Journal of Formative Design in Learning (2021) 5:97–105
https://doi.org/10.1007/s41686-021-00062-w

Exploring the Differences Between Experts and Novices on Inquiry-Based Learning Cases

Andrew A. Tawfik[1] · **Jessica D. Gatewood**[1] · **Jaclyn J. Gish-Lieberman**[1] · **Charles W. Keene**[2]

Accepted: 18 October 2021 / Published online: 29 November 2021

Abstract
Theorists suggest that problem-solving is an important element to engender higher order learning outcomes. According to case-based reasoning (CBR) theory, learners in inquiry-based learning (IBL) are able to engage in deep learning and retain cases over time, which better prepares them for domain practice. Although various studies have explored the experiences of learners as they engage in IBL , few studies have quantified how experts and novices weigh variables within a case and the degree to which they differ. In this study, experts and novices weighed an array of indices (labels) on a series of IBL) cases. Novices' questions were also analyzed. Using the structural-function-behavior (SBF) framework, the study found differences on basic understanding (structure) and systems thinking (function); however, no differences on casual reasoning (behavior). Implications for case-based reasoning retrieval and reuse are discussed, as well as IBL.

Keywords Case-based reasoning · Inquiry-based learning · Problem-solving

Introduction

Research shows that practitioners often encounter complex and ill-structured problems as they resolve domain-specific problems (Hara & Schwen, 2006; Stefaniak, 2020). Because no single solution exists for these types of problems, individuals must assess the viability of solutions in light of the differing constraints and parameters faced within a particular context (Jonassen, 2011). These problems are also highly situated, so individuals must consider an array of factors as they solve these problems, such as the alternative perspectives and domain-specific rules embedded in each case (Jonassen, 1997). Others argue that individuals also process the experiences differently based on their prior cases, which impact their problem-solving strategies and how they engage in collaborative argumentation with their peers (J. Baker et al., 2019).

Given the importance of problem-solving for domain challenges , educators often advocate for inquiry-based learning (IBL) as an instructional strategy, which argues that learners be given similar problems to the types of issues faced by practitioners (Lazonder & Harmsen, 2016). Theorists argue that as learners resolve these issues, they are more likely to engage in problem representation (Ge et al., 2016), question asking (Tawfik et al., 2020a), decision-making (Heinrichs, 2002), and solution generation. Whereas didactic forms of instruction are more focused on dissemination and memorization of information, many argue these higher-order learning outcomes afforded by IBL better prepare learners for the types of contextual problems that experts face in practice (Jamshidi et al., 2021; Koehler et al., 2019).

An important element of IBL is how learners reason through ill-structured problems, which are often provided in the form of cases. It is argued that as learners encounter multiple cases, they are able to build expertise as part of their classroom activities. One way to understand the difference between experts and novices is through the theory of case-based reasoning (CBR), which suggests that individuals process experiences as cases from which they can draw upon over time (Schank, 1999). Specifically, CBR theory argues that learners will reference their internal case libraries when a similar problem is encountered. The prior case helps

✉ Andrew A. Tawfik
aatawfik@gmail.com

[1] University of Memphis, Ball Hall (Office: 421D), 3798 Walker Ave, Memphis, TN 38111, USA

[2] University of Iowa, 21 E Market St, Iowa City, IA 52242, USA

understand the parameters of the extant problem, while also suggesting solutions to resolve the present issue (Kolodner, 1991). CBR theory further posits that individuals can combine solutions from multiple experiences drawn from their case libraries (Jonassen, 2011). Another important element for retrieval and reuse includes indexing; that is, the labels that individuals assign to the case that impact retrieval and reuse during future problem-solving. However, qualitative research and case studies show that experts and novices index the cases in substantially different ways (Jacobson, 2001; Reilly et al., 2019). Research shows that problem-solving experts use well-indexed cases to recognize patterns and cues that aid in focusing on the problem as a whole, whereas novices discard information that does not fit their initial line of thinking (Schubert et al., 2013). Because cases include both latent and salient variables that make learning challenging, there have been calls to implement strategies that best support learners as they understand and reflect on their IBL experiences (Ge et al., 2016; Mamede et al., 2019).

While research has explicated the differences between experts and novices in domain practice, there is limited research as it relates to indexing of cases that learners encounter during IBL. This is important for multiple reasons. First, it provides insight as to how learners understand and weigh the contextual variables within the case. If learners are unable to properly understand and assign value to the various concepts within a case, it will impact learners' future ability to retrieve and reuse the experience for future IBL cases. It also impacts how learners iterate their problem-solving and seek out solutions to remedy their knowledge gaps. While the literature has explored differences between experts and novices using qualitative data in workplace contexts, few studies have explored the differences between these groups within an IBL classroom experience. To remedy this gap, we first present the literature on CBR, as well as empirical studies that compare reasoning processes across experts and novices. We then present a formative project that is part of a larger design-based research project (DBR) that aims to use prior cases as scaffolds during IBL. Specifically, this formative project (a) compares how experts and novices weigh indices and (b) the questions that learners generate during problem-solving.

Literature Review

Inquiry-Based Learning, Case-Based Reasoning

Given the types of ill-structured problems that practitioners resolve, various instructional strategies, such as inquiry-based learning (IBL), argue that learners should be given cases that are representative of domain issues (Lazonder & Harmsen, 2016). These problems are often ill-structured based on a variety of characteristics, including dynamicity, perspectives, and the constraints present within a given context (Jonassen & Hung, 2008). Although definitions vary, IBL often prescribes that learners resolve these complex problems with their peers. While teachers take a more facilitative role, learners are self-directed during instruction as they seek out information to understand the problem (problem representation) and resolve the issue (solution generation) (Ge et al., 2016). Because there is no single pre-set solution, learners generate questions and engage in argumentation for the viability of the solution as they negotiate their collective decision-making (J. Baker et al., 2019; Belland et al., 2020). Studies also show affective components of learning in terms of motivation, self-efficacy, and empowerment (Voet & De Wever, 2017) as learners engage in IBL activities. Therefore, advocates argue that rich settings of IBL cases better prepare learners when compared with more didactic and decontextualized forms of instruction.

One way to understand the benefits of IBL is through the theoretical perspective of CBR. The theory argues that individuals process experiences in four distinct stages — retrieval, reuse, revise, and retain (Schank, 1999; Tawfik & Kolodner, 2016). In the first stage, retrieval is often dictated based on how individuals see similar prior cases in memory (case library) as aligning with the extant problem. If one indexes and labels the case well, they are able to efficiently retrieve the case and understand how it can be used towards the new problem. As learners are able to engage in similarity assessment based on the indices, they will reuse the case to frame the problem and generate potential solutions. If no relevant case is presented based on the indices, they will index the new case and retain it for future use. From a learning perspective, CBR theorists argue that the cases posed in IBL generate rich experiences from which learners can retrieve and reuse, which better prepares them for future use when learners are initiated into practice (Tawfik & Kolodner, 2016).

Structure-Behavior-Framework

An important aspect of case-based reasoning is how learners process and understand the characteristics of an experience and retain it within their case library. Although various theories exist about how individuals assign meaning to an experience, the structure-behavior-function framework (SBF) (Hmelo-Silver & Pfeffer, 2004) serves as a descriptive lens to understand the problem from a holistic and systems level, which is especially important for the dynamic and complex nature of ill-structured problems. Whereas the first level (structure) describes the elements that are inherent within a system, the behavior construct details how said structures work together to achieve a purpose and result in some product. As individuals gain additional understanding, function-level understanding is used when they are able to describe the overall goal for why a concept exists within the broader system. As it relates to understanding expert-novice differences, Hmelo-Silver and Pfeffer (2004) assert that "Structure–Behavior–Function theory may provide a deep principle that is useful for thinking about complex systems. SBF theory accounts for a complex system's multiple interrelated levels, and its dynamic nature." (p. 129–130).

From an SBF perspective, the experience of practitioners engenders knowledge and competencies that distinguish the problem-solving skills between experts and novices (Dwyer et al., 2015; Kim & Klassen, 2018; Pinkus et al., 2015). One way in which novices and experts differ is in terms of problem representation. Novices tend to focus on a limited set of concepts (e.g., structure) (Auerbach et al., 2018; Huang & Li, 2012; Wolff et al., 2016) and exhibit minimal inference (Garfield et al., 2015), whereas experts are able to understand deep structures of a problem based on multiple information sources (Bruggeman et al., 2021). In the initial stages, novices especially struggle to notice key elements within a case or otherwise focus on irrelevant details (Jarodzka et al., 2012; Prytz et al., 2018). In contrast, experts are able to identify both salient and latent concepts within the ill-structured case (Randles & Overton, 2015). As individuals move towards solution generation, research finds that novices exhibit more linear paths of thinking (Schubert et al., 2013) and struggle to formulate their mental models (Fritscher & Pigneur, 2016). Alternatively, experts' mental models are interconnected (Björklund, 2013; Bruggeman et al., 2021) and represent a systems-level understanding of the problem (Jee et al., 2015), which allows them to engage in more pattern recognition (Koszalka & Epling, 2010; Schubert et al., 2013), causal reasoning (Korovin et al., 2020), and evidence-based decision-making (K. M. Baker et al., 2016).

Research Questions

There is considerable research interest about how learners engage in ill-structured problem-solving during inquiry-based learning (Jamshidi et al., 2021; Koehler et al., 2019). In line with case-based reasoning (CBR) theory, advocates of inquiry-based learning argue this instructional strategy affords deep processing of the case, which leads to better cognitive and affective learning outcomes. However, practitioner studies and CBR theory argue that experts and novices process cases in markedly different ways (Bruggeman et al., 2021; Schubert et al., 2013; Wolff et al., 2016). However, the emperical literature is often done from a qualitative perspective and very few studies have attempted to quantify the difference between experts and novices when processing domain-specific cases in classroom contexts. This research gap is important because if novices are not able to identify the relevant concepts or only do so at a surface level, it is therefore questionable the degree to which learners will be able to retrieve and reuse IBL cases over time. If learners struggle to identify the concepts in the case, this is also problematic for those that argue that learners generate a rich set of cases from which they can reference from IBL (Belland et al., 2017; Tawfik & Kolodner, 2016). Based on this gap, we proffer the following research questions.

1. To what degree do experts and novices differ in how they weigh case indices (labels, concepts) as they process an inquiry-based learning case?
    a. To what degree do experts and novices differ in how they weigh case indices (labels, concepts) in terms of *structural* characteristics as they process an inquiry-based learning case?
    b. To what degree do experts and novices differ in how they weigh case indices (labels, concepts) in terms of *behavioral* characteristics as they process an inquiry-based learning case?
    c. To what degree do experts and novices differ in how they weigh case indices (labels, concepts) in terms of *functional* characteristics as they process an inquiry-based learning case?
2. What questions do learners generate as they identify gaps in knowledge and iterate their problem-solving during an inquiry-based learning case?

Methodology

Participants

Participants in the study consisted of both experts and novices. In terms of the former, experts were five participants with over 20 years of practitioner experience in the business domain. Novices were undergraduate business students ($N=87$) who were in the junior and senior year of their sales management studies at a large university, which islocated in the Midwestern region of the USA. All participants completed the consent form approved by the Institutional Review Board (IRB).

Materials

Participants in the study primarily interacted with a learning environment entitled "Nick's Dilemma." The learning environment is an inquiry-based learning activity that poses an ill-structured problem to solve. Nick and his boss, Sheila, are tasked with addressing recurring turnover problems in their medical device sales team. The project is part of a larger DBR initiative, which has explored how learners use prior cases to solve new problems. Some of the issues include how to best scaffold the individual narratives within a case library (Tawfik et al., 2020b) and interaction patterns (Schmidt & Tawfik, 2018) (see Fig. 1). Although prior studies explored how learners employ the case to support their problem-solving, the formative project aimed to understand how learners understand the nuances of the case, which is important for the CBR constructs of retain, retrieval, and reuse.

The main problem to solve (Nick's Dilemma) describes three potential options for the learner — internal hire, external hire, or restart the search. The internal option is an employee who has been loyal to the company in a help desk role, but only has limited experience around extended customer relations that is needed for the open position. Alternatively, the external option has direct experience, but failed to disclose a driving under the influence arrest in college that happened years ago. Finally, the case description also details how a recent company has had to lay off other sales personnel, so learners must consider the prospects of delaying and restarting the search in light of the recent loss of market share. As learners read the case, they are also linked to other narratives in the form of a case library. The cases are connected via a shared index (e.g - employee morale) and learners can read about how an expert encountered a similar problem. In doing so, learners apply the lessons learned from the related case towards the main problem to solve.

Procedure

Experts (N=5) and novices (N=87) were both sent the main problem to solve, Nick's Dilemma. Participants were also given a list of indices derived from the course instructor who helped develop the Nick's Dilemma case. That is, the terms and labels that could be used to interpret the main problem to solve and related cases. In this example, relevant indices included "employee morale," "market share," "mentorship models", and others. The indices were developed by reading the cases and cross-checking the objectives associated with the main problem to solve . In addition, the indices were member-checked by another subject matter expert with experience in the business domain.

In terms of data collection, participants were each sent a link to the learning environment and asked to read the inquiry-based cases. For the novices, learners were informed that this would serve as an existing assignment of the course. At the bottom of the learning environment, the case concluded by asking the participants to click on the data collection form. Participants were given 25 different indices (e.g., employee morale) derived by the subject matter experts and asked to rate each in terms of relevancy towards solving the case on a scale of 1–10. Because an important element of problem-solving is the ability to identify knowledge gaps and iterate, novices were further asked to write down additional questions they deemed pertinent towards solving the problem (Research Question 2).

Data Analysis

To answer Research Question 1, the data was imported into SPSS and analyzed using a linear regression model. As noted in the prior section, participants were given 25 indices that were generated by the instructor of record and who had taught this module multiple times. Prior to analysis, the same instructor mapped each index to the SBF framework. For example, a basic index of "recruitment" was rated as "Structure," while more systems level indices (e.g., "comprehensive job analysis") were rated as "Function." Upon completion, another subject matter expert with experience in business also reviewed the initial SBF categorization. Finally, the two individuals met to ensure consistent interpretation for each index that was assigned using the SBF framework.

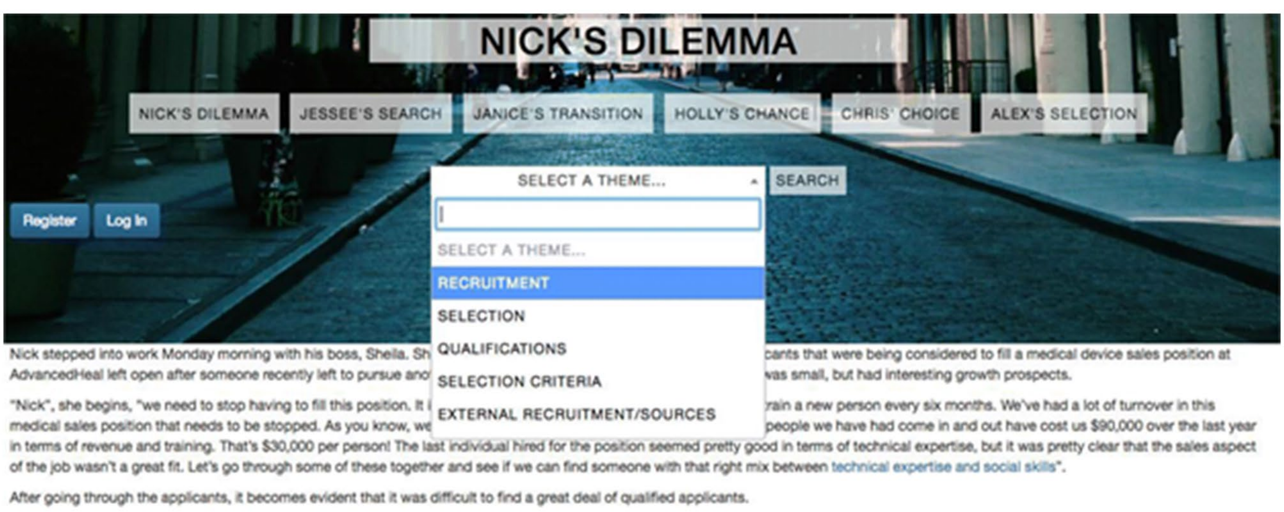

Fig. 1 Recommendation system search and retrieval feature

For Research Question 2, participants submitted questions at the end of the study and researchers later imported the data into a spreadsheet. After transcription, two research assistants independently coded the line items according to the question taxonomy criteria developed in Tawfik et al. (2020a). The codes were further divided into shallow questions, testing questions, or deep/complex questions (Tawfik et al., 2020a). Research assistants completed a preliminary round of coding to better familiarize themselves with the question taxonomy codes. Specifically, the line items were analyzed from the first five participants. After completion of this initial round, the research assistants met with the first author to discuss their differences and to better operationalize each code. Following this meeting, the research assistants independently coded all the line items ($N = 441$). The inter-rater reliability upon completion of the first round was 67%. The two research assistants met to discuss remaining differences in the coding. After this discussion, the research assistants produced a final inter-rater reliability of 98%.

Results

Research Question 1

A logistic regression was conducted to understand differences between experts and novices rating of IBL indices (Research Question 1) and found statistically significant differences ($SS = 187.3$; $df = 5$; $F = 9.14$; $p < 0.01$). It is especially noteworthy that, on average, the experts rated indices as lower (5.13) when compared with the novices (6.33; see Fig. 2).

To further understand the deep processing of the case between experts and novices, the study analyzed differences in terms of structure (RQ 1.A), behavior (RQ 1.B), and function (RQ 1.C). Statistically significant differences were found between experts and novices on structural ($p < 0.01$) and functional ($p = 0.015$) indices; that is, the foundational concepts and systems-level understanding. However, no statistically significant differences were found for the behavioral function ($p = 0.75$).

Research Question 2

The second research question focused on the knowledge gaps learners identify as part of their problem-solving. According to the literature, one way to understand learners' knowledge gaps relates to the depth of questions they generate during learning (D'Mello et al., 2014; Graesser & Olde, 2003). Tawfik et al. (2020a) further argue that quality of inquiry can be understood by how learners identify and connect concepts within a question. To understand the depth of their question generation, two raters coded a total of 441 questions generated by novices. The breakdown using Tawfik's et al. (2020a) taxonomy was as follows: simple/shallow (18.37%); testing (28.80%); deep/complex (52.60%) (see Tables 1, 2, and 3).

Discussion

Theorists assert that IBL is an effective instructional strategy because it provides learners with rich experiences that developproblem-solving skills, such as information seeking, question generation, decision-making, and justification of solutions. According to CBR theory, learners are able to retain and reuse the experiences , which allows them to generate a robust case library from which

Fig. 2 Expert-novice differences using structure-behavior-function (SBF) framework

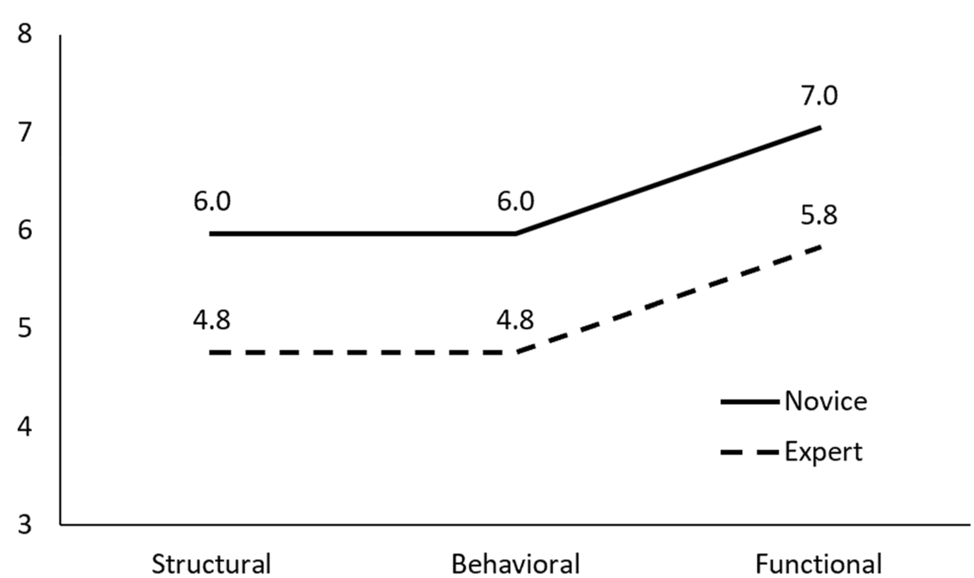

Table.1 Tawfik et al. (2020a) question taxonomy novice questions

1. Verification	Is X true or false? Did an event occur? Does a state exist?
2. Disjunctive	Is X, Y, or Z the case?
3. Concept completion	Who? What? When? Where?

they can draw upon over time (Schank, 1999). The theory further argues that this case library from which individuals draw upon better prepares learners for domain practice (Valentine & Kopcha, 2016). That said, a challenge is how novices with limited experience navigate the rich contexts presented in IBL cases (Reilly et al., 2019). Some further argue the ill-structured nature obscures concepts and challenges learners beyond cognitive load limitations (Elkind, 2004). If learners focus on errant concepts or fail to address salient variables, it is unlikely learners will engage in meaningful learning using this instructional strategy. To date, many IBL studies cite expert-novice studies to understand the learning continuum as students engage in contextualized learning. However, few studies directly compare how experts and novices weigh various indices and its impact on problem-solving in IBL cases.

This formative evaluation builds on a larger design-based research project. In the prior assessments, the research group explored learners' interaction patterns across cases (Schmidt & Tawfik, 2018) and developed recommendation systems to identify the optimal case (Tawfik et al., 2020b). While those initial studies shed light on the problem-solving ability of learners, additional insight was needed to explicate how individuals with varying levels of experience assessed indices with a case (RQ1) and how novices generated questions as part of their problem-solving (RQ2). In doing so, the formative evaluation identified important knowledge gaps and learners' ability to retain an experience, which would allow us to design more comprehensive case library systems that support IBL. Through the frameworks of CBR and SBF, the study addressed this gap by comparing how experts and novices weighed various indices and the questions learners generated during problem-solving. CBR highlights how learners perceive and retain cases, while SBF is a "promising mode of analysis for this domain because it focuses on causal understandings of the relationships among different aspects of the system" (Hmelo-Silver & Pfeffer, 2004). The study found statistically significant differences on measures of structure and function. As noted earlier, structure is used to highlight the primary problem-space and conceptual characteristics of a case, whereas function denotes the systems-level understanding of a case. These results are interesting in light of the lack of differences in behavior; that is, how learners determine the ways in which structures achieve their purpose (Hmelo-Silver & Pfeffer, 2004).

There are multiple potential interpretations for this formative evaluation and future iterations of the DBR project. In terms of difference in the structure construct, the results found that experts weighed the indices as lower, while novices rated them as higher. This coincides with prior research that suggests that learners not only struggle with misconceptions during IBL, but also find it challenging to parse the problem-space (Hmelo-Silver, 2013). This is a noteworthy finding in multiple respects. In IBL, an important issue relates to how learners engage in information seeking to ensure they comprehensively survey the problem-space during their self-directed learning (Belland et al., 2020; Buchanan et al., 2016). In this study, we found novices identified a larger set of concepts as relevant to their problem-solving when compared with experts. Although one might posit that novices have a limited view of ill-structured problem-solving, it could instead be that they assume a large number of concepts are relevant and fail to delineate when something is irrelevant. One potential implication of this formative evaluation thus relates to importance of regular reflection. Tawfik and Kolodner (2016) described how an overlooked activity in IBL is refining indices through reflection. In their discussion, they focused on making the indices more prominent and well-defined. . Rather than focus reflection solely on fortifying topics that students learned during IBL, it may be equally important to also spend time on identifying extraneous ideas and reflecting on the reasons for why learners thought these ideas were relevant during problem-solving. As learners able to remove erroneous concepts, this may support the development of a more refined schema over time.

Table.2 Tawfik et al. (2020a) question taxonomy emerging questions

4. Example	What qualitative properties does entity X have?
5. Feature specification	What are the properties of X?
6. Quantification	What is the value of a quantitative variable? How much? How many?
7. Definition	What does X mean?
8. Comparison	How is X similar to Y? How is X different from Y?

Table 3 Tawfik et al. (2020a) question taxonomy expert questions

9. Interpretation	What concept or claim can be inferred from a static or active pattern of data?
10. Causal antecedent	What state or event causally led to an event or state? Why did an event occur? Why does a state exist? How did an event occur? How did a state come to exist?
11. Causal consequence	What are the consequences of an event or state? What if X occurred? What if X did not occur?
12. Goal orientation	What are the motives or goals behind an agent's action? Why did an agent do some action?
13. Instrumental/procedural	What plan or instrument allows an agent to accomplish a goal?How did an agent do some action?
14. Enablement	What object or resource allows an agent to accomplish a goal?
15. Expectation	Why did some expected event not occur?
16. Judgmental	What value does the answerer place on an idea?

The researchers found statistically significant results on the function construct, which is the highest level of the SBF framework describing systems-level thinking. This is especially noteworthy in light of no statistical difference in the behavior construct that details how concepts operate within a system. Once individuals do have a core set of concepts identified (structure level), it seems the natural inclination of experts and novices is to reason how these ideas connect to other concepts, which would explain the lack of statistical significance on the behavior construct. That is, once ideas are identified, individuals will seek to connect the indices they deem relevant. Differences later emerge because experts are then able to parlay this understanding and advance to holistic and systems-level thinking, as highlighted by the difference in the function constructs. In many ways, this underscores existing research about how experts are more likely to think using a systems-level approach (Björklund, 2013; Bruggeman et al., 2021); however, the results from the structure variable show that it is a more refined and nuanced form of systems-level thinking as opposed to a far-ranging perspective when compared with novices.

The finding of the function construct has important implications for problem-solving instructional strategies, such as IBL. As noted above, a frequent discussion is how facilitators balance the ill-structured nature of IBL as learners focus on a core set of concepts within the problem-space. In some ways, the open-ended nature of inquiry and directed nature of problem-solving in IBL seem antithetical and thus pose a challenge to educators. This may also explain why many of the questions were coded as advanced level (RQ2). As educators seek to scaffold learners, the results of the study highlight how learners may focus on the key ideas (structure) and not naturally connect ideas. Instead, it is important to reflect and encourage learners to generate a more networked mental model. By seeing ideas as more closely connected, this may improve retrieval and reuse as learners engage in future problem solving.

Limitations and Future Studies

While this research builds on prior studies that have explored expert-novice differences, other studies could build on these findings. One notable way to iterate on this study is to ask learners to generate their own indices. In the context of this study, individuals were asked to weigh indices that had been previously generated by two subject matter experts. Although this may have helped reduce some of the variability and open-ended nature of the terms, one might conclude that this was an artificially constrained set of indices and thus impacted the results. By asking learners to share their own indices as opposed to a predefined set, it may have provided further insight into the process of index generation between experts and novices.

Another study could focus on the different measures to assess differences in problem-solving. Although indices were the primary point of comparison, a study could also explore differences in questions between experts and novices. While studies have explored the types of concepts and questions that individuals employ as they engage in problem -solving (Olney et al., 2012), other artifacts could explicate differences in various ways. For example, studies often employ concept maps or causal-reasoning maps as a measure of the learner's mental model or internal schema. The scope of the current research was to focus on how learners individually assessed the relevancy of a concept as a foray into retrieval and reuse, but alternative measures could serve as a way to understand more comprehensive and connected levels of understanding. In that sense, an additional study could explore the degree to which index assignment changes when learners engage in collaborative problem-solving. Although retrieval and reuse are key elements of problem solving, additional follow-up studies could add to the field's understanding of learning theories and instructional strategies.

An additional study could explore other conceptualizations of novice-level problem-solving. Many expert-novice studies typically compare some early-stage career individual with an advanced-level individual, as defined by the number of years or position title. The current study focused on learners in a higher-education setting, which one might argue includes some level of domain knowledge and limited experience; however, it is possible that novice levels may be different upon entry into the workforce. As the field explores other measures of the expert-novice dynamic, it could be important to understand how expertise grows across the experience continuum.

Declarations

Conflict of Interest The authors declare no competing interests.

References

Auerbach, A. J., Higgins, M., Brickman, P., & Andrews, T. C. (2018). Teacher knowledge for active-learning instruction: Expert–novice comparison reveals differences. *CBE—Life Sciences Education*, *17*(1), 1–14.

Baker, J., Andriessen, M., & Schwarz, B. (2019). Collaborative argumentation-based learning. In N. Mercer, R. Wegerif, & L. Major (Eds.), *Routledge international handbook on dialogic education* (pp. 76–88). Routledge.

Baker, K. M., Johnson, A. C., Callahan, C. N., & Petcovic, H. L. (2016). Use of cartographic images by expert and novice field geologists in planning fieldwork routes. *Cartography and Geographic Information Science, 43*(2), 176–187.

Belland, B., Walker, A., Kim, N., & Lefler, M. (2017). Synthesizing results from empirical research on computer-based scaffolding in STEM education. *Review of Educational Research, 87*(2), 309–344.

Belland, B., Weiss, D. M., & Kim, N. J. (2020). High school students' agentic responses to modeling during problem-based learning. *The Journal of Educational Research, 113*(5), 374–383.

Björklund, T. A. (2013). Initial mental representations of design problems: Differences between experts and novices. *Design Studies, 34*(2), 135–160.

Bruggeman, B., Tondeur, J., Struyven, K., Pynoo, B., Garone, A., & Vanslambrouck, S. (2021). Experts speaking: Crucial teacher attributes for implementing blended learning in higher education. *The Internet and Higher Education*, *48*, 100772.

Buchanan, S., Harlan, M. A., Bruce, C. S., & Edwards, S. L. (2016). Inquiry based learning models, information literacy, and student engagement: A literature review. *School Libraries Worldwide, 22*(2), 23–39.

D'Mello, S., Lehman, B., Pekrun, R., & Graesser, A. (2014). Confusion can be beneficial for learning. *Learning and Instruction, 29*, 153–170.

Dwyer, C. P., Boswell, A., & Elliott, M. A. (2015). An evaluation of critical thinking competencies in business settings. *Journal of Education for Business, 90*(5), 260–269.

Elkind, D. (2004). The problem with constructivism. *The Educational Forum, 68*(4), 306–312.

Fritscher, B., & Pigneur, Y. (2016). Classifying business model canvas usage from novice to master: A dynamic perspective. *Business Modeling and Software Design*, 134–151.

Garfield, J., Le, L., Zieffler, A., & Ben-Zvi, D. (2015). Developing students' reasoning about samples and sampling variability as a path to expert statistical thinking. *Educational Studies in Mathematics, 88*(3), 327–342.

Ge, X., Law, V., & Huang, K. (2016). Detangling the interrelationships between self-regulation and ill-structured problem solving in problem-based learning. *Interdisciplinary Journal of Problem-Based Learning, 10*(2), 11.

Graesser, A. C., & Olde, B. A. (2003). How does one know whether a person understands a device? The quality of the questions the person asks when the device breaks down. *Journal of Educational Psychology, 95*(3), 524–536.

Hara, N., & Schwen, T. M. (2006). Communities of practice in workplaces. *Performance Improvement Quarterly, 19*(2), 93–114.

Heinrichs, K. I. (2002). Problem-based learning in entry-level athletic training professional-education programs: A model for developing critical-thinking and decision-making skills. *Journal of Athletic Training, 37*(4), 189–198.

Hmelo-Silver, C. (2013). Creating a learning space in problem-based learning. *Interdisciplinary Journal of Problem-Based Learning*, *7*(1). https://doi.org/10.7771/1541-5015.1334

Hmelo-Silver, C., & Pfeffer, M. G. (2004). Comparing expert and novice understanding of a complex system from the perspective of structures, behaviors, and functions. *Cognitive Science, 28*(1), 127–138.

Huang, R., & Li, Y. (2012). What matters most: A comparison of expert and novice teachers' noticing of mathematics classroom events. *School Science and Mathematics, 112*(7), 420–432.

Jacobson, M. J. (2001). Problem solving, cognition, and complex systems: Differences between experts and novices. *Complexity, 6*(3), 41–49.

Jamshidi, H., Hemmati Maslakpak, M., & Parizad, N. (2021). Does problem-based learning education improve knowledge, attitude, and perception toward patient safety among nursing students? *A Randomized Controlled Trial. BMC Nursing, 20*(1), 70.

Jarodzka, H., Balslev, T., Holmqvist, K., Nyström, M., Scheiter, K., Gerjets, P., & Eika, B. (2012). Conveying clinical reasoning based on visual observation via eye-movement modelling examples. *Instructional Science, 40*(5), 813–827.

Jee, B. D., Uttal, D. H., Spiegel, A., & Diamond, J. (2015). Expert–novice differences in mental models of viruses, vaccines, and the causes of infectious disease. *Public Understanding of Science, 24*(2), 241–256.

Jonassen, D. H. (1997). Instructional design models for well-structured and ill-structured problem-solving learning outcomes. *Educational Technology Research and Development, 45*(1), 65–94.

Jonassen, D. H. (2011). Learning to solve problems: A handbook for designing problem-solving learning environments (1st ed.). Routledge.

Jonassen, D. H., & Hung, W. (2008). All problems are not equal: Implications for problem-based learning. *Interdisciplinary Journal of Problem-Based Learning*, *2*(2). http://docs.lib.purdue.edu/ijpbl/vol2/iss2/4

Kim, L. E., & Klassen, R. M. (2018). Teachers' cognitive processing of complex school-based scenarios: Differences across experience levels. *Teaching and Teacher Education, 73*, 215–226.

Koehler, A. A., Ertmer, P., & Newby, T. J. (2019). Developing preservice teachers' instructional design skills through case-based instruction: Examining the impact of discussion format. *Journal of Teacher Education, 70*(4), 319–334.

Kolodner, J. (1991). Improving human decision making through case-based decision aiding. *AI Magazine, 12*(2), 52–68.

Korovin, L. N., Farrell, T. M., Hsu, C.-H., White, M., & Ghaderi, I. (2020). Surgeons' expertise during critical event in laparoscopic cholecystectomy: An expert-novice comparison using protocol analysis. *American Journal of Surgery, 219*(2), 340–345.

Koszalka, T. A., & Epling, J. (2010). A methodology for assessing elicitation of knowledge in complex domains: Identifying conceptual representations of ill-structured problems in medical diagnosis. In D. Ifenthaler, P. Pirnay-Dummer, & N. M. Seel (Eds.), *Computer-based diagnostics and systematic analysis of knowledge* (pp. 311–334). Springer.

Lazonder, A., & Harmsen, R. (2016). Meta-analysis of inquiry-based learning: Effects of guidance. *Review of Educational Research, 87*(4), 1–38.

Mamede, S., Figueiredo-Soares, T., Elói Santos, S. M., de Faria, R. M. D., Schmidt, H. G., & van Gog, T. (2019). Fostering novice students' diagnostic ability: The value of guiding deliberate reflection. *Medical Education, 53*(6), 628–637.

Olney, A. M., Graesser, A. C., & Person, N. K. (2012). Question generation from concept maps. *Dialogue & Discourse, 3*(2), 75–99.

Pinkus, R. L., Gloeckner, C., & Fortunato, A. (2015). The role of professional knowledge in case-based reasoning in practical ethics. *Science and Engineering Ethics, 21*(3), 767–787.

Prytz, E. G., Norén, C., & Jonson, C.-O. (2018). Fixation differences in visual search of accident scenes by novices and expert emergency responders. *Human Factors, 60*(8), 1219–1227.

Randles, C. A., & Overton, T. L. (2015). Expert vs. novice: Approaches used by chemists when solving open-ended problems. *Chemistry Education Research and Practice*, *16*(4), 811–823.

Reilly, C. M., Kang, S. Y., Grotzer, T. A., Joyal, J. A., & Oriol, N. E. (2019). Pedagogical moves and student thinking in technology-mediated medical problem-based learning: Supporting novice-expert shift. *British Journal of Educational Technology, 50*(5), 2234–2250.

Schank, R. (1999). *Dynamic memory revisited* (2nd ed.). Cambridge University Press.

Schmidt, M., & Tawfik, A. (2018). Using analytics to transform a problem-based case library: An educational design research approach. *Interdisciplinary Journal of Problem-Based Learning, 12*(1). https://doi.org/10.7771/1541-5015.1635

Schubert, C. C., Denmark, T. K., Crandall, B., Grome, A., & Pappas, J. (2013). Characterizing novice-expert differences in macrocognition: An exploratory study of cognitive work in the emergency department. *Annals of Emergency Medicine, 61*(1), 96–109.

Stefaniak, J. (2020). The utility of design thinking to promote systemic instructional design practices in the workplace. *TechTrends, 64*(2), 202–210.

Tawfik, A. A., Graesser, A., Gatewood, J., & Gishbaugher, J. (2020a). Role of questions in inquiry-based instruction: Towards a design taxonomy for question-asking and implications for design. *Educational Technology Research and Development, 68*(2), 653–678.

Tawfik, A. A., Schmidt, M., & Hooper, C. P. (2020b). Role of conjecture mapping in applying a game-based strategy towards a case library: a view from educational design research. *Journal of Computing in Higher Education, 32,* 655–681.

Tawfik, A. A., & Kolodner, J. (2016). Systematizing scaffolding for problem-based learning: A view from case-based reasoning. *Interdisciplinary Journal of Problem-Based Learning*, *10*(1).

Valentine, K. D., & Kopcha, T. J. (2016). The embodiment of cases as alternative perspective in a mathematics hypermedia learning environment. *Educational Technology Research and Development, 64*(6), 1183–1206.

Voet, M., & De Wever, B. (2017). Preparing pre-service history teachers for organizing inquiry-based learning: The effects of an introductory training program. *Teaching and Teacher Education, 63*, 206–217.

Wolff, C. E., Jarodzka, H., van den Bogert, N., & Boshuizen, H. P. A. (2016). Teacher vision: Expert and novice teachers' perception of problematic classroom management scenes. *Instructional Science, 44*(3), 243–265.