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Decision-Based Learning: A Journey from Conception to Implementation to Iteration

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Abstract: *Pedagogical methods for graduate-level statistics courses have rarely focused on the pursuit of conditional knowledge or the ability to choose which concepts/procedures are relevant given a specific research situation. However, utilization of an innovative approach called decision-based learning (DBL) not only provides students with the conceptual, declarative, and procedural knowledge of traditional statistics courses, it also demystifies the process of gaining conditional knowledge; thus decreasing "statistics anxiety." This study examined the impact of a DBL course on students' ability to select appropriate statistical methods based on the wording of story problems, and specifically looked at pre-post differences. Participants were graduate students enrolled in an introductory statistics course who completed a combination of a pre, and post, and follow-up interviews. Interviews were coded and scored based on students' ability to correctly identify statistical methods, run and interpret statistical output. Results indicated that students' conditional knowledge increased significantly from pre- to post- to follow-up (effect sizes of 0.63 to 0.64). This compares favorably with the range of effect size increase from published studies of other innovative approaches (0.21 to 0.52). Results also showed nominal conditional knowledge decay, suggesting that DBL can be an effective and efficient means of teaching introductory graduate-level statistics. Implications for other disciplines are noted.*

Key Words: Decision-based learning, statistics education, conditional knowledge, schema building, problem-based learning

It is not uncommon for Psychology students to state, "I went into the social sciences because I don't do math." However, much to the chagrin of these undergraduate and graduate students, math – in the form of statistics – is generally a required course. Many of these students report an actual (or anticipated) negative and anxiety-ridden experience with statistics (Nesbit & Bourne, 2018; Waples, 2016; McGrath, et al., 2015; Chew & Dillon, 2014), with one study suggesting that up to 80% of psychology undergrads experience some sort of statistics anxiety (Onwuegbuzie & Wilson, 2003).

Unfortunately, this anxiety may be unintentionally exacerbated by well-meaning professors – experts in the field – who have reached a level of "intuitive functionality;" meaning, these experts can do the statistics taught in the course without really thinking about them. It just "comes naturally." This level of knowledge is often referred to as conditional or strategic

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knowledge and requires knowing when and how to apply declarative and procedural facts (McCormick, 1997; Turns & Van Meter, 2011). In other words, conditional knowledge allows the possessor to identify features, associate concepts with those features, and then select the appropriate procedures for the given features and concepts (Sansom, et al., 2019).

According to Sansom, et al. (2019), conditional knowledge "is a characteristic of experts that allows them to solve problems in a variety of situations and conditions, even as the experts are unaware that they are using it" (p. 446). Conditional knowledge is structured in a way which allows the one in possession of it to draw on the relevant concepts and procedures when necessary (Plummer, et al., 2020). Thus, Sansom, et al., (2019) suggest that to students it appears that professors:

> . . . solve problems seamlessly, using the conditional knowledge that they have developed to effectively evaluate a problem and move quickly to a problem-solving procedure. Seeking to emulate experts, students may jump straight to calculation. but they lack the knowledge to identify an appropriate strategy before they begin. (p. 445)

Unfortunately, jumping feet-first into statistics without the proper scaffolding of knowledge serves to intensify anxiety, rather than reduce it. Accordingly, an effective anxiety-reducing course would seek to help students gain declarative knowledge (facts), conceptual knowledge (relationships between facts), and procedural knowledge (what to do with facts; McCormick, 1997; see also Swan, et al., 2020) as well as conditional knowledge. In this same vein, Heck and Thomas (2020) emphasize the need to help novices evaluate the analytical options based on the nature of the data and the nature of the research question, one application of conditional knowledge. Therefore, by integrating all four types of knowledge, students will begin to see "behind the curtain," so to speak. The intuitive nature of expertise will be exposed, and the students will start down a yellow-brick road of understanding, sans anxiety.

The obvious next question is then, "How does one go about incorporating conditional knowledge into an existing course?" While there are many current approaches, one model stands out – particularly in regard to statistics education. Just-in-time Teaching (JiTT) addresses active learning, and is described by McGee, et al., (2016) as a methodology that:

> . . . includes assigning short, web-based conceptual questions or analysis problems to be completed outside of class. The questions or the short assignments must be answered before class and serve two purposes. The first is to encourage students to read or watch the preview material prior to class time. The second, and more important, is to identify misconceptions of the students, so they can be directly addressed and corrected, as called for by the learning principle of identifying erroneous prior beliefs and addressing those beliefs as soon as possible. (pp.16-17)

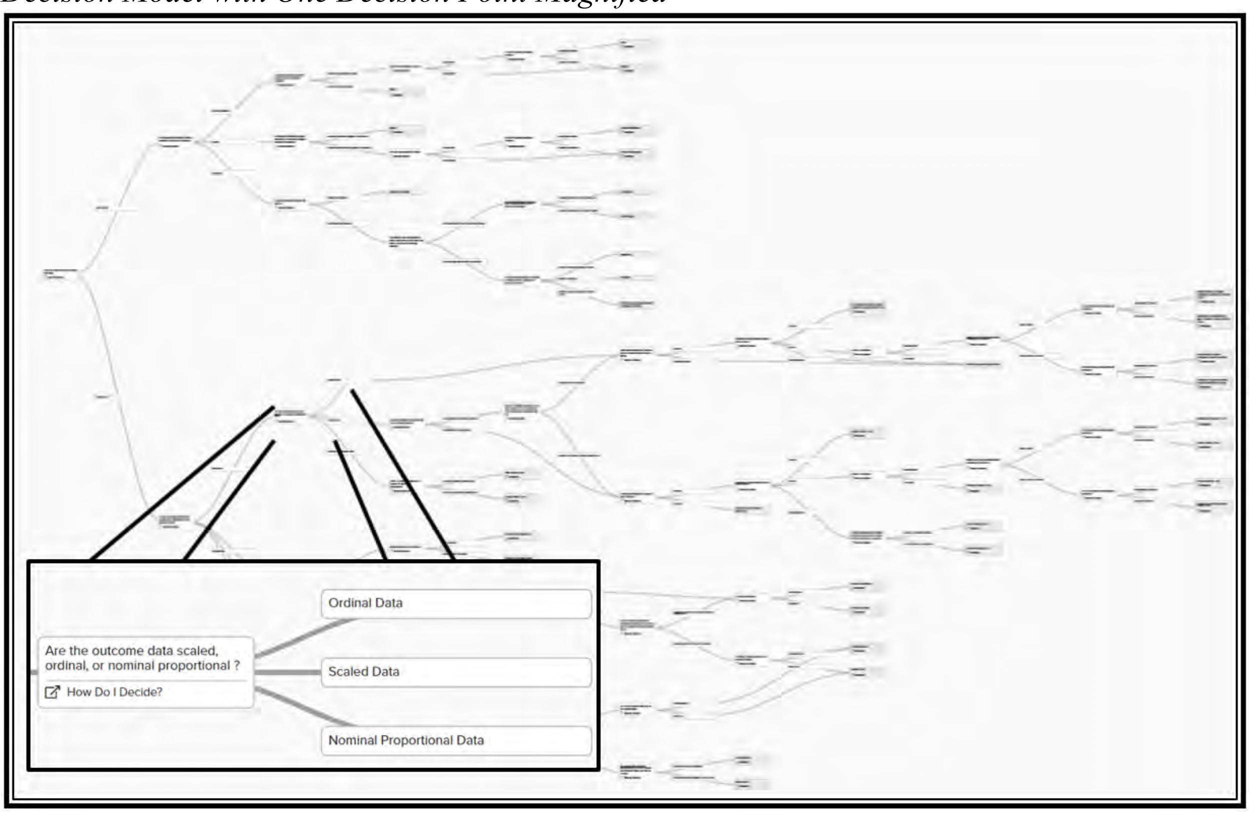
While JiTT has proven effective in the literature and provides a foundation from which to begin, it does not specifically address the intuitive nature of expertise; nor does it overtly provide the four-fold scaffolding of declarative, conceptual, procedural, and conditional knowledge. We therefore wish to present an approach which utilizes parts of the aforementioned teaching style and combines it with the deconstruction of intuition. The result is a pedagogical approach now known as Decision-based Learning (DBL).

WHAT IS DBL

DBL is a teaching method which "explicitly targets the development of functional expertise using conditional knowledge as the entry point and organizing principle. DBL makes conditional knowledge and schema building a first-order learning activity" (Swan, et al., 2020, p. 14). In its simplest form, DBL begins with an expert creating a decision tree, or model, that identifies the decisions involved in choosing a procedure to solve a problem. The expert then works through a multitude of problems utilizing the decision tree, thus ensuring the model accounts for the whole targeted problem space. Finally, students are taught the model concurrently with related conceptual and procedural knowledge, so that they ultimately develop more expert-like schemas regarding the subject material (Sansom, et al., 2019).

Figure 1 is a depiction of the decision model used in the course described in this paper. Decision models like this one begin with an initial decision point (a question with options) shown in the lower far left of Figure 1. Students are presented with a problem and then work their way through the decision model answering increasingly nuanced questions about the problem until they reach an endpoint depicted in a number of places from the middle to the far right of the decision model depicted in Figure 1. The end point is associated with a learning outcome. In this case, by the time students arrive at an end point they are ready to select the appropriate statistical method based on several clues in the word problem. Theoretically, hundreds if not thousands of problems can be taken through a decision model like this one in order to select an appropriate statistical method.

Figure 1
Decision Model with One Decision Point Magnified



Note: The decision model goes from left to right, culminating with a final course of action

At first glance, DBL shares some similarities with problem-based learning (PBL); however, the methodologies differ in the amount of guidance provided to the students when they are first presented with a problem (Plummer, et al., 2020). While PBL underscores the importance of students discovering the knowledge they need in order to solve a problem, DBL "guides students through a decision model in order to help them learn the conditions under which certain decisions are made rather than leaving them to discover these conditions for themselves" (Plummer, et al., 2020, p. 7). DBL may be a good pre-cursor to a PBL experience, because it provides the foundational schematic scaffolding that then gives way to less scaffolded PBL activities.

CONCEPTION OF DBL

DBL can trace most of its origins to Brigham Young University (BYU). Plummer, one of the originators of DBL and co-author of this paper, describes it as a "confluence of many ideas rooted in [his] graduate work developing concept map assessments in an introductory biology course, as well as experiences [he] had teaching Bloom's Revised Taxonomy in a course on assessing learning outcomes" (Fischer, et al., 2021, p. 23). Specifically, as Plummer taught students the difference between execute and implement in Bloom's Taxonomy, it became clear that implement is the act of tackling an unfamiliar problem by recognizing familiar cues or clues within that problem, which form its underlying structure. Based on the recognition of an underlying problem structure, one then selects the appropriate step-by-step procedures or combination of step-by-step procedures to get the job done. The idea of being able to superimpose a familiar, visual template (like a concept map) to handle a variety of unfamiliar problems was intriguing to Plummer. Thus, the initial inklings of DBL were conceived.

BIRTH OF DBL

Enter Fischer, a psychologist by training and profession, who had begun teaching a foundational statistics course for psychology graduate students in order to mitigate the detrimental statistics anxiety that the graduate students in his department were experiencing. Rather than send the students to another department for their statistics courses, Fischer created his own course and structured it with a very pragmatic approach with only three objectives: given any particular research question, and given the nature of the extant data, students should (1) know what statistical test to run; (2) how to run it in a statistical program; and (3) how to interpret the results to answer the research question.

Fischer stated that keeping the objectives simple and repeatable not only seemed manageable, but also seemed like it would help decrease students' fear and loathing of statistics. Although he employed other tactics to reduce anxiety (such as "song and dance," goofiness, and continued repetition), Fischer recognized that one of the best ways to decrease anxiety is to increase real competence; however, he could tell he was not being very successful at implementing the type of repetition students needed to solidify their learning and an increase in competence.

It was at this time that Plummer began observing Fischer's statistics course and shared his DBL inklings with Fischer - to which Fischer exclaimed, "I think like that!" Fischer then proceeded to share with Plummer how he broke down research questions for actual consulting clients he was working with at the time. It was a critical moment for the development of the idea of a "decision template." Plummer was in need of a professor who broke things down in real-world settings and who simultaneously possessed a conceptual command of the subject material, and Fischer's statistical consultations with corporate clients had prepared him to fill that role.

Plummer began asking Fischer about his mental process - his decision template. Plummer asked Fischer to describe a typical problem from a consulting client, and then asked, “What is the first question you ask in order to break down this problem?” Fischer explained that when he works with clients, they rarely know exactly what question they are really asking, so he helps them refine the question. The first question he asks is usually, “Do you just want to know what things look like in your context or do you want to generalize to other contexts?” In statistics terms, “Is it an inferential or descriptive question?” Plummer then asked how he knew just looking at a research question whether it was inferential or descriptive. Fischer proceeded to explain when or under what conditions the clients’ question is an inferential or a descriptive question.

Plummer then asked, “If it is inferential, what is the next question that you ask?” Fischer explained that he asks if they are interested in the differences between groups, relationships between variables in the same group, independence of variables, or goodness of fit. However, in the case that the problem is descriptive rather than inferential, he then asks himself if the question deals with central tendency, dispersion, or symmetry.

This questioning process continued until a decision tree or model emerged, consisting of many interconnected questions and options - much like a choose-your-own-adventure experience. They iterated this process over several months until they had a working decision model, with the beginning of instruction at each decision point. The instruction provided a definition and examples for each option along with practice classifying several new problems. In essence, DBL was born through this process.

Implementation and Evolution of DBL

From 2013 to present, implementation of DBL has followed an iterative process. Changes have occurred as a function of student feedback and instructor analysis of what the exams scores were and were not telling them. What follows is a summary of three major phases in the implementation cycle.

PDF and Early Software Use

The initial implementation of DBL in 2013 took the form of an electronic PDF copy of the decision model with hyperlinks to online documents. A link was placed at each decision point that gave students access to online instructional documents. These documents contained a definition for each option with relevant examples. Students were intrigued with the novelty of the document and commented on its perceived value. However, because it was not integrated into the curriculum through assignments, quizzes, and exams, the document remained a novelty rather than an essential learning tool.

In preparation for the next offering of the course (2014), the PDF decision model was jettisoned for a website with pages that students used to break down story problems in a way that helped them to select the appropriate statistical method. Each decision point in the decision model became its own web page. As students selected an option on one webpage they were brought to another webpage with a new decision point. This continued until they reached the end of a path within the decision model and were directed to select the appropriate statistical method among many other methods. The software was used exclusively outside of the classroom setting as homework. Students were more invested in this application than their predecessors were with the PDF in 2013 because DBL homework assignments were part of their overall grade. However, due to its clunky nature it still felt more like a tack-on than an integral part of the curriculum.

Beginning in the Fall 2015 semester, the number of methods covered by the decision model increased from 24 to 32. Students were given more systematic practice using the decision model to learn how to classify problems in four major statistical categories. In addition, by this time, instructors had anecdotal information and a general sense that students were learning and achieving the learning outcomes (i.e., read, select, calculate, and interpret the results), However, they had not collected pre-post performance data to document the nature of the systematic change in student learning. Thus, they began to interview students using a structured interview protocol. This protocol and the design of the study are described in the method section.

Face-to-Face and Systematic Homework

By 2016, instructors decided to give the students a face-to-face classroom experience with DBL to complement their experience with homework. Because of issues with student cognitive load in the previous year, the number of statistical methods covered was reduced from 32 back to 24. The in-class experience consisted of presenting a word problem to the students using powerpoint and asking them to classify the problem using the information at each decision point in the decision model. After providing students concise instruction about each option at a given decision point, students voted with their fingers as to which option was appropriate for the problem being presented (e.g. lift up your pointer finger if you think the problem is inferential, two fingers if you think it is descriptive, and three if you are unsure). Students were directed to close their eyes while voting so as to not be influenced by those around them. Students were then invited to defend their choice to each other in pairs or to the entire class.

The instructor also showed portions of the decision model as they naturally emerged in instruction. Students were given 11 x 17 paper to draw the decision model as more pieces of it were presented. The hope was that the face-to-face experience and the homework using the web pages would complement one another. During the Spring and Fall semesters of 2016 more pre-post interviews were conducted documenting conceptual change. The approach just described was used in courses offered in 2017 as well.

Improved Scaffolding / Updated Software

By 2018, the webpage DBL experience was replaced by a more professional version of the DBL software (See Figure 1). Instructors integrated this version of the software into a learning management system. Students engaged in the DBL homework prior to class. At this point, a three-pronged scaffolded learning system was implemented:

1. Students completed DBL homework before class. Students took 10 to 12 word problems through the decision model where they: (a) read a word problem; (b) selected an appropriate statistical method guided by the DBL software; (c) calculated the appropriate statistic using a statistical analysis software package; (d) interpreted the result.
2. Students complete non-DBL homework after class. They answered a similar number of equivalent word problems through multiple choice and short answer questions in the learning management system. They were encouraged not to use DBL software for this homework assignment.
3. Students completed non-DBL quizzes after class. They answered a smaller number of word problems on a quiz that mirrored the non-DBL homework assignment.

In addition, each homework and quiz assignment utilized the concept of interweaving old material with new material across all three elements described above. This was done to help prevent recently acquired knowledge from interfering with previously acquired knowledge and to enhance better knowledge integration across all lessons.

Impact of DBL

Anecdotally, the implementation of DBL had a positive effect both on student attitudes and student learning (see discussion section for student quotes). However, of additional interest was the measurable effect of DBL on acquisition and retention of conditional knowledge. Other forms of flipped-classroom learning boast effect sizes for mathematical knowledge acquisition ranging from 0.21 to 0.52 (Cheng, et al., 2019; Farmus, et al., 2020; Vo, et al., 2017; Strelan, et al., 2020; Tutal & Yazar, 2021). Effect sizes for knowledge retention are not as readily available; however, one meta-analytic study suggested a moderate effect size of 0.60 (Tutal & Yazar, 2021). Although DBL differs from traditional flipped-classrooms in its focus on conditional knowledge acquisition, these studies provide a valuable benchmark against which to measure the impact and effectiveness of DBL classrooms on student knowledge acquisition and retention.

Research Questions

With the anecdotal success of DBL and the effect sizes reported in current literature serving as a jumping off point, the research questions for this study were as follows:

1. Are the effect sizes for conditional knowledge acquisition in a DBL comparable to published effect sizes for knowledge retention?
2. Are the effect sizes for conditional knowledge retention in a DBL course comparable to published effect sizes for knowledge retention?

Method

Participants

Participants in this study were graduate students (N=18) from a large, private university in the western United States. Most of the students were enrolled in the university's School of Education (16 out of 18 or 88%) and identified as female (14 out of 18 or 77%). Participant age ranged from mid-20's to 50's, with the majority being in their mid-20's. Five students were interviewed at the beginning and the end of the Fall 2015 academic term. Five additional students were interviewed at the end and four months after the end of the Spring 2016 term and eight students were interviewed at the beginning, end, and four months after the end of the Fall 2016 term. All participants were required to take this specific statistics course for their programs of study, and had varying degrees of statistical experience - ranging from no experience to having taken more than one statistics course previously. The instructor had 20 years of statistical teaching experience. All participants were fluent English speakers. Participants were compensated a $10 university bookstore card for their time.

Measures

Participant learning was measured in an interview setting. Interviews consisted of eight question sets. Each question set included five parts where students: 1) read a research question; 2) selected a statistical method to answer the question; 3) explained their rationale for that selection; 4) verbally described how they ran the statistical method in SPSS software as they ran it; 5) interpreted the output. There were a total of 32 methods with which the students practiced selecting, running and interpreting. Eight of these methods were purposefully sampled to ensure that major method categories were represented.

Beginning of course interviews ranged between 10 to 20 minutes, whereas end and post-course interviews averaged between 40 to 50 minutes - owing largely to the fact that the students had more knowledge to draw on toward the end of the semester. Questions were identical across interviewing occasions. In most cases there were four months between interviewing occasions. With that amount of time between interviews, the ability to recall the exact questions is minimal.

PROCEDURE

Interviews were conducted across three academic periods: Fall (Sept-Dec) 2015; Spring (May-June) 2015; and Fall (Sept-Dec) 2016. Due to resource constraints, the timing and number of interview sessions varied slightly: Fall 2015 (n=5) at beginning and end of course; Spring 2016 (n=5) at end and four months post-course; and Fall 2016 (n=8) at beginning, end, and four months post-course. All interviews were recorded and transcribed.

In coding the interviews, points were assigned to two abilities: selecting the correct method and interpreting the results correctly. Interviewees could receive a total of 16 points. Initially, our hope was to assign points to students' ability to reason through a research problem in order to select each method. However, despite the careful protocol we implemented to ensure uniformity in thinking aloud across the 23 participants on multiple interview occasions, the degree to which they were willing to express their thinking was uneven across groups and the 49 interview occasions. We therefore, determined to infer from their ability to select a correct method that this reasoning was happening. Since at the reading of each problem they had to select one method among 32, we knew that there was a very high probability that the ability to reason through multiple decisions to an appropriate answer was present.

Due to the small number of participants in each study group, a paired samples Wilcoxon test was utilized to answer the two research questions. Effect sizes for this nonparametric method were calculated by dividing the z-statistic by the square root of N_{obs} as suggested by Pallant (2020).

RESULTS

In order to answer the first research question regarding knowledge acquisition, we compared interview scores from the beginning of the course with interview scores at the end of the course. The resulting *z*-statistic indicated a statistically significant difference in the two sets of scores, with medium effect size (see Table 1). This outcome was comparable to those cited previously, suggesting that DBL is an effective means of facilitating the acquisition of conditional knowledge.

To answer the second research question regarding knowledge retention, we compared scores from the end of the course with scores four-months post-course. Using the same nonparametric method, the resulting *z*-statistic indicated a significant difference between the two sets of scores, however the effect size was small (see Table 1). Thus, the analysis suggested that conditional knowledge was sufficiently retained.

As an additional test for both research questions, we examined only the Fall 2016 course and compared all combinations of interview scores. These supplementary analyses provided *z*-statistics and effect sizes that were nearly identical to those from the original analyses (see Table 2), providing further evidence that conditional knowledge was both acquired and did not severely decay over time. Overall, the analyses suggest that DBL is an effective means of facilitating the retention of conditional knowledge.

Table 1
Summary of Wilcoxon Analyses

Timeframe	Course(s)	N_{obs}	Mdn1 (IQR)	Mdn2 (IQR)	*z*-statistic	*p* value	Effect Size
Beginning vs End	Fall 2015 & Fall 2016	26	0.00 (1.0)	9.00 (3.0)	3.20	0.00	0.63
End vs Post	Spring & Fall 2016	26	11.00 (3.0)	7.00 (5.0)	-2.16	0.03	-0.42

Table 2
Summary of Supplementary Wilcoxon Analyses

Timeframe	Course(s)	N_{obs}	Mdn1 (IQR)	Mdn2 (IQR)	*z*-statistic	*p* value	Effect Size
Beginning vs End	Fall 2016 Only	16	0.50 (1.5)	11.00 (2.5)	2.55	0.01	0.64
Beginning vs Post	Fall 2016 Only	16	0.50 (1.5)	7.00 (4.5)	3.28	0.02	0.59
End vs Post	Fall 2016 Only	16	11.00 (2.5)	7.00 (4.5)	1.70	0.09	-0.43

DISCUSSION

Heck and Thomas (2020), in their multi-leveling modeling text, noted the specific need to instruct students in conditional knowledge. They stated,

> Another of our guiding principles is that the responsible researcher should consider approaches that are likely to take full advantage of the features of particular data structures and goals of the overall research when making decisions about analytic methods. We illustrate our point about decisions regarding methods of analysis and fully exploiting features of our data with a series of short examples. This may seem like taking the 'long way' around the block, by walking through several modeling considerations with simple examples, but we have found when our students approach us for help, they are often concerned with how to structure their data appropriately and how to make an analytic choice that will best examine the relationships of interest embedded in their data (p. 11).

Heck and Thomas's (2020) text then explored univariate, multivariate, multilevel, and structural equation examples of the same data set. This approach is very similar to the initial learning objective of the introductory statistics course in this study: given the nature of the research question and the nature of the data, students will know how to select the correct statistical procedure, run it in SPSS, and correctly interpret the output to answer the research question. The challenge of conditional knowledge is probably similar across most applied statistics courses.

Although Heck and Thomas's text is more advanced than this introductory statistics course, they reported the same challenge.

This course has addressed the challenge of conditional knowledge by codifying a decision-based model with exercises and tutorials attached to every decision pathway. Although there were vagaries in combinations of students included in the data analyses, the initial trends in results are quite encouraging. There was a nine-point mean gain in correct responses from the beginning to the end of the course. Importantly, the baseline mean was almost zero correct responses. Students entered with very little basic information and seemed to have progressed significantly within a four-month semester.

The follow-up test showed only a four point median decay in correct responses. It would appear that to some degree, students retained the conditional knowledge tested by the interviews. They were able to identify the crucial aspects of the course: to select the correct statistical procedure, run it in SPSS and correctly interpret the output. This seems particularly important and consistent with the qualitative statement illustrated by student #3 in the next section. Especially for master's degree students, this course is designed to support their thesis projects. The comment by student #3 is typical of many of the master's degree students. The explicit development of their conditional knowledge helps them be independent in selecting the correct statistical analyses for their research. While this initial study did not include a comparison group, the pre-post gains and reasonably sustained conditional knowledge observed in these students is encouraging.

Student Perspectives

In terms of student feedback, responses were initially mixed. The novelty of a new learning experience was received positively; however, over the years student feedback began to focus more on their new found abilities and less on how much they enjoyed the course. Below are three statements that typify the positive comments for the course.

> Student 1 stated:
> I found that the DBL module was an effective way to develop a base understanding of material by providing "just-in-time" information and resources. However, the real power of the DBL module was the way the learning was scaffolded and I was able to make meaningful connections between my base knowledge and subsequent material. The "on-the-spot" application and immediate feedback was invaluable to my understanding and retention of the material. Rather than memorization, I found myself critically thinking through the data presented to consider all alternatives before coming to my own conclusion. I really appreciated how I would receive feedback that if I came to the correct conclusion, but through an incorrect process, I was quickly able to identify, in a low-pressure situation, where my understanding was weak. My engagement and learning were off the charts and felt like I was in control of my own learning process.

> Student 2 stated:
> I feel like this is probably the best class on campus for training us on how to select the most appropriate stats test for the given research question and the data provided. This is a very important skill to becoming an independent researcher that the other stats class I have taken didn't cover well. The online aspect of this class made it

> very accessible for me to complete the requirements around a busy graduate research schedule.

Finally, Student 3 stated:

> This class allowed me to reason, to puzzle, and to figure things out, rather than to just plug things into equations . . . Until now, stats has always just been a useful tool to find things out about biology. Now, I'm starting to see the beauty and elegance that underlies the interconnected ideas and patterns. Thank you for that vision.

Negative comments initially focused on issues with cognitive load, problems with organization, miskeyed DBL problems, non-DBL homework problems, and quiz problems, and misalignment between word problems and associated data sets. A few students wanted to dive more deeply into theoretical foundational concepts, but most preferred not to do this based on their experience with other statistics courses where they retained very little of the deeper conceptual emphasis. Instructors attempted to address most of these concerns over time.

CONCLUSION

Typically, intro statistics courses for graduate students systematically cover procedures and concepts, but they often do not systematically cover the process of selecting methods. WIth our DBL course, we attempted to teach selection of methods in a systematic way and found statistically significant differences in students' selection and reporting abilities (conditional knowledge) from the beginning to the end of semester. In addition, at follow-up four months after the course ended, there was still a significant difference in student conditional knowledge. Although this knowledge did show decay, as is typically expected, the decay was minimal in comparison to the gains experienced during the course of the semester.

Thus, it appears that the DBL approach to teaching graduate-level statistics courses is a viable methodology that not only results in specific, achievable, and lasting learning-outcomes, it also provides a structure that reduces anxiety for students and allows for instructors to modify in-person instruction content based on student needs.

What are the implications for other disciplines? Frequently we are asked if DBL can play a role in instruction for other disciplines – STEM and/or Non-STEM. It is our experience that DBL is appropriate for any discipline where decision making is an important learning outcome. The process explicitly modeled by DBL, namely to analyze a problem, process, product, task, work of art, etc., subsumes the ability to recognize multiple features in one of these that would suggest a certain final course of action. We assert that this elemental process is not exclusive to the narrow learning outcome in this study, nor the discipline of statistics, but has application throughout the academy (Swan, et al., 2020).

LIMITATIONS

We acknowledge that the sample size for the current study was smaller than is typically desirable; however, as the study focused on one specific course, we were limited to participants who self-selected into the course and were willing to participate in additional assessments for research purposes. Additionally, the lack of control group makes it hard to accurately compare

DBL to instruction-as-usual. Again, due to registration constraints and other administrative considerations, a control group was not a viable option for this study.

Recommendations for Future Studies

It is recommended that future studies seek to overcome the limitations listed in the previous section, primarily utilizing a control group and a larger sample size. This will most likely be achieved by studying the implementation of DBL in a currently-running course with multiple available sections so that DBL can be more accurately compared to instruction-as-usual. Additional studies could also focus on other elements of conditional knowledge elements within a statistics course (e.g. selecting the appropriate design, selecting the appropriate alpha level, selecting procedures based on the configuration of data sets, etc). Finally, while a few studies have considered the role and impact of DBL in chemistry (Sansom, et al., 2019), religion (Plummer, et al., 2020), and math (Plummer, et al., 2022), more studies are welcome to explore a whole host of dimensions of DBL in a variety of disciplines.

Final Comment

We are encouraged by both the theory and outcomes associated with Decision-based Learning. There are now multiple courses in multiple diverse departments on multiple campuses that are developing decision-based models to enhance conditional knowledge. If the objective is to have students think like experts in their fields, the acquisition of conditional knowledge seems to play a helpful role.

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