of rules. To ensure the effective size, 100 rules were sampled from each week with 50 under each scaffolding condition. Levene's test was conducted and showed that there was no homogeneity of variance ($p > .05$) for the sampled rules.

The ANOVA results show that there was statistically significant interaction between the effects of scaffolding condition and time on the student argumentation rule quality, $F(2, 299) = 3.809$, $p = 0.023$. Then a post-hoc Tukey's test was conducted to examine the effect in detail. The Tukey's test demonstrated that there was no statistical significant difference in rule quality for the argumentation in Week 1 between the sustained and faded condition ($p = .999$), but in Week 2 and Week 3, the rule confidence for the students in sustained group was statistically significant better than the rule confidence for faded group students ($p = .001$ for Week 2, and $p = .009$ for Week 3) as shown in Figure 5.

TABLE 6 ABOUT HERE: ***Number of Rules and Confidence Value from Association Rule Mining***

FIGURE 4 ABOUT HERE. Visualization of number of rules and confidence over condition and time

FIGURE 5 ABOUT HERE. Rule mean confidence over time under different conditions

Discussion and Conclusion

Scaffolding and Design of Learning Environments

Because ill-structured problems often lack a single way to solve a problem, students must be able to develop well-reasoned and justifiable arguments for their proposed solutions during PBL. The current study explored two important aspects of scaffolding: the role of scaffolding in supporting argumentation and the effect of fading scaffolding on argumentation. While much of the problem solving literature compares different designs of scaffolds (Jeong & Lee, 2008; Jonassen & Cho, 2011; Stegmann, Weinberger, & Fischer, 2007), the current study was unique given the temporal element of scaffolds and its impact on argumentation. In addition to the longitudinal approach to measuring effects of fading, this study also included a transfer week to explore the effects of the different scaffolds.

The longitudinal and temporal aspects may have important implications for scaffolding theory and the design of learning environments that support argumentation. The nonlinear and differential results about the different parts of the argument (initial, counterclaim, rebuttal) may provide insight on how deep learning is developed. In terms of argumentation, research shows that students have difficulty with developing counterargument because it requires learners to generate an alternative perspective given the same evidence (Crowell & Kuhn, 2014; Kuhn, 1993; Tawfik & Jonassen, 2013). However, much of the argumentation literature examines a single evaluation of student argumentation scores rather than understanding how these skills improve or diminish over time. While it is often assumed that scaffolding is best when faded, the longitudinal approach of the current study suggests that scaffolds may be “ramped up” with additional and targeted scaffolds as opposed to the conventional practice of removing scaffolds at a fixed rate. On the other hand, the scaffolding provided should be specifically target students’ weak areas that needs specific support, such as making a counterargument. Additionally, scaffolds should also be aligned with the subtasks of what students are being asked to do. In the case of the current study, students in the faded condition were only supported with making justification and monitoring evaluation in Week 2, but not supported for problem representation and developing solutions. Alternatively, the counterargument and rebuttal may have needed additional scaffolding in Week 3 because this aspect of problem solving could be more challenging.

Our study compared fading schedules (sustained, faded) and examined the artifacts of students from the conditions in multiple ways. The findings of this study are consistent with the findings of a pilot meta-analysis on scaffolding conducted by Belland and colleagues (Belland, Walker, Olsen, & Leary, 2015), which indicated that cognitive outcomes were superior when scaffolding was not faded versus when it was faded on a fixed schedule. Given that the scaffolds include four unique problem-solving elements (problem representation, solution generation, making justifications, monitoring/evaluating), our results build on the research by exploring what competencies to fade from a transfer and longitudinal perspective. The results find that students in the sustained scaffold group performed better in Week 2 and Week 3 than the conditions that faded problem representation and developing solutions scaffold group.

As noted earlier, the knowledge structures of the full scaffold group were more similar to the expert's than the gradual faded scaffold group in terms of similarity index and centrality index. Spector and Koszalk (2004) maintained that learning progress can be viewed as cognitive changes into the direction of expert-like knowledge structure. According to the literature on expertise and novice differences (Anderson, 2015; Ifenthaler, 2010, 2014; Loh, Sheng, & Li, 2015), the expert's knowledge structure is organized in meaningful ways that reflects a holistic understanding of knowledge structure, which is an indicator of deep learning. The similarity to the expert argumentation was not only true for the week that learners had access to the scaffold (Week 2), but also in the transfer week (Week 3). The alignment in Weeks 2 and 3 suggested that the longer, more in depth exposure to the prompts allowed learners to engage learners in deep learning by constructing arguments that were more similar to the expert arguments.

The results of the knowledge structure are interesting when triangulated with the associated rule mining, which found that participants in the faded condition had a greater number of rules when compared with the sustained condition. Given that the knowledge structures in the sustained group were higher, the associated rule mining suggests the sustained scaffolding group had more directed and targeted arguments, whereas the faded group tended to make incorrect connections between concepts that were not warranted. Hmelo-Silver et al (2007) assert that novices have a “tendency to erroneously reduce the complexity of a phenomenon” (p. 309). Although deep learning literature suggested that learners with surface learning might not be able to connect the relevant components of the problem space (e.g. Biggs, 1987), the results of the current study suggested that they could instead connect unrelated concepts. This interpretation of the associated rule mining reinforces other literature and data sources that novices often struggle to make correctly connect key concepts when compared with experts (Grotzer & Solis, 2015; Hmelo-Silver, Marathe, et al., 2007; Jacobson, 2001) and confirmed the importance of adequate scaffolding in PBL (Kirschner et al., 2006). Although scaffolding literature suggested the importance of fading (Pea, 2004), the current study indicated that design of learning environments cannot be rushed to fade the required scaffolds before students have fully acquired all the problem-solving and metacognitive competencies (Salomon et al., 1989)

Besides the timing of fading, another key issue is the choice of fading; that is, what to fade and at what time. The current scaffolding literature does not show clearly what kind of scaffolds to keep and what kinds of scaffold to fade at a certain point of time (Belland et al., 2017; Bulu & Pedersen, 2010). Since the faded condition removed problem representation and generation solutions scaffolds, we suspect that scaffolding might need to be delivered using a multifaceted approach due to the complexity of an ill-structured problem-solving task, including all the four problem-solving processes (i.e., problem representation, solution, argumentation, and monitoring and evaluation) (Ge & Land, 2003), instead of fading out a piece of scaffolding at a time in order to obtain the optimal scaffolding effects.

Assessment Methods for Deep Learning in PBL

Another important element of our study is the way in which argumentation were assessed. The current study applied three different methods to measure students' argumentation using rubrics analysis (Jonassen & Cho, 2011) and learning analytics (Xing, Guo, Petakovic, & Goggins, 2015). In our first approach, we scored the argumentation artifacts using rubrics adapted from Jonassen and Cho (2011) and found no statistically significant results. However, the other two methods of learning analytics (GIKS, associated rule mining) were able to identify seemingly latent differences between the groups. It is possible that the traditional assessment method using rubrics might not be sufficient to capture the processes of deep learning. Recently, some have questioned whether previous forms of assessment are sensitive enough to detect differences in deep learning (Gijbels, Dochy, Van den Bossche, & Segers, 2005). Our result is consistent with prior PBL assessment literature that suggest outcomes may be found when different analytical methods are employed (Gijbels et al., 2005). Therefore, we suggest that for future studies continue to explore alternative means to measure deep learning.

Limitations and Future Studies

This study attempted to addresses a gap about how the withdrawal of scaffolds in learning environments support deep learning. It is our hope that both the instructional design and experimental design of this study offer some merits in advancing our understanding about scaffolding theory. While the study addressed a gap regarding the timing of scaffolding, there are multiple opportunities to build upon the current research. As noted previously, the participants were initially scaffolded in terms of problem representation, developing solutions, justifications, and monitoring and evaluations of solutions. In the week that followed, one condition only received the justification and monitoring and evaluation prompts. While we chose to keep the scaffolds related to argumentation, other research shows that learners often have difficulty representing problems, so it could have been more pertinent to maintain this scaffold over time. Future research could explore how the different combinations could be maximized to support problem solving and argumentation over time.

Another opportunity to build on the research is by exploring different types of scaffolding. Reiser (2004) suggests that scaffolds can be designed to problematize or systematize problem solving. The former scaffolds students' understanding of problem complexity, while the latter provides structural support to the students. In the current study, students were scaffolded using problematization scaffolds and scaffolded in terms of problem-representation, developing solutions, making justifications, and monitoring evaluation. However, the study may have yielded different results if the scaffolds had been designed to systematize the procedural aspects of argumentation, but problematize the ill-structured nature of things. While these scaffolds strategies are often posited as an “either/or” approach, it is possible that a design including some mix of problematization or systematization would be more beneficial. Future studies could then build upon our research by exploring how sustained or faded scaffolding schedules may be approached differently.

Another opportunity to build on our research is by applying prompts that are specifically designed for argumentation. In the current study, we applied variations of the Ge and Land (2003) prompt which includes constructs, such as developing solution and justifications, that are similar to argumentation. Alternatively, computer-supported collaborative argumentation (CSCA) has designed prompts that are specifically for developing competency argumentation skills, albeit within group settings. A study could build upon these results by comparing how sustained or faded scaffolds developed in the CSCA domain compares with the Ge and Land (2003) prompts.

A final suggestions for future research could be exploring the differential effects of scaffolding using different forms of assessment. As noted earlier, researchers have suggested that traditional means of assessment may not be able to detect deep learning patterns (Gijbels et al., 2005). Indeed, the current study found that rubric scoring did not detect significant differences, whereas analytic methods such as knowledge structure comparison and associated rule mining were able to find differences between different conditions. Additional studies could explore other forms of analytics to better assess gains in deep learning.

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Table 1

Scaffolding Conditions and Procedures

Week	Faded Scaffolding	Sustained Scaffolding
1	Full Problem-Solving Prompts (Problem-representation, developing solutions, making justifications, and monitoring evaluation)	Full Problem-Solving Prompts (Problem-representation, developing solutions, making justifications, and monitoring evaluation
2	Faded Problem-Solving Prompts Justification and Monitoring Evaluation Prompts	Full Problem-Solving Prompts (Problem-representation, developing solutions, making justifications, and monitoring evaluation)
3	Transfer Task (No Prompt)	Transfer Task (No Prompt)

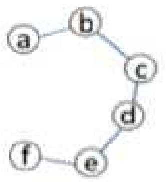
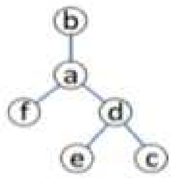
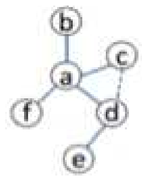
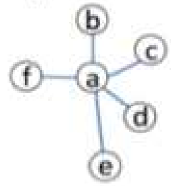
Map structure	chain/linear	tree/hierarchical	network/net	spoke/star
				
Cognitive structure	Achievement, drive and goal directed behavior	Simple and rigid expertise	Complex and fluid expertise	Superficial and undeveloped knowledge of a subject
C_{graph}	0-0.2	0.2-0.4	0.4-0.6	0.6-1.0

Table 3

Rule Sample

Participant	Rule
Participant 1	<live, cost> => <San Francisco >
	<keep, career> => <promote>
	<increase, raise> => <salary>
	<top, sale, hire, new> => <train>
	<third, sale> => <asset>
Participant 2	<keep, career> => <promote>
	<increase, raise> => <salary>

Table 4

Descriptive statistics of students' argumentation quality

		SUSTAINED		FADED	
		Mean	SD	Mean	SD
Week 1	Initial	3.21	0.68	3.03	0.91
	Counter	2.00	1.16	2.21	1.35
	Rebuttal	2.55	1.06	2.72	1.13
Week 2	Initial	2.62	1.45	2.66	1.11
	Counter	2.59	1.27	2.66	1.17
	Rebuttal	2.00	1.31	2.31	1.44
Week 3	Initial	2.54	1.23	2.67	1.24
	Counter	2.32	1.39	2.40	1.22
	Rebuttal	2.54	1.37	2.13	1.20
Grand Mean		*2.48*		*2.53*	

Table 5.
The average similarity of participants' KS network graphs in each condition with the expert KS network graphs (as % overlap) and the average graph centrality (as a measure of KS form), with Cohen's effect size d (using pooled standard deviation) and significance level (p)

		SUSTAINED		FADED		*d*	*p*
		Similarity	Centrality	Similarity	Centrality		
Week 1	Initial	59%	.33 Hierarchical	61%	.39 Hierarchical	-0.81	.42
	Counter	29%	.11 Linear	31%	.13 Linear	0.35	.15
	Rebuttal	38%	.54 Network	42%	.36 Hierarchical	0.66	.43
Week 2	Initial	62%	.31 Hierarchical	47%	.17 Linear	1.12	.00
	Counter	49%	.39 Hierarchical	52%	.34 Hierarchical	0.50	.45
	Rebuttal	40%	.17 Linear	31%	.51 Network	0.90	.01
Week 3	Initial	56%	.34 Hierarchical	45%	.10 Linear	1.10	.00
	Counter	38%	.15 Linear	37%	.18 Linear	-0.30	.15
	Rebuttal	43%	.19 Linear	38%	.33 Hierarchical	0.40	.16
	Grand M	*46%*		*43%*		*0.35*	*.15*

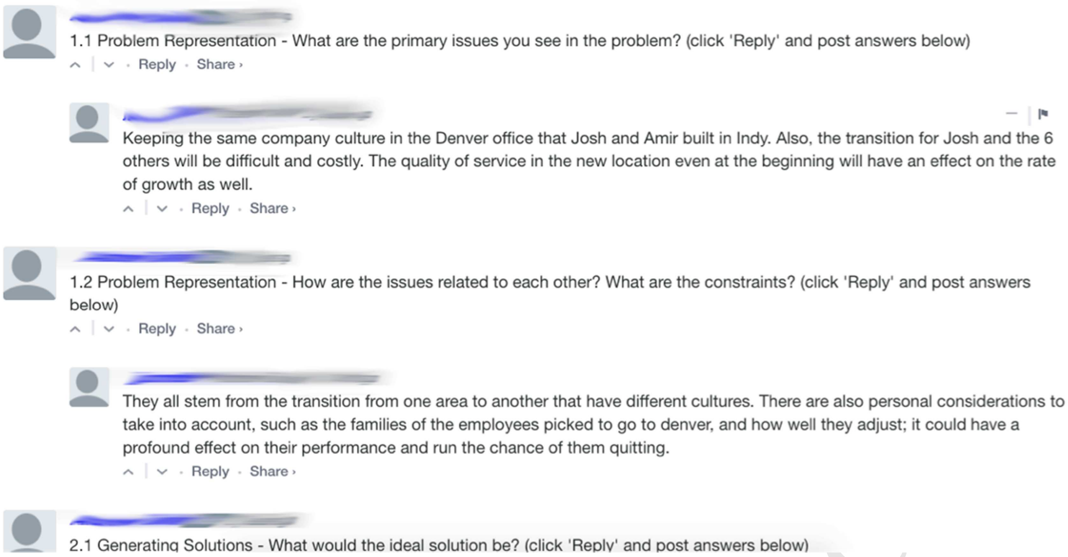
Note: Expert's KS graph centrality values = .33 (*hierarchical*) for initial, .31 (*hierarchical*) for counter, and .11 (*linear*) for rebuttal argument.

Table 6.

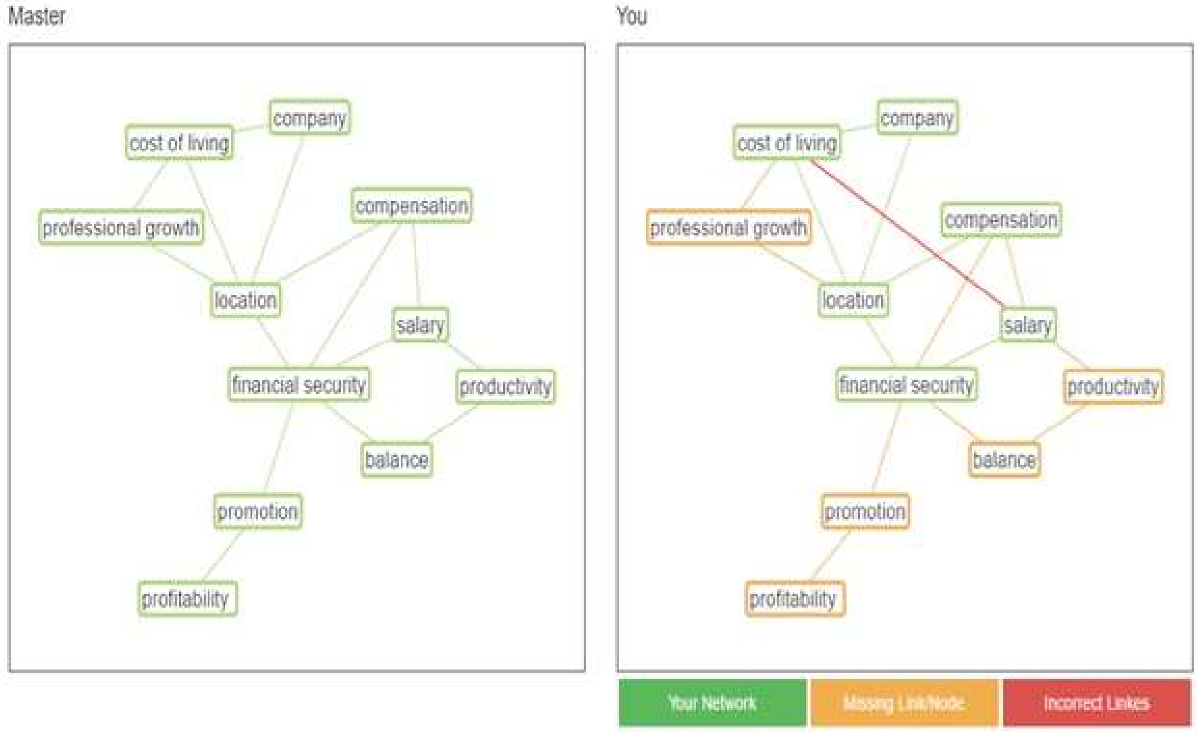
Number of Rules and Confidence Value from Association Rule Mining

	Sustained Scaffolding		Faded Scaffolding		*p*
	Number of Rules	Confidence Mean	Number of Rules	Confidence Mean	
Week1	516	0.797	279	0.793	.999
Week2	619	0.831	1894	0.683	.001***
Week3	111	0.771	150	0.645	.009**

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$



1.1 Problem Representation - What are the primary issues you see in the problem? (click 'Reply' and post answers below)
Reply · Share ›
Keeping the same company culture in the Denver office that Josh and Amir built in Indy. Also, the transition for Josh and the 6 others will be difficult and costly. The quality of service in the new location even at the beginning will have an effect on the rate of growth as well.
Reply · Share ›
1.2 Problem Representation - How are the issues related to each other? What are the constraints? (click 'Reply' and post answers below)
Reply · Share ›
They all stem from the transition from one area to another that have different cultures. There are also personal considerations to take into account, such as the families of the employees picked to go to denver, and how well they adjust; it could have a profound effect on their performance and run the chance of them quitting.
Reply · Share ›
2.1 Generating Solutions - What would the ideal solution be? (click 'Reply' and post answers below)


Master
company
cost of living
professional growth
compensation
location
salary
financial security
productivity
balance
promotion
profitability
You
company
cost of living
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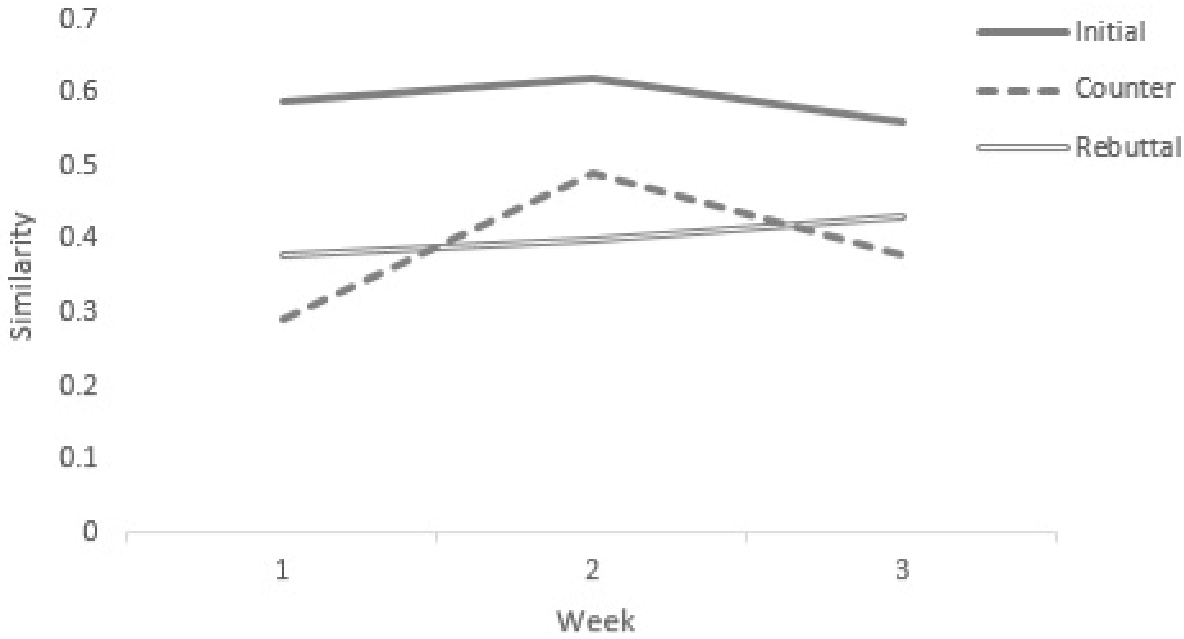
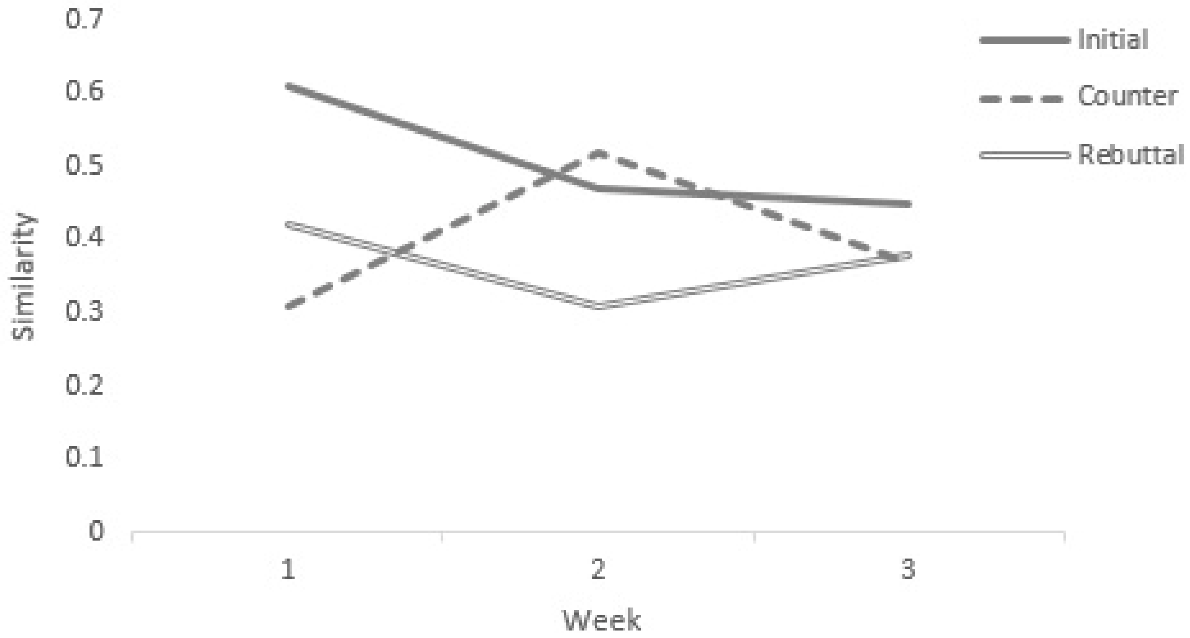
compensation
location
salary
financial security
productivity
balance
promotion
profitability
Your Network
Missing Link/Node
Incorrect Linkes


0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Similarity
1
2
3
Week
Initial
Counter
Rebuttal


0.7
0.6
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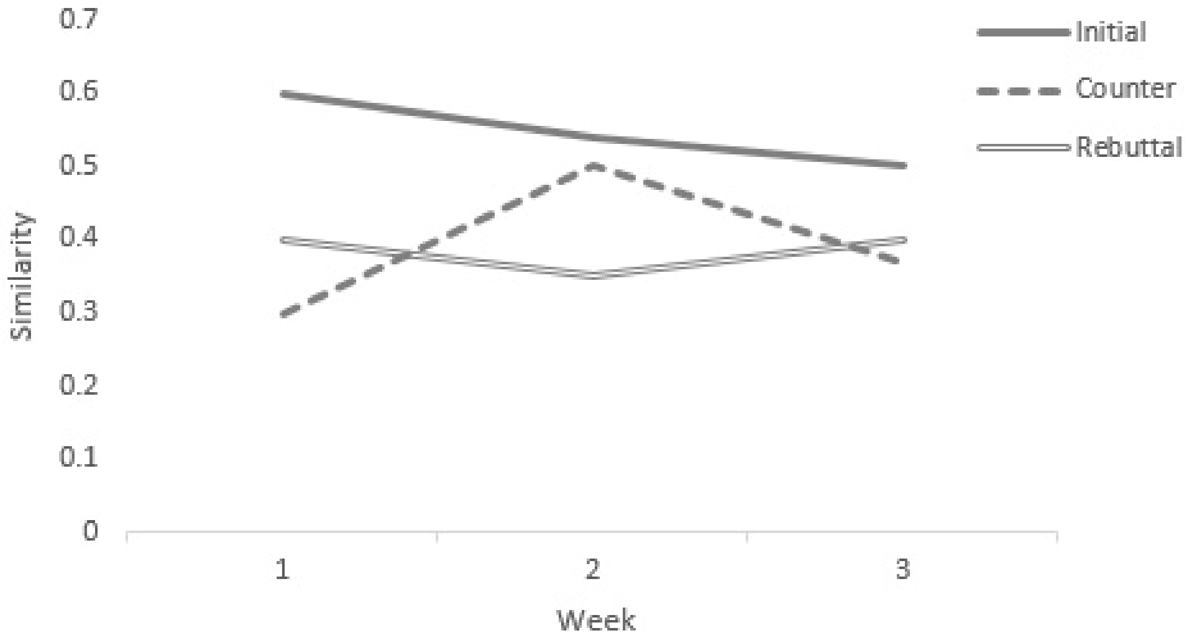
0
Similarity
1
2
3
Week
Initial
Counter
Rebuttal


0.7
0.6
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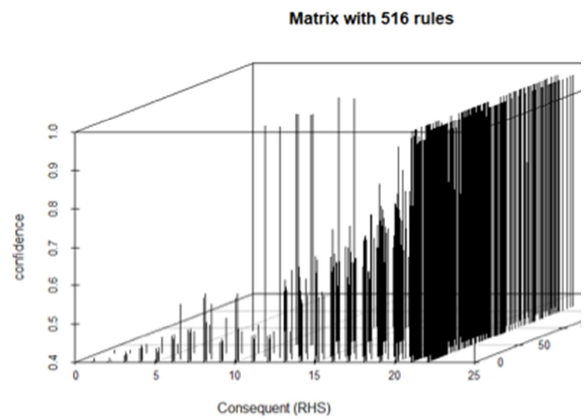
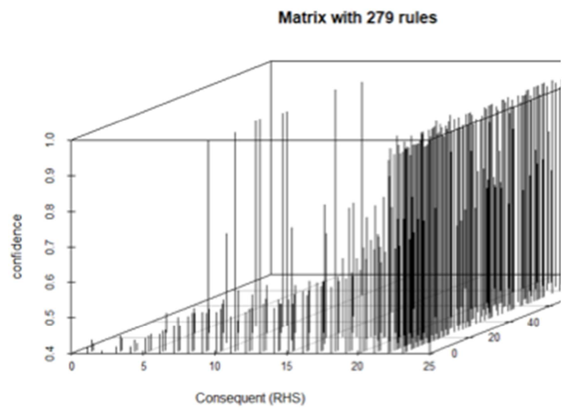
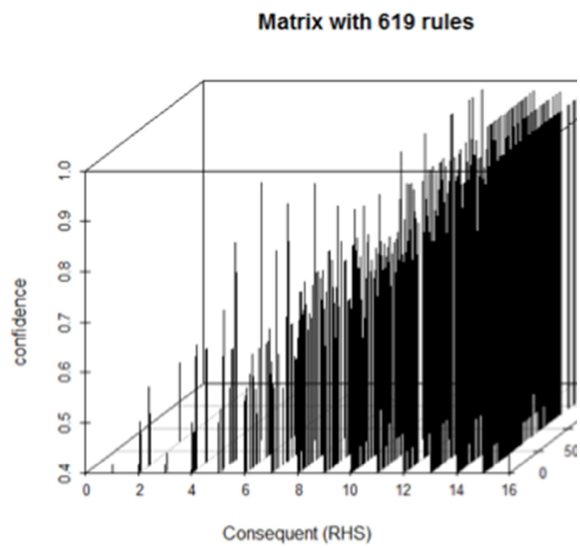
0.3
0.2
0.1
0
Similarity
1
2
3
Week
Initial
Counter
Rebuttal



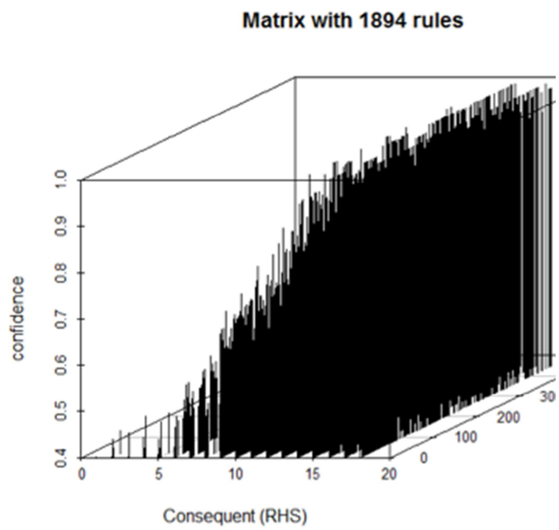
(a) Sustained Condition in Week 1



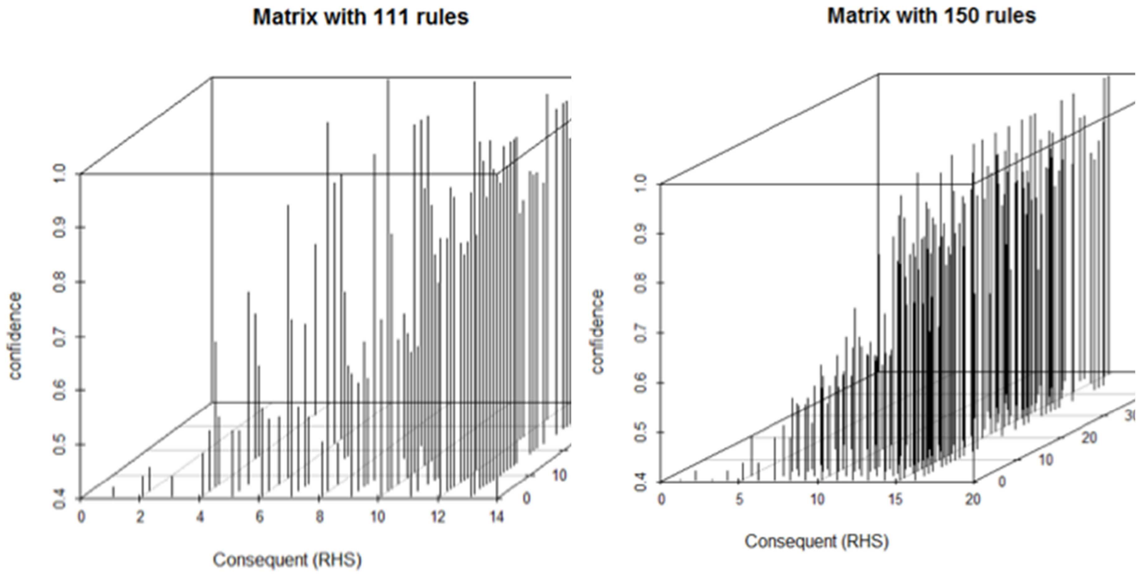
(b) Faded Condition in Week 1



(c) Sustained Condition in Week 2



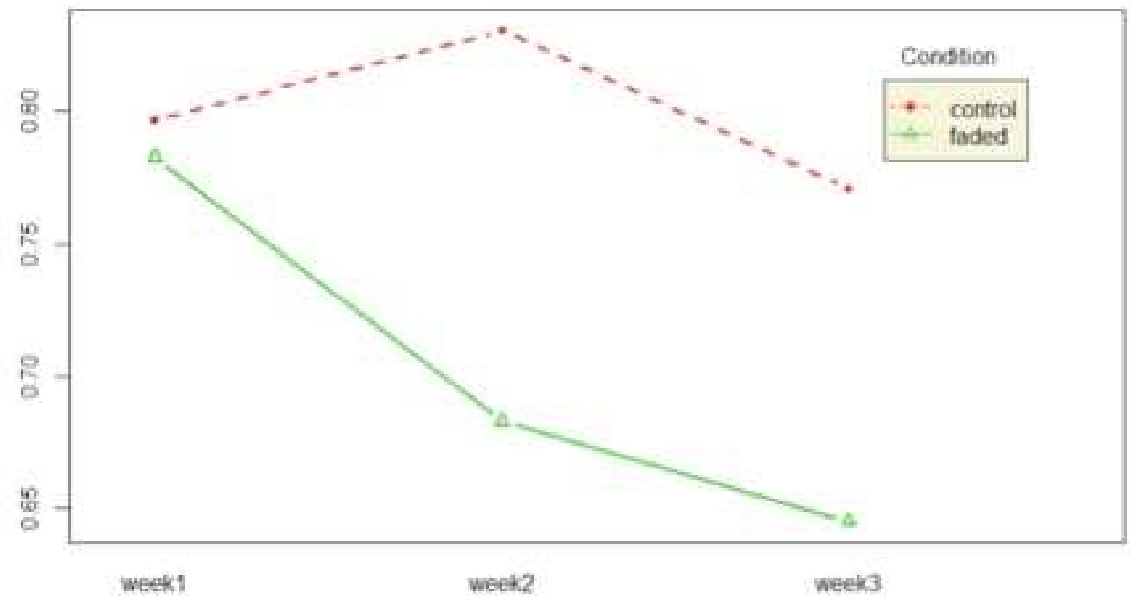
(d) Faded Condition in Week 2



(e) Sustained Condition in Week 3

(f) Faded Condition in Week 3

Figure 4. Visualization of number of rules and confidence over condition and time


Condition
control
faded
0.80
0.75
0.70
0.65
week1
week2
week3

Research Highlights

Scholars suggest scaffolding support is important for deep learning

Current types of scaffolding rather than the schedule of how to fade scaffolds

Current study longitudinally compared sustained vs faded scaffolds

Results stronger for the sustained condition when scaffolds were removed

Results indicate students need to be scaffolded longer for learning gains to persist