Triangulating Learning in Board Games: Computational Thinking at Multiple Scales of Analysis

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Abstract: In this paper, we delve into the connections between multiple methods for investigating game-based learning. We focus on three, connected analyses related to a single case (uncovering computational thinking in the play of the collaborative strategic board game *Pandemic*). We describe an approach for connecting *content analysis*, *learning analytics*, and *d/Discourse analysis* into a framework that both meaningfully chains quantitative and qualitative methods, as well as provides a useful means to generate new hypotheses for future games and learning research.

Introduction

In recent years, games and learning research has often focused on the important role that these forms of interactive media may play for understanding situated forms of learning and literacy within contemporary media cultures. And yet, much remains still unexplored in terms of determining efficacious ways to employ and synthesize multiple methodological approaches toward uncovering learning in complex game play environments. If a goal for this growing field is to understand how the play of games gives rise to learning practices, we posit that it is important to better understanding levels of analysis in capturing the learning present within game play. We are faced with the critical task of understanding the appropriate lenses by which we can investigate learning practices, as well as how to connect the insights learned through each.

In the present study, we describe a multi-methodological approach to the understanding of learning, illustrating the connections between methods through the analysis a single case of game-based learning: the forms of computational thinking that arise during the play of *Pandemic* (Leacock, 2007), a collaborative board game. Through a multi-site study of player talk through multiple runs of the game, we attempt to uncover learning on multiple scales, with three major methodological approaches employed. In doing so, we attempt to delve into the variety of learning practices and activities engaged upon by participants by “triangulating learning” through the use of three approaches: content analysis, learning analytics, and d/Discourse analysis techniques. We hypothesize that a coordinated attempt to understand learning across multiple scales may reveal both how computational thinking is instantiated in the practices of game play as well as how we may usefully focus on multiple scales of analysis to investigate learning in games.

In the following sections, we first describe the overall program of investigating computational thinking in *Pandemic*, then a brief description of each of these three approaches, finally discussing lessons learned on the applicability of these approaches for understanding computational thinking (e.g., Wing, 2006; National Research Council, 2010). We attempt to further the goal of better connecting multiple methodological approaches for the explication of learning with games (be they digital or otherwise), while investigating what this combination of analytic techniques may tell us about understanding learning in play-based spaces.

Computational Thinking in *Pandemic*

Berland and Lee (2011) established *Pandemic* (Leacock, 2007) as an interesting and important site for investigating computational thinking in games. A collaborative strategic board game, *Pandemic* requires between one and four players in the basic game, all working together to rid the planet of four diseases concurrently ravaging the globe. Each player adopts a different role in the game, with different abilities but a common goal of clearing the board of the diseases (participants either achieve this goal collectively, or all fail). As the game is entirely collaborative, it has served as a useful site to capture the ways that complex problem-solving practices are embedded within an off-the-shelf game’s play, and are exhibited through discussion.

In a series of studies conducted at two universities in 2010 and 2011, we studied how participants played *Pandemic*, focusing on the forms of computational thinking displayed in their verbal exchanges while playing the game. We created new rule manipulations intended to elicit different computational thinking practices (including "Strategy Debugging," "Rules Debugging," "Simulation," "Algorithm Building," "Conditional Logic"; see Table 1 below). In each case, all talk during the game was recorded, broken down by turns in the game, and matched with individual participant roles within the game.

	Site	**n**	**Additional Rule**	**Hypothesized Change in Comp Thinking**
Group 1	Texas	4	No Rule Change/ "Vanilla"	Control Group
Group 2	Texas	3	No Rule Change/ "Vanilla"	Control Group
Group 3	Texas	3	"Cheat Sheet"	Increase in *Strategy Debugging*
Group 4	Texas	2	"Cheat Sheet"	Increase in S*trategy Debugging*
Group 5	Ohio	3	"Ghost Player"	Increase in *Simulation*
Group 6	Ohio	2	"Ghost Player"	Increase in *Simulation*
Group 7	Texas	2	"Disease"	Increase in *Rules Debugging*
Group 8	Texas	4	"Disease"	Increase in *Rules Debugging*

***Table 1*: A breakdown of all eight groups.**

And yet, with this raw data, multiple scales of analysis presented themselves as useful for understanding computational thinking within this environment. In the following sections, we outline three approaches, connecting nomothetic (between-subjects, analyzed in the aggregate) to idiographic (focused on the individual) approaches, first applying content analysis coding schemes to understanding the prevalence of computational thinking practices. Next, building upon the content codes, learning analytics approaches were employed toward investigating idealized paths through the problem spaces of the game. Finally, from these, d/Discourse analyses are used to capture specific meaning-making exchanges within the gaming transcripts. In the following sections, we will trace one chain from content analysis to learning analytics to d/Discourse analysis from data in the ongoing computational thinking in *Pandemic* research, as a means of illustrating the connections between methodologies and scales of analysis. For details on the specifics of computational thinking within collaborative board games, we suggest the reader reference Berland and Lee (2011) or Berland and Duncan (2012)—for the purposes of this paper, the emphasis will be on methodological concerns and ways to connect multiple scales of analysis.

Content Analysis

As detailed in Berland and Lee (2011) and in Berland and Duncan (2012), an early inclination with studying computational thinking in this domain is to first characterize the prevalence of computational thinking in game play, as assessed using an *a priori* coding scheme (a la Steinkuehler & Duncan's, 2009, assessment of informal scientific thinking in online gaming spaces). With this approach, the prevalence of each hypothesized code was determined, as well as the differences between each experimental condition (different rule manipulation, as in "Vanilla" or "Cheat Sheet"). A set of four coders iterated a computational thinking coding scheme, coding 366 player-turns (6870 individual utterances), and achieving an inter-rater agreement of over 95% on this coding scheme. Please see Figure 1 below for a simplified breakdown of the results from this stage of analysis.

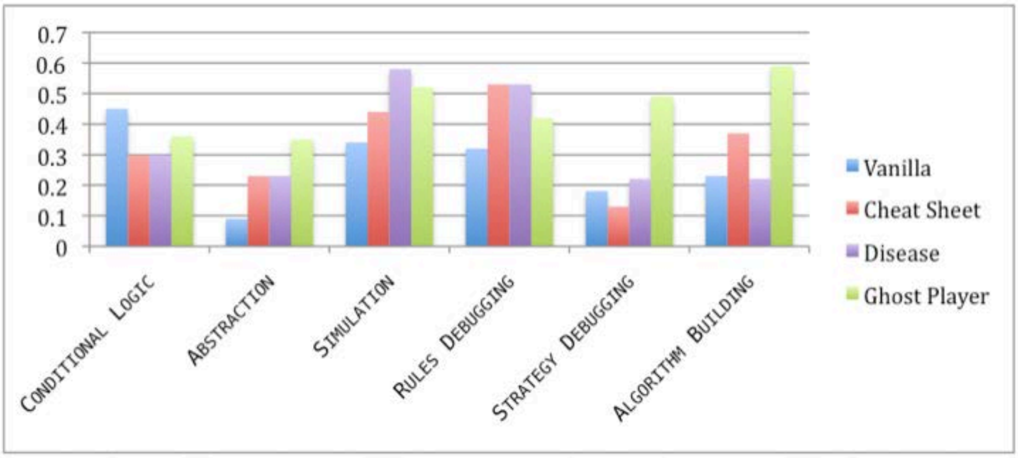

***Figure 1*: Content analysis code saturation by condition.**

As can be seen in this graph, analyses of this sort are necessarily conducted in the aggregate—participant talk is coded by turn, tallied for each of the codes, and then assessed both graphically as well as for statistical regularities (see Berland and Duncan, 2012, for detailed analyses beyond the scope of this paper). In sum, the approach laid out here is nomothetic in nature—aimed at addressing the overall prevalence of computational thinking practices, and assessing the influence of modifications to the game in a between-subjects manner.

How might we use these data and analyses, then, to help us move past a scale of analysis that characterizes the collection of design talk in the *aggregate*, while valuing the lessons learned from this level of analysis? In the next section, we outline an approach that builds upon the content analysis to provide a hypothesized idealized path through the problem space of the game.

Learning Analytics

One useful approach is to focus on "learning analytics," or hypothesized, idealized path based upon the data gleaned for the content analysis scale of analysis. If the first stage is to identify regularities and patterns in the entire corpus of talk present within the game, the next is to develop generalized insights that help us to understand not all of the activities present within the play of *Pandemic*, but instead a "distilled" set of these computational thinking practices, connected into a path of activities.

To determine a *trace* (as per Berland, Martin, Benton, Ko, & Smith, submitted), we found the most likely transitions between "types" of logic. This is an exploratory measure designed to further highlight relationships between these data. In this case, we were interested in an ordering of the computational thinking codes in the data. To determine the ordering, we collected all of the instances in which a turn showing a particular code (say, Algorithmic Thinking) followed another turn with a different code (say, Conditional Logic); this is called a (first-order) *transition*. A second-order transition would find all of the instances in which one code followed another code then followed another code. We computed the complete set of first- and second-order transitions for our dataset and solved for the highest likelihood ordering of transitions (1). This method allows us to see broader-scale relationships across our dataset so as to identify patterns to investigate more thoroughly at the discourse level. Below, in Figure 2, we present the elements of a trace focused on "Strategy Debugging."

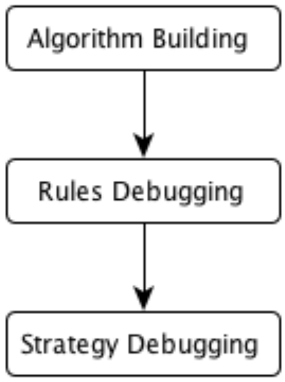

***Figure 2*: A learning "trace" abstracted from learning analytics methods.**

In the *Pandemic* work, we first identified the prevalence of these computational thinking practices, then employed a second-order, computational method for tying these codes to one another. By creating a hypothesized chain computational thinking practices (of Algorithm Building → Rules Debugging → Strategy Debugging), we argue that learning analytics provide a useful "glue" between nomothetic and idiographic approaches, serving as to filter insights developed from content coding to further justify the selection of data to qualitatively analyze using d/Discourse analysis methods.

d/Discourse Analysis

Using the Algorithm Building → Rules Debugging → Strategy Debugging chain, we can now apply conclusions drawn from Learning Analytics toward the *selection* of data for qualitative analysis. As Duncan (2011) argued, d/Discourse analysis methods—including Gee's (2010) "big-d Discourse analysis"—suffers from the problem of how one justifies the selection of data to analyze. That is, if it is important to connect insights gained from *idiographic* methods to other means of understanding game-based learning (and scales of analysis), then determining principled ways of selecting the data for such analyses becomes a critical task.

In the case of computational thinking in *Pandemic*, we can take what's learned through the Learning Analytics approaches to find an exchange of interest. In this specific case, it means following the chain from content analysis (determining the prevalence of computational thinking codes) to learning analytics (determining an idealized path through the problem space of the game) through to a case of the talk between participants that fits the idealized path. While typicality is clearly not the only means of justifying the selection of data for d/Discourse analyses, the chain of previous analyses leads the researcher to investigate how meaning is made and negotiation occurs in the course of some of the most common moments in the play of game.

Take, for example, an Algorithm Building → Rules Debugging → Strategy Debugging chain found in the *Pandemic* data: turns 9 through 11 of Group 6 (see Table 1, above). In this case, the game was taking a turn for the worse—two players ("White" and "Red") had misunderstood an earlier rule that was now beginning to impact their game, and in turn 10, in particular, they attempted to debug the rules that were clearly beginning to malfunction (and impair their progress). A selection from Group 6, turn 10, is replicated below, focusing specifically on terminology used to flag individual actions (in italics; emphasis ours) with group strategies/actions (in bold) and actions of a "Ghost Player" controlled by both other players (underlined):

> 1 - White: "Okay, *my* turn. *I'll* take out Cairo first, since **we** just drew that card, 1,2,3 - so three turns. Should **we** take out all 4 in Cairo, why not? **We** don't have anything else to do."
> 2 - Red: "Yeah."
> 3 - White: (reading card) "'Research station..' Oh wait, where should **we** add it? Here? No, it doesn't matter..."
> 4 - Red: "Okay, here."
> 5 - White: "... then draw 2 of these..."
> 6 - Red: "…alright." (moves game tokens and cards)

7 - White: “Okay, take 1, 2, 3, cure disease - in order to cure disease *you* play 4 cards and now (reads cards & moves cards) St. Petersburg, add 3 cubes to any city, which one is it? Wait a sec - if the epidemic causes… but **we** have the cure for it, don't **we**?” (grabs instruction book)
8 - Red: “Doesn't it mean...” (looks to instruction book) “**Let's** just go over the cure...”
9 - White: “*I* don't know...” (reads from instruction book) “... if *your* pawn, discovered cures...”
10 - Red: “Oh, okay, **we've** eradicated it.”
11 - White: (reading from book) “…cards of this color… okay, it doesn't matter, so screw the blue card.”
12 - Red: “Even though **we** are in epidemic?”
13 - White: “Yeah, that was on there, *I* think that's all it means is, it's on the (points to board)
14 - Red: “Okay, yeah, alright...”
15 - White: “Is it *your* turn?”
16 - Red: “*You* just went?”
17 - White: “He just went, **we** eliminated this disease now.”
18 - Red: “Yeah.”
19 - White: “So, **we're** done with blue...”
20 - Red: “*I* say - um - *I* mean it's *your* -”
21 - White: “*Your* turn, it's 6 cards now, we can't toss 7.”

In this exchange, we see an interesting balancing between three individual (two real player, one Ghost Player) and collective actions, while also attempting to unpack the cause of a malfunctioning rule (coded as “Rule Debugging”). In this case, the interesting mixture of individual and collective goals gives way to a set of collective, collaborative goals, before finally turning into confusion as players try to remember whose turn it is next.

We can drill down past the aggregate or even hypothesized traces through the content codes, and investigate the specific exchanges that may serve as foundational for potential further studies. In this case, a cursory examination yields an interesting interplay between participants over strategies—White first lays out a strategy for both him and Red to enact (utterances in lines 1-7). Next, as confusion arises over the game’s rules (end of line 7), both players refer to the game’s instructions in order to clarify it, and, most interestingly (lines 15-21) end the turn with confusion over their individual roles in the game (“Is it your turn?” in line 15, and “I say - um - I mean it’s your -” in line 20). Thus, a new hypothesis emerges—a focus on Rules Debugging may be correlated with a focus on the collaborative goals, and thus confusion regarding individual strategies and responsibilities.

By “drilling down” from the content analysis to the learning analytics and then to a d/Discourse analysis level, the framework outlined here both fleshes out exchanges that may not have been adequately capturable with a nomothetic approach such as content analysis, and provides future avenues for investigation into the nature of collaborative problem-solving and computational thinking.

Multiple Scales of Game-Based Learning

As we have argued through this brief example, much can be learned through the exploration of multiple methods, and the principled connection of methods toward the investigation of different levels of complex learning practices in games. In Figure 3 below, we can lay out a general framework for connecting these three methods, as well as identifying the forms of data that are applicable to each method, as well as the kinds of claims/uses of each scale of analysis.

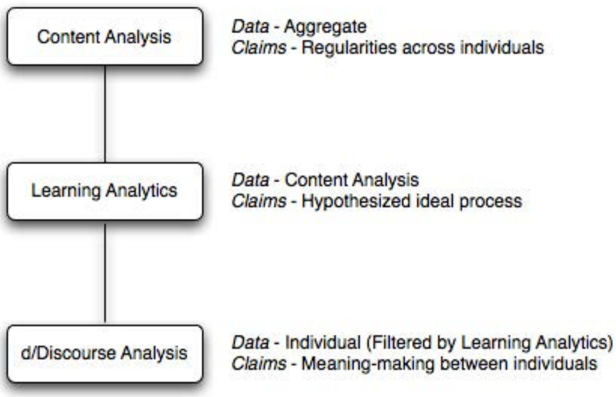

***Figure 3*: A general framework for connecting methods and scales of analysis.**

Though at this point this is a provisional framework, it does lead us to suggest that there is utility in specifying the ways that different methodologies connect to provide a better understanding of the different levels of complex reasoning that occur in game-based learning. In the case of *Pandemic*, we can develop a characterization of the aggregate activity through the use of content analytic approaches, while using learning analytics methods in a more-or-less instrumental fashion, to clarify ideal paths through the problem space of the game and to justify the selection of data for d/Discourse analyses. Connecting the nomothetic and idiographic approaches in this fashion allows the research to address both the typicality of a particular kind of learning practice, as well as raising new questions about the phenomena under study often best uncovered through a careful read of individual exchanges.

In general, developing principled ways of connecting multiple levels of analysis and employing multiple methods can help us to (1) justify the selection of data used in qualitative methods used to uncover learning and literacy in game spaces; and (2) give us cause to investigate the ways that complex problem-solving and learning may instantiate in very different ways at different levels of analysis. In game-based learning in particular, there is an increasing call for researchers to quantitatively justify claims about the productive potential of these media, while at the same time, many of the most intriguing learning practices are best uncovered through qualitative analysis. We argue that formally connecting the quantitative and qualitative may help to address both the need for "harder" data to substantiate claims of game-based learning, while also addressing the socially- and culturally-situated forms of learning that are part and parcel of engaged gaming talk.

Endnotes

(1) While this trace is generated from the Markov chains, it is not itself a Markov chain (for more detail, see Berland, Martin, Benton, Ko, & Smith, submitted).

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A Framework for Conducting Research and Designing Games to Promote Problem Solving

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Abstract: While problem solving is lauded as a benefit of video games, little empirical evidence exists to support this assertion. Current definitions and taxonomies are often contradictory and do not capture the complexity and diversity of modern games. Many video game researchers are also unfamiliar with the 75+ years of problem solving research in Europe and the United States. We propose a classification of game*play* that accounts for the cognitive skills during gameplay, relying in part on Mark Wolf's concept of grids of interactivity. We then describe eleven problem types and the dimensions along which they vary. Finally, we use the shared dimensions of gameplay and problem types to align gameplay types and problems. We believe that this framework for thinking about games and problem solving can guide future design and research and design on problem solving and games.

Statement of the Problem

Many have argued that games address critical thinking and problem-solving skills (e.g., Gee, 2007; Greenfield, 2010; Van Eck, 2006 & 2007). Unfortunately, what research exists on this tends toward the descriptive rather than the empirical. Descriptive analysis can illustrate how some kind of problem-solving *process* is occurring within a game (e.g., scientific method), but it cannot tell us about the *kind* of problems, how often they occur, for how long, and, most importantly, how effective a given game is at promoting problem solving skills.

Unfortunately, we are not prepared to conduct the kind of research that will answer these questions. Current game taxonomies are inconsistent and often contradictory, having their origins in film studies and relying on common parlance. Conducting empirical research on problem solving and games will require that we be able to manipulate and control for different types of games so that we can examine what *kinds* of games promote problem solving better than others. At the same time, we recognize that games that share the same genre can be very different experiences and that some games cross genre boundaries (e.g., action-adventure). Even were this not the case, any given game is likely to vary in terms of pace of play, amount of interactivity required, number of problems presented, and so forth. These are differences that must somehow be accounted for if we are to examine how any given game impacts problem solving.

This challenge is compounded by a lack of awareness on the part of most serious games researchers regarding existing problem types and problem-solving research. We require the same level of precision in our treatment of problem solving as we do in our definition of game typologies. To design a game to promote problem solving, we must know what kind of problem we are interested in: creating a menu for guests who have different diet restrictions, troubleshooting a car that won't start, diagnosing a patient's back pain problem, or solving global warming? Each type of problem differs significantly in structuredness, requirements for prior knowledge, ability to embed other subproblems, and cognitive structure, and therefore require different means of instruction (or game design).

Fortunately, cognitive psychology and instructional design have been studying problem solving for many years, and a rich body of research exists which can help inform our studies and design of problem solving in games. In this chapter, we attempt to bridge theory and practice by examining the relationships between games, problems, their cognitive processes, and instructional design.

Problem Solving

It is generally accepted in cognitive psychology that a problem has an initial state and a goal state. The initial state is the set of information and resources present at the beginning of the problem. The goal state is the information and resources that will be present when the goal has been met. The problem solver uses a representation of that goal state when considering how to proceed, which usually takes the form of doing things to reduce the disparity between the initial state and the goal state. The strategies s/he uses and the process by which s/he thinks about moving toward the goal state within the constraints of the problem and his/her prior knowledge are collectively referred to as the problem space. Most recently, Jonassen (2000, 2002) and Jonassen and Hung (2006, 2008) have proposed a typology of problems and associated prescriptions for the design of problem-based learning and instruction to promote problem solving in general. If games themselves are examples of problem solving, they should share to the same kinds of characteristics as different problems have. A closer inspection of this literature to see if and how it can be mapped to the study and design of serious games may yield important findings.

Games and Problem Solving

Jim Gee (2007) has argued that all games are situated, complex problem solving, and others have made the same point (e.g., Kiili, 2007). The core of our argument is that problems are highly differentiated by context, purpose, and domain, that different types of gameplay have their own affordances, and that it is necessary to understand problem types and gameplay types in order to align them meaningfully in the design of games to promote problem solving, or to conduct research on the effects of gameplay on problem-solving skills. There are three dimensions upon which a problem itself may vary: structuredness, cognitive components, and domain knowledge. Space does not allow a full accounting these dimensions, and the reader is referred to our work on this elsewhere (Hung & Van Eck, 2010). Likewise, we rely on an in-depth analysis of gameplay types, which we are able only to touch upon here, and the reader is referred to the aforementioned chapter for full accounting of gameplay types and interactivity.

Problem Structuredness

Jonassen (1997) argues that structuredness describes the *reliability* of the problem space in terms of the ratio of the information about the problem known and unknown, the number of variables, the number of possible solutions, and the degree of ambiguity involved in being able to assess one's success in solving the problem. Video games (or, more precisely, the gameplay that makes up different video games) also vary on a continuum from highly structured to poorly structured, so structuredness becomes one dimension upon which we can categorize both games and problems.

Cognitive Processes in Problem Solving

Solving different problems also relies on different kinds of cognition. There are six main cognitive processes relevant to problem solving as we discuss it: Logical thinking (the mental process that infers an expected event as a result of the occurrence of its preceding event or evaluates the validity of the conditional relations of these events); analytic thinking (identifying and separating an object, essay, substance, or system into its constituent components, examining their relationships as well as understanding the nature, behaviors, and specific functions of each component); strategic thinking (an integration process of synthesizing and evaluating the analytical results of a given situation and generating the most viable plan with intuition and creativity); analogical reasoning (the mental process by which an individual "reason[s] and learn[s] about a new situation (the target analogue) by relating it to a more familiar situation (the source analogy) that can be viewed as structurally parallel" (Holyoak & Thagard, 1997); systems thinking (the cognitive reasoning processes that consider complex, dynamic, contextual, and interdependent relationships among constituent parts, and the emerging properties of a system, (Capra, 2007; Ossimitz, 2000); and metacognitive thinking (the cognitive process that an individual is consciously aware of and which he or she articulates to various aspects of his or her own thinking processes). Different problems and different kinds of gameplay will support these types of thinking in different ways. Therefore, they become important for understanding how gameplay and problem solving can be aligned.

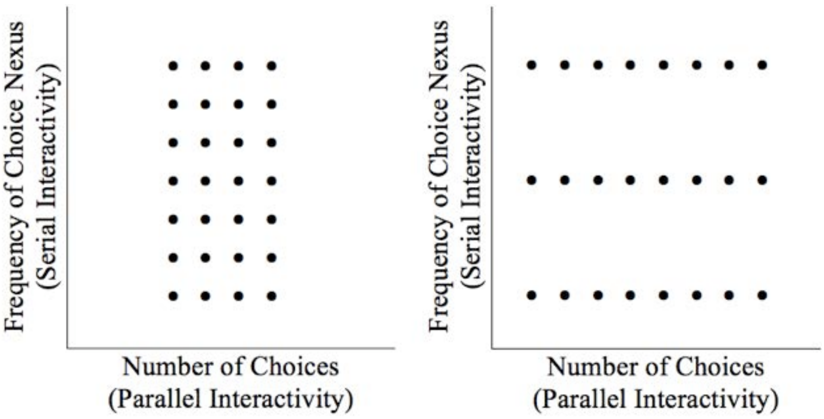
Classifying Gameplay Types using iGrids

The variance of problems along dimensions of structuredness and cognitive processes presents one challenge to the research and development of games for promoting problems solving. Yet games themselves vary greatly as well, as can be seen in classification systems (e.g., Apperley, 2006; Frasca, 2003). And because no one classification system is widely accepted nor completely compatible, our task is made even more difficult. Games often employ multiple gameplay strategies from different genres within the same game, leading to hybridized descriptions like action-adventure that work against meaningful classification. So how are we to distinguish among games (or types of gameplay) in a way that makes possible the empirical research and design of games to promote problem solving? While serious game researchers may not agree on different game genre classifications, most might agree that interactivity is one of the hallmarks of video games. This provides one means of classifying gameplay in a way that crosses all game types:

> The smallest unit of interactivity is the choice. . . . Choices are made in time, which gives us a two-dimensional grid of interactivity that can be drawn for any game. First, in the horizontal direction, we have the number of simultaneous (parallel) options that constitute the choice that a player is confronted with at any given moment. Second, in the vertical direction, we have the number of sequential (serial) choices made by a player over time until the end of the game (Wolf, 2006).

Wolf (2006) calls this a Grid of Interactivity, and we refer to them as iGrids. Frequency of choice and number of choices make good initial measures of pace, complexity, and cognitive load, and we believe these constructs impact problem solving and problem typology differentially. Wolf points out that it is not possible to map an entire game space on a graph, nor do we mean to suggest they otherwise. Nonetheless, such plots remain a useful tool for conceptualizing the issue of interactivity and one which we can rely on as a first step to further defining the kinds of gameplay that differentially support different problem types.

Although genre-based taxonomies of games are problematic, for now we will refer to genre-based terminology for the purposes of illustration. To understand an iGrid, imagine Aristotelian archetypes of different game genres such as "action" and "simulation" (see Figure 1).



e.g., Left 4 Dead (Valve, 2008) e.g., Civilization Series Games

Figure 1: iGrids for two different gameplay types.

The x-axis represents parallel interactivity, which is the number of choice options a player has at a given point in time (called a choice nexus), while the y-axis represents how often the player is presented with a choice nexus. For example, the game represented by the iGrid on the left of Figure 1 forces the player to make choices frequently over the course of the game with little time *between* choices but presents *few options* to choose from at those points. In the iGrid on the right, we see a game that presents *many options* to choose from but which forces the player to make choices *fewer times* over the course of the game with long periods of time between choices. Of course, there are action games with more parallel choices (e.g., weapons, running vs. hiding, inventory, armor, etc.) and periods of gameplay with lower choice nexus frequency. Likewise, games like those in the Civilization series *allow* near-continuous serial opportunities for interaction, but they do not *require* it.

iGrids, as measures of gameplay, become useful tools for discussing the differences in games that are likely to impact learning. While not sufficient on their own to fully delineate different types of gameplay, they at least provide an additional point of reference for communicating what is meant by whatever labels we use to describe games (e.g., action or strategy). Further, and most importantly, they allow us to describe game*play*, which after all can vary dramatically over the course of a single game. It will be important to be able to describe the key characteristics of gameplay in our quest to measure the ability of different types of gameplay to promote different types of problem solving.

By combining iGrids with an analysis of game/gameplay types using the same dimensions and characteristics that are used to differentiate problem types, we are able to develop a framework for describing games/gameplay that makes further study possible. In our discussion, we will rely on terminology regarding gameplay, which we have fully articulated elsewhere (Hung & Van Eck, 2010). Rather than generate new terminology and labels for the resulting taxonomy, we rely on existing taxonomies (e.g., Apperley, 2006) with some modifications. The resulting classifications are in some cases significantly different than common parlance, however. For example, Frasca's (2003) classification would list *SimCity* and *Flight Simulator* as simulations, whereas our analysis of gameplay suggests that *SimCity* is a strategy game (optimizing a system by strategically balancing factors) and *Flight Simulator* is a simulation game (a test of coordination of perception, cognition, and muscular control). Likewise, Apperley's classification would put FIFA Soccer and SimCity together as simulations, whereas we maintain that by virtue of gameplay and cognitive characteristics, FIFA Soccer is an action game. Space does not allow a full accounting of game play types (Action, Strategy, Simulation, Adventure, Role-Playing, and Puzzles), but Figure 2 presents the iGrids for each type. It should be noted that our categories are not intended to represent entire games as products; any given game will embed a variety of these different gameplay types as the situation warrants. But by focusing on the essential characteristics of gameplay *at any given moment*, we can make better determinations about what kinds of learning activities may or may not be best supported at a given time. The full analysis of by which we arrive at these different gameplay types can be seen in our previous work (Hung & Van Eck).

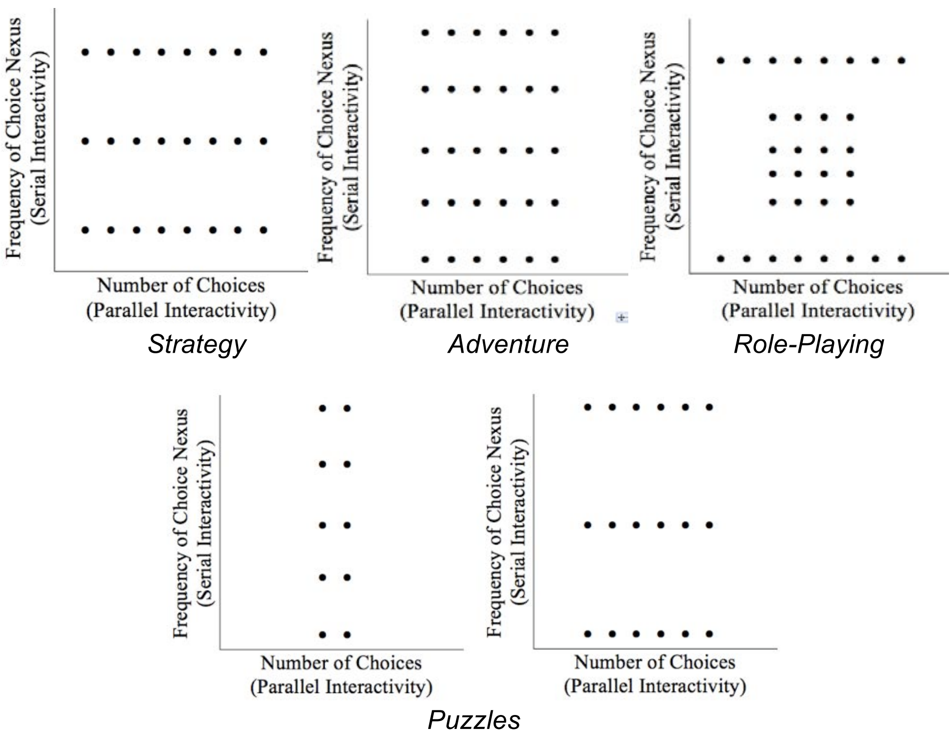


Figure 2: iGrids for five other gameplay types.

Problem Typology

Now that we have outlined our gameplay typology, we turn out attention to problems themselves. Jonassen (2000) has constructed a comprehensive typology consisting of 11 types of problems:

- Logical problem
- Algorithm problem
- Story problem
- Rule-use problem
- Decision-making problem
- Troubleshooting problem
- Diagnosis-solution problem
- Strategic performance problem
- Case analysis problem
- Design problem
- Dilemma problem

Space does not allow for a full accounting of all these problem types and examples. The reader is referred to Jonassen's text referenced above, as well as our previous work (Hung & Van Eck, 2010).

Suffice it to say that each of these problem types varies along key dimensions of cognitive composition (e.g., types of reasoning), structuredness, and requirements for domain-specific knowledge.

Blending these dimensions with iGrids and our analysis of gameplay types, including game-specific dimensions like psychomotor skills and the affective domain, it becomes possible to align problem-types and gameplay types along the dimensions that both share, and thus propose a framework for which kinds of gameplay types will support which kinds of problems, best (see Figure 3).

Knowledge and Cognitive Process														
	Domain–specific knowledge[1]				*Higher–order thinking*						*Psychomotor skills*[2]		*Attitude change*[2]	
Problem type	Declarative	Procedural	Concepts	Principles	Logical	Analytic	Analogical	Strategic	Systemic	Metacognitive	Muscular movement	Muscular–cognitive coordination	Shift of belief system	**Game type**
Logical					+	+								Adventure; Puzzle
Algorithmic		+	+	+	+									Adventure; Puzzle; Action
Story	+	+	+	+	+	+	+							Adventure; Puzzle
Rule-use	+	~	~	+	+	+								Action; Strategy; Roleplaying; Adventure; Puzzle
Decision–making		~	+	+	+	+		+	~	~				Action; Strategy; Role-playing; Simulations; Adventure
Troubleshooting		+	+	~	+	+	+	+	~	~				Simulations
Diagnosis–solution		+	+	+	+	+	+	+	+	+				Simulations; Strategy
Strategic Performance		+	+	+	+	+	+	+	+	+	+	+		Action; Roleplaying; Simulations; Adventure
Case Analysis			+	+	~	+	+		~	+			~	Strategy
Design			+	+	+	+	+	+	+	+				Strategy
Dilemma				+	+	+	~	+	+	+			+	Strategy; Roleplaying

1 For Psychomotor Skills and Attitude Change: domain-specific procedural and principle knowledge and metacognitive thinking are assumed.
2 For the learning type under Domain Knowledge, application of the knowledge is also assumed in this chart.
+ signifies “always required.”
~ signifies “sometimes required.”

Figure 3: Framework for aligning problem and gameplay types.

This allows for both the design of games to promote specific kinds of problem solving and for the design of research to test the effects of varying specific kinds of gameplay on different kinds of problem solving. We can then also examine things like varying pace of play, frequency of problem solving, length of play over days, and other variables to establish heuristic design models and an empirical research base on problem solving and games. Knowing about different problem types allows us to see existing games in a new light. For example, dilemma problems can be seen in persuasive games such as *Darfur is Dying* (mtvU, 2009). But more importantly, knowing how those problem types themselves vary along the dimensions of domain-specific knowledge and required cognitive processes shows us that what superficially may appear to be similar games are in fact quite different in terms of their ability to support problem solving. For example, many might say that *September 12* (Newsgaming.com, 2003) and *Darfur is Dying* are both dilemma games, when in fact *September 12* is too well structured and stripped of context to fully support dilemma problems.

Relying on iGrid typologies of gameplay rather than on genre classifications similarly promotes more precise analyses of games and problem solving. By focusing on archetypal gameplay styles, we can see how strategy and role-playing games seem best suited for dilemma problems, for example. Further, we are able to apply this reasoning to hybridized games that might at first glance appear to not support different kinds of problem solving. Space does not allow a full accounting of every problem type and every gameplay type (iGrid), nor how they each are aligned but this general description and the following example may suffice to illustrate the logic behind blending problem and game typologies.

Extending our example of the dilemma problem, the game *Bioshock* (2K, 2007), which many might categorize as adventure-action hybrid, is in fact a hybridization of action, adventure, and strategy. The game *Bioshock* pits the player against a variety of challenges in an underwater city named Rapture. As with *Left 4 Dead* (Valve, 2008), the player must make their way through the city without being killed by Big Daddies (giant modified humans in diving suits) and demented humans while collecting weapons and resources. Among these resources are plasmids, which grant special powers by virtue of genetic modifications, and which are injected via syringes. They key to unlocking the powers of plasmids lies in the collection of ADAM, which can only be obtained in the game from Little Sisters, who appear to be preadolescent girls. Little Sisters are always accompanied by Big Daddies, who must be killed before the player can collect ADAM. The dilemma problem in the game occurs with the decision on how to harvest the ADAM. One way results in the death of the Little Sister but results in a large amount of ADAM. The other way saves the Little Sister but results in less ADAM. While this choice seems to be pretty simple (two choices) the choices have a significant impact on the difficulty of the game and the way it proceeds. Additionally, whereas the binary choice in *September 12* (Newsgaming.com, 2003) is limited to the same instances and has the same results easily seen in a short period of time, in *Bioshock* these choices are distributed over the course of up to 50 hours of gameplay with relatively high frequency (medium serial interactivity), and the effects of these choices are not fully realized until near the end of the game. Thus, it is possible to support dilemma problem solving across the full arc of a game which itself is interspersed with other gameplay types, which in their own right may support other kinds of problem solving.

Finally, while our purpose is to outline a mechanism by which problem types with their associated cognitive requirements can be matched to different styles of gameplay, the end result also provides significant guidance for design and development of the games themselves. Because the study of problem solving within education and instructional design has been going on for decades, a rich body of research and best practices exists for supporting problem solving. Knowing, for example, that a problem is highly structured implies that less support should be provided for its solution, while ill-structured problems will require addition scaffolding and strategies to avoid cognitive overload. On the other hand, well-structured problems that occur during games with hybridized gameplay styles may indicate the need for more support than otherwise. When the problem solving itself is driving the game design, we may deliberately modify the form and frequency of a different gameplay styles in order to better support the problem (once we have conducted the empirical research to know how to promote different problem types, that is!). Knowing the kinds of cognitive processes involved also may help guide our selection of in-game tools, story structure, and objectives as well.

If we are to build games that promote problem solving, we must build on existing problem solving research. If we are to make claims about problem solving and games, we must generate new research and design heuristics based on the alignment of problem solving and different gameplay types, and test those empirically. In this paper, we have outlined a way to begin to meet both of these challenges. We used Jonassen's typology of problem types to help analyze the cognitive processes involved in different types of gameplay and, in turn, dissected gameplay that brought the essential characteristics (for problem solving, at any rate) to light. With an understanding of the cognitive, physical, and domain knowledge requirements of each type of gameplay, instructional designers and game developers will have a better idea of what types of gameplay will most appropriately afford given problem-solving learning goals and objectives.

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