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Cover Page Footnote

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LEARNING IN CONTEXT: EXPLORING STUDENT COGNITIVE MAPS[1]

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ABSTRACT

This study examines how concept-by-concept learning can provide students with a robust conceptual cognitive map for the area under study. In-context learning indicates that students understand how individual concepts are related and apply to real-world situations. Our results show that insights can be gained from understanding the degree of in-context learning in a course. Faculty can use this information to guide instruction in real time and make curriculum adjustments. This approach is also helpful because it can be replicated in any course to develop knowledge about students' conceptual understanding.

Disclosure Statement
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INTRODUCTION: IN-CONTEXT LEARNING

The pedagogy of undergraduate teaching often seems at odds with the ultimate goals of education (Chan 2016). This is the case whether we consider the students' or the institution's goals. Student goals tend to be "instrumental and personal," whereas institutions often favor idealized goals, focusing on "life-and society-changing consequences" (Chan 2016, 1). To accomplish either of these objectives, higher-order thinking skills are needed (Bloom et al. 1956), which rely on analyzing, evaluating, and creating (Mumtaz et al. 2020). As noted by Zapalska et al. (2018), movement to these higher levels is the essence of the development of critical thinking skills, which depend on a student's ability to "detect relationships among different concepts and elements" and "explain patterns and meaning" based on their knowledge of the "whole picture of concepts and theories" (Zapalska et al. 2018, 295). Hence, students are best served when in-context learning occurs, which enables them to become more aware of critical real-world relationships. In-context means that the student learns how individual concepts are related and can be used in the real world; students need to develop a "cognitive map" that captures real-world conceptual interrelationships.

Unfortunately, students often learn concepts as single entities, especially at the undergraduate level. Therefore, they are unable, in real-world situations, to identify or link a particular concept to other concepts, theories, or models. For example, Peters (2006) discusses the importance of in-context learning for executives. While business schools do a great job of teaching separate

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disciplines, they may be less adept at ensuring that students understand the interrelationships of business concepts.

To help students gain fundamental, usable competencies while developing real-world "cognitive maps," higher-education instructors employ several strategies. For example, many undergraduate degree programs rely on a final capstone experience. The stated goal of such capstones is to help students assimilate what they have learned in foundational courses by dealing with real problems. Capstones can take several forms, from students working with external customers to working within a simulation (Kuh 2008; Johnson and Halabi 2011). At times, the capstone is centered on a specific project, especially for undergraduate engineers. This also allows engineers to work with students from other majors, making the experience as close to the real world as possible.

The problems with learning in context are particularly acute for introductory courses. Faculty who teach foundational courses, such as introductory accounting or marketing, know that their students would be best served by understanding the context and conceptual interrelationships that inform the entire course. However, it can be difficult to provide real-world experiences when students have little knowledge of basic course concepts. As a result, instructors in introductory courses tend to adopt a concept-by-concept or block-by-block approach. Because teachers know that interrelationships matter greatly, they constantly fine-tune the journey through their courses to convey a complete cognitive map. For example, teachers change how concepts are taught or periodically insert a synthesis lesson (Elliott 2021).

A further educational concern is that the problems and questions in which students are tested in foundational courses are concept specific. Again, because students have little knowledge of basic notions in early courses, it is difficult to teach concepts in context or monitor the extent to which students are developing a complex cognitive map representing important conceptual interrelationships. Nevertheless, pedagogical efforts have been made to foster in-context learning, including case studies, problem-based learning, and the flipped classroom (Dunlap 2005).

However, there is always a tradeoff between helping students understand individual concepts and assisting them in comprehending how they are related, especially in introductory courses. As a result, teachers spend more time ensuring that students understand basic concepts, reducing the time available to teach and assess their mastery of the "map" of interconnections among the many course concepts.

In the present research, we explore ways to measure how concept-by-concept learning can lead students to understand the interconnections or "cognitive map" of the foundational area being studied. In addition, we examine the link between students' understanding of the course map and the grades earned. Finally, we discuss how instructors can explore and develop insights into the cognitive map implicit in their course's journey. Investigating the relationships among crucial concepts helps instructors understand where to invest additional teaching time. Specifically, teachers can better understand how a course is helping or not helping students with these critical relationships.

COGNITIVE STRUCTURES

The notion of "cognitive structure" is critical to this work. The American Psychological Association defines a cognitive structure as "a mental framework, pattern, or schema that maintains and organizes a body of information relating to a particular topic" (VandenBos 2007). Although this definition fully informs how cognitive structures will be addressed in this research, we acknowledge that cognition can be defined differently. For instance, Liu et al. (2019) examined cognitive structures in two ways: from the point of view of the initial knowledge level of the learners and from that of how new knowledge is structured. In addition, artificial intelligence (AI) researchers tend to take a multiphase view of cognition. For example, Langley (2017) discusses some of the phases employed by different AI models. Nonetheless, although a multiphase definition of cognition can help explain cognition from a computational perspective, it can fall short when applied to human cognitive processes (Stillman and Pruess 2014).

In this paper, we examine cognitive structures per the American Psychological Association's "mental framework" that students use to structure the items or concepts they have learned in a particular course (VandenBos 2007). Based on this definition, we track the changes in cognitive structures for students in an introductory systems course. Specifically, our systems faculty identified critical systems concepts and specified how these are related, creating a conceptual map for the course, as discussed below.

Cognitive structures can be represented in many ways, as noted by Verissimo et al. (2017). We employed the Pathfinder Associative Network initially developed by Schvaneveldt (1990), which has demonstrated its usefulness in many contexts. These include showing how external representations can influence an individual's knowledge structures (Lee and Clariana 2022), helping managers improve corporate training efforts that could enable employees to more productively access the knowledge embedded in enterprise systems (Davis and Brattin 2019), examining how the arguments used in trials impact jury decision making (Rawn et al. 2022), investigating the development of mathematical cognitive structures (Veríssimo et al. 2017), helping instructors understand how their undergraduate design course impacted students' views about sustainability concepts (Yilmaz and Kapkin 2021), determining how the introduction of a competitive component influenced students' mental models and structural knowledge (Riemer and Schrader 2022), and exposing the higher-level connections that bind the study of business, management, and accounting (Santos and Mayoral 2020).

Pathfinder generally represents relationships between concepts better than multidimensional scaling (Cooke 1992; Rentsch 1995), although the two methods are often employed together (Yilmaz and Kapkin 2021) or sequentially. In the latter case, Pathfinder outputs are further analyzed using multidimensional scaling (Gulacar et al. 2019) in a way that explores both aspects of Liu et al.'s (2019) definition of cognitive structures. However, for some types of spatial relationships, multidimensional scaling may be better than Pathfinder (Furlough and Gillan 2020). This study uses the Pathfinder approach coupled with a nonparametric analysis.

THE PRESENT STUDY

This study aims to illustrate how instructors can investigate how their course structure will produce a journey that allows students to understand the relationships among course concepts. Our study invites instructors to be more intentional about the course journey they provide by developing deeper insights into the relationships among concepts and how well students understand these relationships. As noted, students benefit the most when in-context learning occurs as it enables them to become more aware of critical real-world relationships (Chan 2016). Additionally, we anticipate that improved conceptual understanding will be correlated with higher grades earned on course exams.

Based on the literature reviewed above, we formulate two causal hypotheses and a third question that is exploratory.

Cognitive Map Hypothesis

To what extent can we measure students' understanding of and progress toward the cognitive map that informs a particular course, the sometimes-implicit map that guides course development? For students enrolled in our introductory management systems course, we postulate the following.

> (H1) Hypothesis 1: Students' cognitive maps will move closer to the experts' cognitive map during the course based on pre-post measures (Chan 2016).

Cognitive Map and Course-Performance Hypothesis

Exploring how students' cognitive maps relate to course grades is also important. Specifically, while the students' cognitive maps should move toward the experts' maps, fairness and consistency demand that students who develop the best understanding of the course's cognitive map should generally also earn the best grades. Our specific hypothesis is as follows.

> (H2) Hypothesis 2: Each student's cognitive map will positively influence their grades (Chan 2016).

METHODOLOGY

Participants

The participants of this research were from multiple sections of a semester of our introductory management systems course. There were 45 students in total across the sections, 39 of whom completed the starting and ending concept inventory.

Determining Key Concepts and Cognitive Structures

To measure and compare cognitive structures, we used the Pathfinder software's graphical methods approach to create conceptual maps for each student. These maps expose how each student believes the major course concepts are related. We then compared students' cognitive maps with expert (teacher) maps to explore how the course drives students toward a better understanding of how the concepts are related. An example of the Pathfinder output expert map for our introductory management systems course is shown in Figure 1.

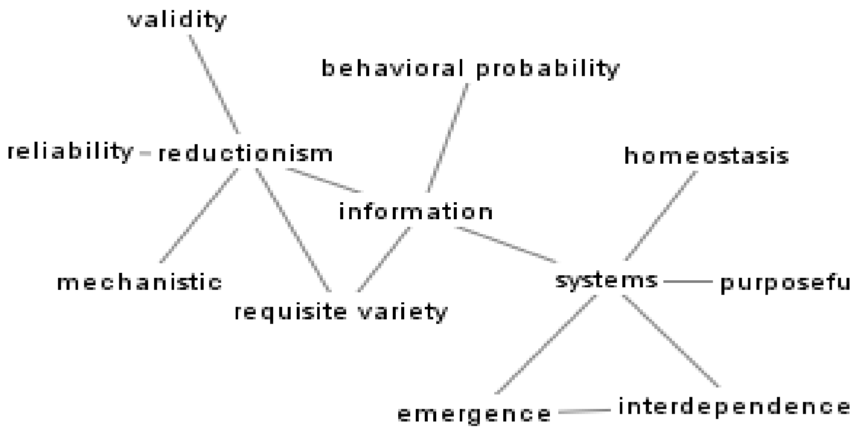

Figure 1. Expert concept map for the introductory management systems course

A short explanation of the Pathfinder software is in order:

> Pathfinder software is based on graph theory, which uses proximity data representing the nearness, similarity, or relatedness of pairs of concepts in a set as the input for generating networks. Each node is a concept; links represent relationships between nodes. Pathfinder statistically ensures that linked nodes are more related than indirectly linked or unlinked nodes. The Pathfinder process begins with all nodes completely linked; however, a direct link between nodes is kept if and only if the distance in the proximity matrix is less than or equal to all other indirect paths. Links that remain represent the shortest distances between concepts.
>
> Pathfinder uses two parameters, *r* and *q*. The *r*-parameter is the Minkowski *r*-metric, which determines how the distance between two nodes is computed. The *r*-parameter can range from 1 to infinity, with the appropriate setting of *r* for ordinal data being *r* = infinity. The *q*-parameter limits the length of the network. The *q*-parameter can range from 2 to n - 1, where n is the number of concepts in the set. When *q* = n - 1, there are no limits on the number of links allowed in the network because the longest possible path has n - 1 links. Further information related to Pathfinder can be found in-depth in Schvaneveldt (1990) or more briefly in White (2004). (Strbiak et al. 2008, 41)

Before using the procedure described above to create student cognitive maps, a referent (expert) cognitive or network map was developed:

> Pathfinder networks can be compared to a referent structure, thereby creating a measure of similarity (Acton et al. 1994). As noted by Ruiz-Primo and Shavelson (1996), using referent networks to gauge trainee progress has produced statistically robust results. For example, West et al. (2000) showed that this type of comparison could be used to predict later performance of medical students; Mayfield et al. (1999) demonstrated the validity of using a referent Pathfinder network in their study of novice versus experienced counselors.
>
> Pathfinder uses a measure of similarity or "netsim" to represent the number of links in common between two networks, considering the probability of two networks having a certain number of links in common. Netsim values range from -1 to +1. Positive netsim values indicate a non-random similarity between two networks; negative netsim values indicate a non-random dissimilarity between two networks. A *t*-probability, which is

> similar to a *t*-test, shows whether or not the two networks are significantly similar (Gomez et al. 1996). (Strbiak et al. 2008, 42)

For this study, four instructors who previously taught our introductory management systems course constructed a referent network map. Each instructor was asked to bring a list of course concepts that they thought were important to the course. Many of the lists overlapped, and they eventually reached a consensus and identified the twelve key course concepts in Table 1.

Table 1. List of key concepts for the introductory management systems course

Information	Requisite variety	Interdependence
Reliability	Validity	Systems
Reductionism	Purposeful	Homeostasis
Behavioral probability	Emergence	Mechanistic

This list is specifically adapted to our introductory management systems course. As is true for many areas of study, from marketing to information systems, the specific academic journey, text, and implicit or explicit cognitive map vary from instructor to instructor and across intuitions. In summary, the cognitive map for a course is strongly informed by the particular "journey" captured by a particular course's implementation. Since course structure should be an intentional process, instructors often start with a list of concepts crucial to understanding the study area. Part of what we are encouraging with this research is greater intentionality about the next step, that is, the development of an intentional map that captures the relationships among crucial concepts. As noted previously, such an understanding strengthens how the course prepares students for the "in-context" real-world application of these concepts.

As described above, Pathfinder examines the relationships among all concepts implied by the relationships between each set of pairs. This means that the number of concepts that can be used must be limited because Pathfinder requires respondents to specify distances between every pair of concepts. Thus, if three terms or concepts (x, y, z) are used, respondents must provide information about three pairs of relationships (x to y, x to z, and y to z). As more concepts are added, the number of relationships rises dramatically. For twelve variables, respondents must evaluate sixty-six separate relationships. Importantly, there is a limit to how many concepts can be examined practically; for example, if an instructor wanted to look at the relationships among twenty concepts, 190 distinct relationships would have to be evaluated, which is overwhelming for survey takers.

For our four expert evaluators, the twelve variables in Table 1 were presented as sixty-six pairs on our survey instrument. The experts and students were asked to evaluate each pair on a five-point Likert scale. The scale allowed the respondents to characterize the relationship between each pair of concepts from "highly related" to "unrelated." Table 2 presents a small excerpt of the rating form. For the first set of terms in Table 2, for example, students had to decide how related the terms "information" and "emergence" were, from "unrelated" to "very strongly related." After compiling the expert results, we noted that some relationships were unstable. Therefore, we reduced the number of relationships the students were asked to evaluate from sixty-six to thirty-nine.

Table 2. Excerpt from the survey containing sixty-six pairs of variables

For each pair of terms below, specify how closely related they are	Unrelated	Slightly Related	Somewhat Related	Strongly Related	Very Strongly Related
Information ⟷ Emergence					
Emergence ⟷ Homeostasis					
Reductionism ⟷ Purposeful					

The expert evaluators were the initial respondents to test and validate the survey. The expert evaluators validated the variables and their relationships in two ways. First, the instructors were expected to demonstrate strong congruence in the concepts of their cognitive structures. This was tested using Pathfinder to ensure that the cognitive maps produced by different instructors were similar. In addition, we tested the stability of the relationships among the variables identified by each expert. To accomplish this, the expert evaluators took the survey on three occasions, each six weeks apart. When there was substantial disagreement about the relationships among the expert evaluators or when an expert diverged in their response by more than two blocks, the relationship was considered unusable. However, we fully expected to find many such relationships because, for some of the pairs, the relationship's closeness can be reasonably argued in either direction.

Ultimately, our experts demonstrated the cognitive validity of many conceptual relationships while identifying other relationships lacking stability. Table 3 shows the sixty-six potential relationships. Those that are numbered were stable. Those noted 0 were not (gray highlighting). Therefore, unstable pairs were not used in the final expert cognitive maps. The expert maps were then merged to create a more robust comparison tool or, as described above, a "referent network." This research proposal will use an expert cognitive map that asks students to rate thirty-nine relationships.

Table 3. Relationships used to develop and compare expert maps

	Red	Sys	Inf	Mec	Pur	Req	Beh	Hom	Eme	Val	Rel
Reductionism (Red)											
Systems (Sys)	0										
Information (Inf)	2	12									
Mechanistic (Mec)	3	13	0								
Purposeful (Pur)	4	14	23	31							
Requisite variety (Req)	5	15	24	0	0						
Behavioral probability (Beh)	0	0	25	0	40	46					
Homeostasis (Hom)	7	17	26	34	41	0	0				
Emergence (Eme)	8	18	0	35	42	0	0	57			
Validity (Val)	9	0	0	0	0	0	54	58	61		
Reliability (Rel)	10	0	0	0	0	0	55	59	62	64	
Interdependence (Int)	11	21	0	38	45	0	0	60	63	0	0

ANALYSIS

Hypothesis #1: Evolution of Student Cognitive Maps

Comparing the Pathfinder cognitive maps produced by each student on their first day of class with the expert map revealed that the students initially had little knowledge of the subject area. As previously discussed, Pathfinder compares each student map with the expert (referent) map and provides a similarity score. For the student maps created on the first day, the average similarity ("netsim") score was 0.180, as shown in Table 4 below. For context, when Pathfinder compares two maps, the hypothesis is that the two individuals have the same understanding of a set of relationships. A similarity value of 0.160 corresponds to a p-value of approximately 0.50; therefore, the 0.180 netsim finding shows that the students generally took guesses about each relationship. Once the concepts were covered in class, the students took the survey again, producing new cognitive maps. For these new maps, the average similarity rose to 0.315 (Table 4). According to the Pathfinder algorithm and statistics, the hypothesis that the students described the same relationships as the experts was now quite significant, with a p-value of <.016.

In summary, the average student's cognitive map on day one was unrelated to the expert (referent) map. Figure 2 below, which was generated by the Pathfinder software, helps to visualize this randomness. The figure integrates the day-one student maps. As Figure 2 demonstrates, students randomly connected concepts on the first day of class and produced too many connections. The referent (expert) map (Figure 3) contains fewer but more meaningful connections.

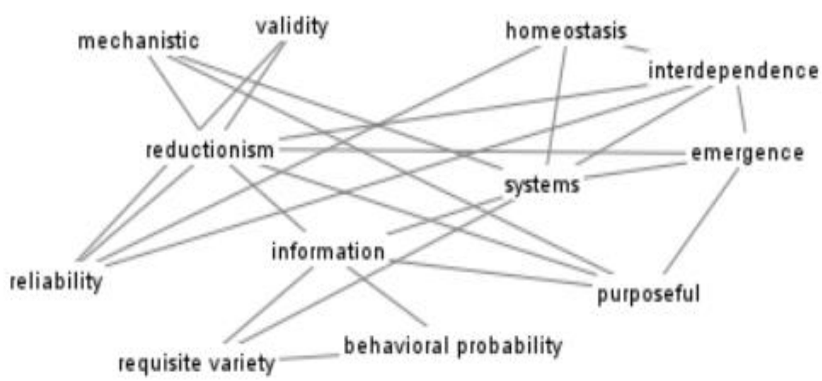

Figure 2. Map for the average student, first day of class

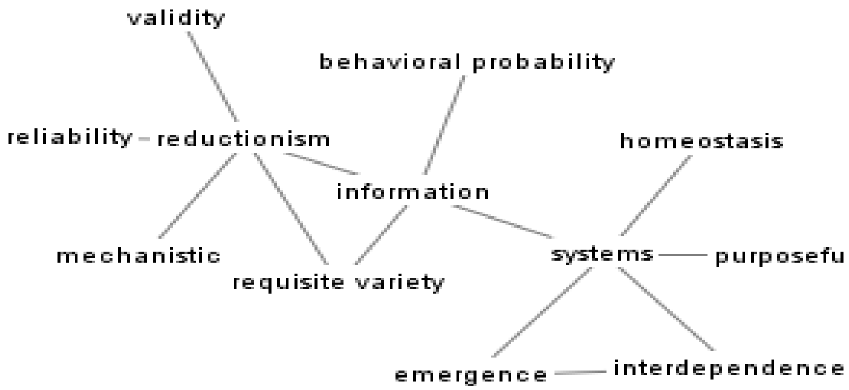

Figure 3. Expert (referent) map

As previously explained, each student produced another cognitive map after all the concepts had been covered. These second maps revealed significant student progress toward the expert map. The average similarity score for all students, as reported by Pathfinder, rose to 0.315, which corresponds to $p<.016$.

A Wilcoxon signed-ranks test was performed (Table 5) to further confirm the gains between the cognitive maps produced on the first day and after the material was covered in class. As shown in Table 6, the test's result was significant ($p<.00$).

Table 4. Descriptive statistics

	N	Mean	Std. deviation	Minimum	Maximum
Map1	39	0.180	0.0727	0.020	0.310
Map2	39	0.315	0.1125	0.132	0.567

Table 5. Wilcoxon signed-ranks test

		N	Mean Rank	Sum of ranks
Map2 – Map1	Negative Ranks	5[a]	6.800	34.000
	Positive Ranks	34[b]	21.940	746.000
	Ties	0[c]		
	Total	39		

a. Map2 < Map1.
b. Map2 > Map1.
c. Map2 = Map1.

Table 6. Test statistics netsim score[a] tracking student improvement from Map 1 (day 1) to Map 2 (after all concepts had been addressed in the course)

	Map2 – Map1
Z	-4.968[b]
Asymp. Sig (two-tailed)	0.000

a. Wilcoxon signed-ranks test.
b. Based on negative ranks.

In summary, both Pathfinder and the Wilcoxon tests support our first hypothesis. Furthermore, as the course progressed, students' understanding of the relationships among the concepts improved significantly based on the expert cognitive map.

Hypothesis #2: Connection between Cognitive Maps and Students' Exam Performance

To examine how students' improved understanding of conceptual relationships translated into better grades on course exams, we used the Mann-Whitney and Kolmogorov-Smirnov tests, primarily favoring the latter due to our small sample size. Specifically, we tested the extent to which "A" students had significantly better cognitive maps, as measured by their similarity scores, than "B" students. Table 7 shows the results of the Mann-Whitney test, and Table 8 displays the results of the Kolmogorov-Smirnov test. In both cases, the tests strongly supported Hypothesis 2, with p-values of 0.000 and 0.001, respectively.

Table 7. Mann-Whitney tests for differences between A and B students, test statistics[a]

	Netsim score
Mann-Whitney U	52.000
Wilcoxon W	328.000
Z	-3.771
Asymp. Sig (two-tailed)	0.000
Exact Sig. [2*(one-tailed)]	0.000[b]

a. Grouping variable: control2.
b. Not corrected for ties.

Table 8. Kolmogorov-Smirnov tests for differences between A and B students, test statistics[a]

		Netsim score
Most extreme differences	Absolute	.658
	Positive	.658
	Negative	.000
Kolmogorov-Smirnov Z		2.020
Asymp. Sig. (two-tailed)		.001

a. Grouping Variable: control2.

The tests strongly supported Hypothesis 2 (Mann-Whitney $p = 0.000$; Kolmogorov-Smirnov $p = 0.001$). In addition, Pathfinder can visually demonstrate the differences between students at different grade levels. For example, Pathfinder created Figures 4 and 5, corresponding to the average final cognitive maps of "C" and "A" students, respectively. From Figures 4 and 5, it is clear that, when compared with the "C" students, the "A" students are more selective in terms of links, and the links they identify are much more synchronized with the expert map (Figure 3).

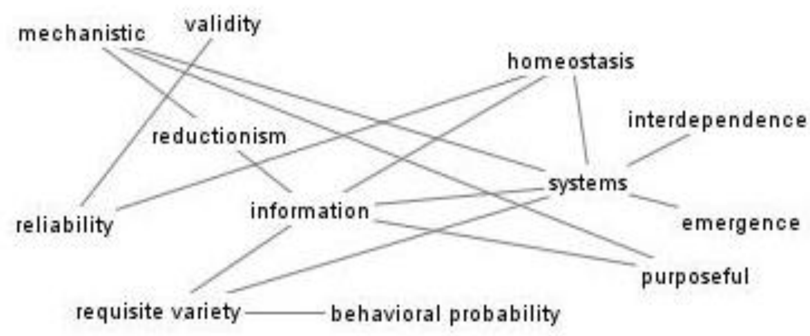

Figure 4. Average "C" student Pathfinder cognitive map

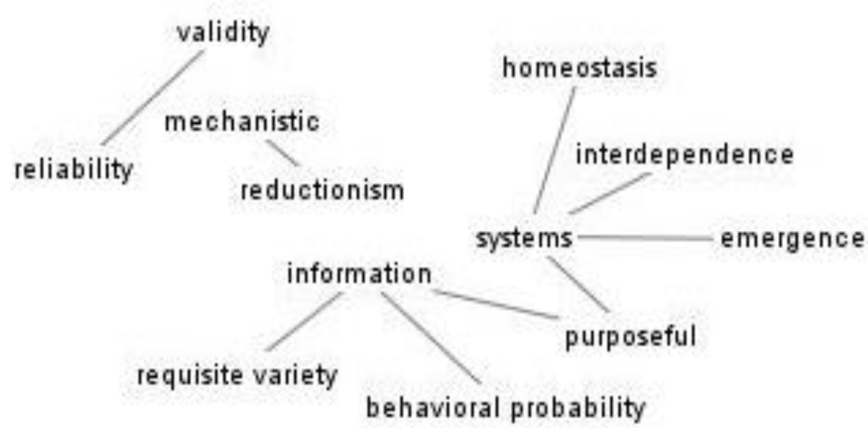

Figure 5. Average "A" student Pathfinder cognitive map

Exploratory Research: Developing insights about the course map

The strong support for Hypothesis 1 demonstrates that our course greatly improved students' understanding of the relationships among course concepts. The results regarding Hypothesis 2 indicate that the best grades were earned by the students who had developed the best understanding of these relationships.

Nevertheless, there is still much for the instructors to consider. We can gain tremendous insight into a course by examining how students differ in their understanding of specific dyadic conceptual relationships for this course. For example, which relationships seem well understood by nearly every student? Which relationships separate the top students from the others? Which relationships are missed by most students? Answers to these questions provide instructors with information about where additional examples and time should be spent to ensure that students develop a robust mental map.

To examine students' understanding of these dyadic relationships, we separated the students into two groups: those who scored above 70% on the course exams and those who scored below

70%. The exams were all essays and quite challenging; scoring above 70% usually earns students a B+ or better. We then returned to the Mann-Whitney test and the Kolmogorov-Smirnov test.

For this exploration, we will discuss several relationships (Table 9). For instructors employing this method, important information can be gained by carefully considering the results for each dyadic relationship. However, since this analysis is course specific and can be expected to change as instructors act on the findings, we will only provide a few examples.

Table 9. Examination of six dyadic relationships (see Table 3 for the concept pairs)[a]

		3	4	18	21	61	63
Most extreme differences	Absolute	0.446	0.503	0.514	0.364	0.495	0.321
	Positive	0.446	0.000	0.514	0.364	0.000	0.321
	Negative	0.000	-0.503	0.000	0.000	-0.495	0.000
Kolmogorov-Smirnov Z		1.369	1.544	1.578	1.119	1.519	0.985
Asymp. Sig. (two-tailed)		0.047	0.017	0.014	0.164	0.020	0.286

a. Grouping variable: control2.

We first consider relationship #3 (see Table 3), namely, the dyadic relationship of "reductionism" and "mechanistic." Our nonparametric Kolmogorov-Smirnov test showed that students scoring in the top half on exams were more likely to identify these as highly related concepts ($p = 0.047$, as noted in Table 9). While the overall course concerns systems, it is important to compare systems with reductionism as a secondary concept, which makes this a fundamental relationship. Although the fact that those scoring best on the exams correctly mapped this relationship is positive, as instructors, we want to ensure that everyone understands this basic relationship better, which would make it a "less significant" discriminator in test scores.

Relationship #63 ("emergence" and "interdependence") and relationship #21 ("interdependence" and "systems") are perhaps the two key dyadic relationships in a systems course. Again, although the fact that the best students were more likely to understand these relationships is a positive finding, it is probably also positive that neither relationship was a significant predictor of better grades ($p = 0.286$ and $p = 0.164$, respectively). For instructors, all students must come away with a basic understanding of these relationships.

Relationship #4 ("purposeful" and "reductionism") reminds us as instructors that a full understanding of a course's cognitive map requires students to identify when concepts are unrelated. This type of relationship is deeper than the basic relationships, so it is unsurprising that better-performing students better understood this type of relationship ($p = 0.017$).

Finally, relationship #61 ("emergence" and "validity") highlights the importance of knowing when a relationship does not make sense given the journey in the course. Yet, again, the better students do not have to make guesses about these non-relationships because they have a better overall cognitive map ($p = 0.02$).

DISCUSSION

The present study demonstrates how instructors can investigate the extent to which their course development has produced a journey that allows students to understand the relationships among course concepts. For example, for our introductory management systems course, we showed that our students made significant progress toward understanding the cognitive map that informs the course. Further, the students' understanding of this map was strongly correlated with the grades earned on course exams.

Our exploratory question invites instructors to be more intentional about the course journey they provide by developing deeper insights into the relationships among concepts and how well students understand these relationships. For instance, information can be gained concerning which relationships best predict total performance.

This study extended the goals of previous research (Veríssimo et al. 2017; Arias-Masa et al. 2019; Stoen et al. 2020), which sought to explore the extent to which student maps converge toward those of instructors or experts in a particular area. It also supported the notion that expert knowledge maps may be more about the proper organization of conceptual relationships than the overall density of the connections (Furlough and Gillan 2018). We also demonstrated that the Pathfinder method can be combined with additional statistical analysis (Gulacar et al. 2019; Furlough and Gillan 2020) to inform instructors as they try to create valuable in-context learning.

Several previous studies suggest important considerations and potential limitations for the findings of this study. At a basic level, it would be useful to start by considering how students' initial attitudes about a course could impact their cognitive progress. In particular, resistance on the part of the students might make it impossible for them to accept and understand critical conceptual relationships (Chen et al. 2022). Instructors must also consider pedagogy. For example, Bierstaker et al. (2018) found that learning via stories produced better cognitive structures (i.e., structures more aligned with those of experts) than serial or checklist types of learning.

Prior subject knowledge may be a more concerning confound, especially for non-introductory courses (Thurn 2021; Lee and Clariana 2022). Further, this concern may extend beyond course-specific knowledge. For instance, it may be useful to take into account the portfolio of courses that a student takes before entering a particular course. Santos and Mayoral (2020) suggested that student cognition can be driven by an understanding of how various courses in business and management are related and how the field is connected to other disciplines.

The ultimate goal of any course should be to help students gain real, usable competencies while also developing actionable real-world "cognitive maps." The approach examined in this study proposes a method for examining the extent to which students are achieving this outcome and provides additional insights that can help faculty improve the academic journey. As AI researchers have explained (Langley 2017), possessing an accurate mental map is necessary to apply knowledge in the real world. However, cognitive structures must also contain the symbolic structures that allow that knowledge to be applied in a relational pattern-matching process. We did not address this question in the present article, but it can be summarized as the challenge of getting students to recognize situations for which they have a cognitive map so they can use their knowledge to search for potential problems and solutions. This sentiment is captured by Eesley (2013, 37), who notes that instructors should strive to provide students with "information [that] is retained in long-term memory, where it can be sorted and arranged in a mental map," which allows "students to interpret new information more quickly."

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