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Game-XP: Action Games as Experimental Paradigms for Cognitive Science

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Abstract

Why games? How could anyone consider action games an *experimental paradigm for Cognitive Science?* In 1973, as one of three strategies he proposed for advancing Cognitive Science, Allen Newell exhorted us to "accept a single complex task and do all of it." More specifically, he told us that rather than taking an "experimental psychology as usual approach," we should "focus on a series of experimental and theoretical studies around a single complex task" so as to demonstrate that our theories of human cognition were powerful enough to explain "a genuine slab of human behavior" with the studies fitting into a detailed theoretical picture. *Action games* represent the type of experimental paradigm that Newell was advocating and the current state of programming expertise and laboratory equipment, along with the emergence of Big Data and naturally occurring datasets, provide the technologies and data needed to realize his vision. Action games enable us to escape from our field's regrettable focus on novice performance to develop theories that account for the full range of expertise through a twin focus on expertise sampling (across individuals) and longitudinal studies (within individuals) of simple and complex tasks.

Keywords: Cognitive skill acquisition; Skilled performance; Extreme expertise; Expertise sampling; Longitudinal studies; Action games; Video games; Computer games; Verbal protocol analysis; Space Fortress; Tetris; StarCraft; Halo; Chess; Cohort analysis

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1. Introduction

In 1973, as one of three strategies he proposed for taking Cognitive Science forward, Allen Newell exhorted us to "accept a single complex task and do all of it." More specifically, he told us that rather than taking an *experimental psychology as usual approach* (my italics, not his):

> An alternative is to focus on a series of experimental and theoretical studies around a single complex task, the aim being to demonstrate that one has a sufficient theory of a genuine slab of human behavior. All of the studies would be designed to fit together and add up to a total picture in detail. (p. 303)

In the time since, there have been few strong exemplars of this approach. The strongest, in terms of productivity and number of engaged researchers, is the game of chess (e.g., Charness, 1992; Chase & Simon, 1973a,b; de Groot, Gobet, & Jongman, 1996; Gobet & Simon, 2000; Simon & Gilmartin, 1973). For whatever reasons, *accepting a single complex task and doing all of it* has not become a mainstream paradigm for advancing cognitive research and theory. This issue of *Topics in Cognitive Science* (*topiCS*) is evidence that now is different and that action games are posed to become the general cognitive science paradigm for *doing all of a single complex task*.

This, *Action Games as Experimental Paradigms for Cognitive Science* (Game-XP), issue of *topiCS*, includes papers from eight diverse researchers, followed by commentaries from four distinguished cognitive scientists. Toward the end of this overview, each of these fine works is introduced, followed by a brief introduction to each commentator. Here I begin by introducing our subject, *Game-XP*, explain what it is and what it is not, discuss some of its short history, argue that it presents a *right-sized target* for meeting Newell's challenge of "demonstrat[ing] that one has a sufficient theory of a genuine slab of human behavior," and explain why having such a "sufficient theory" would be a significant milestone in the application of cognitive theories to human behavior.

1.1. Three types of research using games

Although there are many ways in which games might be used in research, three ways are currently dominant within the cognitive and related sciences: *Gamification, Games as Treatment Conditions,* and *Game-XP*.

1.1.1. Gamification

Attempts to identify the elements that make games challenging, motivating, and enjoyable with the goal of altering the elements of traditionally nongame activities or instruction "to afford ... [the] motivating, enjoyable experiences" characteristic of gameplay

(Deterding, 2015) (see also, Mayer, 2014; Rapp, Cena, Gena, Marcengo, & Console, 2016; Wikipedia, 2016a).

1.1.2. Games as treatment conditions

Many, maybe most, usages of games in the behavioral sciences treat the activities involved in playing games as a black box and examine differences in pre- versus post-game performance on some measures. An example of this would be the use of Tetris^{TM} to improve the spatial abilities of engineering students (Martin-Gutierrez, Luis Saorin, Martin-Dorta, & Contero, 2009), as a treatment for posttraumatic stress disorder (Holmes, James, Coode-Bate, & Deeprose, 2009), or as a form of brain training in an attempt to reduce differences between sexes on some measures of spatial abilities (Linn & Petersen, 1985; Okagaki & Frensch, 1994; Sims & Mayer, 2002; Terlecki, Newcombe, & Little, 2008).

1.1.3. Game-XP

In common with the *extremely simple paradigms* (ESPs) used in most behavioral science laboratories, Game-XP focuses on the basic processes of cognition, perception, action, dynamic decision making, method discovery, and skill acquisition. However, in contrast to ESPs, Game-XP also focuses on how the various cognitive processes act together in the acquisition and performance of *manageably complex behavior*.

(a) Manageable Complexity: Though more complex than most ESPs, in common with ESPs games often have a structure in which certain elements recur many times. The game may be chosen, altered, or sometimes created so as to be manageably complex on the research question(s) of interest with data collection and condition manipulation features built in. The classic example of this is *Space Fortress* (Donchin, 1989, 1995) and a more recent example is *Meta-T* (Lindstedt & Gray, 2015) that turns classic Tetris^{TM} into a managably complex experimental paradigm.
(b) Engagement: The tasks players are asked to perform in GAME-XPs are often more motivating than those of ESPs, with the result that players may be more willing to follow instructions, more willing to acquire expertise within the game paradigm, and more willing to play for longer or multiple sessions.
(c) Well-Defined Goals and Side Metrics: Overall player performance is typically measured by one score but may be accompanied by various *side metrics* of gameplay, such as player's health, resource consumption, and so on. Hence, unlike even simple laboratory tasks whose structures and goals may be unclear to subjects, what players are trying to achieve in a well-designed game is identical to what researchers regard as the overall measure of performance with the side metrics signaling differences in methods for how that objective is achieved. Having an explicit goal and side metrics may advance theory by enabling us to narrow "the space

of predicted behaviors through analysis of the payoff achieved by alternative strategies, rather than through fitting strategies and theoretical parameters to data" (Howes, Lewis, & Vera, 2009).

(d) Expertise Sampling (across individuals): As most games exist outside the laboratory, it may be possible to *sample expertise* across a wide range of performance, especially on college campuses. According to McGonigal (2011), "the average young person racks up 10,000 h of gaming by the age of 21." This implies that expertise in many action games is widely distributed among campus populations. Rather than a forced focus on novice performance with ESPs that can be mastered in 10 min, played at asymptotic levels for 30 min, and followed by a 10 min debriefing; researchers may select players based on the level of expertise they achieved prior to coming to the laboratory.

(e) Longitudinal Studies (within individuals): Long-term studies of acquisition of skilled performance and expertise will always be difficult but, due to the motivating aspects of game play, it may be easier to recruit and retain players for long-term laboratory studies than for many other tasks. For web-based or cellphone-based games, it may be possible to obtain a complete record of skill acquistion by mining Big Data sources.

(f) Big Data: Many of the most popular games are web-based or cellphone-based with the side effect that much or all of the interactions, decisions, and keystrokes made during the game are available in datafiles on the internet. Hence, researchers can obtain Big Data (Griffiths, 2015) and/or *naturally occurring datasets* (NODS, see Goldstone & Lupyan, 2016), which contain hundreds of thousands or millions of records (e.g., Huang, Yan, Cheung, Nagapan, & Zimmermann, 2017; Sangster, Mendonca, & Gray, 2016; Stafford & Haasnoot, 2017; Thompson, McColeman, Stepanova, & Blair, 2017).

(g) Joint Action and Teams: It seems fair to say that, outside of studies of language, the cognitive revolution has not greatly influenced the study of people in cooperative or competitive settings. In recent years, Joint Action (e.g., Knoblich, Butterfill, & Sebanz, 2011; Sebanz & Knoblich, 2009) has emerged primarily as the study of interactions between two humans. It may be that Joint Action has opened a path to the cognitive study of teams and that cognitive studies of interteam competition as well as within-team cooperation may be possible (see also Cooke & Hilton, 2015; Cooke, Gorman, Myers, & Duran, 2013) The essence of a team is (a) common objectives, (b) skilled individuals, and (c) familiarity with other team members. Unfortunately, these essences, their manipulation, measurement, and team outcomes are difficult to study in laboratory environments, in vivo, or by questionnaires. However, massive amounts of data are collected from teams and team members of online games,[1] and the Big Data aspects of team games may provide a better path to advancing theories of individual and team interactions than do current attempts to study emergency response teams, design teams, combat teams, surgical teams, or others in vivo by low-volume observational data or by questionnaires.

1.2. The challenge and allure of Game-XP

Game-XP chooses games at a (a) manageable level of complexity which are (b) engaging and (c) have well-defined goals and well-defined side metrics, which may be used to infer differences in player methods and strategies. As some games are played by a large proportion of the college-age population, rather than finding a few people who can put in tens or hundreds or thousands of lab hours becoming expert, it may be possible (d) to sample expertise or (e) conduct longitudinal studies in the laboratory. Perhaps even more alluring, (f) web-based games and cellphone-based games have already harvested hundreds and, in some cases, billions of hours of game play which might be mined for players at vastly different levels of expertise. Finally, (g) the activities of individuals as members of teams and the activities of teams has always been difficult to study in the laboratory or by other means. The existence of team-based sports games and MOBAs may provide an important Big Data source for studies of individual and team performance.

To summarize, I can do little better than to quote Tom Stafford; namely, Games represent:

> a skill development domain in which automated data collection at a large scale is plausible. Unlike other skill development domains—for example, spoken language, playing the violin, soccer—each action taken during a game, is conducted through a computer and so may be unobtrusively recorded. (Stafford & Haasnoot, 2017)

2. The once and future paradigm

Clearly this collection of researchers is not the first to suggest that the games people play can be profitably studied to advance cognitive, behavioral, or social science theories. Indeed, in the 1960s and 1970s, studies of chess were so common and so important to advancing cognitive theory that chess was termed the "Drosophia of cognitive science" (e.g., Chabris & Hamilton, 1992; Charness, 1976; Chase & Simon, 1973a,b; de Groot, 1965; Gobet & Simon, 1996; Simon & Barenfeld, 1969). In contrast to chess, the study of action games had to await the invention of modern computing.

2.1. *Breakout*™

The first detailed study of action games was not by a cognitive scientist, but by one of the fathers of ethnomethodology, David Sudnow. His 1983 book, *Pilgrim in the Microworld*, details his quest to master the game Breakout as a first-person narrative. The details provided in the book allow us to follow Sudnow's evolving understanding of the game with a particular focus on his invention and testing of a series of methods for *where to look*—at the paddle, the ball, or somewhere else.

Sudnow's work on games seems to have been a *one off* within the field of Ethnomethodology. However, it has recently been rediscovered by Reeves, Brown, and Laurier (2009), picked up from that source, and introduced to the Cognitive Science community by Gray and Lindstedt (2016), with much of its essence being reviewed and discussed in this issue of *topiCS* by Reeves, Greiffenhagen, and Laurier (2017).

2.2. Space Fortress—The Learning Strategies Project

The Learning Strategies Project was initiated in the 1980s by a group of researchers, headed by Emanuel Donchin (1989), distributed among a half dozen or so universities and research institutes and, initially, funded by DARPA (the Defense Advance Research Projects Agency). In its first formal announcement, the program was described this way:

> It is the primary mission of this program to test the assumption that there are learning strategies that do indeed, in some circumstances, make practice more efficient. We furthermore test the assumption that these strategies can be implemented in the microprocessor based simulation games and that, therefore, training can be improved by incorporating learning strategies in the games. (Donchin, 1989, p. 4)

Thirty years after the project began, a search on *Web of Science™* (2016.11.07) found 52 papers that used "Space Fortress" either in their title, abstract, or keywords, with five of these being published in 2015 (the last full year of indexing available at the time of this writing). By one count (Destefano, 2010), Space Fortress has been reprogrammed five times with the most recent version being a PyGame implementation.

2.3. "Problems that arise…" and issues emerging…

As Space Fortress is the original instantiation of Game-XP, it is interesting to review two "problems that arise" that Donchin (1995) saw "in the choice or design of video games when they are to be used as tools in the study of human information processing." I will then bring in two points made by Newell (1973) in his famous "You can't play 20 questions with nature and win" paper that can be interpreted as taking a complementary stance on these issues. I end this section with a "that was then, this is now" discussion of how issues emerging from the Game-XP authors contrasts with both Newell and Donchin.

2.3.1. Control over parameters and data collection

> A game is useful as a research tool if, and only if, the investigator can exercise systematic control over the game's parameters. Furthermore, unless the game can yield very detailed measures of performance, as well as capture the actual game for replay, the research will be impoverished. (Donchin, 1995, p. 218)

It is hard, if not impossible, for ordinary researchers to access the internals of commercial video game software. Indeed, it seems likely that this lack of access to the internals of most games explains the continued popularity of "Games as Treatment Conditions" (as discussed above). However, despite obstacles, the researchers of four of the eight papers in this topic can "exercise control over the game's parameters" (see the *Parameter Control* column of Table 1).

On the other hand, the creation of web-based games and cellphone-based games has required that many aspects of gameplay be processed remotely. Although these games fail at a strict interpretation of Donchin's first criterion, they strongly support his second criterion as an unintended by-product of remote processing is that data which would have been inaccessible in a home console game are potentially available at remote locations. Indeed, four of the papers in this topic take advantage of this (see the *Big Data* entries in the Approach column of Table 1).

Table 1
Index to authors, games, and approach

Researchers	Game	Approach	Parameter Control[a]	Group/ Individual	Sampling/ Longitudinal[b]
Boot et al.	Space Fortress	Protocol analysis	Yes	Single subject	Longitudinal
Huang et al.	Halo Reach & StarCraft 2	Big Data	No	Individuals	Longitudinal[c]/ Sampling[d]
Reeves, Greiffenhagen, & Laurier	Warcraft III, Soccer, Counter-Strike, Lord of the Rings	EMCA[e]	No	Individuals, two players, small groups	Maybe
Schrodt et al.	Super Mario Bros.	Cognitive architecture	Yes	SuperM	NA[f]
Sibert, Gray, & Lindstedt	Tetris	ML models + human data	Yes	Individuals	Sampling
Stafford & Haasnoot	Axion	Big Data	No	Individuals	Sampling[g]
Thompson et al.	StarCraft 2	Big Data	No	Individuals	Sampling[g]
van der Maas & Nyamsuren	Math Garden	Big Data	Yes	Individuals	Sampling

Notes. [a]The ability of the researcher to "exercise systematic control over the game's parameters" (Donchin, 1995, p. 218).
[b]"Sampling" implies the selection of individuals known to differ in their level of game expertise (i.e., between-players). "Longitudinal" implies a study that collected repeated measures on the same individuals at different points in time (i.e., within-players).
[c]For Halo Reach.
[d]For StarCraft.
[e]Ethnomethodogical and conversational analysis.
[f]Not applicable.
[g]Note that these researchers had data that could have enable longitudinal analysis of player performance across time; however, their research questions of interest were most directly addressed by an expertise sampling approach.

One paper, van der Maas and Nyamsuren (2017), is counted twice in this tally as the researchers created their own web-based educational game which provides them with a Big Data approach as well as direct control over the game's parameters. Hence, seven of the papers in the topic access or incorporate software that capture "very detailed measures of performance."

The eighth paper is the exception that proves the rule. Reeves et al. (2017) look at gameplay through the lens of ethnomethodogical and conversational analysis (EMCA). The questions they ask are higher level questions that focus on interactions among human players or in the experience of game play for individual players. These questions are at a different level of analysis than are the second by second, millisecond by millisecond analyses of basic cognitive processes interacting with a dynamic task environment favored by cognitive psychologists. However, many of the details of interactive behavior favored by EMCA researchers can be captured by videotaping performers as they are playing the game. Hence, in each of our eight papers, Donchin's requirement to obtain "very detailed measures of performance" is met.

2.3.2. Constraining or understanding the human player

> No matter how fancy or complex the game, we must be sure that the way in which the game/task is set up constrains the subject to view the task, and to perform it, in accordance with the experimenter's model of the task's role in the research. (Donchin, 1995, p. 218)

> First Injunction of Psychological Experimentation: Know the method your subject is using to perform the experimental task. (Newell, 1973, p. 294)

> Second Injunction of Psychological Experimentation: Never average over methods. (Newell, 1973, p. 295)

A perennial worry in cognitive research is that of imposing a theory or model that may fit the task data but does not capture what humans actually are doing. Donchin explicitly worries that the complexity of the task may lead the player to view it differently than the experimenter. The worry here is that if the methods that players deploy differ from those assumed by the researcher, then theoretical constructs underlying those methods will also differ.

Newell explicitly acknowledges that a given task may be performed by different methods and that different people may bring different methods to bear on the same task. Clearly averaging over methods expectly to find a core "truth" is a bit like expecting to paint a rainbow by mixing together the colors in the paint box.

For Game-XP, the more complex the task, the more subtle the possible differences in the methods discovered and deployed by different players may be. For example, Sibert, Gray, and Lindstedt (2017) compare human data to machine learning classifers that were trained on one of four different "objective functions"—that is, different methods for achieving the goal of gaining the most points possible. Some of these classifiers optimized the number of lines cleared while others optimized points per zoid (a "zoid" is a Tetris piece). Human players tend to optimize "points per zoid" by clearing multiple lines at once as clearing four lines with one zoid awards 30 times as many points as does using four zoids to clear one line each. However, there are individual differences. For example, in unpublished data gathered from Tetris tournaments held at Rensselaer, one of the finalists played for a very long duration and achieved a very high score by clearing off one line at a time and avoiding two-line clears, three-line clears, and four-line clears (Tetrises). This strategy requires different methods and results in the building of different Tetris boards than does the "points per zoid" strategy.

At this point, it should be clear that the promise of Game-XP is not that it is easy but that it provides a way to collect massive amounts of detailed performance data that can be teased and tortured to test theories of human performance while providing insights into the invention or discovery of methods as skill progresses from novice to expert levels. Its true promise is in the amount and detail of data it can provide us. The opportunity is that modern tools and techniques make the collection and analyses of these data feasible.

2.4. Summary of this section

Game-XP puts a name on an activity that has influenced research and theory for three decades (at least since Sudnow, 1983). However, sampling expertise or measuring changes in longitudinal performance is not unique to Game-XP but is well represented by studies of memory (e.g., Chase & Ericsson, 1982), music (Ericsson, Krampe, & Tesch-Römer, 1993), chess (Chabris & Glickman, 2006; Charness, 1992; Gobet, 2015), and in ESPs such as those favored in studies of perceptual learning (Fine & Jacobs, 2002). Indeed, this twin focus on expertise sampling and longitudinal studies of simple (Ebbinghaus, 1885/1913) and complex tasks (Book, 1908; Bryan & Harter, 1897) extends back to the beginnings of experimental psychology. In the case of *typewriting*, non-game studies that sample skilled performance at novice through expert levels began early (Book, 1908; Swift & Schuyler, 1907), continued through the 1970s (Shaffer, 1975), 80s (Gentner, 1983), 90's (John, 1996), and continue to this day (Logan & Crump, 2011; Logan, Ulrich, & Lindsey, 2016). What is different about Game-XP is the variety of tasks, the wide variation of expertise in these tasks in college-aged populations, and massive amounts of performance data available online.

3. Introduction to the papers of this topic

Having already touched each of our new research papers at least once, it is time now for a more systematic introduction. Although each paper examines different aspects of cognition, there are some commonalities in methods or approaches. Hence, we group papers together based on the commonalities they share with each other on one or more dimension shown in Table 1.

3.1. The ethnomethodogy of games

3.1.1. Authors

Stuart Reeves (University of Nottingham), Christian Greiffenhagen (Chinese University of Hong Kong), and Eric Laurier (University of Edinburgh).

3.1.2. Title

Video Game Playing as a Practical Accomplishment: Ethnomethodology, Conversation Analysis, and Play.

As discussed earlier, Games-XP is a minority view on games within cognitive science and several of its closely related disciplines. Hence, I was pleased to stumble on another discipline that was studying games not for their side effects but as "a genuine slab of human behavior" (to borrow Newell's term). This is the discipline of ethnomethodological and conversation analytics (EMCA).

Often when one field writes for another field, they spend a lot of the paper pretending they are doing a first-semester graduate seminar introducing the concepts, terms, and detailed theories from their field to the students. This is almost always a mistake. Fortunately it is a mistake that Reeves and colleagues have avoided. Instead of dazzling us with a lot of terminology with which we are unfamiliar, they demonstrate the utility of their approach and how it contrasts with cognitive science approaches and goals in simple terms we can understand. This paper is a gem. It is well worth reading by all cognitive scientists, and we hope that it will lead to productive interchanges between our fields which further the study of complex individual and group behaviors.

3.2. Cognitive and mathematical modeling of game play

3.2.1. Authors

Fabian Schrodt, Jan Kneissler, Stephan Ehrenfeld, and Martin V. Butz (all Universität Tübingen).

3.2.2. Title

Mario Becomes Cognitive.

There are few cognitive models that attempt to interact with complex video games in real time. The only one that comes to mind is Bonnie John's work on a series of Soar models that explored time-constrained learning in the very interactive task of SuperMario™ (Bauer & John, 1995; John & Vera, 1992; John, Vera, & Newell, 1994; Peck & John, 1992).[2] Interestingly, after a long hiatus and with no prior knowledge of John's work, SuperMario was rediscovered as a paradigm by Martin Butz and forms the basis of a new hybrid cognitive architecture that is presented to the world in this issue of *topiCS* (Schrodt, Kneissler, Ehrenfeld, & Butz, 2017).

3.2.3. Authors

Catherine Sibert, Wayne D. Gray, and John Lindstedt (all Rensselaer Polytechnic Institute).

3.2.4. Title

Interrogating Feature Learning Models to Discover Insights Into the Development of Human Expertise in a Real-Time, Dynamic Decision-Making Task.

That people learn perceptual categories has been accepted for decades (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976; Simon & Gilmartin, 1973). But why they learn what they do and not something else remains largely a mystery, especially in complex tasks such as Tetris. In Sibert, Gray, and Lindstedt, we tackle this problem by turning to a machine-learning approach, cross-entropy reinforcement learning, that attempts to maximize an objective function by discovering the optimal weightings for each feature of a set. By varying the objective function, we show that the one favored by the Machine Learning community does not produce human-like choices, whereas other objective functions do. Hence, although the mechanisms of the machine learning models do not attempt to mimic human learning, the outcome of this modeling shows how a common goal in a common task environment influences behavior in similar ways for machine and human learners and, by so doing, sheds light on the nature of expertise.

3.2.5. Authors

Han van der Maas (University of Amsterdam) and Enkhbold Nyamsuren (Open University).

3.2.6. Title

Cognitive Analysis of Educational Games: The Number Game.

Can "gamification" provide a Games-XP paper? Gamification, as discussed above, transforms an educational or training task into a game. However, for those interested in cognitive processes and theory, what is important is whether "the investigator can exercise systematic control over the game's parameters" and obtain "very detailed measures of performance" (Donchin, 1995, p. 218). By these criteria the van der Maas and Nyamsuren paper is a perfect example of Game-XP, and it also provides a perfect example of Pasteur's Quadrant research (Stokes, 1997) in that the discoveries they have made about how students solve a certain class of math problems have the potential to change how math is taught.

3.3. Protocol analysis of a single subject

3.3.1. Authors

Walter R. Boot, Anna Sumner, Tyler J. Towne, Paola Rodriguez, and K. Anders Ericsson.

3.3.2. Title

Applying Aspects of the Expert Performance Approach to Better Understand the Structure of Skill and Mechanisms of Skill Acquisition in Video Games.

There is an tradition in cognitive science, going at least as far back as Newell and Simon (1972), of collecting *think-aloud* data from people as they perform tasks. Classics in this approach include Chase and Simon (1973a, b), Anzai and Simon (1979), Chi, Bassok, Lewis, Reimann, and Glaser (1989), and Card et al. (2001). The first modern book on this topic is de Groot (1965). The definitive book on this topic is by Ericsson and Simon (1993). However, to our knowledge, this approach has not been applied to dynamic tasks, such as action games.

Well, that was then, this is now. Now Wally Boot and colleagues have modified the think-aloud (TAL) procedure and used it to collect TAL data from players during action games. However, verbal protocol analysis procedures have always been labor intensive and have always required well-trained subjects; the procedure used by Boot and colleagues is no exception. They collect detailed, longitudinal performance and TAL data from one very cooperative player over 20 h of gameplay. The insights into player exploration and invention of new methods is extraordinary and could only have been obtained via this modified version of the *Expert Performance Approach* (Ericsson & Ward, 2007) to dynamic skill acquisition.

3.4. Big data approaches to strategies, motor skills, and motor learning

3.4.1. Authors

Jeff Huang, Eddie Yan, Gifford Cheung, Nachiappan Nagapan, and Thomas Zimmermann.

3.4.2. Title

Master Maker: Understanding Gaming Skill Through Practice and Habit From Game-Play Behavior.

Huang and colleagues introduce us to *cohort analysis* in the context of Halo Reach^{TM}, wherein players are grouped by the date they first played the game, with their patterns of play analyzed in an attempt to determine how those who eventually become higher skilled differ from those who do not. They see players who advance in their game as engaged in “group deliberate practice” (Gobet & Campitelli, 2007) that is similar to but different from the usual view of *deliberate practice* as a solitary activity.

The second part of their paper switches to StarCraft 2^{TM} with a research focus on “habitual game actions” in situations where they are not needed, that is, in “relaxed” (i.e., not time-pressured) situations. To be clear, these habitual actions are essential in time-pressured situations and represent skills which advanced players possess that novices do not. The research question of interest is why these are used at all in relaxed situations. This focus on well-practiced sequences of keystrokes is echoed and deepened in the Thompson et al. (2017) paper.

3.4.3. Authors

Joseph James Thompson, Caitlyn M. McColeman, Ekaterina R. Stepanova, and Mark R. Blair.

3.4.4. Title

Using Video Game Telemetry Data to Research Motor Chunking, Action Latencies, and Complex Cognitive-Motor Skill Learning.

Thompson and colleagues take a new look at an old topic; namely, first action latencies of motor sequences. They examine in-game actions of 3,317 players across seven skill levels, and 996,163 *perception action cycles* (which are defined in their paper). The differences in skill levels of players reflect vast differences in expertise due, at least in part, to vast differences in the number of hours spent playing StarCraft 2. The discovery and mystery is that long first action latencies are observed for even the most expert group of players.

3.5. Innovative usage to address an interesting theoretical issue

3.5.1. Authors

Tom Stafford and Erwin Haasnoot.

3.5.2. Title

Testing Sleep Consolidation in Skill Learning: A Field Study Using an Online Game.

Stafford and Haasnoot's paper is literally in a category by itself and demonstrates the promise of Big Data to raise questions that have little or nothing to do with the paradigm used to collect the data. Few of us would have expected that data collected from a cell-phone action game could be used to address questions of *sleep consolidation in skill learning*. However, using the power of Big Data, Stafford and Haasnoot realized that the number of hours between game playing could be used as a metric for the distribution of practice. They also realized that some of the long periods between game playing occurred late at night and other periods occurred during work hours. Hence, they examine game play after gaps <15 min ("no gap" condition with 9,388 players) versus after a single gap of 7–12 h. This latter category is divided into "sleep" (761 players) versus "wake" (423 players) categories based on the time of day the gap occurred.

4. Commentators to Game-XP

I would be remiss to not introduce the four senior researchers who, by the time this introduction is published, will have written commentaries on the Game-XP issue of *topiCS*. While none of our commentators is a one-dimensional figure, all four have used chess as a paradigm for seminal work on cognitive theory.

Chris Chabris, using chess as his paradigm, has examined sex differences in intellectual performance (Chabris & Glickman, 2006), hemispheric-specialization of perceptual organization (Chabris & Hamilton, 1992), and the blunders made by grandmasters (Chabris & Hearst, 2003). Chris is also known for his studies of *change blindness* (Chabris & Simons, 2010; Simons & Chabris, 1999), his demolition of the *Mozart effect* (Chabris, 1999), and for other contributions, too numerous to mention here.

Neil Charness has a research arc which began with an interest in chess expertise (e.g., Charness, 1976 1991, 1992) and has lately focused on the cognitive science of aging (e.g., Charness, 2008) with issues as diverse as barriers to technology use (Charness & Boot, 2009) and how the way a decision is framed differentially affects decisions make by the young and the elderly. Perhaps not surprisingly, some of his research lines overlap as when he examines the effects of skill and age on selecting the best chess moves (Moxley & Charness, 2013). The scope of Neil's work is impressive; indeed, he recently joined with, among others, discussant Chris Chabris and author Walter Boot in a massive review by the title and topic of *Do "Brain-Training" Programs Work?* (Simons et al., 2016).

Fernand Gobet is an expert on expertise with five books (the most recent was published in 2015) and many highly cited journal papers on the subject. A particular focus of his is chess expertise, where he has developed computational cognitive models (Gobet & Simon, 2000; Gobet et al., 2001), explored and challenged the most common definition of *deliberate practice* (Campitelli & Gobet, 2011), and generally advanced *studies of expertise* by his detailed probing and poking at chess.

Andrew Howes is best known for his work on interactive behavior, which began with an interest in human-computer interaction (Howes & Payne, 1990) and has developed to include the *Rational Adaptation Theory* that provides "a new approach to modeling and understanding cognition... that sharpens the predictive acuity of general, integrated theories of cognition and action" (Howes et al., 2009; Howes, Lewis, & Singh, 2014). Interestingly, although not known for his work on chess, he has used chess as a paradigm to test whether memory chunks for chess positions are formed based on the spatial proximity of pieces or by their opportunity for interaction, specifically as an encoding of attack/defense relationships (McGregor & Howes, 2002).

5. Gazing toward the future or are we there yet?

Is Game-XP the sort of methodology that will bring us closer to realizing Newell's vision of cognitive science? Maybe... maybe not. It is, however, the shared vision of the authors who have contributed to this issue of *topiCS*. The editor and authors of these papers ask those who are skeptic to consider another saying that Newell used more than once during public lectures and at least once in print (Newell, 1990, p. 38), "Don't bite my finger, look where I'm pointing." As you read the research papers and commentaries, please consider the following.

(a) Is Game-XP the sort of methodology that might bring us closer to realizing Newell's vision? The authors of this issue of *topiCS* propose Game-XP as a promising path, not as a *fait accompli*. Only time plus a lot of hard work by many inspired researchers will tell.

(b) With the exception of the work by Boot, Sumner, Towne, Rodriguez, and Anders Ericsson (2017), none of the authors have published more than one or two journal or journal-quality papers on their paradigm. (As a lower limit, let me confess that the paper published by my lab [Sibert et al., 2017] is our first on Tetris.)

(c) Unlike chess, action games are not one paradigm but many.

(d) Like chess, action games present a natural paradigm in which to study differences in player expertise. However, also like chess, they present paradigms for studying many other facets of human cognition.

Game-XP enables a wide variety of incremental advances that seem bound to spur the advance of cognitive and related sciences. The level of task complexity can be increased without loss of control and with the same millisecond precision as our ESPs. The potential for sampling expertise from a college-age population is huge as is the ability to find people willing to spend 10, 20, 40, or more hours in lab-based, longitudinal studies playing these games. The use of Big Data and NODS is part of the zeitgeist in other fields of the behavioral social sciences and in many new niches of cognitive science; however, action games may be the largest Big Data source for human performance data. Perhaps best of all, as the papers in this topic attest, these benefits and this future are available now.

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Notes

1. As one example, the category of web-based games called *MOBAs* (multiplayer online battle arena games, Wikipedia, 2016b) pits one team of human players against another (Sangster et al., 2016). It is estimated (Kenreck, 2012) that for just one of these games, *League of Legend*^{TM} (LoL), each month more than 1 billion hours of the game are played.
2. The reader will note that due to the expressed concern of the funding agency in the 1990s, there is no indication in either the title or the abstract of these papers that the paradigm studied was an action game.

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