Decision Making and Problem-Solving: Implications for Learning Design

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Educators are increasingly applying problem-solving through instructional strategies, such as inquiry-based learning. An important aspect of problem-solving includes the decision-making process and the rationale for learners' choices. Although prior theories and models indeed yield important insight in other areas of problem-solving (e.g. - scaffolding, argumentation, reflection), the decision-making process has only been implicitly referenced within learning design. To better understand the role of decision-making and apply it towards design, the article reviews the theoretical basis of the following overarching frameworks: normative, descriptive, prescriptive, and case-based decision-making theory (CBDT). For each approach, an example is included that instantiates the theory within learning design. The article concludes with a discussion of how decision-making theory aligns with existing theories that are foundational to problem-solving, along with implications for future learning design.

Introduction

Practitioners in various domains are often faced with ill-structured problems. For example, teachers devise lesson plans that consider learners' prior knowledge, curriculum guidelines, and classroom management strategies. Similarly, engineers must develop products that meet safety standards, yet achieve project guidelines that meet client needs. Given the types of problems that practitioners face in everyday decision-making, educators have increasingly begun to adopt inquiry-based learning, which better exposes learners to the types of issues faced within a domain (Hung et al., 2019; Koehler & Vilarinho-Pereira, 2021). This instructional approach includes multiple changes to the educational experience when compared to the teacher-centric classroom approach (Reigeluth & Carr-Chellman, 2009). As opposed to a didactic strategy to instruction, students take ownership of their learning and generate questions among their peers, while teachers serve as facilitators (Lazonder & Harmsen, 2016; Loyens & Rikers, 2011; Savery, 2009). The central focus of these strategies also includes ill-structured cases that are similar to the types of problems practitioners face. The complexity of these problems often consists of interconnected variables (latent, salient) and multiple perspectives, so there is rarely a single predetermined solution that satisfies all options (Ifenthaler, 2014). Additionally, these problems are challenging because they include multiple criteria for evaluation (Jonassen, 2011b; Ju & Choi, 2017), which makes it challenging to definitively determine when a 'right' answer has been achieved.

There are a number of skillsets needed for problem-solving instructional strategies, such as the inquiry process (Glazewski & Hmelo-Silver, 2018), collaboration (Koehler & Vilarinho-Pereira, 2021), and argumentation (Noroozi et al., 2017). Another important element of problem-solving includes decision-making; that is, the process by which individuals make choices as they resolve the ill-structured case. Understanding decision-making is important because individuals engage in a myriad of choices throughout the problem representation and solution generation phases of problem-solving (Ge et al., 2016). Moreover, learners must engage in multiple and interconnected decisions as they select evidence and determine causal chains during various stages of problem-solving (Shin & Jeong, 2021). The decision-making process is also closely linked with failure and the iterative choices needed to overcome errors in the problem-solving cycles (Schank et al., 1999; Sinha & Kapur, 2021). As such, decision-making is key for learners' agency as they engage in self-directed learning and take ownership of ill-structured cases.

Despite its importance, the field of learning design only minimally addresses theories and models specifically associated with decision-making. The decision-making processes required for inquiry-based learning necessitates a more in-depth analysis because it is foundational to problem-solving as individuals weigh evidence, make strategic choices amidst an array of variables, and causal reasoning. In addition, an advanced understanding of this skill set would allow educators to develop systems that leverage specific decision-making strategies within design. Based on this gap, we survey broad decision-making paradigms (normative, descriptive, and prescriptive), along with case-based decision-making theory (Gilboa & Schmeidler, 1995; Kolodner, 1991). For each category, we then proffer an example that instantiates the theory. Finally, the article concludes with implications for practice.

Literature Review

Inquiry-based learning is an instructional strategy that affords learners with agency as they solve ill-structured problems. Although variations exist (problem-based learning, project-based learning, case-based instruction), the strategy often situates a contextual case to the learners that is representative of the domain (Lazonder & Harmsen, 2016; Loyens & Rikers, 2011). When compared with teacher-centric approaches where the instructor acts as the 'sage on the stage' (Reigeluth & Carr-Chellman, 2009), students in inquiry-based learning engage in a variety of learning actions in the problem representation and solution generation stage. The former necessitates learners define the problem, identify variables, and determine the underlying causal mechanisms of the issue (Delahunty et al., 2020; Ertmer & Koehler, 2018). Solution generation requires learners propose a way to resolve the issue, along with supporting evidence (Ge et al., 2016). This latter stage also includes how learners test out a solution and iterate based on the degree to which their approach meets its goals. As learners engage in these tasks, they must remedy knowledge gaps and work with their peers to reconcile different perspectives. Beyond just retention of facts, learners also engage in information seeking (Belland et al., 2020), question generation (Olney et al., 2012), causal reasoning (Giabbanelli & Tawfik, 2020; Shin & Jeong, 2021), argumentation (Ju & Choi, 2017; Noroozi & Hatami, 2019), and other higher-order thinking skills.

Another important aspect of inquiry-based learning also includes decision-making, which describes the choices learners select as they understand the problem and move towards its resolution. To that end, various theories and models that explicate the nuances of problem-solving have implicitly referenced decision-making. When describing the solution generation stage, Jonassen (1997) asserts that learners' "resulting mental model of the problem will support the learner's decision and justify the chosen solution" (p. 81). Ge et al. (2016) proposed a conceptual model of self-regulated learning in ill-structured problem-solving in which "students not only must make informed decisions and select the most viable against alternative solutions, but also must support their decisions with defensible and cogent arguments" (p. 4). In terms of encountered failure during problem-solving, Kapur (2008) explains how students must "decide on the criteria for decision making or general parameters for solutions" (p. 391) during criteria development.

Indeed, these foundation theories and models of problem-solving highlight the importance of decision-making in various aspects of inquiry-based learning.

Despite its importance, very little understanding is known within the learning design field about the specific decision-making processes inherent within problem-solving. Instead, there is a large body of literature dedicated to strategic approaches to self-directed learning (Xie et al., 2019), collaboration (Radkowitsch et al., 2020), and others. However, specific attention is needed towards decision-making to understand how learners seek out information, weigh evidence, and make choices as they engage in problem-solving. A review of theories argues for three distinct overarching theoretical paradigms of decision-making (Schwartz & Bergus, 2008): normative, descriptive, and prescriptive. There is also a related body of literature around case-based decision-making theory (Gilboa & Schmeidler, 1995), which describes how prior experiences are used to inform choices for new problems. Below we define the theory and related literature, along with a design example that instantiates the decision-making approach.

Table 1

Outline of Decision-Making Theories and Constructs

Theory	Definition	Constructs
Normative Decision Making	Provides choices of action for making the best decisions (Gati et al., 2020)	Subjective utility: the value of the outcome Probability: the degree that the selected action will lead to a certain outcome
Descriptive Decision Making	Focuses on how decisions are made in real-life rather than prescribing procedures for optimal decision making (Divekar et al., 2012)	Satisficing: individuals attempt to maximize their choices First option: individuals will likely choose the first option that satisfices their desire
Prescriptive Decision Making	Concerned with providing aids to make the best decisions (Divekar et al., 2012).	Pragmatic value: the realistic value of the decision being made DA: past knowledge PDA: Available future knowledge
Case-Based Decision Making	Learners recall previous cases that are similar to the current case and select the solution that has had the most success in the past (Gilboa & Schmediler, 1995; Pape & Kurtz, 2013)	memory (M): a set of cases q ∊ Q: the problem a ∊ A): possible act chosen in the problem (r ∊ R): Resulting consequence

Normative Decision-Making

Normative decision-making theoretical foundations

Normative decision-making describes how learners make choices based on the following: (a) perceived subjective utility and (b) probability (Gati & Kulcsár, 2021). The former focuses on the values of each outcome, especially in terms of how the individual assesses expected benefits and costs associated with one's goals and preferences. Alternatively, probability describes the degree to which individuals perceive that a selected action will lead to a specific outcome. Hence, a key assumption - and potential criticism - of normative decision-making is that individuals are logically consistent as they make choices under the constraints of rationality, which has been called into question.

Another important element of normative decision-making includes 'compensatory models'; that is, how the benefits of an alternative outweigh the disadvantages. The most common compensatory model described in the literature is multi-attribute utility theory (MAUT), which is used to account for decision-making amidst multiple criteria (Jansen, 2011). MAUT thus aligns well with ill-structured problem-solving because it assumes that choices are made amongst a variety of competing alternatives. In a conservation example, one might select a green energy alternative to reduce carbon emissions, but it may be disruptive to the existing energy sources (e.g., fossil fuels) and raise costs in the short term. In the context of medicine, a surgery might ultimately resolve an issue, but it poses a risk for post-procedure infections and other complications. As individuals consider each alternative, MAUT is a way of "measuring the decision-maker's values separately for a set of influential attributes and by weighting these by the relative importance of these attributes as perceived by the decision-maker" (Jansen, 2011, p. 101). MAUT component of normative decision-making specifically argues individuals progress in the following five steps (Von Winterfeldt & Edwards, 1993):

1. Individuals explicate the various alternatives and salient attributes associated with each choice.
2. Each alternative is evaluated separately based on each attribute in terms of the following: complete (all essential aspects are addressed), operational (attributes can be meaningfully used), decomposable (deconstructing aspects of evaluation as to simplify evaluation process), non-redundant (remove duplicates of aspects), and minimal (keep a number of attributes focused and central to the problem).
3. Individuals assign relative weights to each attribute
4. Individuals sum the aggregate weight to evaluate each alternative.
5. Individuals make a final choice.

Rather than pursue a less than optimal selection, MAUT argues that "they [individuals] strive to choose the most beneficial alternative and obtain all information relevant to the decision, and they are capable of considering all possible outcomes of the choice, estimating the value of each alternative and aggregating these values into a composite variable" (Gati et al., 2019, p. 123). Another characteristic is how individuals select the factors and assess the degree to which they can be compensated. Some individuals (e.g., expert, novice) may weigh a specific factor differently, even if the other aspects align with their desired outcomes. Given that individuals are not always rational and consistent in decision-making, some argue that the normative decision-making model is not truly representative of how individuals actually engage in everyday problem-solving (Gati et al., 2019; Jansen, 2011; Schwartz & Bergus, 2008).

Normative decision-making theoretical application

Normative decision-making approaches applied to learning design make choices and probabilities salient to the learner, such as in the case of learner dashboards (Valle et al., 2021) or heuristics. Arguably, the most common application of decision-making in learning technologies for inquiry-based learning includes simulations, which situate individuals within an authentic context and posit a series of choices, and allow them to model choices (Liu et al., 2021). Systems that especially exhibit normative decision-making often consist of the following: (a) encourages learners to consider what is currently known about the phenomena vs. what knowledge the decision-makers lack, (b) makes probability associated with a choice clear, and (c) observes the outcomes of the decision.

One example of normative decision-making applied to design includes *The Wildlife Module/Wildfire Explorer* project developed by Concord Consortium. In this environment, learners are tasked with lowering wildfire risk in terms of fires and other natural hazards (see Figure 1). The decision-making is especially focused on choices around terrain and weather conditions, which add to or limit the amount of risk that is posed to each town. As learners make decisions, the interface allows individuals to manipulate variables and thus observe how certain choices will result in higher benefits relative to others. For instance, reducing the amount of brush in the area will better prevent wildfire when compared with cutting fire lines. In another instance, they explore how dry terrain and 30 mile per hour (MPH) winds would increase the potential wildfire risk of an area. The learning environment thus instantiates aspects of normative decision-making as learners select the parameters and discern its effects on the wildfire within the region.

Figure 1

Wildlife Module/Wildfire Explorer as Applying Normative Decision-Making

Estimating risk

Wildfires become natural hazards when they bring fire and smoke to regions where people live. In this activity, we will investigate risk using the WIldfire Explorer model.

Below is a snapshot of the Wildfire Explorer. Three towns are located on the map, two are in the mountains and one is in the plains. The wind is blowing to the northeast and the fire has started at the spark.

Is it possible to estimate the level of risk to each town given the initial conditions?

Question #5

If the conditions stay as they are, which town is at a highest risk of being impacted by this fire?

- ◯ Skyview
- ◯ Evensville
- ◯ Happy Valley

Question #6

Explain your answer.

Please type your answer here.

Example of Normative Decision-Making

Question #24

Look at the graphic to the right.

Why would developing a "defensible zone", an area with sparse trees and vegetation, help prevent wildfires from burning property? Use the Fire Triangle in your answer.

Please type your answer here.

Question #25

What other ways could a wildfire be contained, extinguished, or slowed down? Check all that apply.

- ☐ Meeting a natural barrier such as a lake or river
- ☐ Meeting an area that was previously burnt
- ☐ Rain falling on the fire
- ☐ Being sprayed with water or fire retardant

Make your property less susceptible to wildfires by removing dead trees and other vegetation, keeping shrubs and trees spaced far apart, and keeping vegetation well trimmed.
California Fire Resources

Descriptive Decision-Making

Descriptive decision-making theoretical foundations

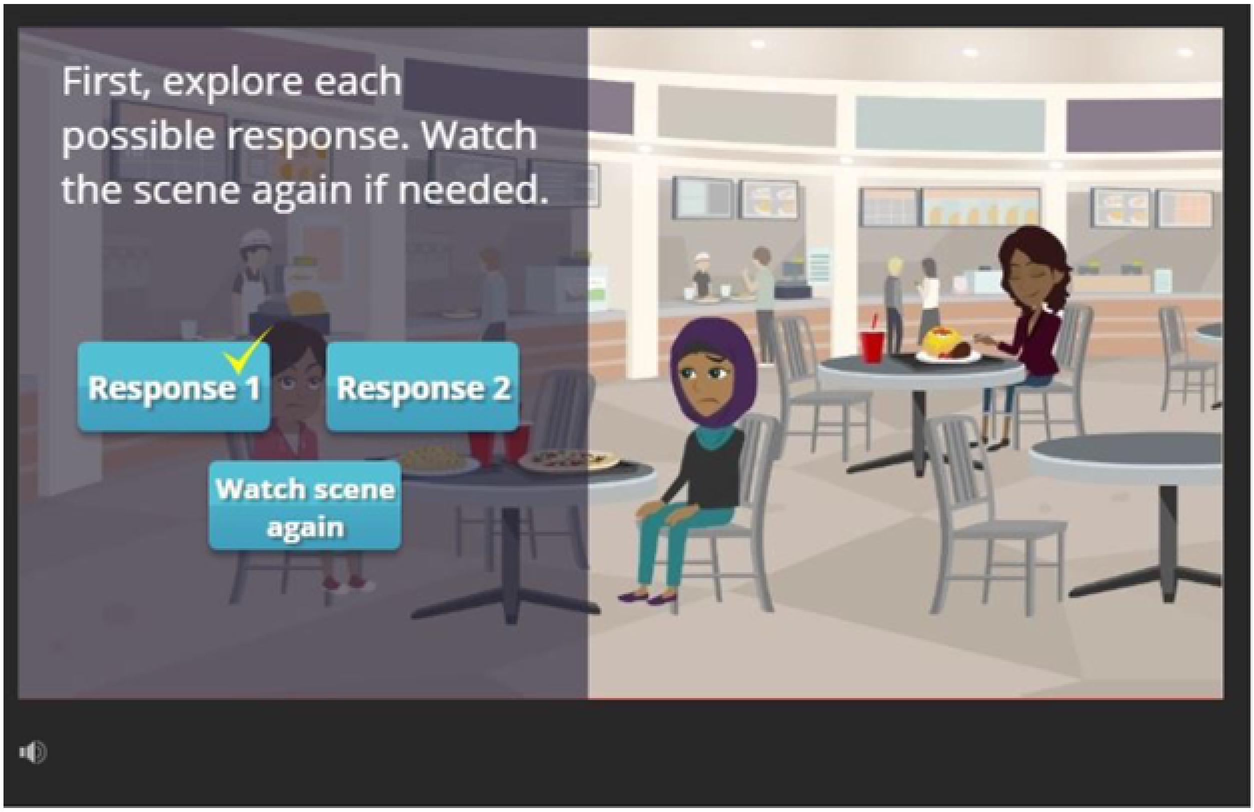
Whereas the normative decision-making approaches assume individuals make rational decisions that maximize choices, descriptive decision-making illustrates the gap between optimal decision-making and how people actually make choices (Gati et al., 2019). Although it is sometimes criticized for the lack of clarity, there are some elements of descriptive decision-making that have emerged. One key component includes satisficing, which posits that individuals attempt to make decisions based on how choices are maximized and meet specific goals. As outlined in the seminal work by Simon (1972), individuals aspire to engage in complex rational selections; however, humans have limited cognitive resources available to process the information available during decision-making. Because choices for ill-structured problems often have competing alternatives, individuals settle for decisions that meet some kind of determined threshold for acceptance in light of a given set of defined criteria. The theory further argues individuals will likely choose the first option that satisfices the desire; so while the final selection may be satisficing, it may not necessarily be the best and most rational decision (Gati et al., 2019). This is especially true in ill-structured problems that include multiple perspectives and constraints that make an ideal solution difficult. Rather, individuals instead strive for a viable choice that can be justified in light of multiple criteria and constraints.

Descriptive decision-making theoretical application

One example includes the EstemEquity project (Gish-Lieberman et al., 2021), which is a learning environment designed to address attrition rates for women of color in STEM through mentorship strategies aimed at building self-efficacy. Because the dynamics of mentorship can be difficult, the system relies heavily on decision-making and reflection upon choice outcomes (see Figure 2). The first steps of a scenario outline a common mentor/mentee challenge, such as a mentee frustrated because she feels as though the mentor is not listening to her underlying problem as she navigates higher education in pursuit of her STEM career. The learning environment then poses two choices that would resolve the issue. Although no single solution will fully remedy the ill-structured mentorship challenge, they must make value judgments about the criteria for success and the degree to which their decision meets the requirements. Based on the goals, the learning environment provides feedback as to how the choice satisfices given their determined threshold of optimal mentor and mentee relationships.

Figure 2

EstemEquity as Applying Descriptive Decision-Making



Example of Descriptive Decision-Making

Prescriptive Decision-Making

Prescriptive decision-making theoretical foundations

The aforementioned approaches highlight how individuals engage in sense-making as they make a selection among latent and salient variables. To better support ideal decision-making, the prescriptive approach is concerned with providing overt aids to make the best decisions (Divekar et al., 2012). Moreover, prescriptive decision-making “bridges the gap between descriptive observations of the way people make choices and normative guidelines for how they should make choices” (Keller, 1989, p. 260). Prescriptive decision-making thus provides explicit guidelines for making better decisions while taking into consideration human limitations. For example, physicians may use a heuristic that outlines a specific medication based on symptoms and patient characteristics (e.g., height, weight, age). Similarly, a mental health counselor may select a certain intervention approach when a client presents certain behavioral characteristics. In doing so, prescriptive decision-making outlines a series of “if-then” scenarios and details the ideal choice; that is, the pragmatic benefit of the decision to be made given a set of certain circumstances (Gati et al., 2019).

There are multiple challenges and benefits to the prescriptive approach to decision-making. In terms of the former, some question the degree to which a single set of heuristics can be applied across multiple ill-structured problems with varying degrees of nuance. That said, the prescriptive approach has gained traction in the ‘big data’ era, which compiles a considerable amount of information to make it actionable for the individual. An emerging subset of the field includes prescriptive analytics, especially in the business domain (Lepenioti et al., 2020). Beyond just presenting information, prescriptive analytics distinguishes itself because it provides the optimal solution based on input and data-mining strategies from various sources (Poornima & Pushpalatha, 2020). As theorists and practitioners look to align analytics with prescriptive decision-making, Frazzetto et al., (2019) argues:

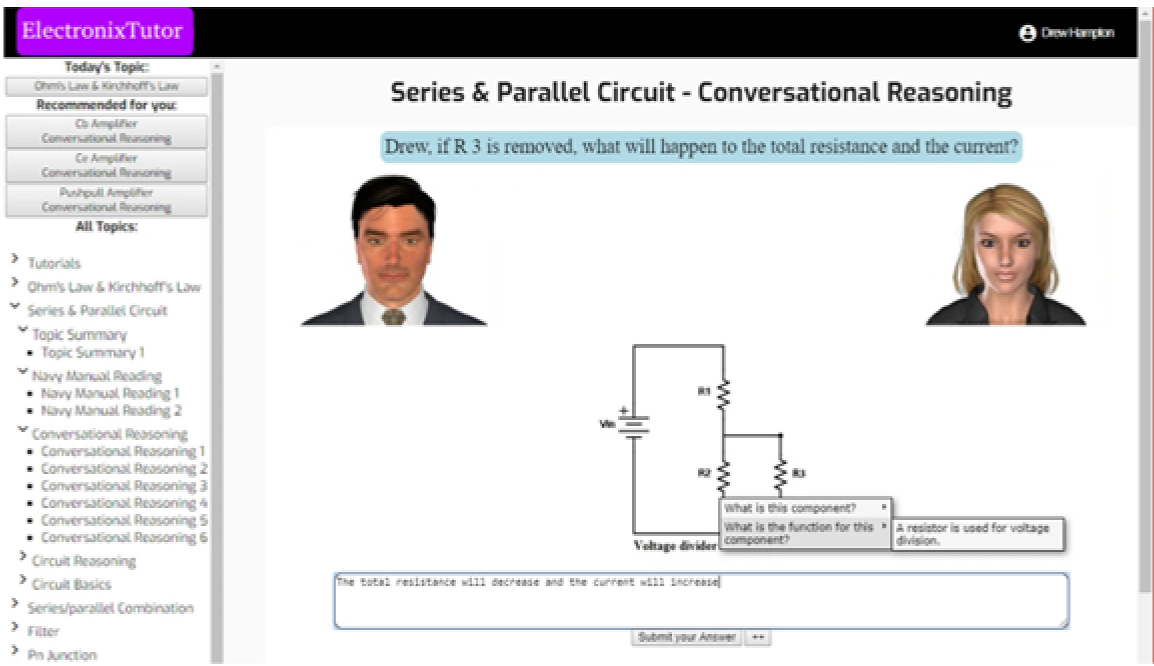
> *If the past has been understood (descriptive analytics; ‘DA’), and predictions about the future are available (predictive analytics; ‘PDA’), then it is possible to actively suggest (prescribe) a best option for adapting and shaping the plans according to the predicted future (p. 5).*

Prescriptive decision-making theoretical application

Prescriptive decision-making approaches arguably are most used in adaptive tutoring systems, which outline a series of "if-then" steps based on learners' interactions. ElectronixTutor is an adaptive system that helps learners understand electrical engineering principles within a higher educational context (see Figure 3). Rather than allowing the learner to navigate as desired or make ad-hoc selections, the recommender system leverages user input from completed lessons to prescribe the optimal lesson choice that best furthers their electrical engineering knowledge. For example, after successful completion on the "Series and Parallel Circuit" (the "if"), the system prescribes that the learner advance to the next "Amplifier" lessons (the "then") because the system has determined that as the next stage of the learning trajectory. When a learner inputs the correct decision, they are prompted with the optimal selection the system deems as best advances their learning. Alternatively, a wrong selection constrains the choices for the learner and reduces the complexity of the process to a few select decisions. In doing so, the adaptive system implements artificial intelligence to prescribe the optimal path the learner should take based on the previous input from the learner (Hampton & Graesser, 2019).

Figure 3

Autotutor as Applying Prescriptive Decision-Making



Example of Prescriptive Decision-Making

Case-Based Decision-Making Theory

Case-based decision-making theoretical foundations

The literature suggests case-based decision-making theory (CBDMT) is another problem-solving approach individuals employ within domain practice (Gilboa & Schmeidler, 1995). The premise behind CBDMT is that individuals recall previous experiences which are similar to the extant issue and select the solution that yielded a successful resolution (Huang & Pape, 2020; Pape & Kurtz, 2013). These cases are often referred to as 'repeated choice problems' whereby individuals see available actions as similar between the new problem and prior experiences (Ossadnik et al., 2013). According to the theory, memory is a set of cases that consists of the following constructs: problem, a potential act chosen in the problem, and ensuing consequence. Specifically, "the memory contains the information required by the decision-maker to evaluate an act, which is specific to the problem" (Ossadnik et al., 2013, p. 213). A key element in a case-based approach to decision-making includes the problem features, the assigned weights of said features, and observed consequences as a reference point for the new problem (Bleichrodt et al., 2017).

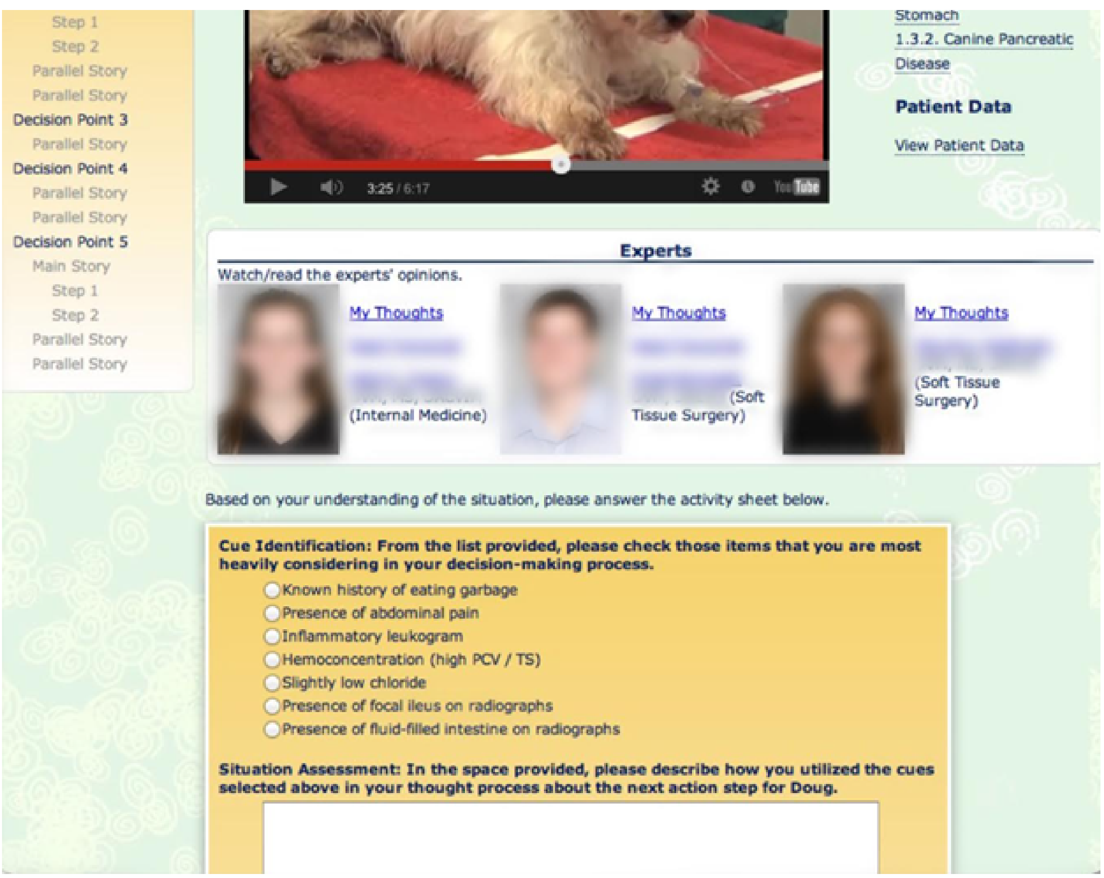
The CBDMT approach is similar to the normative approach to decision-making in that it describes how learners make a summative approach to decision-making; however, it differs in that it explicates how one leverages prior experience to calculate these values. Moreover, the value of a case for decision-making is evaluated through a comparison of related acts of other known issues when the new problem is assessed by the individual. Specifically, Gilboa and Schmeidler (1995) propose: “Each act is evaluated by the sum of the utility levels that resulted from using this act in past cases, each weighted by the similarity of that past case to the problem at hand” (p. 605). In this instance, utility refers to the benefits of the decision being made and the forecasting of outcomes (Grosskopf et al., 2015; Lovallo et al., 2012). The individual compares the new case to a previous case and then selects the decision with the highest utility outcome. As one gains expertise, CBDMT proffers one can “combine variations in memory with variations in sets of choice alternatives, leading to generalized versions” (Bleichrodt et al., 2017, p. 127)

Case-based decision-making theoretical application

Because novices lack prior experiences, one might argue it may be difficult to apply CBDMT in learning design. However, the most often applied approach is by leveraging narratives as a form of vicarious experience (Jonassen, 2011a). In one example by Rong et al. (2020), veterinary students are asked to solve ill-structured problems about how to treat animals that go through various procedures. As part of the main problem to solve, learners must take into consideration the animal’s medical history, height, weight, and a variety of other characteristics. To engender learners’ problem-solving, the case profiles multiple decision points, and later asks the learners to make their own choice and justify its selection. Decision-making is supported through expert cases, which serve as vicarious memory and encourage the learners to transfer the lessons learned towards the main problem to solve (Figure 4). In doing so, the exemplars serve as key decision-making aids as novices navigate the complexity of the ill-structured problem.

Figure 4

Video Exemplars as Applying Case-Based Decision-Making Theory



Example of Case-Based Decision-Making Theory

Discussion and Implications for Design

Theorists of education have often discussed ways to foster various elements of ill-structured problem-solving, including problem representation (Ge et al., 2016), information-seeking (Glazewski & Hmelo-Silver, 2018), question generation (Olney et al., 2012), and others. While this has undoubtedly advanced the field of learning design, we argue decision-making is an equally foundational aspect of problem-solving that requires further attention. Despite its importance, there is very little discourse as to the nuances of decision-making within learning design and how each perspective impacts the problem-solving process. A further explication of these approaches would allow educators and designers to better support learners as they engage in inquiry-based learning and similar instructional strategies that engender complex problemsolving. To address this gap, this article introduces and discusses the application of the following decision-making paradigms: normative, descriptive, prescriptive, and CBDMT.

The above theoretical paradigms have implications for how these theories align with other design approaches of learning systems. In many instances, scaffolds are designed to support specific aspects of problem solving. Some systems are designed to support the collaborative process that occurs during inquiry-based learning (Noroozi et al., 2017), while other scaffolds outline the argumentation process (Malogianni et al., 2021). Alternatively, learning environments may embed prior narratives to model how practitioners solve problems (Tawfik et al., 2020). While each of these theories supports a critical aspect of problem solving, there are opportunities to further refine these learning systems by more directly supporting the decision-making process. For example, one way to align these design strategies and normative decision-making theories would be to outline the different choices and probabilities of expected outcomes. A learning system might embed supports that outline alternative perspectives or reflection questions, but could also include scaffolds that explicate optimal solution paths as it applies a prescriptive decision-making approach. In doing so, designers can simultaneously support various aspects of ill-structured problem solving.

There are also implications as it relates to the expert-novice continuum, which is often cited as a critical component of problem-solving (Jonassen, 2011a; Kim & Hannafin, 2008). Indeed, a body of rich literature has described differences as experts and novices identify variables within ill-structured problems (Jacobson, 2001; Wolff et al., 2021) and define the problem-space within contexts (Ertmer & Koehler, 2018; Hmelo-Silver, 2013). Whereas many post-hoc artifacts have documented outcomes that describe how novices grow during inquiry-based learning (e.g., concept map, argumentation scores), less is known about *in situ* decision-making processes and germane design strategies novice learners engage in when they are given problem-solving cases. For example, it may be that novices might benefit more from a prescriptive decision-making design strategy given the inherent complexity and challenges of cognitive load presented within an inquiry-based learning module. Alternatively, one might argue simulation learning environments designed for normative decision-making would make the variables more explicit, and thus better aid learners in their choice selection when presented with a case. The simulation approach often employed for normative decision-making might also allow for iterative decision-making, which may be especially advantageous for novices that are newly exposed to the domain. A further understanding of these decision-making approaches allows educators and designers to better support learners and develop systems that emphasize this higher-order learning skillset.

As learners engage in information-seeking during problem-solving, it follows that a choice is made based on the synthetization of multiple different sources (Glazewski & Hmelo-Silver, 2018). Future explorations around information seeking and decision-making would yield important insights for problem solving in multiple respects. For instance, the normative decision-making approach argues individuals assign values to various attributes and use this assessment to make a selection. As learners engage in inquiry-based learning, designers can use understanding of normative approaches to determine how individuals search for information to satisfice an opinion, use this to assess the probability of an action, and the resulting choice. From a descriptive decision-making approach, learners weigh various information sources as they seek out an answer that satisfices. Finally, a case-based decision-making theory approach may find learners search for information and related weights for the following: problem ($q \in Q$), a potential act chosen in the problem ($a \in A$), and ensuing consequence ($r \in R$). Although the design of inquiry-based learning environments often overlooks the intersection of information-seeking approaches and decision-making, a better understanding of the role of theory would aid designers as they construct learning environments that support this aspect of problem solving.

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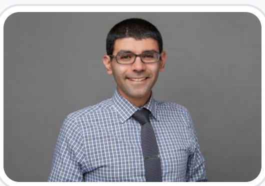

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