INCIDENTAL LEARNING IN COMPLEXITY:

MEASURING THE ROUGHNESS OF LEARNING

by

JILL K. JINKS

(Under the Direction of Karen E. Watkins)

ABSTRACT

The purpose of the CraftDawg study was to apply principles of complexity science to identify and quantify the roughness of learning variable in the human learning process and attempt to isolate the role of incidental learning as theorized by Marsick and Watkins (1990) in the adaptive process used by humans in complex contexts. Using Robert May's (1975) logistic map as the theoretical framework, the CraftDawg study used the serious game of Minecraft: Survival to simulate a complex context. Ninety-five participants completed a series of instruments to identify latent variables and the influence (strength and direction) of these variables on the outcome of the game over five play sessions. By harvesting data directly from game play, the shape of learning was captured and plotted to allow a fractal dimension to be measured. Rescaling the fractal dimension to match the scale used by May (1975) allowed the researcher to interpret the level of complexity in the context as experienced by groups based on experience with the context.

The result of study found a strong, positive relationship between incidental learning and adaptiveness (research question one); uncertainty reduces adaptiveness (research question two);

and the roughness of learning variable describes how complexity influences learning and thus adaptiveness (research question three).

The CraftDawg study offers five contributions: Robert May's logistic model (1976) can be used as an index of complexity in learning contexts; Marsick and Watkins' (1990) informal and incidental learning theory is further supported empirically; the roughness of learning (RoL) is a variable that quantifies complexity-based dimensions identified by Marsick and Watkins (1990); an integrated, technology-based method can be used to collect and harvest learning data for patternization examination; and Minecraft is a viable platform for examining adult learning in a simulated complex environment.

INDEX WORDS: Incidental learning, Complexity science, Fractal dimension, Adaptiveness, Uncertainty, Simulated complex context, Structural equation modeling, Index of complexity, Minecraft.

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DEDICATION

"He died [a few months] ago, while winter filled the air

And though I cried, I was so proud

To love a man so rare

He's somewhere on the ocean now

A place he oughtta be

With one hand on the starboard rail,

he's waving back at me."

(Buffet, 1970)

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CHAPTER 1

INTRODUCTION

Kolb and Kolb (2009) define human learning as "the basic process of human adaptation" (p. 42). In developing their experiential learning theory (ELT), Kolb and Kolb (2009) relied on

> the work of prominent twentieth century scholars who gave experience a central role in their theories of human learning and development – notably John Dewey, Kurt Lewin, Jean Piaget, William James, Carl Jung, Paulo Freire, Carl Rogers and others to develop a dynamic, holistic model of the process of learning from experience and a multi-linear model of adult development" (p. 43).

Kolb and Kolb (2009) noted that ELT is "a holistic theory that defines learning as the major processes of human adaptation involving the whole person" (p. 43). This is consistent with the essence of complexity science that studies processes that create the whole, including the interactions that create adaptive capacity and adaptive behaviors (Holland, 1998, 2006; Mitchell, 2009).

Combining Kolb and Kolb (2009) with the more granular informal and incidental learning theory (IIL) of Marsick and Watkins (1990) provides a theoretical framework to define and isolate a learning variable suggested by the principles of complexity science: *roughness of learning*. Conceptually, this variable is an estimate of the *turbulence* in the learning process and is based on the notion of entropy and energy and time needed to engage in a human adaptive effort. *Consistent with complexity science, the roughness of learning variable assumes that all*

prior learning is present in the now and can be used to create new learning and new knowledge acquisition.

Marsick and Watkins (1990) note the "ugliness of learning" and highlight the incidental learning process as part of informal learning. A review of the literature finds limited research that isolates incidental learning. The studies examined do not define the role of incidental learning in effecting the roughness of learning in a given context or environment (Harner, 2013; Silva, 2007; Taber et al., 2008). In developing the roughness of learning variable for purposes of this study, the researcher considered incidental learning as a *marginal* input in the learning process and knowledge acquisition.

Human adaptive responses and adaptive capacity enable creativity and imagination to mix with incidental learning and informal learning to craft novel and innovative adaptive processes and behaviors to quell turbulent states and environments. In this study, the roughness of learning variable measures this dynamic alchemy as a variable measured as the fractal dimension of the *shape* of learning.

The Learning Curve and the Roughness of Learning

The "learning curve" is typically the measure used to describe the time and effort humans assert to gain knowledge (Hirschmann, 1964). As explained by the Indeed editorial team (2021), learning curve theory suggests "a way to understand the improved performance of an employee or investment over time. The idea is that the more an employee does something, the better they will get at it, which translates to lower cost and higher output in the long term" (n. pag.). Learning curve theory acknowledges

- Learning progress is influenced by a number of variables, including time, previous experience, quality of training and so on. As a result, tracking only one of these variables might give … misleading data.
- Some performance progress is difficult to quantify and measure. If there is no specific deliverable, such as a product or a sale, it can be hard to define a single unit of output for the purpose of measuring progress.
- It's incomplete on its own. Because there are so many variables that can impact performance, it's important that the learning curve model is used in combination with other methods of tracking performance for a more complete picture. (Indeed Editorial Team, 2021)

Hermann Ebbinghaus was the first person to describe the shape of the human learning effort as a "learning curve" (Wozniak, 1999). Research since then has accepted that learning maybe hard and that there is a learning curve. This assumption minimizes the roughness and irregularity of human learning as an adaptive behavior and it does not consider the role of prior learning. Similarly, the learning curve does not represent the retention of the learning experience by the learner as useful knowledge to be applied in different and future contexts. Thus, the *wholeness* of the experience is not considered learning in learning curve theory. The only learning 'valued' is learning that reduces the time needed to complete a given task. The omission of the unvalued learning endorses a myopic notion of learning and knowledge acquisition that is task and skill focused.

By applying the notion of wholeness to the learning process and knowledge acquisition as inspired by complexity science (Holland, 1998; Miller, 2015; Mitchell, 2009), the value of all learning and knowledge acquisition is recognized and can be leveraged in novel ways (Juarrero,

1999; Pendleton-Julian & Seely Brown, 2018). This notion of wholeness aligns well with the work of Dewey (1938), Lewin (1935, 1943/2014) and Rogers (1959). By including more variables in the measure of learning and knowledge acquisition to overcome the noted weakness in learning curve theory, a more substantial model can be created that recognizes greater dimensionality in the learning and knowledge creation process.

As conceptualized, the roughness of learning variable is multidimensional and assumes that all prior learning and knowledge acquisition is relevant in any given context. Complexity science offers a platform for estimating the roughness of learning to allow the inclusion of this dimension of human learning to be measured and included in the study of human learning and human adaptive practices (Holland, 1995, 1998; Miller & Page, 2007; Mitchell, 2009; Rebout et al., 2021). Greater insight into the dimensionality of human learning as described by the roughness of learning will allow researchers to examine broader sets of inputs in understanding both the learning process and the knowledge acquired, which may be much larger than previously acknowledged and valued.

Figure 1.1 presents a graphical representation of this concept.

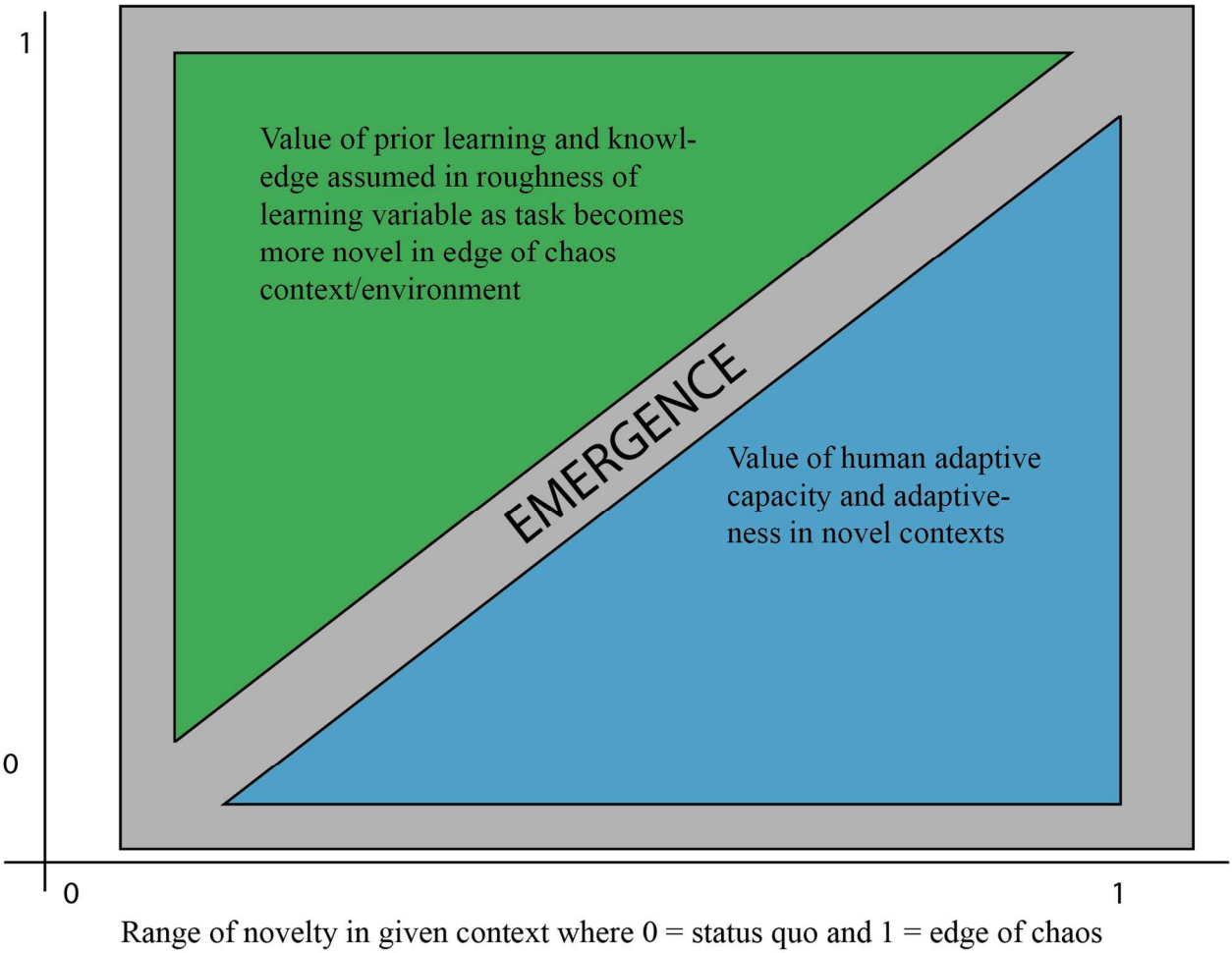


Figure 1.1. Conceptualization of tradeoff between prior learning, emergence, and edge of chaos context.

Ebbinghaus (Wozniak, 1999), in defining the learning curve, estimated improvement in a given skill over time. Thus, terms like *steep learning curve* suggest the learning activities and learning expectations should be configured to accommodate such. This is a form of linear thinking that is inconsistent with the learning described by Marsick and Watkins (1990), Eraut (2004), and others (Livingstone, 1999; Mezirow, 1997) who recognize the irregularity and

ambiguity associated with human learning. Ebbinghaus also omits prior learning and knowledge as well as the novelty of the task objective as variables that effect the slope of the learning curve. The roughness of learning variable attempts to measure that irregularity and ambiguity, and provide a proxy measure to estimate the energy, entropy and time associated with a learning effort. As conceptualized, the roughness of learning, by definition, includes prior learning and experience in terms of its inputs. Depending on the prior learning experience, the input variables associated with prior learning, in the form of experience and time vary from learner to learner. Similarly, the ability to aggregate prior learning and experience at a community or organizational level, is reflected in the collective roughness of learning associated with a given state.

Challenges with Defining and Measuring the Roughness of Learning Variable

As Dewey notes, "we know we don't know, and we know we don't know what we don't know. We also know that if we know more, right, or wrong, we will have advanced our craft. Failure is instructive. The person who really thinks learns quite as much from [his, hers and our] failures as from [his, hers and ours] successes" (Dewey, 1938). Many scholars and researchers accept that our current understanding of the learning process and knowledge acquisition and emergence (defined as new knowledge) resembles is inadequate (National Academies of Sciences, Engineering, and Medicine, 2018). Complexity science provides both the quantitative and qualitative platform to apply an interdisciplinary approach to probe the vacancies and gaps in our understanding. According to Bar-Yam and colleagues (2022), "using concepts and methods of the study of **complex systems** for providing direction and strategies" will support deeper understanding of learning (p. 1).

Developing a roughness of learning variable using methods from complexity science builds on the work of Marsick and Watkins (1990) and others to bolster IIL by adding a new

measure that quantifies the complexity associated with the learning effort. A review of the literature finds that current measures of learning are developed by using linear methods for assessing learning on the basis of self-assessment and self-reporting (Harner, 2013; Silva, 2007; Taber et al., 2008).

The base model inspiration for this effort is the logistic population growth model presented by Sir Robert May (1975) to illustrate the behavior of a system at various states that range from stability to edge of chaos to dissipation. The model is $x_{n+1} = rx_n(1-x_n)$. x_n is a number between 0 and 1 that represents the ratio of the existing population to the maximum possible population. The values of interest for the parameter r are those in the interval [0,4], so that x_n remains bounded on [0,1]. The nonlinear difference is intended to capture two effects:

- *Reproduction*, where the population will increase at a rate proportional to the current population when the population size is small.
- *Starvation* (density-dependent mortality), where the growth rate will decrease at a rate proportional to the value obtained by taking the theoretical carrying capacity of the environment less the current population. (May, 1976)

Translating May's model to develop the roughness of learning model focuses on developing a measure of complexity associated with the human learning process that is a proxy for the parameter represented by rx_n. Summarizing this using time series analysis, if the learner increases adaptiveness through learning and knowledge, the complexity in the context decreases at some rate and the learner sustains or returns to a stable state. Applying May's model there is a floor and a ceiling for adaptiveness to meet environmental turbulence. If there is inadequate adaptiveness either as a result of inadequate capacity or *complexity in the context*, the environmental turbulence cannot be adequately reduced and a chaotic state emerges.

A review of the literature found several studies used qualitative methods to *identify* informal and incidental learning (Harner, 2013; Silva, 2007; Taber et al., 2008). In general, these studies identified the use of informal learning was supplemented by incidental learning based on the nature of the context and the level of turbulence felt in the context. The source of the turbulence manifested as uncertainty in how to respond and ranged from novelty in the moment (never seen the context before) to known crisis in the moment where consequences of knowledge gaps were extreme (death and destruction of property). These studies noted the use of reflection both in the moment and post experience as sources of knowledge creation.

A review of prior research found different *methods* to *measure* different dimensions of incidental learning. Boechler, Steffler and Mansour (2005) examined incidental learning in hypermedia environments using Marsick and Watkins (2001) to define incidental learning. The study hypothesized that incidental learning during hypertext searches "occurs when one acquires information peripheral to the goal of the search task even when the goal may be adjusted during the task" (p. 120). To measure incidental learning Boechler, Steffler and Mansour (2005) suggest "one obstacle to making use of incidental learning is developing a method for measuring knowledge that is conscious only at retrieval…. One way of accessing implicit memory is through *priming tasks* [italics added] *that require the participant to give a response without a direct request for the target information* [italics added]…." (p. 120).

Crawford and Machemer (2008) examined incidental learning through the lens of problem-based learning (PBL) and used "a combination of qualitative and quantitative methods to define dimensions of incidental learning in a studio setting. Patterns of student's preferences for certain incidental learning skills [were] identified" (p. 104). Crawford and Machemer (2008) used a written survey to collect data from 21 participants in an 8-week PBL based course. The

instrument included 19 items using a 5-point Likert scale asking participants to "rate how the PBL experience impacted their learning for each of the 19 incidental learning outcomes" (p. 108).

The methods identified in prior research are context specific and the emphasis ranges from identifying applications of incidental learning (Harner, 2013; Silva, 2007; Taber et al., 2008); specific dimensions of incidental learning, (Crawford & Machemer, 2008); and methods for extracting incidental learning influence in a given context (Boechler et al., 2005). As the context for this study was to examine the influence of incidental learning on adaptiveness in a novel context, new instruments (informed by prior research in incidental learning in uncertainty) were created as part of the study.

Instruments exist to measure adaptive capacity and rate of adaptiveness in the context of climate change and coping capacity. To the extent that the underlying influences on adaptiveness were generalizable, these instruments were used to estimate adaptive behavior identifying latent variables and their relationship amongst each other. Ultimately, the latent variables of individual incidental learning, uncertainty and adaptiveness are identified and modeled using structure equation modeling methods.

Human Knowledge as Adaptive Capacity

In this model, *individual adaptive capacity* is defined as the *range within which a unit of interest may change its behavior to respond to a stimulus in pursuit of an objective*, either to improve an outcome or avoid adverse consequences (Smit & Wandel, 2006; Yohe & Tol, 2002). Included in this range is the ability of the unit of interest to use warehoused *rules* from prior learning. The unit of interest may be a human, an ant, an organization, or an economy. To increase individual adaptive capacity, the effective adaptive range must be increased by some

means (Smit & Wandel, 2006; Yohe & Tol, 2002). In the context of this study, the effective adaptive range is increased through forms of human learning.

David Kolb (1984) describes humans as *"the learning species"*, where human learning provides the primary source of our adaptive process:

> Human beings are unique among all living organisms in that their primary adaptive specialization lies not in some particular physical form or skill or fit in an ecological niche, but rather in identification with the process of adaptation itself – the process of learning. We are thus the learning species, and our survival depends on our ability to adapt not only in the reactive sense of fitting into physical and social worlds, but in the proactive sense [through innovation] of creating and shaping those worlds….We have cast our lot with learning, and learning will pull us through. But this learning process must be reimbued with the texture and feeling of human experiences shared and interpreted through dialogue with one another. (pp. 1–2)

Expanding upon Kolb, Pendleton-Jullian and Seely Brown (2018) and Siemens (2005) emphasize that *contexts trigger, and networks facilitate* the adaptive process of human learning. Pendleton-Jullian and Seely-Brown (2018) borrow from ecology to use ecosystem dynamics to describe social ecology as the network of

> relationships and interactions between individuals, and between individuals and the world, in terms of social exchanges and influences. Just as ecosystems in nature can be studied at different scales and with different relationships – they border, overlap, and nest within each other – we need to understand social ecosystems as [human] communities that do the same. Ranging in scale from families, to neighborhoods, to cities, to regions, whether face-to-face or digitally networked communities, they can be approached,

> studied, and understood as webs of entangled exchanges between people situated in temporal and spatial contexts. (pp. 37–38)

Applying principles of complexity science, Pendleton-Jullian and Seely Brown (2018) highlight the interconnectedness of the whole through self-organizing, interacting processes as the starting place for human learning that results in emergence. Quoting Steven Johnson (2001),

> self-organizing systems…solve problems by drawing on masses of relatively stupid elements, rather than a single, intelligent "executive branch." *They are bottom-up systems, not top-down.* They get their smarts from below…. In these systems, agents residing on one scale start producing behavior that lies one scale above them: ants create colonies; urbanites create neighborhoods; simple pattern-recognition software learns how to recommend new books. *The movement from low-level rules to higher-level sophistication is what we call emergence*." (p. 18, 170)

Rate of Human Adaptiveness – How and When We Learn

Numerous scholars have shared insights into how and when we learn. Many leave out the variables of time and environmental state in examining the rate of human adaptiveness supported by human learning. George Siemens offers a learning theory that embeds this notion of rate of adaptiveness through learning methods.

Combining the concepts of wholeness as defined by networks and interactions within networks described by Pendleton-Jullian and Seely-Brown (2018) with the concept of enabling constraints to define the context as described by Juarrero (1999), George Siemens (2005) provides a learning theory deeply rooted in complexity science and the unique adaptive behavior of humans to *make meaning from learning*. Echoing other proponents of complexity science as a platform for imagining the world, Siemens (2005) embraces the notion of

> chaos as a new reality for knowledge workers…. Chaos is the breakdown of predictability, evidenced in complicated arrangements that initially defy order…. Chaos states that meaning exists – the learner's challenge is to recognize patterns which appear hidden. Meaning making and forming connections between specialized communities are important. (p. 3)

George Siemens, in an interview on 10/19/2020, brings additional dimensionality to the role of context in distinguishing between machine "learning" and human learning in a given context (Watkins & Nicolaides, 2020b). Specifically, Siemens notes the ability of the human to include *sensemaking* that provides for a broader comprehension of the context in terms of time, space and place where the past and the future are considered. Siemens' sensemaking and Juarreno's enabling constraints are variants of a process human's use to establish adaptive capacity and ignite the rate of adaptiveness as part of the self-organizing process used in edge of chaos contexts. Siemens (2005) describes his learning theory for the whitewater world as connectivism:

> Connectivism is the integration of principles explored by chaos, network, and complexity and self-organization theories. Learning is a process that occurs within nebulous environments of shifting core elements – not entirely under the control of the individual. Learning (defined as actionable knowledge) can reside outside of ourselves, is focused on connecting specialized information sets, and *the connections that enable us to learn more are more important than our current state of knowing* [italics added]. (p. 3)

Embedding the complexity science notions of sensitive dependence on initial conditions and self-organizing criticality as adaptive triggers to maintain a given phase state, connectivism

> is driven by the understanding that decisions are based on rapidly altering foundations. New information is constantly being acquired. The ability to draw distinctions between important and unimportant information is vital. The ability to recognize when new information alters the landscape based on decisions made yesterday is also critical. (Siemens, 2005, p. 4)

Fusing Siemens (2005), Juarrero (1999), Pendleton-Jullian and Seely Brown (2018) with Marsick and Watkins (1990, 2017) provides a platform for adding principles from complexity science to a human learning theoretical base that adds dimensions of time (sensitive dependence on initial conditions [prior learning and knowledge as well as context] with self-organizing efforts in the moment [applied incidental learning methods] to offer more structure to human learning motivation and efforts.

Role of Informal and Incidental Learning in Estimating Roughness of Learning

Likely many factors are present in the measurement of the roughness of learning, including instinct, the senses, and latent adaptive responses beyond human learning and human knowledge. This study attempted to isolate a primary adaptive method used by humans to respond to their environment: learning, specifically, learning that is described by Marsick and Watkins (1990, 2017) as IIL.

Depending on the nature of the environmental challenge, the reliance on learning and knowledge likely differs. For instance, the split-second effort to avoid an accident is likely more influenced by basic survival instincts than some defined form of learning. Fortunately, our need to use basic survival instincts are few and our primary form of adaptiveness is our ability to learn and use prior knowledge. As Marsick and Watkins (1990, 2017) and others note (Eraut, 2004; Livingston, 1999), most of the learning is informal and certainly that is no surprise, and the

advent of formal education and training programs is less than 300 years old. Informal and incidental learning has been and remains the prevalent form of human learning. We learn from each other and we learn from experience. The roughness of learning adds a measure of effort and complexity to our understanding of the learning experience.

Statement of the Problem

Human learning is a complex activity according to numerous studies and theories. Applying the principles of complexity science to the process of human learning to identify the roughness of learning is the goal of this study. The problem addressed in this this study is to isolate and measure the roughness of informal and incidental learning as defined by Marsick and Watkins (1990) as it emerges in a complex gaming environment. This study used the principles of complexity science to identify the roughness of learning variable in the human learning process and attempt to isolate the role of incidental learning in the adaptive process used by humans in edge of chaos situations.

Purpose of the Study

The purpose of the CraftDawg study was to identify, develop and analyze a new variable associated with the informal and incidental learning process as conceptualized by Marsick and Watkins (1990, 2017). The learning variable of interest was the fractal described as the *roughness of learning*. At its core, the roughness of learning variable was conceptualized to measure the complexity of the learning challenge based on context and assess how this complexity changes (if at all) over time. As Holland (1995, 1998) noted, complexity was defined by its non-linear behavior and potentially erratic behavior over time. The roughness of learning variable was developed to capture this form of complexity in the human learning effort at points in time.

To accomplish this purpose, the research questions shown in Table 1.1 were examined.

Table 1.1

CraftDawg Study Research Questions

Number	Question
RQ 1	To what extent does incidental learning affect adaptiveness in a novel situation?
RQ 2	What is the relationship between uncertainty and adaptiveness in a novel situation?
RQ 3	Is there a roughness of learning variable that measures complexity in adaptiveness?

Significance of the Study

Machine learning is advancing at an exponential rate and a rate much greater than human learning. While machine learning is able to advance from its small base quickly, it relies on two inputs: the power of the computer to rapidly model and predict outcomes and the ability of humans to make meaning of those outcomes. Machines are computationally quicker at calculations and producing complicated simulations with multivariant interactions. *Yet machines cannot make meaning—they can simply produce output*. Certainly, AI, deep learning and machine learning are creatures of human ingenuity, but without humans to apply constraints in the form of values and culture, machine learning will not be the value added, human made tool it might be. As Polanyi (2009) reminds us, "we know more than we can tell" (p. 4). This is the *hold back* that cannot be made available to the *fast-learning* machines.

The significance of this study arises from adding a new, quantifiable insight to the study of informal and incidental learning by adding a measure of complexity to the learning that arises in novel contexts. By advancing the work of Marsick and Watkins (1990), Eraut (2004) and Livingston (1999), with the addition of both the concept and method for measuring learning complexity and change in learning complexity, development methods can be designed to recognize the irregularity in the learning process using a quantitative measure. This also allows disparate learning contexts to be compared on the basis on the roughness of learning. By being able to compare, methods of learning can be better designed, managed, and assessed.

CHAPTER 2

REVIEW OF THE LITERATURE

This chapter is divided into three sections. The first section presents several streams of literature to explore the convergence and divergence of two learning theories: experiential learning theory (ELT) as conceptualized by Kolb (1984) and informal and incidental learning theory (IIL) as developed by Marsick and Watkins (1990). The purpose of this review is to identify the foundational links of these two theories. Critiques of these theories are limited to the theoretical level.

A second stream of literature is presented to review the core features of complexity science and complex adaptive systems as a derivative of complexity science. Applicable aspects of complexity science; the nature of complex adaptive systems; and the adaptive process used to maintain system integrity are described. As complexity science has advanced beyond the theoretical stage, the critiques are limited to a brief review of the lack of consensus on the nature of complex adaptive systems.

These literature streams provide the grounding for a review of an emerging learning theory based on the concepts of complexity science, the holistic nature of experiential learning as a process of knowledge creation, and the specifics of the learning process associated with informal and incidental learning.

The second section presents and critiques empirical studies that examine forms of experiential learning and informal and incidental learning in complex contexts. The emphasis in

selecting the studies included involved examining how the researchers analyzed human adaptive practices in the form of learning while experiencing edge of chaos situations.

The third section presents the theoretical framework, the hypotheses associated with the study and the research questions guiding the study.

Experiential Learning as an Adaptive Process

Kolb and Kolb (2009) define human learning as "the basic process of human adaptation" (p. 42). In developing ELT, Kolb (1984) synthesized the work of Dewey, Lewin, and Piaget "to develop a dynamic and holistic model of the process of learning from experience and a multi-linear model of adult development" (p. 43). The holistic nature of ELT defines "learning as the major processes of human adaptation involving the whole person".

This is a broad definition of human learning that is strongly rooted in gestalt philosophy, specifically Lewin's field theory. Lewin (1943 embraces the wholeness of the learning moment by "identifying the present situation as being maintained by the interaction of environmental forces with the person" (p. 17):

> One should view the present situation – *the status quo* – as being maintained by certain conditions and forces. A culture…is not a static affair but a live process like a river which moves but still keeps a recognizable form. In other words, we have to deal, in group life and individual life, with what is known in physics as "quasi-stationary" processes…. Neither group "habits" nor individual "habits" can be understood sufficiently by a theory which limits its consideration to the processes themselves and conceives of the "habit" as a kind of frozen linkage, an "association" between these processes. Instead, habits will have to be conceived of as a *result of forces in the organism and its life space, in the group and its setting* [italics added] …. The process is but the epiphenomenon, *the real*

> *object of study is the constellation of forces* [italics added]. Scientific predictions or advice for methods of change should be based on an analysis of the "field as a whole", including both its psychological and nonpsychological aspects. (Lewin, 1943/2014, pp. 17–18)

John Dewey (1938) applies Lewin's "constellation of forces" in identifying and describing the chaotic and clumsy nature and pattern of adult learning through experience. The rough and irregular nature of experience

> does not mean that all experiences are genuinely or equally educative. Experience and education cannot directly equate to each other. For some, experiences are *mis-educative* [italics added]. Any experience is mis-educative if it has the effect of arresting or distorting the growth of further experiences…. Experiences may be so disconnected from one another that, while each is agreeable or even exciting in itself, they are not linked cumulatively to one another. *Energy* [italics added] is then dissipated and [the] person becomes scatterbrained. (Dewey, 1938, p. 25)

According to Dewey, the nature of adult learning through experience to grow adaptive capacity is reasonably described as nonlinear and ambiguous; it is rough and irregular (Marsick & Volpe, 1999). It is pattern-based, with a continuous, asynchronous flow. When studied at a proper scale, a learning pattern is discernible over time. Dewey (1938) says it well "*the central problem of an education based upon experience is to select the kind of present experiences that live fruitfully and creatively in subsequent experiences* [italics added]" (p. 26). Dewey's observation is consistent with a complexity science notion that learning (behavior) is neither right nor wrong, but instead follows a pattern, as all experiences are educative. However, as Dewey (1938) notes, *not* all experiences are of equal value in learning, and some may have

negative value initially (and thus growing or reducing adaptive capacity) (p. 25). Dewey (1938) contends that "*every experience* [italics added] enacted and undergone modifies the one who acts and undergoes, while this modification affects whether we wish it or not, the quality of subsequent events" (p. 34).

Essential to adaptive capacity change is an openness to and incorporation of *feedback* to inform current positions and advise future choices and needs. In the context of human adaptive capacity, Argyris and Schöen (1974) incorporate the notion of feedback (single and double-loop learning protocols) and reflection in their model of adult learning. Argyris (1976) describes the role of feedback in assessing the effectiveness of a given action (behavior):

> Effective action is more a succession of comparison between actions (behavior) and feedback from the environment, which provide information for the next action or decision. Since decisions are made on necessarily incomplete information, once executed, feedback is *required* [italics added] to evaluate their effectiveness. (p. 365)

Feedback is the catalyst for adaptive behavior and triggering the rules to use in adapting behavior as reflected in learning from experience.

In approaching learning as a process informed by experience, Kolb (1984) notes "experiential learning theory…proceeds from a different set of assumptions. Ideas are not fixed and immutable elements of thought but are formed and re-formed through experience" (p. 26). Synthesizing the work of Lewin, Dewey and Piaget, Kolb (1984) holds "learning is an emergent process whose outcomes represent only historical record, not knowledge of the future" (p. 26). Conceiving of learning as a process and not an outcome, positions it on a continuum that ranges from the comfort of predictability to doubt and uncertainty:

> How do I reconcile my own sense of continuity and predictability with what at times appears to be a chaotic and unpredictable world around me? I move through my daily round of tasks and meetings with a fair sense of what the issues are, of what others are saying and thinking, and with ideas about actions to take. Yet I am occasionally upended buy unforeseen circumstances, miscommunications, and dreadful miscalculations. *It is this interplay between expectation and experience that learning occurs* [italics added]. (Kolb, 1984, p. 28).

Kolb (1984) positions learning as "[a] holistic process of adaptation to the world" (p. 29):

> Experiential learning is not a molecular educational concept, but rather is a molar concept describing the central process of human adaptation to the social and physical environment…. To learn is not the special province of a single specialized realm of human functioning such as cognition or perception. It involves the integrated functioning of the total organism – thinking, feeling, perceiving, and behaving. (Kolb, 1984, p. 31)

Kolb (1984) boldly holds that "in addition to addressing the nature of specialized human functions, experiential learning theory is also concerned with how these functions are integrated by the person into a holistic adaptive posture toward the world" (p. 32). He declares that

> learning is *the* major process of human adaptation. This concept of learning is considerably broader than that commonly associated with the school classroom. It occurs in *all* [italics added] human settings…. Therefore, it encompasses other, more limited adaptive concepts such as creativity, problem solving, decision making, and attitude change that focus heavily on one or another of the basic aspects of adaptation. (Kolb, 1984, p. 32)

In summary, Kolb (1984) provides the definition of learning that informs this study:

> *Learning is the process whereby knowledge is created through the transformation of experience*…. This definition emphasizes several critical aspects of the [human] learning process as viewed from the experiential perspective. First is the emphasis on the process of adaptation and learning as opposed to content or outcomes. Second that knowledge is a transformation process, being continuously created and recreated, not an independent entity to be acquired and transmitted. Third, learning transforms experience in both its objective and subjective forms. Finally, to understand learning, we must understand the nature of knowledge, and vice versa. (p. 38)

Kolb (1984) synthesizes Lewin, Dewey and Piaget in noting that

> to understand learning, we must understand the nature and forms of human knowledge and the processes whereby this knowledge is created…. Knowledge is the result of the transaction between social knowledge and personal knowledge. The former, as Dewey noted, is the civilized objective accumulation of previous human cultural experience, whereas the latter is the accumulation of the individual person's subjective life experiences. Knowledge results from the transaction between these objective and subjective experiences in a process called learning. (pp. 36–37)

As Kolb implies, the adult learner must expend energy (increase entropy) to develop adaptive capacity. It occurs at a deeper cognitive level, according to Collell and Fauquet (2015), who describe the human brain as "a thermodynamic device aimed at processing information. Consequently, brain activity has often been modeled in thermodynamic terms and cognitive processes in information terms" (p. 1). The first and second laws of thermodynamics confirm that thermodynamic devices require an energy source to work.

Kolb (1938), Lewin (1984), and Dewey (1935) emphasize a human's *latent ability* to learn (individually and as communities of practice) as a primary source of increasing adaptive capacity. In addition to a human's latent adaptive traits, *time* is an essential variable in the study of how individuals develop their adaptive capacity. While Kolb acknowledges that time and space are elements in the learning process, these are used more to delineate learning between performance and development.

Critiques of Experiential Learning Theory

A review of the literature provides many critiques of given aspects of Kolb's comprehensive model and theory. Greenaway (n.d.) provides a compilation of scholarly critiques that address details of the theory. Webb (2003) summarizes the critique noting " the contradictions and unresolved foundational assumptions inherent in ELT rapidly accumulate when one turns to an examination of the constructs promulgated to develop the Experiential Learning Model" (p. 16). Webb (2003) challenges ELT

> as an attempt to integrate *incompatible* domain assumptions, using fallacious and erroneous first principles as starting premise. The result is inherent inconsistency and contradiction. The remedy lies in either, (1) choosing sides, taking first principles and domain assumptions from one stream of intellectual thought or the other; (2) designing a third dimensional, philosophical system of thought; (3) abandoning the theory; or (4) justifying the inconsistencies as they presently exist. (p. 73)

Based on these critiques, reconciling the "remedy options" is not doable. Thus, for this study, this side is chosen, and these foundational principles of ELT are accepted:

1. Learning is best conceived as a process, and time and space (context) are elements in the process (learning is not defined by outcomes);

2. Learning is a continuous process grounded in experience of the learner(s);
3. The process of learning requires the resolution of conflicts between dialectically opposed modes of adaptation to the world;
4. Learning is a holistic process of adaptation to the world;
5. Learning involves transactions between the person and the environment; and
6. Learning is the process of creating knowledge.

Kolb's ELT provides theoretical and philosophical support to examine informal and incidental learning as conceptualized by Marsick and Watkins (1990). With the same philosophical foundations from Dewey and Lewin, IIL allows the adaptive process through learning described by Kolb to be more narrowly examined based on the Marsick and Watkins' (1990) definition of IIL. This limiting brings the focus to embedded processes humans use to *recognize the need for and increase adaptive capacity through learning in environments that are less structured, less managed, more ambiguous, more self-directed, and more self-motivated, an environment that better mimics the natural world.*

Overview of Informal and Incidental Learning as a Source of Human Adaptiveness

Dewey, Lewin, Follett, Knowles, and Mezirow, are among the most influential theorists of adult learning (Conlon, 2004). Synthesis of select work from Dewey (1938), Lewin (1935, 1943), and Knowles (1978) provides foundational support for Marsick and Watkins's (1990) IIL. Each theorist provides a deeper understanding of how adults develop their habits, beliefs, and truths, and offers direction on how adults *adapt* their habits, beliefs, and truths based on the effects of disorienting dilemmas (perturbances) (Dewey, 1938; Lewin, 1935). The roots of experiential learning and informal and incidental learning align through these theorists. The

notion of wholeness in the learning process and learning as an adaptive process are common to both theories.

Individual Adaptive Capacity Developed Through Range of Informal and Incidental Learning

Marsick and Watkins (1990) IIL, based on the work of Dewey (1938), Lewin (1935, 1943), and Argyris and Schöen (1974) is the primary guide for this study. Marsick and Watkins (1990) define informal and incidental learning as a derivative of adult learning, describing it as:

> Informal learning, a category that includes incidental learning, may occur in institutions, but it is not typically classroom-based or highly structured, and control of learning rests primarily in the hands of the learner. Incidental learning, a subcategory of informal learning, is defined by Watkins as a byproduct of some other activity, such as task accomplishment, interpersonal interaction, sensing the organizational culture, trial-and-error experimentation, or even formal learning. Informal learning can be deliberately encouraged by an organization, or it can take place despite an environment not highly conducive to learning. *Incidental learning, on the other hand, almost always takes place in everyday experience, although people are not always conscious of it* [italics added]. (p. 12)

Marsick and Watkins (1990) suggest adults may decide *not* to learn from experience, relying instead on "presuppositions without questioning the need to do anything differently, not considering the experience as an opportunity for learning, or simply rejecting the option of learning" (p. 20). They imply an intentional and active (though possibly not conscious) decision is made. In complexity science, energy (based on entropy levels) is expended either consciously or not to engage in learning. The level of energy expended, and the level of consciousness is a

function of the *phase state* the person is in relative to his or her environment. Translated through the prism of complexity science, a person's sensitive dependence on initial conditions dictates the level of interest he or she would have in actively engaging in a learning effort: formal, informal, or leveraging incidental learning.

Marsick and Watkins (1990) describe "informal and incidental learning as taking place along a *continuum of conscious awareness* [italics added]" (p. 20). Van Noy, James, and Bedley (2016) offer descriptions of informal learning based on a meta-review of over 600 publications published from 1986 – 2015. They populate their "continuum of formality" with a range of learning activities distinguished by a set of attributes including the location in which the learning occurs, whether learning is instructor or student led, the extent to which content learned is an organized curriculum, and one's purpose for seeking knowledge (van Noy et al., 2016, p. i). They categorize informal learning as ranging between organized informal learning and everyday informal learning, which is distinguished by a "range of intentionality in which learning can be self-directed, incidental, and/or embedded in the process of socialization" (van Noy et al., 2016, p. i).

Studies by Eraut (2004), Livingston (2001), and Malcolm, Hodkinson, and Colley (2003) are consistent in distinguishing informal learning based on the intent of the learner and the methods used to learn. Similarly, Marsick and Watkins (1990) also emphasize a person's intent and associated level of consciousness aroused in the person to actively engage in an informal learning pursuit. The notion of intentionality is critical in accepting informal learning as a method of changing individual adaptive capacity, primarily when used in the context of complexity science's principle of self-directed criticality in complex adaptive systems. Criticality arises when a system (a human, an organization) approaches the edge of chaos (Bak et al., 1988).

As part of his research of *unconscious cognition*, Reber (1989) studied "the phenomenon of implicit learning, the process by which knowledge about rule governed complexities on the stimulus environment is acquired independently of conscious attempts to do so" (p. 219). Reber (1989) suggests *implicit learning as* a source of adaptiveness that increases with encroaching criticality (novel stimulus circumstances). The system (individual) has an increasingly acute awareness on some level of systemic instability and dysfunction. The triggering event may be subtle or explosive, but an intuitive level of awareness of something changing arises. With his or her level of consciousness triggered, the level of awareness increases and active engagement in more explicit informal learning ensues.

> Livingstone (2004) distinguishes explicit informal learning
>
> from everyday perceptions, general socialization, and other tacit learning by *peoples' conscious identification of the activity as significant learning* [italics added]. The important criteria that distinguish explicit informal learning are retrospective recognition of both a new significant form of knowledge, understanding, or skill acquired on one's own initiative and also recognition of the process of acquisition. (p. 4)

Marsick and Watkins (1990) contend that the distinction between incidental learning and informal learning is the level of attention or consciousness used. Eraut (2004) suggests a level of planning distinguishes types of learning. He distinguishes unplanned "reactive learning or opportunistic learning that is near-spontaneous and deliberative learning that is more considered" (Eraut, 2004, p. 250).

The literature consistently holds experience is a significant impetus for both informal and incidental learning. As Marsick and Watkins (1990) note, "a central feature of informal and incidental learning is learning from and through experience" (p. 15). Eraut (2004) emphasizes

notions from Dewey (1938), noting, "we learn from distinctive experiences in a continuous flow of experiences that we are embedded in throughout life" (p. 250). Eraut (2004) alludes to the *triggering* of learning occurring when an experience is somehow disorienting or novel, i.e., distinctive on some basis. This triggering ignites our consciousness and drives our awareness, driving us to adaptation through learning.

Eraut (2004) describes "discrete experiences are distinguished from this [continuous] flow and become meaningful when they are accorded attention and reflected upon" (p. 251). Mezirow (1997) calls it a *disorienting dilemma* when a person faces a crisis of knowledge and a conflict of understanding. According to Mezirow (1997) reflective learning, no matter its source: formal, informal, or incidental, becomes transformative, as it changes a prior frame of reference, whenever "assumptions or premises are found to be disorienting, inauthentic, or otherwise invalid. Transformative learning results in new or transformed meaning schemes or, when reflection focuses on premises, transformed meaning perspectives. To the extent that adult education [achieves] reflective learning, its goal becomes one of either confirmation or transformation of ways of *interpreting experience*" (Mezirow, 1997, p. 6). The triggering event forcing the individual to confront the disorienting dilemma is associated with the sensitive dependence on initial conditions. To the extent the event is novel or inconsistent with prior beliefs, the person reacts and attempts to adapt to the event.

The research of Herriott, Levinthal, and March (1985) aligns well with Marsick and Watkins's (1990) IIL and provides a "class of differential equation models for examining incremental experiential learning by economic actors" including organizations and individuals (p. 298). The models of Herriott et al. (1985) "reflect features of adaptive behavior drawn from observations of decision making in organizations. They see choice as stemming from *decision*

rules that adjust cumulatively on the basis of trial-by-trial monitoring of the success or failure associated with past adjustments [italics added]" (p. 299). Herriott et al. (1985) also note their models are based on prior work on organizational learning and adaptive economics combined with modeling of elementary learning by humans and other animals. In their research, they introduce "modest complexities, particular in ways in which learning occurs along several interacting dimensions and within an *ecology of learning* [italics added]" (Herriott et al., 1985, p. 298). This study is of note as it addresses research questions related to assessing a form of informal learning; *trial-by-trial learning* (Herriott et al., 1985, p. 300).

Herriott et al.'s (1985) trial by trial form of informal learning matches well with the creeping awareness of environmental change arising in systems moving towards the edge of chaos. Trial by trial learning is an *intentionally incremental* form of explicit informal learning embedding forms of feedback as part of its method. It is not trial and error, but rather trial, feedback, revise, repeat, and through each iteration, knowledge is gained and leveraged individually and systematically.

Incidental Learning – A Subcategory of Informal Learning

"We can know more than we can tell" is how Polanyi (1966; 2009, p. 4) described tacit knowledge of humans. Autor (2014) labelled this description as the Polanyi Paradox to highlight a basic element of incidental learning that cannot be emulated by machines – the innate ability of humans to acquire (through incidental learning) and deploy (as tacit knowledge) learning in "tasks requiring flexibility, judgement and common sense [that] contemporary computer science seeks to overcome…by building machines that learn from human examples, thus inferring the rules that we [humans] tacitly apply but do not explicitly understand" (p. 2).

This human ability to use tacit knowledge and incidental learning to self-organize in the novel situations is highlighted by Marsick and Watkins' (1990) IIL. Identifying the effect of incidental learning in the adaptive process allows a deeper appreciation for this uniquely human ability. This study relies on the Marsick and Watkins' (1990) conceptualization of incidental learning as "a by-product of some other activity, such as task accomplishment, interpersonal interaction…,or trial-and-error experimentation. Incidental learning is never planned or intentional, whereas informal learning can be planned or intentional" (p. 6). As Marsick and Watkins (1990) argue, "Incidental learning…almost always takes place in everyday experience although people are not always conscious of it" (p. 12).

> Marsick and Watkins (1990) define incidental learning through examples, noting that it includes learning from mistakes (including how people frame experiences as mistakes), learning by doing (including trial-and-error experimentation), learning through a series of covert interpersonal experiments…. Mistakes are potent tools for learning, in part, because individuals so often feel brittle about making them. As a result, they will be more likely to reflect on the mistake to determine its causes and to prevent its repetition. (p. 13)

Consistent with Autor's description of the Polanyi Paradox, Marsick and Watkins (1990) emphasize the role of meaning as playing a "central role in [human] learning" even though it is "difficult, if not impossible, to observe and measure behaviorally. Meaning is derived through reflection on experience" (p. 20). Logically, it can only be observed as a change in behavior *after the meaning is being made or is made*.

Supportive of the idea that informal and incidental learning are powerful human adaptive practices as defined by complexity science, Marsick and Watkins (1990) "believe that informal and incidental learning are needed most when individuals experience a situation as non-routine.

Learned responses and habitual ways of acting are least likely to work under [novel] conditions. The situation might be completely new and thus fully non-routine; or it might be potentially routine but treated as non-routine for some reason" (p. 20). Marsick and Watkins (1990) highlight the flexibility of informal and incidental learning as applied in a novel situation. They also note the roughness and wholeness of the informal learning process, citing McClellan's (1983) descriptions of "the nature of the inquiry [in a non-routine situation] remains 'messy, multivariate, back-forth-many-stages-all-at-once'" (Marsick & Watkins, 1990, p. 23).

Recognizing the nature of complex situations, Marsick and Watkins (1990) suggest incidental learning may be the more flexible and primary source of knowledge in responding to a

> given complex situation, when our attention is being pulled to a specific task, [and] we must decide what to include or exclude from our interpretation of a situation. We draw on our past experience and, most importantly, we typically draw on frameworks for understanding which we have already developed because we do not have time to build a new framework from scratch. It is only when we think that the framework does not match the experience that we develop a new framework. (p. 24)

According to Marsick and Watkins (1990), "Incidental learning is delimited by the primary activity being undertaken. When incidental learning is coincident to task accomplishment, the nature of the task defines the substance, the purpose, the time available for learning, and the criteria for success" (p. 24). Marsick and Watkins (1990) recognize that "the way in which a person frames or sets the problem [is a critical factor that delimits incidental learning], since the messy nature of reality does not easily lend itself to the scientific purity of laboratory conditions" (p. 25). According to Marsick and Watkins (1990),

> problem framing is crucial to incidental learning. People can focus solely on the task at hand, or they can widen their vision to include aspects of the context in which the problem rests and thus open themselves to both multiple definitions of the problem and to an examination of other learning related concerns. (pp. 25–26)

Intellectual capability is also included as a delimiter of incidental learning by Marsick and Watkins (1990, p. 26). This is a similar concept to adaptive capacity as used in the study. Identifying as the most significant of Jacque's (1986) findings

> was that individuals vary considerably in their time frame or work capacity: [where] capacity "comprises a person's cognitive power and psychological tools and orientation. Cognitive power is the mental force a person can exercise in processing and organizing information and in creating a complex world; it is measurable in what I call time frame. (p. 372)

Responding to the novel and dynamic nature of edge of chaos states and situations may require individuals to "know more [and do more] than they can tell" (Polanyi, 2009, p. 4) by relying on the powerful domain of incidental learning as part of informal learning. As described by Marsick and Watkins (1990), incidental learning enables creative and innovative adaptive responses that arise from interactions that produce novel, chaotic and ambiguous situations.

Weaving Complexity Science Concepts and Informal and Incidental Learning

Marsick et al. (2017) suggest their conceptualization of informal and incidental learning provides adaptive capacity and adaptive practices by considering "where informal learning is situated in the continuum of ambiguity and unpredictability of complex learning situations, and how this understanding might reshape our perspective of informal learning" (p. 30). In their more

recent conceptualizing, Marsick et al. (2017) see complexity science as offering a foundation for positioning human learning as part of dynamical systems adaptive processes:

> Advances in complexity science, combined with cognitive sciences are applied to understand and inform human action…. Complexity science helps us discern the characteristics of a context with regard to cause and effect, and if we pay attention, how to develop capacities to respond in ways that are closer to the reality of the context, situation, and/or event. (p. 30)

Recognizing the natural turbulence associated with most contexts, Marsick, et al. (2017) accept Juarrero's (1999) description of complex systems as a "dynamic, a mess of interactions and relationships that are constantly evolving, creating ripeness for emergence, and a disruption of learned responses" (p. 30). This recognition of the interaction of systems as creating the messiness in the contexts humans encounter, provides an opening to explore human adaptive capacity through informal and incidental learning. Marsick and Watkins (1990) provide guidance on how complexity and informal and incidental learning cooperate to create adaptive capacity and emergence. This is conceptually the same generalized process described in different words by Kolb.

Rethinking Informal and Incidental Learning Through Complexity Science

Marsick et al. (2017) position complexity as creating the dynamics of a given context or environment within which informal and incidental learning occur. "Complexity science helps us discern the characteristics of a context with regard to cause and effect, and if we pay attention, how to develop capacities to respond in ways that are closer to the reality of the context, situation, and/or event" (Marsick et al., 2017, p. 30). According to Marsick et al. (2017), "A complexity science perspective embraces 'messiness,' recognizing that – within the relationships

infused by contextual characteristics, history and dynamic interactions – knowing, understanding, and perception emerge to generate action" (p. 32).

Table 2.1 compares the original model with their proposed complexity inspired model.

Table 2.1

Comparison of Marsick & Watkins' (1990) Informal and Incidental Learning Model

Select Dimensions	Original: Model 1	Complexity: Model 2
What is informal and/or incidental learning in the workplace?	A challenge triggers a fresh look at the situation, followed by a search for alternative responses, taking action, and evaluating results; incidental learning is what occurs at the interstices – what emerges when we unintentionally learn something new	A process of discerning cause and effect in the obvious and complicated domains – informal learning produces good and best practice results in response to a recognized problem.
Perceived relationship between forms of learning (formal, informal, and incidental)	Formal, informal, and incidental are a conceptual continuum of control over the learning process; on intentionality over what is learned.	Informal learning is decoupled from incidental learning to enable a goodness-of-fit perspective of prevailing learning modalities in four domains. Informal fits with obvious and complicated domains; incidental fits with complex and chaotic domains
Who learns?	Individual	The system learns – the past is integrated with the present as the elements evolve with one another and with the environment
How learning occurs (processes and practices)	Contextually supported, often self-directed process of problem solving; incidental learning is a by-product of another activity that could be formal or informal learning (the hidden curriculum)	Relationships within the system are infused by contextual characteristics, history, and dynamic interactions such that understanding, and perception emerge to generate action

Role of social interaction and social relations in learning	Unexplained	Complex systems are dynamic, a mesh of interactions and relationships that are constantly evolving creating ripeness for emergence and a disruption of learned responses

Note. Adapted from "Rethinking Informal and Incidental Learning in Terms of Complexity and the Social Context," by V. J. Marsick, K. E. Watkins, E. Scully-Russ, & A. Nicolaides, 2017, *Journal of Adult Learning, Knowledge and Innovation*, *1*(1), 27–34.

Experiential Learning and Informal and Incidental Learning Summary

Both Kolb (1984) and Marsick et al. (2017) embrace learning as an adaptive process that occurs in response to some environmental or contextual stimulus. Both acknowledge the messiness of the process and that prior learning informs the process methods. Kolb (1984) is more specific in noting the role of time in the learning process. Kolb (1984) is specific in defining both learning and knowledge while Marsick and Watkins (1990) are process specific while not defining either learning or knowledge. Both learning theories are spawned by the same foundational thinking of Lewin (1935) and Dewey (1938). Consolidating the foundational elements of these two theories provides a reasonable starting place for aligning them with the core principles of complexity science. Using Kolb's (1984) definition of the learning process and knowledge creation as a transaction between the learner and the environment with the granularity of Marsick and Watkins' (1990) IIL establishes a multidimensional foundation for further the research for both theories. Complexity science in the form of complex adaptive systems research provides a broad research platform that already includes the study of human behavior and adaptive processes in other contexts such as economics and social practices.

Complexity Science as a Foundation for the Study of Human Learning

"Human nature is full of riddles and contradictions; its very complexity engenders art – and by art, I mean the search for something more than simple linear formulations, flat solutions, and oversimplified explanations" (Solzhenitsyn, 1976, p. 125) . This eloquent description of our human experience summarizes why complexity science provides a rich and incisive platform to examine our world in a more holistic, integrated and interdisciplinary manner. Gell-Mann (1994) offers another perspective:

> all around us are facts that are related to one another. Of course, they can be regarded as separate entities and learned that way. But what a difference it makes when we see them as part of a *pattern* [italics added]! Many facts then become more than just items to be memorized – their relationships permit us to use a compressed description, a kind of theory, a schema, to apprehend and remember them. They begin to make some sense. The world becomes a more comprehensible place. (p. 89)

According to Gleick (2008), the study of complexity reveals "the irregular side of nature, the discontinuous and erratic side – these [sides that] have been puzzles to science, or worse, monstrosities" (p. 3). This description aligns well with the description of the messiness of experiential learning and specifically informal and incidental learning as described in Marsick et al. (2017).

Using complexity science as a foundation for studying human adaptiveness through learning provides a platform that is consistent with the wholeness described by Dewey (1938), Lewin (1943), James (1977), and others. It provides the language and the concepts that allow human learning as an adaptive process described by Kolb (1984) to be generalized and researched more broadly. Lewin's field theory is easily translated into Gleick's (2008)

description of complexity as “the science of the global nature of systems [and their interactions and patterns]” (p. 4). As Marsick et al. (2017) revisit IIL through the lens of complexity science, they acknowledge that “a complexity science perspective embraces “messiness”, recognizing that – within the relationships infused by contextual characteristics, history and dynamic interactions – knowing, understanding, and perception emerge to generate action” (p. 32).

Arthur (2015) summarizes why complexity science is gaining increased interest and study in a broad range of disciplines:

> Every so often a discipline gets thrown into a period of upheaval where its old ideas once taken for granted seem no longer reliable, and its practitioners search for what to put in their place. Economics is in such a period now. Slowly, over the last three or more decades, a feeling has grown among economists that their key assumptions of perfect rationality, equilibrium, diminishing returns, and of independent agents always facing well-defined problems are somehow not trustworthy, too restrictive, somehow forced. Now in the air are ideas of behavioral rationality, nonequilibrium, increasing returns, and of interconnected agents facing fundamental uncertainty in problems of decision-making. Economics has opened up to other approaches besides the standard neoclassical one. (p. ix)

In summary, the old ways are not producing reliable predictions, and it is not just in economics. Other social sciences are grappling with similar incongruencies between reality and modeled expectations. Perhaps a new paradigm will reduce this incongruency through the development of new models including the laws of nature, not just the wishes of man. Identifying predictive patterns inspires research in complexity science. Complexity science and its derivative theories provide a platform for imagining our world using different thinking, math, and dynamics

to produce predictive models based on observed data, acknowledged blindness, and appreciation of our collective integration.

The realms of complexity science and complexity theories encompass gaps between what science tries to explain and what it has yet to explain or re-explain. Over the last forty years, momentum in advancing complexity science and expanding complexity-based theories increased rapidly and in parallel with advances in computing technology and widely expanded communication networks (Mitchell, 2009). A radically improved electronic infrastructure enabled curious scientists, researchers, and scholars to explore more efficiently, share more readily, and theorize on an interdisciplinary basis (Gleick, 2008; Holland, 1998; Mitchell, 2009).

Different kinds of *regular irregularity* found in complex systems intrigued a range of scientists. Researched under an alternative scientific paradigm (Poincaréian as opposed to Newtonian), anomalies dismissed as measurement error from imprecise tools began to reveal surprising order. According to Gleick (2008),

> Physiologists found a surprising order in chaos that develops in the human heart, the prime cause of sudden, unexplained death. Ecologists explored the rise and fall of gypsy moth populations. Economists dug out old stock price data and tried a new kind of analysis. The insights that emerged led directly into the natural world – the shapes of clouds, the paths of lighting, the microscopic intertwining of blood vessels, the galactic clustering of stars. (p. 4)

Gleick (2008) describes the beginnings of the revolution we know today as complexity science:

> When Michael Feigenbaum began thinking about chaos at Los Alamos, he was one of a handful of scattered scientists, mostly unknown to one another. A mathematician in Berkley, California had formed a small group dedicated to

> creating a new study of "dynamical systems". A population biologist at Princeton University was about to publish an impassioned plea that *all* [italics added] scientists should look at the surprisingly complex behavior lurking in some simple models. A geometer working at IBM was looking for a new word to describe a family of shapes – jagged, tangled, splintered, twisted, fractured – that he considered an organizing principle in nature. A French mathematical physicist had just made the disputatious claim that turbulence in fluids might have something to do with a bizarre, infinitely tangled abstraction that he called a strange attractor. (p. 4)

Until complexity scientists began studying *the whole* and behaviors arising from interactions, our predictive ability was limited to the simplest elements in controlled environments (Gleick, 2008). As stated by Miller (2015),

> Our traditional scientific way of thinking relies on reductionism, an idea that has given us both the Archimedean tools to move the world and the delusion that we understand what we are doing. We inhabit a world, where even the simplest parts can interact in complex ways, and in so doing, create an emerging whole that exhibits behavior seemingly disconnected from its humble origins. This is at once both a magical and dangerous world, where out of simple beginnings can emerge either a marvelous outcome or an awe-inspiring catastrophe. (p. xviii)

The emergent behavior found in complex systems is easy to anticipate and hard to predict (Miller, 2015, p. xviii). Mitchell (2009) identifies Newtonian reductionism as a source of our ignorance on the nature of the whole:

> Since the time of Descartes, Newton, and other founders of the modern scientific method until the beginning of the twentieth century, a chief goal of science has been a reductionist explanation of all phenomena in terms of fundamental physics…. In spite of its great successes explaining the very large and very small, fundamental physics, and more generally, scientific reductionism, have been notably mute in explaining the complex phenomena closer to our human-scale concerns…. Many phenomena have stymied the reductionist program: the seemingly irreducible unpredictability of weather and climate; the intricacies and adaptive nature of living organisms and the diseases that threaten them; the economic, political, and cultural behavior of societies; the growth and effects of modern technology and communication networks; and the nature of intelligence and the prospect for creating it in computers. (p. x)

The gestalt notion of emergence, *in which the whole is greater than the sum of its parts*, summarizes the contrarian view to scientific reductionism and defines the study of complexity. Consistent with gestalt philosophy, emergence forms the foundation of complexity science and complexity theory (Holland, 1998). Interest in emergence leads to the study of synergistic-like behaviors in and of whole systems, be they chemical, ecological, economic, *and combinations thereof*.

Complex systems, defined by the behavior of their interactions with their environment, are the focus of complexity science and theory. Complexity science incorporates "an interdisciplinary field of research that seeks to explain how large numbers of relatively simple entities organize themselves, without the benefit of any central controller, into a collective whole that creates patterns, uses information, and, in some cases, evolves and learns." (Mitchell, 2009,

p. 4). Embracing the interdisciplinary applicability of complexity science principles, Manson (2001) notes that

> any definition of complexity is beholden to the perspective to bear upon it. While it is possible, therefore, to examine complexity on a discipline-by-discipline basis, breaking down complexity research into three major divisions affords a more coherent understanding of complexity theory. (p. 405)

Manson (2001) describes the divisions as algorithmic complexity, deterministic complexity, and *aggregate complexity* (p. 405).

The proposed study applies Manson's aggregate complexity to model and estimate human adaptiveness as a function of individual adaptive capacity, the rate of adaptiveness as a function informal and incidental learning and the roughness of learning associated with this process. Consistent with the interdisciplinary traditions in complexity science, the study combines a base model from biology and research from ecology with *scales* from IIL with fractal dimensionality from physics.

Complex Systems Theory (a Derivative of Complexity Science) in Development

Thurner, Hanel, and Klimek (2019) summarize the current understanding of complex systems theory as

> the theory of generalized time-varying interactions between elements that are characterized by states. Interactions typically take place on networks that connect those elements. The interactions involved may cause the state of the elements themselves to alter over time. The essence of a complex system is that the interaction networks may change and rearrange as a consequence of changes in the states of the elements. The theory of complex systems builds partly on

> previous attempts to understand systems that interact in nontrivial ways, such as game theory, cybernetics, or systems theory….It can be regarded as an independent scientific branch, which – due to its quantitative, predictive, and testable nature – is a natural science. The elements of a theory of complex systems are becoming clear: dynamical multilayer networks, scaling, statistical mechanics of algorithmic dynamics, evolution, and coevolution, and information theory. (pp. v–vi)

Thurner et al. (2019) argue that an algorithmic description of a system

> provides a framework for systems that can *endogenously change their internal interaction networks, rules of functioning, dynamics and even environments, as they evolve in time* [italics added]. Algorithmic dynamics, a characteristic of complex dynamical systems, may be a key to the quantitative and *predictive understanding* [italics added] of many natural and man-made systems.… Algorithmic dynamics describe how living, social, environmental, and economic systems unfold. (pp. vi–vii)

Other authors argue there is no generalizable complexity theory, but rather "a number of theories concerned with complex systems gathered under the general banner of complexity research" (Manson, 2001, p. 405). Instead of theory, Mitchell (2009) proposes "a definition of the term *complex system*, a system in which large networks of components with no central control and simple rules of operation give rise to complex collective behaviors, sophisticated information processing, and adaptation via learning or evolution. (Sometimes a differentiation is made between complex adaptive systems, in which adaptation plays a large role, and nonadaptive complex systems, such as hurricanes)." (p. 13).

Learning as a Source of Self-Organizing, Nontrivial, and Emergent Behaviors

> The *self-organizing* nature of complex adaptive systems is a distinctive behavior [that] arises without an internal or external controller or leader…. Since simple rules produce complex behavior in hard-to-predict ways, the macroscopic behavior of such systems is sometimes called emergent…. An alternative definition of a complex system is **a system that exhibits nontrivial emergent and self-organizing behaviors.** *The central question of the sciences of complexity is how this emergent self-organizing behavior comes about* [italics added]. (Mitchell, 2009, p. 13)

Mitchell's question situates the proposed study as applied aggregate complexity in adaptive systems. In contrast to algorithmic and deterministic complexity, aggregate complexity "attempts to access the holism and synergy resulting from the interaction of system components" (Manson, 2001, p. 409). Aggregate complexity is distinguished by "relationships between entities; internal structure and the surrounding environment; learning and emergent behavior; and the different means by which complex systems change and grow" (Manson, 2001, p. 409).

Table 2.2 summarizes Manson's (2001) analysis of the key attributes of aggregate complexity.

Table 2.2

Summary of Components in Complex Adaptive Systems as Defined by Aggregate Complexity

Concept	Summary Description
Relationships	A complex system is defined more by relationships than by its constituent parts. Subsystems and individual components typically have functions or goals. Still, given the complexity of relationships between components, it is impossible to characterize the system on the whole as having a unified purpose. Subsystems and components are largely limited to local

Concept	Summary Description
	interactions. There is no omniscience or constantly updated common body of information.
Internal Structure	Relationships of different strengths between component-parts define the internal structure of a system. Components with especially tight connections from sub-systems, so even homogenous components can support internal diversity through realignment of relationships to create non-identical systems.
Environment	A complex system owes its existence to relationships with its environment, defined as anything outside of the system. Regardless of the actual boundary between a system and the environment, the former passes information, matter, and energy through its internal structure.
Learning & Memory	A complex system is not beholden to the environment – it actively shapes, reacts, and anticipates. Components and sub-systems with the capacity to accommodate the influx of energy, matter, and information from the environment will grow. A complex system can deal with truly novel situations because it has a wide array of internal components and sub-systems linked by complex relationships. In rare cases, when no suitable components or sub-systems exist, the system cannot respond to new relationships with the environment, with potentially catastrophic results. The destruction of complex, diverse internal relationships may lead to a lack of resilience and adaptability in [the system's] ecosystem
Emergence	Capacities of a complex system are greater than the sum of its constituent parts. A system can have *emergent* qualities that are not analytically tractable from the attributes of internal components. Emergence is a function of synergism whereby system-wide characteristics…result from interactions among components. Emergent phenomena may lie beyond our ability to predict and control.
Change & Evolution	A complex system constantly changes, largely through three different types of transition. (1). Self-organization, the property that allows it to change its internal structure in order to better interact with its environment. Self-organization allows a system to *learn through piecemeal changes in its internal structure* [italics added]. (2). A system becomes dissipative when outside forces or internal perturbations drive it to a highly unorganized state before suddenly crossing into one with more organization. (3). Self-organized criticality refers to the ability of complex systems to balance between randomness and stasis. Instead of occasionally weathering a crisis, a system can reach a critical point where its internal structure lies on the brink of collapsing without actually doing so. Self-organizing criticality is a form of self-organization where the rate of internal restructuring is almost too rapid for the system to accommodate but necessary for its eventual survival.

Note. Adapted from "Simplifying Complexity: A Review of Complexity Theory," by S. M. Manson, 2001, *Geoforum*, *32*, 405–414.

Consistent with Manson, Mitchell (2009, p. 13) notes that the adaptive behavior of complex systems is founded in *their ability to self-organize through learning or evolutionary process when faced with an environmental perturbance*.

Poincaré, Nonlinearity and the Rate of Adaptive Capacity Model

The work of Henri Poincaré provides the mathematical foundation for the proposed study. Mitchell (2009) describes Poincaré as "the founder and probably the most influential contributor to the modern field of dynamical systems theory…. Poincaré discovered sensitive dependence on initial conditions when attempting to solve a much simpler problem." (p. 21). According to complexity science, sensitive dependence on initial conditions defines the system dynamics (and thus its algorithmic model) over successive time steps (Holland, 1995; Lansing, 2003; Miller, 2015; Mitchell, 2009). Mitchell (2009) quotes Poincaré's description of the sensitive dependence on initial conditions:

> But even if it were the case that the natural laws had no longer any secret for us, we could still only know the initial situation approximately. If that enabled us to predict the succeeding situation with the same approximation, that is all we require, and we should say that the phenomenon has been predicted, that it is governed by laws. But it is not always so; it may happen that small differences in the initial conditions produce very great ones in the final phenomenon. A small error in the former will produce enormous error in the latter. Prediction becomes impossible. (p. 21)

The CraftDawg study adopted the logistic model of Robert May (1975, 1976) to model another feature of complex adaptive systems: nonlinear relationships. A core assumption in the study was that the dynamics of nonlinear relationships (as manifested in the interactions of intersecting dynamical systems) are *the hosts of emergence*. Mitchell (2009) describes a

nonlinear system as “one in which the whole is different from the sum of its parts” (p. 23). The interaction of the system components produces outcomes based on power laws (nonlinearity). Population biologist Robert May (1975, 1976) proposed an algorithmic, logistic model for population growth in the presence of overcrowding. He included the elements of a dynamical, nonlinear system: change over time, environmental boundaries and individual capacity, and a formula that models a rate of adaptive behavior based on those variables. Specifically, his model includes birth rate, death rate, and carrying capacity (Gleick, 2008; Mitchell, 2009).

Mitchell (2009) and Thurner et al. (2019) suggest that algorithmic models are our best solution in estimating the behaviors of dynamical systems as there is not yet a generalized method for measuring complexity. We can measure elements in systems, but we have yet to measure the emergence produced by the adaptive response (Holland, 1998; Mitchell, 2009). We can estimate behaviors and system states that produce increasing levels of entropy (disorder) in the system. As we learn from interdisciplinary efforts in applied complexity, we will gain more significant insights into questions of complexity measurement (Holland, 1998, 2006).

Empirical Studies

Prior empirical research contributes to the design and research questions proposed in this study. Empirical studies were selected that examined learning in “organized chaos” contexts; learning associated with human innovation process; contextual factors influencing human learning; human learning from failure; and human learning from complexity. In each of these studies the learning examined is some form of informal and/or incidental learning as broadly defined by Marsick and Watkins (1990) as applied in a complex environment. In general, these studies note the influence and impact of the context and time on the processes of learning which

is consistent with a definition of the roughness of learning that includes adaptive capacity and rate of adaptiveness.

Applied Complexity Science in Human Learning

Research studies of learning that occurs in chaotic situations through the lens of complexity science provides direct and tangential evidence that can inform the proposed study. The purpose of the Goldman et al. (2009) study was to "understand how, when, and why emergency medicine residents learn while working in the chaotic environment of a hospital emergency room" (p. 555). Using a qualitative interview methodology with thematic data analysis, four different types of learning episodes were revealed. "The episodes varied intensity, duration and the degree of motivation and self-direction required by the learner. One episode could prompt another. Learning occurred both individually and in social interaction in the workplace during the episode, as well as outside of the workplace environment after the experience had occurred" (Goldman et al., 2009, p. 555).

Similarly, the *context* of an "edge of chaos" environment is relevant as well. In the emergency room environment, these learners (residents) confront edge of chaos interactions repeatedly and must use all forms of learning to create adaptive responses. As noted in the findings of this study, the residents are aware of their learning and adaptive processes and the need to leverage those to respond to the novel situations they encounter. The study authors (Goldman et al., 2009) echoing Marsick and Watkins (1990), note that

> historically, environmental dynamics such as disruption, confusion and chaos were seen as negative factors, often indicating the impending demise of [a system]. Now these conditions are considered by complexity theorists to be normal and necessary…. Yet little is known about how people learn in a chaotic workplace environment:

- What factors facilitate learning?
- What does the learning process look like?
- What can be done to maximize the learning that occurs? (Goldman et al., 2009, p. 556)

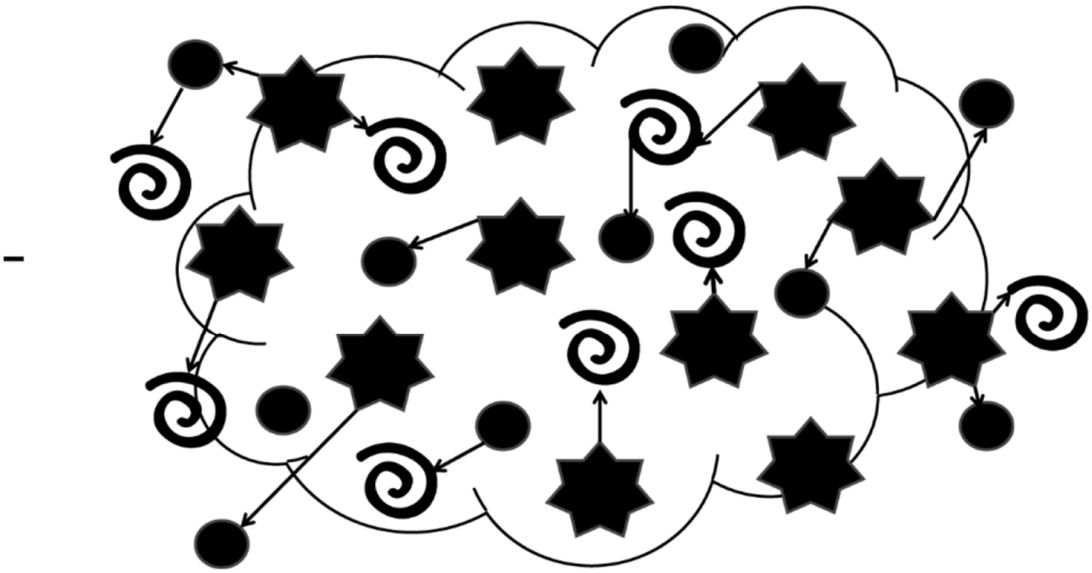
Theoretically, the study relies on situated learning, a form of informal learning, and chaos theory, a derivative of complexity science. The study promotes a description of learning from a chaos and complexity point of view "as an activity of interdependent people taking place in social processes. According to Stacey (2003), learning is neither individual nor collective, but "shifts in the patterning of communicative interaction and power relating […] the emerging transformation of inseparable individual and collective identities" (pp. 330–331). Citing the work of Fenwick (2008), Goldman et al. (2009) summarize that

> learning is defined as an adaptive activity that results from the actions and relations of complex systems, particularly in response to a disturbance. Fenwick also notes that context is viewed in the literature as either:
>
> - A container the individual moves about in; or
> - A web of relationships. (p. 559)

This was a qualitative study based on semi-structured interview with 12 emergency medicine residents at a large teaching hospital. Phenomenological techniques were used to guide the data analysis. The team of researchers "reviewed the data by components of the learning process, e.g., learning catalysts, learning strategies, learning challenges, and supports" (Goldman et al., 2009, p. 562).

The study found that certain environmental characteristics are important to learning in a chaotic environment. Another finding identified four different types of learning activities or

events during which the participants noted learning occurs: participation in the environment; focused learning moments; repetitive cycles and intense experiences (Goldman et al., 2009, pp. 563–566). These findings are summarized in Figure 2.1, illustrating the "possible relationships among the types of episodes, depicting what learning in the [study context] "looks like" (Goldman et al., 2009, p. 567). There is a "pattern of chaos" depicted.



Key: Stars = Intense Experiences; Dots = Focused Moments; Spirals = Repetitive Cycles; Cloud = the ED Environment

Figure 2.1. Symbolic representation of the shape of learning based on episodes of learning. From "Learning in a Chaotic Environment," by E. Goldman, M. Plack, C. Roche, J. Smith, & C. Turley, 2009, *Journal of Workplace Learning*, *21*(7), p. 568.

Of interest in this study is the connection to complex adaptive systems notion of self-organizing. According to the authors, "while many of the participants lived for the "pearls of knowledge" provided by the attending physicians, the most striking finding about learning in the chaotic […] environment was how much self-direction was involved" (Goldman et al., 2009, p. 568). The study concluded that

> learning in a chaotic environment does not involve substantially different learning facilitators than learning in a non-chaotic [environment]: observation, practice, mistakes, feedback, questioning, and reflection…. What is different about how learning occurs is the relationship of the episodes and the amount of motivation and self-direction required by the learner. (Goldman et al., 2009, p. 568)

This finding is consistent with a primary hypothesis in the proposed study that in a chaotic environment the rate of adaptiveness during episode and adaptive capacity are related to the learner's interpretation of the learning context.

Taber, Plumb and Jolemore (2008) conducted a similar study examining how firefighters and paramedics learn in "grey" areas and "organized chaos". Using a case study method of a Canadian paramedic organization with about 900 paramedics and a firefighting department with approximately 400 firefighters, the researchers conducted "in-depth, semi-structured interviews with senior administrators, training staff, and front-line personnel; observations of training sessions; and "ride-alongs" with paramedics and firefighters in the field" (Taber et al., 2008, p. 277). According to the study authors (Taber et al., 2008, p. 272), this research builds on research of informal and incidental (tacit) learning as described by Marsick and Watkins (2001), Hansman (2001), Lave and Wenger (1991), Wenger (1998), and Wilson (1993). Consistent with the Goldman study, the researchers found "the notion of situated learning is insufficient to explain

the dramatic performance of emergent, creative, and autonomous actions often required of individual emergency personnel in crisis situations" (Taber et al., 2008, p. 272). The researchers found that in the case of the paramedics, "many held that, while the extensive protocols regulating work often provide a useful overarching frame for action, these protocols were inadequate for dealing with the "grey areas" – situations unanticipated by the protocols" (Taber et al., 2008, p. 278). Specifically, the researchers conclude that "situated learning offers little help explaining the dramatic performance of emergent, creative, and autonomous actions often required of individual emergency personnel in crisis situations" (Taber et al., 2008, p. 273). The paramedics noted that

> "you do a better service to the general public if you do not necessarily follow the protocols exactly but make your own judgements…. You can adapt the protocol to fit…and that's something you learn with experience…not every case is going to be the same, because you have to adapt your treatment…. You are constantly adapting your pathway, choosing your protocol." (Taber et al., 2008, p. 279)

Consistent with Goldman's (2009) findings, the paramedics confirmed the notions of connectivism as described by Siemens (2005), with the researchers reporting "[the paramedics] articulated the importance of utilizing many sources of information concurrently, unencumbered by protocols" (Taber et al., 2008, p. 279). Consistent with Marsick and Watkins (1990), the paramedics acknowledge the use of tacit learning where in "very unique and unprecedented situations, the very best paramedics also are willing to act in ways that even experience [from informal learning] has not prepared them" (Taber et al., 2008, p. 280).

The analysis of the firefighters in this study is of interest as it suggests the protocols are designed to "organize chaos". This is similar to Pendleton-Julien and Seely Brown's (2018)

design for emergence approach which embraces the notions of complexity science and adaptive practices. The researchers note that firefighters "continuously refer to the fact that regardless of their level of training or previous experiences, they do not see any call as routine – anything can happen. Looking ahead, preparing for the worst, and being ready to adapt are keys to success in firefighting due to its unpredictable nature" (Taber et al., 2008, p. 280).

By embracing the "unpredictable nature" of the activity, the firefighters organize using an "incident command system" (ICS) that

> provides a framework for responding to a variety of emergencies, providing steps to follow so as to manage an emergency situation. It is a policy that combines guidelines with flexibility and lays out the standard method to carry out actions once a decision has been made, allowing firefighters to adapt to any situation as required. (Taber et al., 2008, p. 280)

The firefighters understand the nature of chaos and complexity and have willfully developed a process to "organize chaos" and coordinate action, helping all firefighters work as a team with one goal and assigned tasks. The researchers learned that the ICS as implemented "more closely resembles a living organism than a static policy. Every call is unique and the response to each call change depending on the situation and the personnel involved. It is this human element that takes a linear model and makes it adaptive because "everything is great on paper, but nothing ever goes that smooth" in reality. [We] must "organize chaos" and "adapt, adjust, adjust, adjust, adjust, adjust" (Taber et al., 2008, p. 281).

Much like the paramedics, the researchers found the firefighters acknowledge the influence and impact of tacit (incidental) learning in operating in edge of chaos situations:

> One [firefighter] stated that what they do is impossible to describe and must be experienced personally to be understood. It is therefore very difficult to pass on these tacit understandings to new firefighter in any way other than engaging with them in the flow of unfolding situations. (Taber et al., 2008, p. 282)

The researchers acknowledge the type of learning that is most influential and required in the edge of chaos moments described by the paramedics and firefighters:

> Through learning in practice and from each other, these paramedics and firefighters have developed the ability to respond to emergent situations, adapt policy into practice, and navigate through the grey areas and organized chaos of their professions. However, in these terrible moments, when all things anticipated or thought known dissolve, and when a firefighter or paramedic stands alone or with a comrade needing to make just the right decision, *another kind of active, creative, fast-as-lightening learning must be deployed* [italics added]. (Taber et al., 2008, p. 284)

This tacit learning and knowledge may well be the organic, free-radical learning that is most prevalent in edge of chaos adaptive practices.

Research using context that is inherently an edge of chaos environment (emergency rooms, paramedics, and firefighting) confirms the self-organizing criticality as triggering the adaptive response through learning. The turbulent state of the context is obvious. The learners are knowingly intervening in the environment and are comfortable with their ability to adapt to the unpredictability of the interactions in the environment. The adaptive capacity and rate of adaptiveness are developed and sized for the "controlled chaos." Further, the reliance on tacit knowledge to provide additional adaptive capacity and increase rate of adaptiveness is suggested in the research.

Research including context as a variable in studying learning in "normal" environments suggests Siemens' (2005) connectivism learning theory and Marsick and Watkins' (1990) IIL couple to provide the learning structure relied upon to sustain a needed level of learning in the organization to maintain competitive position. Ellinger and Cseh (2007) researched "how employees facilitate others' learning and the contextual factors that influence employees' facilitation of others' learning in a workplace setting" (p. 435). Relying on Marsick and Watkins's (1990) theory of informal and incidental learning to frame the research as mediated by context, Ellinger and Cseh (2007, p. 440) framed their research around three research questions:

- How do employees facilitate another employee's learning in the workplace?
- What are the contextual factors that influence employees' facilitation of others' learning in the workplace?
- How do contextual factors influence employees' facilitation of others' learning in the workplace?

The research setting was a US-based consumer focused manufacturer having been in business for over 75 years and employing about 3500 employees in multiple locations. The company was facing turbulence from the global marketplace and was implementing "several changes designed to position the organization for longer-term growth and viability including changing from a very traditional, functional, and more hierarchically structure organization to one that is more process focused" (Ellinger & Cseh, 2007, p. 439). Within this context of organizational change and management turnover, 13 employees were interviewed using "critical incident technique and personal-face-to-face semi-structured interviews" (Ellinger & Cseh, 2007, p. 440).

The findings found external and internal "catalysts for facilitating others' learning" (p. 441) . The primary external catalyst was "changing industry context focusing on low cost" (p

441). Internal catalysts identified included the influx of new technology in the organization, and the influx of new processes in the organization. These catalysts are consistent with the interactions associated with complexity science that trigger self-organizing adaptive behaviors that require human learning. The human learning was facilitated within the organization consistent with both Siemens (2005) and Marsick and Watkins (1990). The researchers noted the learning facilitators (within the learning network) were engaged in the adaptive process when:

- They sought my expertise;
- There were challenging assignments and projects;
- There were critical, visible, and high priority tasks;
- Key project responsibilities were being turned over to others
- Wanting to develop others; and
- The need for performance feedback (Ellinger & Cseh, 2007, p. 442)

The findings are interesting in explaining context-based inability to adapt as "five broad categories emerged as contextual factors that negatively detract from facilitating learning:

1. Leadership/management not committed to learning.
2. Structural inhibitors.
3. Lack of time manifested by workloads.
4. Fast pace of change is overwhelming.
5. Negative attitudes. (Ellinger & Cseh, 2007, p. 447)

Of particular interest, as noted in other studies presented, *is the importance of time and the pace*, both are considered in determining adaptive capacity and rate of adaptiveness. These two variables are embedded in the concept of roughness of learning and the roughness of learning is a function of the context as noted in the various studies. While the researchers note

their research is not generalizable based on their findings, it is consistent with the principles of complexity science in terms of time and pace as well as network-based learning of Siemens (2005) and provides additional support for Marsick and Watkins (1990) by noting the influence of time and pace on learning in a complex context.

Findings from Harner (2013) are consistent with the other studies examined here. Similar to the study conducted by Goldman (2009), Harner researched incidental learning in a health care organization which is an inherently complex context. Harner's (2013) research emphasizes incidental learning described by Marsick and Watkins (1990) as being "learning that takes place as a result of interactions with others without conscious intention of learning or knowledge acquisition" (p. 22). It is learning that is not goal oriented as defined in informal learning, but rather learning that is the result of reflection. Harner (2013) quotes Reischmann (1986) in describing incidental learning as "learning *en passant*" to describe "learning taking place in life situations where there is nothing like prepared curriculum, learning is identified by looking back, and takes place when learning is not a prime motivation" (pp. 21–22).

Using the incidental learning model developed by Marsick and Watkins (1990) and described by Cseh, Marsick and Watkins (1999), Harner (2013) summarizes that

> learning takes place from experience, and under nonroutine conditions, people frame the situation they encounter (diagnosis) by using judgement based upon prior experience and knowledge (problem framing). In order to deal with the situation, options are viewed through the lens of context, assessing the disparity between feasibilities and limitations of a possible solution (contextualization). (p. 27)

Harner (2013) notes the difficulty in parsing incidental learning from learning in general by noting "attempting to control the interactions that are inherent in incidental learning cannot be

accomplished over a sustained period of time. Unanticipated ways of doing daily activities will emerge as a result of incidental learning" (p. 29). This is consistent with Pendleton-Julien and Seely Brown (2018) and Marsick and Watkins (1990) and suggests that incidental learning is best described as a context inspired process that is engaged in versus an outcome. Whereas informal learning has an outcome to motivate its acquisition, incidental learning is inspired by context in the moment.

Viewing incidental learning through the lens of complexity science, Harner (2013) notes the learning is governed by the interactions of the adaptive processes in a given context. The research environment is a patient-visit environment which he describes as a complex adaptive system. Harner (2013) describes a typical "hidden learning process" that arises out of the inherent gaps in the formal and informal training processes:

> Managers and supervisors try to create systems, processes, and training to accomplish successful goals and objectives. Due to the potential unknown variables from sources outside of the prescribed system, the established processes and training may not be sufficient. *Insufficiencies in knowledge will force incidental learning to occur as employees look for solutions to unanticipated problems. Rapid decisions and instant responses required by time constraints result in incidental learning and subsequent unintended behavior that may or may not be desirable.* (Harner, 2013, p. 43)

According to Harner (2013) the adaptive capacity of a given system to change "may be dependent upon incidental learning episodes, [the] circular response of workers interacting, and where power resides and shifts among system participants" (p. 43).

The distinction in the Harner (2013) study from Goldman (2009) is the roles of the participants in the study. Goldman's emphasis is on the learning of medical students working in

emergency care. Harner's study participants are support staff and nurses in a group of medical facilities in a context of primary care clinics operated by a large midwestern university medical school. The Harner (2013) study included a wide range of participants in terms of education, roles and responsibilities. A qualitative study using naturalistic inquiry paradigm was conducted with 21 participants. Semistructured interviews were conducted to answer the research questions:

1. What incidental learning elements do employees use to complete work tasks?
2. What transpires within a formalized system to influence incidental learning? (Harner, 2013, p. 66)

The analysis of the interviews found that

> the two emergent themes most relevant to question one are incidental experiential learning and collaborative learning. Three additional themes emerged that contribute to answering question two: power, complexity and learning environment…. An additional factor that surfaced, based upon the interviews and observations, was how incidental learning was embedded in the situation that each participant was describing. The inclusion of the situation as a characteristic of incidental learning is consistent with its definition…. The situation [context] contributes to the incidental learning that many of the participants experience as they do their best to accomplish job tasks. (Harner, 2013, p. 64)

Silva (2007) studied incidental learning in the workplace to examine three research questions:

1. What is the nature of incidental learning in the workplace?
2. How does professional context impact incidental learning?
3. How do incidental learners know they know in the workplace?

Like Harner, Silva relies on the work of Marsick and Watkins (1990) in defining incidental learning as "a byproduct of some other activity, such as task accomplishment, interpersonal interaction, sensing the organizational culture, trial-and-error experimentation, or even formal learning" (Silva, 2007, p. 3).

Silva (2007) acknowledges that "much of the research on incidental learning is contradictory or inconclusive" (p. 4). This summary may arise from

> a variety of definitions of learning. A few studies conceptualize learning as the acquisition of factual information. Many studies focused on interpersonal and attitudinal learning. Incidental learning was found to occur as individuals interacted with experiences, with other individuals, with experts, with a particular work project, or with the context in which they lived or worked. (Silva, 2007, p. 4)

Silva uses a hermeneutical phenomenological approach to gain insights into the incidental learning with emphasis on the role of context, both situationally and from the "general perceptions and experiences of learning" described by the participant (Silva, 2007, p. 5). The broader context of the study included analysis on the occupational culture within which the participant engaged. The central purpose of the study "was an exploration of how individuals know they know when they learn something in the incidental manner" (Silva, 2007, p. 5). This purpose was designed to "provide insights into why some individuals learn in a given situation while others do not" (Silva, 2007, p. 6). This is of importance to the proposed study here as it may provide insight into both adaptive capacity and the rate of adaptiveness. To the extent an individual adapts while others do not, this will add to the research presented by Silva.

In the study three semi structured interviews were conducted. The first focused on the life history to provide context of each participant's experience with emphasis given to the

participant's occupational history and past learning experiences (Silva, 2007, p. 59). The second interview emphasized current experiences as they relate to incidental learning experiences. The third interview was to "provide an opportunity for the participant to express the meaning of his or her experiences" (Silva, 2007, p. 59).

Study participants were limited to professional level employees who self-selected based on membership in three professional organizations. Fourteen participants enrolled in the study. Forty-two interviews were conducted. Silva's findings are consistent with other studies presented here emphasizing the importance of context in incidental learning. Silva identified that when the organizational context is aligned with the learners preferred style of learning, incidental learning is greater (Silva, 2007, p. 209). Silva (2007) also found that an individual's perception of learning "guides their openness to learning in certain situations" (p. 209), remarking that "Those [individuals] who tended toward a deep approach to learning had more incidental learning experiences to share and richer stories" (p. 210). In answering the central research question of the study, Silva (2007) found that

> most incidental learning in the workplace is validated in a manner akin to Schön's notion of reflection-on-action. In addition, in some instances participants checked with multiple sources or with "experts" – those who should know about the topic at hand. (p. 213)

This summary is consistent with both Marsick and Watkins (1990) and Siemens' (2005) connectivism theory of learning as the use of networks to both find information but to also "validate" the quality of the information is part of the reflective process.

Another study looked at the innovation process to study learning processes. Innovation is a form of adaptation that relies on learning processes in humans (Holland, 1998). According to the research findings of Cheng and Van de Ven (1996),

> the two most commonly-used explanations of innovation process, that it follows either an orderly periodic sequence of stages or a random sequence of "blind" events, are not valid where chaos is found. Chaos tells us that the innovation process consists of a nonlinear dynamical system, which is neither orderly and predictable nor stochastic and random. The findings of chaos also expand existing definitions of organizational [human] learning. Learning in chaotic conditions can be viewed as an expanding and diverging process of discovery. Learning during more stable and periodic conditions is viewed as a narrowing and converging process of testing. (p. 593)

The authors describe innovation as "the emergence of novelty" that arises from an "exploration into the unknown process" (Cheng & van de Ven, 1996). The study examines the extent to which "the seemingly-random process of innovation development may in fact not be random; it may be chaotic. Advances in dynamical systems theory (complexity science) provide mathematical tools for examining chaos as an alternative explanation of the innovation journey" (Cheng & van de Ven, 1996, p. 594).

The study is based on a simple logistic model, $X_t = kX_{t-1}(1 - X_{t-1})$, where X_t is the percentage of action innovators might devote to exploiting a course of action at time *t* (assumed to be 100% minus the percent of actions devoted to exploration). According to Cheng and van de Ven (1996),

> This logistic equation states that the value of variable X in the given time period (*t*) is determined by its value in the previous time period (*t-1*) and a constant *k*. This parameter, *k*, governs the degree of nonlinearity of the equation, which might be substantively viewed as the relative demands placed on innovators to complete the innovation journey. (p. 595)

This study uses the same theoretical model as the proposed study where the variables are measuring different concepts.

This study examined data based on "conceptual categories in the learning model": continue or change in action course; positive or negative outcomes (feedback); and context events (Cheng & van de Ven, 1996, pp. 598–599). Of interest for the proposed study is that this study describes the concept of "the roughness of learning," noting that

> our research findings indicate that learning, [defined as experiential process of acquiring knowledge about action-outcome relationships and the effects of environmental events on these relationships], did not occur during the beginning period of innovation development when both action and outcome events followed a chaotic pattern, but that learning did occur after the action and outcome time series transitioned from chaotic to periodic patterns during the ending period....This leads to the conclusion that the innovation units either learned nothing during their first four to six years of development efforts, or that they engaged in some other type of knowledge acquisition not included in the definition of learning [used in this study]. It also begs the questions about the prerequisites for learning and how it originates. Learning presumes some a priori knowledge about the task to be learned. In particular, the definition of learning presumes that learners have some *a priori* knowledge about (1) alternative courses of action that are desired, and (3) the institutional rules, resources and settings in which the task is undertaken. How is the prerequisite knowledge created? (Cheng & van de Ven, 1996, p. 607)

The authors note that

> our research findings suggest that learning in chaotic conditions is an expanding and diverging process of discovering possible action alternative, outcome preferences, and

> contextual settings, while learning during more stable periodic conditions is a narrowing and converging process of testing which actions are related to what outcomes. (Cheng & van de Ven, 1996, p. 607)

This description of applying the principles of a nonlinear dynamic model informs the notion of the roughness of learning to be examined in the proposed study. According to Cheng and van de Ven (1996),

> The empirical results obtained in this study provide important clues for guiding future work. Chaos provides hope by suggesting what dynamical model of learning during the innovation journey might look like. Low-dimensional chaotic patterns have a hidden order which typically consists of a relatively simple nonlinear dynamic system of only a few variables. Since learning is our substantive focus, the core variable in our system will most likely include the actions entrepreneurs take, the judgements they make about outcome preferences or goals, and the contextual events they experience as they travel the innovation journey. This system incorporates the key concepts in existing theories of behavioral and cognitive learning. (p. 607)

Applying similar reasoning as used by Cheng and van de Ven (1996), Thietart and Forgues (1997) used a case study to examine the creation of context by the actions of an organization's actors. As with previously presented studies, this study is consistent with Pendleton-Julien and Seely Brown's (2018) notion that past learning creates the future adaptive learning path, and the goal of learning is to provide adaptive methods for interacting in the context. Thietart and Forgues (1997) found that

> once initiated, the context tends to develop a dynamic of its own, which escapes the control of the organizational actors. *In consequence, the context becomes the determining*

> *factor of the actor's initiatives.* Voluntarism has created its own determinism which will eventually shape the organizational actors' futures. (p. 1)

Thietart and Forgues (1997) employed a case study method to examine a crisis, where

> actors have contributed to enact a context that they cannot fully control and have little say in the way events unfold. Their voluntarism creates the seed for deterministic chaos, with its apparent randomness, to appear. The meaning of discovering chaos is that system behavior is the consequence of deterministic rules which originate from the actions of the actors themselves. Causality, though, runs in both directions. System behavior elicits actions and actions shape system behavior. Recursive relationships take place between cause and effect. Effect becomes the cause, end becomes the origin, actions create structure and structure determines action. (p. 2)

The research is based on complexity science and complex adaptive systems principles. Crisis is the state being studied which is analogous to an edge of chaos state. The authors believe that "a crisis is a good candidate for being indicative of an underlying chaotic behavior. Various causal agents (e.g., exogenous shocks) could possibly be used to explain a sudden and temporary period of instability" (Thietart & Forgues, 1997, p. 2). This belief leads to the primary research question for the study regarding what actor behaviors and adaptive efforts arise in crisis that create the context and alter the context of the crisis. The study focuses on "the transactions between organizational actors" where the transactions are a proxy for the interactions between the actors in the crisis. This allows a quantitative analysis since

> the dynamics of a non-linear dynamic system can be validly represented by one of its variables; in this case, a transaction in its phase space (i.e., the space where the variable at time t is given as a function of the same variable at time t_1, t_2, etc.). Studying the

> dynamics of the transactions is the equivalent to studying the dynamics of the crisis. If the dynamics have a deterministic origin, we can infer that the transactions and the crisis itself are induced by a succession of actions which lead to unwanted and/or unexpected consequences. (Thietart & Forgues, 1997, p. 4)

The study examines the well documented Iranian hostage crisis at the American Embassy in Teheran. The study reconstructs the system dynamics on a daily basis to provide a "temporal description of the situation and its evolution" (Thietart & Forgues, 1997, p. 5). The observed variable in the research is the transaction, which "takes place between organizational actors. [Transactions are between human actors, even though these individuals may themselves be acting as representatives of groups]…. Transactions measure the degree of interaction between actors. They include information exchanges, group decision making, negotiations, etc." (Thietart & Forgues, 1997, p. 6). Two hundred and five transactions were observed over a 445-day period and coded. To determine whether the system was chaotic, an algorithm using Lyapunov exponents to determine "the time span in which the system becomes unpredictable which is also a "measure of the rate at which the dynamic process destroys information" (Thietart & Forgues, 1997, p. 6). Based on the analysis the researchers concluded that

> if chaos could not be eliminated by these complementary tests (that is, if chaos was likely) we would infer that what was observed in the crisis was partly constructed by the [behavior and adaptive efforts] of the actors themselves. Through their multiple actions, organizational actors create a situation which becomes impossible to control. Instead of being actors, they become subjects of a situation (chaos) which transcends their individual actions. (Thietart & Forgues, 1997, p. 6)

The findings of this research are consistent with that of others who consider the whole of the interacting systems and the dynamics of those interactions. Specifically, when the findings are interpreted through the principles of complexity science the implications for organizational and human learning are notable:

> It is unlikely that the same action, taken twice, will lead to the same result…. The very actions which once produced excellent results might lead one day to failure. Not only are the results unpredictable but, even in the case where actions are based on similar past experiences, results are different. (Thietart & Forgues, 1997, p. 8)

The uniqueness and novelty of interactions in chaotic contexts stresses the adaptive responses (adaptive capacity and rate of adaptiveness) available to humans and their organizations. Thus, organizational learning as driven by human learning is likely governed by the interactions in the dynamic contexts created by the recursive forces described. As noted in this study time is a variable that allows the system dynamics to interact with the adaptive responses of the actors. Marsick and Watkins (1990) and others would hold that during this time informal and incidental learning create the adaptive response for each actor and Siemens (2005) would argue that the network dynamics of these multiple actors would shape that adaptive response all contributing to the complex interactions that alter the context.

Table 2.3 summarizes the empirical studies used in this study.

Table 2.3

Summary of Empirical Studies

Study Purpose	Methodology	Participants	Primary Research Questions	Findings	Summary Discussion
Goldman et al. (2009). The purpose of the study was to understand how, when and why emergency medicine residents learn while working in the chaotic environment of a hospital emergency room.	Qualitative interview method with thematic data analysis	12 emergency medicine residents in a large teaching hospital in the US	In this chaotic environment – What factors facilitate learning? What does the learning process look like? What can be done to maximize the learning that does occur?	Four different types of learning episodes were identified. Episodes varied in intensity, duration and degree of motivation and self-direction by the learner. Learning occurred both individually and in social interaction during the learning episode as well as post episode after reflection.	Self-directed learning in various ways was found to be the most notable finding about learning in the chaotic environment where the learners are by definition lacking in the necessary skills. Learning is the expected outcome in its various forms.
Taber, Plumb and Jolemore (2008). The purpose of the study was to examine how firefighters and paramedics learn in "grey" areas and "organized chaos".	Qualitative case study method using in-depth, semi-structured interviews with senior administrators, training staff, and front-line personnel; observations of	Select members of a Canadian paramedic organization with about 900 paramedics and a firefighting department with approximately 400 firefighters.	How do firefighters and paramedics learn in chaotic environments?	The researchers found "the notion of situated learning is insufficient to explain the dramatic performance of emergent, creative and autonomous actions often required of [first	The paramedics noted the gaps in the protocols that situations unanticipated by the protocols. Embracing an adaptive approach to deal with the protocol gaps was learned over time.

Study Purpose	Methodology	Participants	Primary Research Questions	Findings	Summary Discussion
	training sessions; and ride-alongs with [first responders]			responders] in crisis situations"	This study offers a contrasts in how these first responders organizationally acknowledged the chaotic nature of the job.
Ellinger and Cseh (2007). Examine how employees facilitate others' learning and the contextual factors that influence employees' facilitation of others' learning in a workplace setting.	Qualitative study using semi-structured interviews of 13 employees using critical incident technique and face-to-face interviews.	13 participants from US based consumer focused manufacturer having been in business for over 75 years and employing about 3500 employees in multiple locations.	How do employees facilitate another employee's learning in the workplace? What are the contextual factors that influence employees' facilitation of others' learning in the workplace ? How do contextual factors influence employees' facilitation of others' learning in the workplace?	Contextual catalysts for learning were identified both internally and externally. External catalyst was "changing industry context focused on low cost". Internal catalysts included influx of new technology in the organization and associated new processes.	The catalysts are consistent with self-organizing adaptive behaviors. The learning associated with this adaptive effort is consistent with Siemen's connectivism learning theory.
Harner (2013). Isolate incidental learning as used in	Qualitative study using naturalistic inquiry paradigm	21 support staff and nurses in a group of medical facilities	What incidental learning elements do employees use	Two emergent themes were identified to answer	This study attempts to isolate the role of incidental learning

Study Purpose	Methodology	Participants	Primary Research Questions	Findings	Summary Discussion
a complex environment by support staff and nurses	from semi-structured interviews.	providing primary care services operated by a large midwestern (US) university medical school.	to complete work tasks in the given context? What transpires with the formalized system to influence incidental learning?	question one: incidental experiential learning and collaborative learning. Three additional themes emerged to answer question two: power, complexity and learning environment (context) An overall theme emerged of how incidental learning is embedded in the situation that each participant described. What insights are revealed into why some individuals learn in a given situation and others do not.	in a given context. The findings of the study suggest that on the basis of definition, incidental learning is context initiated and sustained as it is an embedded adaptive response in a novel situation.
Silva (2007). An exploration of how individuals know they know when	Three sets of semi-structured interviews. First interview provided	14 participants enrolled in the study. 42 interviews were conducted.	What is the nature of incidental learning in the workplace?	The findings confirmed prior studies emphasizing the importance of	Silva's findings are consistent with Marsick and Watkins

Study Purpose	Methodology	Participants	Primary Research Questions	Findings	Summary Discussion
they learn something in an incidental manner.	occupational history and past learning experiences. Second interview emphasized current experiences as they relate to incidental learning. Third interview provide opportunity for participant to express meaning making from incidental learning experiences.		How does professional context impact incidental learning? How do incidental learners know they know in the workplace?	context in triggering incidental learning experiences.	differentiation of incidental learning on the basis of reflection. The findings are also consistent with Siemen's connectivism theory emphasizing the use of networks of peers and experts to supplement incidental learning experiences for deeper learning.
Cheng & van de Ven (1996). Examine the human innovation process through the lens of complexity science.	Quantitative analysis of the innovation development process described as the emergence of novelty.	Two product innovation efforts were examined over a six-year period.	To what extent does the innovation process follow a nonlinear dynamical model?	Learning in chaotic conditions is an expanding and diverging process of discovering possible alternative, outcome preferences and contextual settings, while learning during more stable periodic conditions is a narrowing and converging process of testing which	This study adapts Robert May's logistic model to examine the research questions in a quantitative manner. This finding is also consistent with the work of Juarreno in looking at enabling constraints in lieu of cause and effect linear models.

Study Purpose	Methodology	Participants	Primary Research Questions	Findings	Summary Discussion
				actions are related to which outcomes	
Thietart and Forgues (1997). Apply the principles of complex adaptive systems to examine the creation of context that emerges from the actions of actions of an organization's actors	Quantitative analysis of case study of Iranian Hostage crisis using publicly available data	Quantitative analysis using observed variables of transactions amongst crisis participants. Using dynamical analysis to measure complexity over the course of the crisis and how the level of complexity changed during the crisis based on transactions between actors in the crisis.	What actor behaviors and adaptive efforts arise in crisis that create the context and alter the context of the crisis?	The researchers found that "once initiated, the context tends to develop a dynamic of its own, which escapes the control of the organizational actors. In consequence, the context becomes the determining factor of the actor's initiatives. Recursive relationships take place between cause and effect where effect becomes cause, end becomes the origin, actions create structure and structure determines action.	The nonlinearity associated with complex adaptive systems creates unpredictability that requires recognition of the nature of the interactions and an adaptive response that considers the dynamical interactions. The whole of the interacting systems produces the reality that the outcomes are not predictable.

Summary of Empirical Studies

The themes in the empirical studies examined include the importance of context and how that determines the type of learning relied upon; the role of incidental learning to manage the level of complexity in a given context; the role of the individual actors in creating chaotic context that cannot be stabilized by the same actors; and the importance of elapsed time in developing a critical mass of learning to address the level of complexity in a given context. A notable gap in these studies is the omission of level of complexity in the learning process, that is the roughness of the learning process and how it emerges and abates through adaptive capacity (the ability to learn and change) and the rate of adaptiveness (how quickly emergence from learning can be applied to the given context through various forms of learning). In addition, the role of incidental learning as defined by Marsick and Watkins (1990) appears to emerge as the marginal differentiator in how chaotic environments are managed when the "protocols and procedures do not exist" for a given challenge.

This gap in the research is an opening to explore more deeply the roughness of learning in a chaotic context where time is a variable. The role of incidental learning as used to address challenges in a chaotic and unfamiliar environment is available for further research. Defining a new variable that measures the roughness of learning in the learning process and identifying the relevance of incidental learning in chaotic environments will extend the research and research paths.

Theoretical Framework

Consistent with Manson (2001), Mitchell (2009, p. 13) notes the adaptive behavior of complex systems is founded in *their ability to self-organize through learning or evolutionary process when faced with an environmental perturbance*. The working hypothesis that informs the

proposed study is human learning in the form of informal and incidental learning, as defined by Marsick and Watkins (1990), is instrumental in the adaptive process used by humans, and *is bounded by time and cultivation methods*. Informal and incidental learning as a primary source of an individual's ability to self-organize [adapt in a given context] provides the foundation for the individual's level of self-organizing criticality.

Remapping Marsick and Watkins' (1990) IIL

Table 2.4 is a "remapping" of Marsick and Watkins' (1990) IIL as conceptualized through complexity science.

Table 2.4

Remapping of Marsick and Watkins' (1990) Informal and Incidental Learning Theory

Marsick & Watkins – Original IIL Model	Reimagining M&W Through Complexity Theory (Adaptive Process Mode) Using the Language of Complexity & Physics	Comment
Context (Environment of Performance)	Initial conditions—phase state	
Triggering Event (disorienting dilemma)	Sensitive dependence on initial conditions—phase state perturbance	
Process of Identifying & Trying Solutions (advanced by feedback loops and error realization/recognition)	Cognitive entropy increases to trigger self-organizing criticality: link between entropy increase and energy required avoid chaos (edge of chaos state) based on critical attractors—roughness of learning as measured by fractal dimension of learning—which incorporates both error and achievement.	Note: the role of error is integral to the adaptive process as part of self-organizing criticality. It is measured in the fractal dimension of learning. There is no learning without error as part of the effort. Chaos and entropy live in error.
Reflection & Debriefing	Entropy reduced and emergence acknowledged (the critical attractor) …Second Law of Thermodynamics and First Law of Psychology	

Note. All text by author.

Robert May's (1975) Logistic model and Marsick and Watkins (1990, 2017) provide the theoretical foundation for the study by providing the basis for defining and measuring adaptiveness and roughness of learning

Adaptiveness is a broad measure that is theoretically influenced by dimensions of learning as identified by Marsick and Watkins (1990). Incidental learning and uncertainty are

two of those dimensions. Theoretically, they are measured in a given context and used to predict adaptiveness. Using time series to capture both adaptive capacity and rate of adaptiveness creates the broader measure of adaptiveness. Adaptiveness becomes a predictor measure of an outcome in a given context over time.

$Persistence_n = f(adaptiveness_n)$

$Adaptiveness_n = f(adaptive\ capacity_n * rate\ of\ adaptiveness_n)$

Figure 2.2 represents the theoretical model of the study in terms of the relationship of adaptiveness and the learning context over time. By applying May's logistic map framework, the theoretical model is depicted as

$$adaptiveness_{n+1} = learning_context * adaptiveness_n\ (1 - adaptiveness_n)$$

Figure 2.2. Formulaic depiction of theoretical model.

Roughness-of-learning is a description of the holistic nature the relationship as quantified in Figure 2.2. It is calculated by measuring the fractal dimension of the *shape of learning in a given context over time*.

The application of fractal geometry is consistent with Poincaré and Aleksandr Lyapunov's qualitative theory of differential equations, which, according to Wikipedia (2019),

> studies the behavior of differential equations by means other than finding their solutions. There are relatively few differential equations that can be solved explicitly. Still, using

> tools from analysis and topology, one can "solve" them in the qualitative sense, obtaining information about their properties. ("Qualitative Theory of Differential Equations," 2019)

The Roughness of Learning

Aligning with theories and research in adult learning (Dewey, 1938; Lewin, 1935), the proposed generic model of learning includes a triggering event (perturbance), provoking a response-based application of past learning (simple rules). This is followed by assessment of the outcome; followed by, if necessary, additional, refined response (different application of simple rules); followed by reflection; then internal or external debriefing including assessing the results of the efforts and the "take-aways for the next time" (emergence). The generic experiential learning model is in Figure 2.3. The roughness of learning builds on Kolb's (1984) notion of learning as a process and Marsick et al. (2017) description of learning as a "messy" process. The roughness of learning (RoL) is distinguished from comparisons to the learning curve as RoL includes complexity science-based concepts of entropy, energy, time, and nonlinear interactions within the learning process.

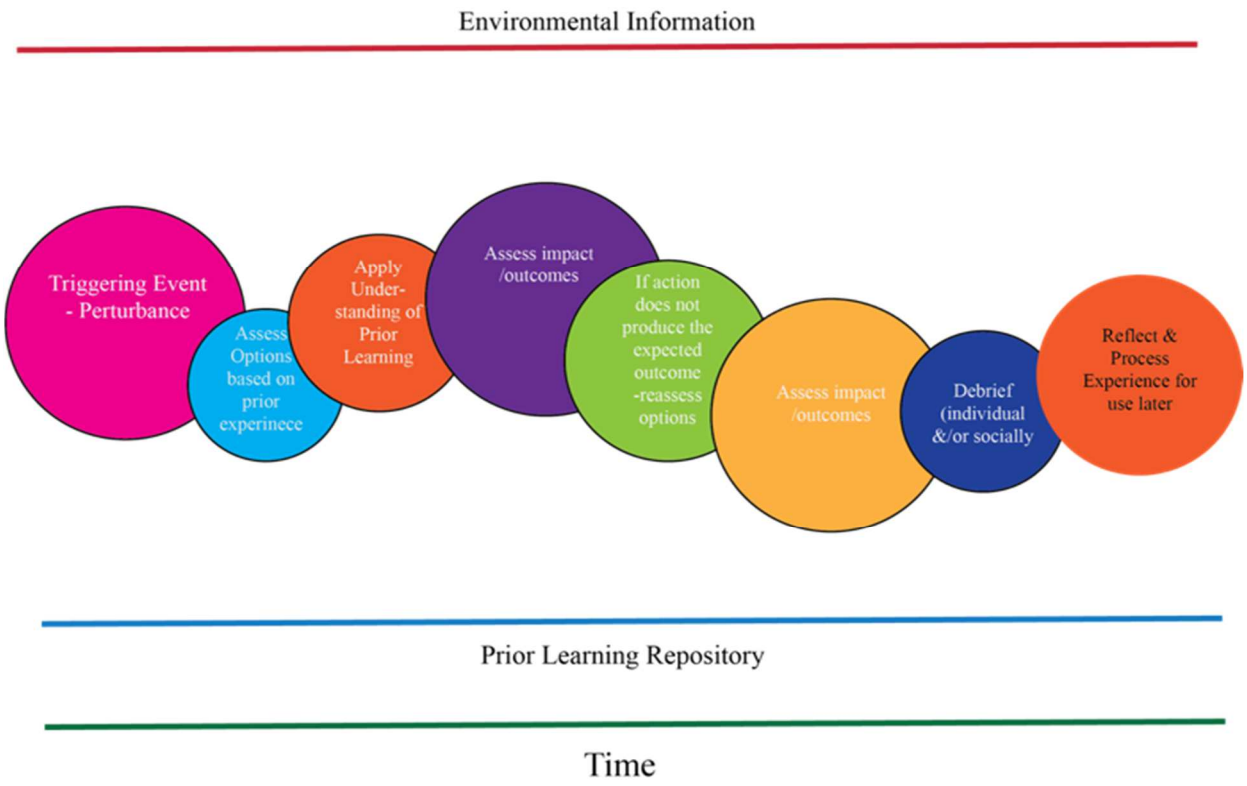


Figure 2.3. Generic experiential learning model.

Figure 2.3 depicts the macro-level inputs to the process: environmental information, prior learning repository (wealth of experience using simple rules), and time. Marsick and Volpe (1999) describe informal learning occurring "in a haphazard fashion. It is … often idiosyncratic…and driven by serendipity" (p. 7). Learning can be jagged, irregular, and rough, yet at a given scale, we can identify a pattern as visualized in Figure 4. Research suggests learning patterns vary based on the nature of the learning and the learner (Livingstone, 2004). To the extent learning behavior can be observed and mapped, such as a series of stock market trades over time in a given environment, an estimate of the roughness of learning can be used in a

model of adaptive capacity by calculating the fractal dimension of the *learning-map* we create, much like an EKG maps heartbeats and pressure.

The social sciences use fractals to measure irregularity to provide a quantitative measure of observed and latent behavior over a defined time period. For example, Skjeltorp (2000) used concepts from chaos (a derivative of complexity) theory and applied fractals "to investigate the validity of the much-used assumptions that stock market returns follow a random walk and are normally distributed" (p. 405). Accepting that complex systems derive their potential for dynamical behavior from sensitive dependence upon initial conditions, Skjeltorp (2000) notes complex chain reactions limit our ability to predict the future. Still, this quality "also incorporates a kind of long-term memory effect in different processes". (p. 487). Skjeltorp (2000) applies chaos theory and fractal geometry, "which embody their own simple laws" to study the "messiness of the stock market," stating that:

> Through chaos theory and fractal geometry we have access to tools and a new way of thinking that has been widely used within the physical sciences to describe complex systems and processes. If we believe that the financial markets are complex nonlinear dynamic systems, then these tools will be very useful to obtain a better description of the financial markets. (p. 487)

Skjeltorp's (2000) approach rejects the Newtonian assumption

> that a system when left alone tends to equilibrium" in favor of "the emerging, and new capital market paradigm [treating] the markets as complex, interdependent systems where the state of the system is continuously fluctuating, with no natural equilibrium state. The market has long-term correlations and trends due to *feedback effects* [italics added] and can be more or less erratic under certain conditions, conditioned upon earlier events….

> Some characteristic features one would expect from non-random, nonlinear behavior are: long-term correlations and trends (feedback/memory effects), erratic markets under certain conditions and certain times (volatility clustering), the series may have self-similar and self-affine characteristics, a fractal structure and less reliable forecasts due to the sensitivity of such a system on initial conditions. (pp. 497–498)

Economists such as Skjeltorp (2000) argue that human adaptive behaviors drive financial markets by using simple rules following the same process shown in Figure 4; and to the extent complexity theory and fractals estimate market behaviors, similar techniques can estimate individual and social learning in a dynamical situation. Guo (2017) conducted a study based on data collected from online learning and tutoring systems:

> The study shows that the dependence of online data may be characterized by the fractal dimension as a summary statistic locally and globally. The rate of correct responses and the global and local fractal dimensions of individual students' responses may *indicate their learning behavior in short and long learning windows* [italics added]. The results may shed light on when individual students are experiencing difficulties in the learning process. (p. 1)

Building on the research of Skjeltorp (2000) and Guo (2017), the study presented here proposes to us using a *serious game*, Minecraft, as a complex environment where game and player events are captured, mapped, and measured. From this data, models can be created to estimate adaptive capacity, rate of adaptiveness and the mediating influence of informal and incidental learning as they interact to estimate the roughness of learning in a complex adaptive system. The method and model are expected to provide insights into a proof-of-concept

application for measuring the roughness of learning and the relevant latent variables in less structured and controlled contexts.

Games and Emergence

John Holland and others (Holland, 1998; Miller & Page, 2007; Mitchell, 2009) proposed simulations as a source of insight into adaptive behaviors existing in complex adaptive systems. Holland employs games for simulations as a set of simple rules governs them. He uses *game theory* to inform his proposal of how complexity arises in rule-based games (versus games of chance) and how emergence governs future play of the game (Holland, 1998). Holland uses the arrangement of the game board at any point in time as the *state of the game*:

> From that point on, the play of the game depends only on the arrangement, not on how it was attained…. In short, the state of the game at any point in the play is a sufficient summary of past history for determination of all future possibilities. (Holland, 1998, p. 27)

A decision tree structure shows the execution of simple rules through the filtering (based on prior learning) of a player executing an internal strategy and responding to the play of another player. The interaction of the game's simple rules creates complex behaviors in the system; an asymmetrical vortex of action, response, reflection, recalibrated action, response, reflection, recalibrated action, assess, reflect, revise strategy (change behavior), action. The game play reveals strategies employed by the players within the simple set of rules governing the game. The execution of the strategy and change in the strategy leverages prior learning, either formal or informal.

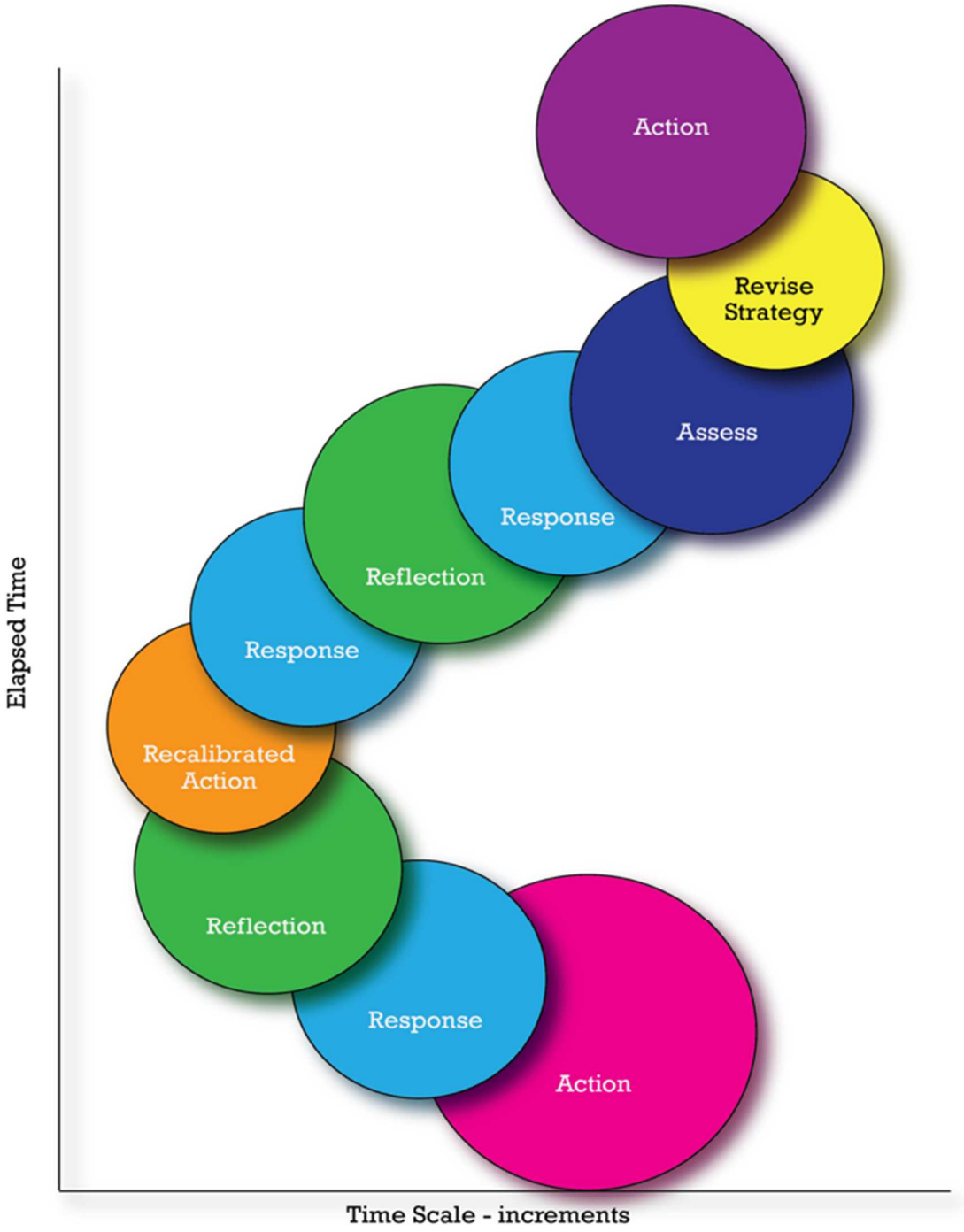


Figure 2.4. Visualization of gameplay as a function of time.

Figure 2.4 is an idealized visualization of game playing as a function of time. Each sphere is represented with a different shape. Shape size is based on prior knowledge base, new learning, time used, and effort (energy versus entropy). Holland (1998) describes the development of insights (learning) gained from experience in playing the game against an opponent who is applying their own knowledge and learning within the boundaries of the game rules. He notes all the players in the game are learning, and their strategies for play are changing as they learn and apply new strategies and assess the outcomes of those strategies against some expectation:

> A more realistic view is that *all* players are *simultaneously* trying to build models of what the other players are doing…. Even if [an observer who] knows the initial strategies and the details of individual learning procedures, it is next to impossible to predict the outcome of the game. Emergence and perpetual novelty are ever-present in games where the opponents are *adapting to each other* [italics added]. (Holland, 1998, p. 32)

Holland (1998) describes this notion of individual player's adaptations as coevolution, where each individual's strategy adjusts to its experience with its opponent:

> This coevolution exhibits the creativity we expect of any evolutionary process; the [player] is continually getting into parts of the [decision] tree not previously observed. Species of play rise to dominance and disappear, players mimic each other, and so on…. Prediction is difficult in these circumstances…. Everything depends on the level of detail we require of the prediction. Complexity and chaos do not forestall our study of emergent phenomena. The key to deeper understanding…is to determine the level of detail and the relevant [variables]. Using [variables] as building blocks, we can construct models that exhibit emergent phenomena in much the way that interacting strategies in a game

> produce *patterns of interaction* [italics added] not easily anticipated from inspection of the game's rules…. By attending to selected details, we can usually extract *recurring patterns* [italics added]. When these recurring patterns are regularly associated with events of interest, we call them *emergent* properties. (p. 34)

Holland describes the adaptive process players use to apply the game's rules and respond to the play of an opponent. Repeated play of the game allows the player to leverage past play and familiarity with the opponent's play to form new strategies. This combination provides for the level of emergence the player produces available for use in future play of the game.

Research Hypotheses Based on Review of the Literature and Research Questions

Based on the purpose of the study, review of the literature and research questions of interest, hypotheses were developed to add to the literature based on the findings of the study. The theoretical framework used to design the study is based on Robert May's (1976) logistic map. Table 1.1 (repeated below as Table 2.5) summarizes the research questions used in the study. Research questions RQ1 and RQ2 are based on the fusion of IIL as conceptualized by Marsick and Watkins (1990, 2017) with notions of emergence as defined through the lens of complexity science and conceptualized by Holland (1998) and Mitchell (2009). The third research question applies methods from complexity science to identify and measure a new learning variable described as the roughness of learning.

Table 2.5

CraftDawg Study Research Questions

Number	Question
RQ 1	To what extent does incidental learning affect adaptiveness in a novel situation?
RQ 2	What is the relationship between uncertainty and adaptiveness in a novel situation?
RQ 3	Is there a roughness of learning variable that measures complexity in adaptiveness?

Adaptation of Robert May's Logistic Map

In this adapted format, the conceptual model used in this study represents the current knowledge base (x_{n+1}) based on the past knowledge base as modified by adaptive behaviors.

$$\boldsymbol{x_{n+1} = r x_n (1 - x_n)}$$

This model provides both the quantification and visualization of how chaotic behavior can arise from a simple nonlinear dynamical equation. For this purpose, x_n represents the *past adaptive capacity of a learner (individual or organization) as a percentage of maximum adaptive capacity*. '*r*' represents the rate of adaptiveness with a range of 1 (no change) to 4. Rate of adaptiveness is the result of changes in the environment(context) plus the learner's efforts to change to meet the environmental challenges. The growth rate represented as rx_n, is moderated by the *inefficiency or dormancy* in the use of adaptive capacity (1 – current adaptive capacity), where current adaptive capacity is x_n.

An example of this in shown in Figures 2.5, 2.6 and 2.7. These figures were created by populating this model over time series calculations t = [1, 200] to show the chaotic behavior that emerges as the model is applied using the stated variables. Setting x_0 (past adaptive capacity utilization) to 50% of maximum adaptive capacity and using a rate of adaptiveness $\boldsymbol{r}$ of 3.0

produces Figure 2.5. The graph shows the pattern of behavior and allows us to estimate further development. It also suggests that there is capacity to meet the environmental challenge in that the adaptive range shows a consistent “smooth” pattern. If the time series is run out further, we will find that the two lines become very close, but do not merge. The system is in a stable state and can sustain itself.

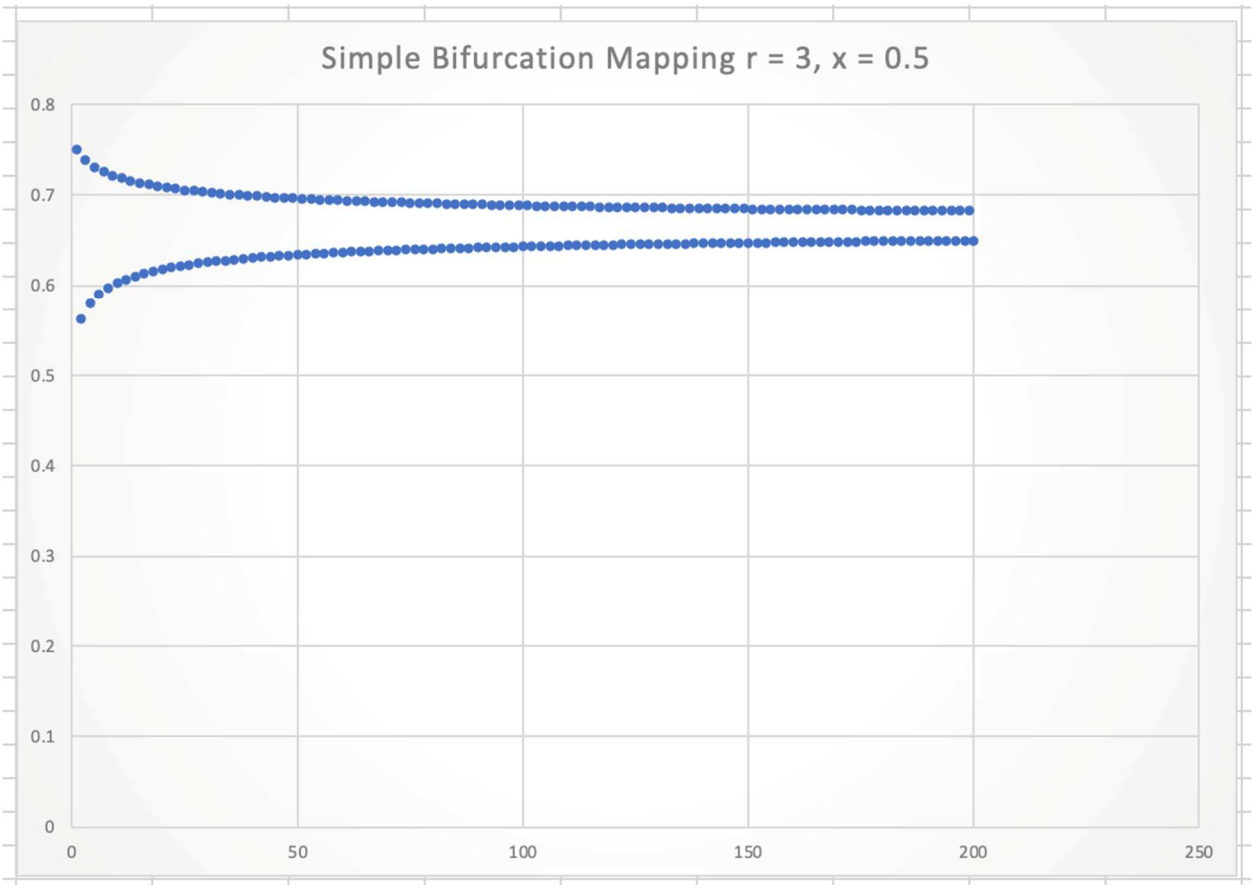


Figure 2.5. Bifurcation mapping, $r = 3.0$, $x_0 = 0.50$.

Setting the values to x_0 = 50% and r = 2 shows a very distinctive pattern in Figure 2.6. This pattern allows for prediction and estimation. The pattern shows a stable, predictable pattern and the system can sustain itself within itself. There is no notable threat of dissipation.

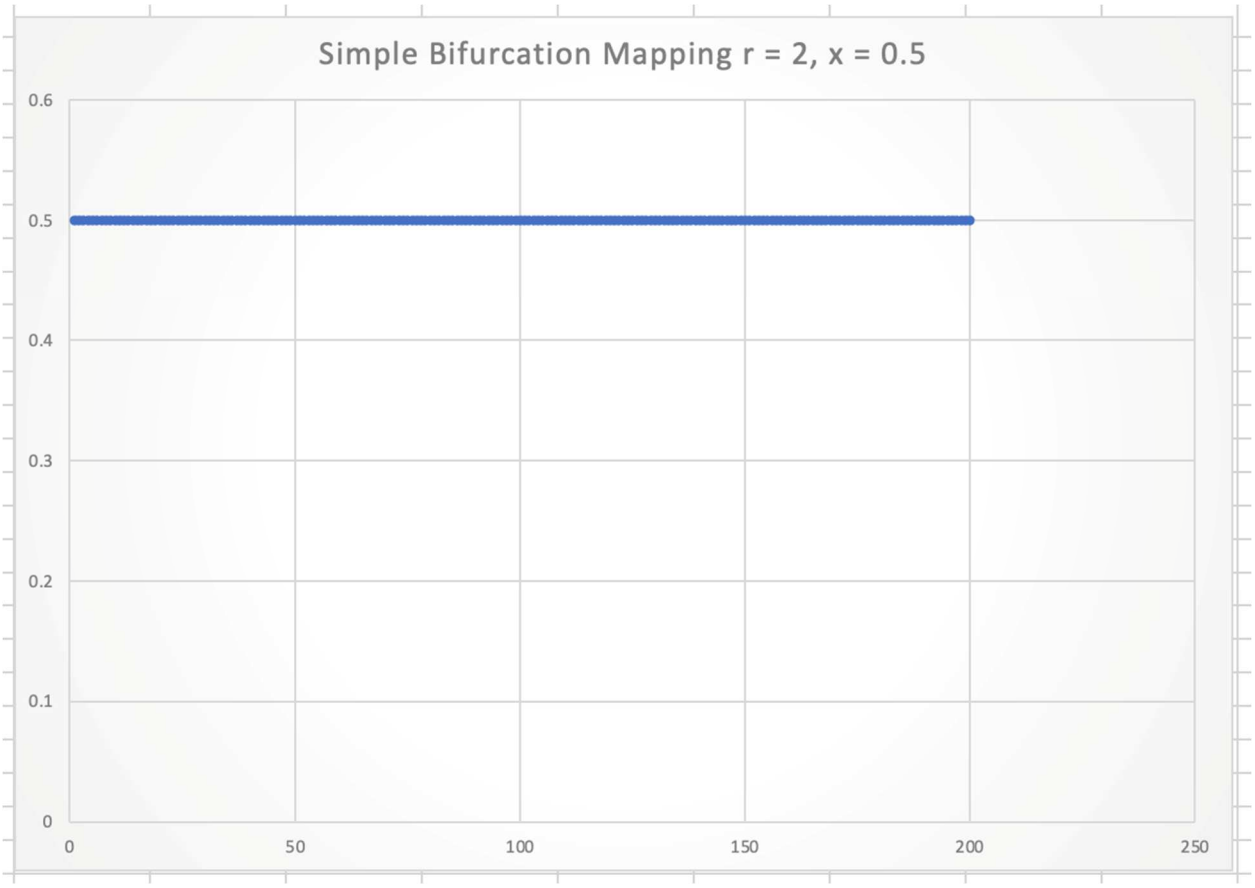


Figure 2.6. Bifurcation mapping, $r = 2.0$, $x_0 = 0.50$.

Figure 2.7 shows the model "patterns" when the initial value of $x_0 = .75$ and r = 3.75. There is a pattern, but there is something else emerging that precludes us from using estimation methods. According to May and others (Holland, 2012; May, 1975; Mitchell, 2009), this is the behavior that we expect to see at the *edge of chaos*. In complexity science the edge of chaos is a phase state where the system is facing a dissipative threat and must trigger its adaptive responses to sustain itself. To the extent the adaptive response is adequate, the system sustains and returns to a stable state, yet it may be weaker for the effort or it may be stronger for the effort as a

function of "learning" as defined by the discipline. In human learning, this would be defined as emergence.

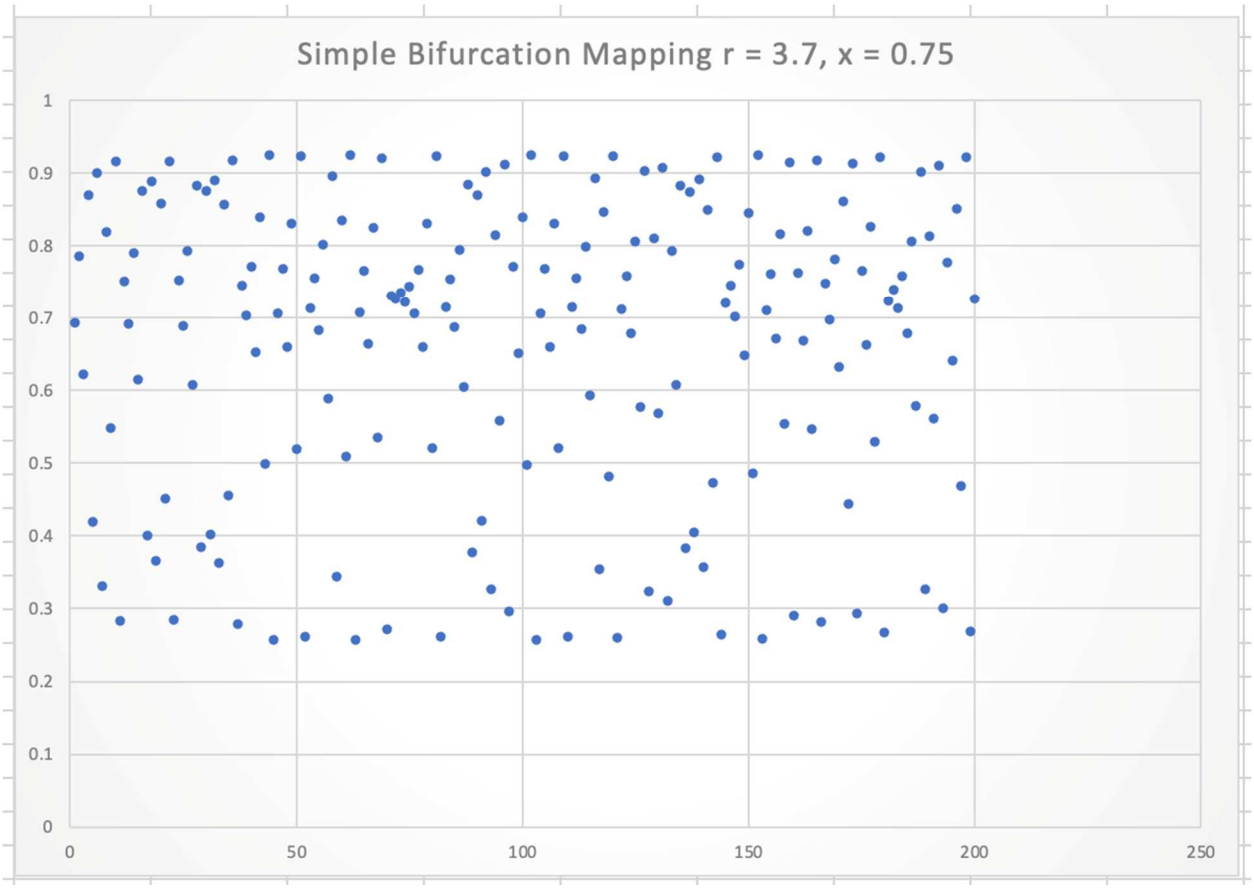


Figure 2.7. Bifurcation mapping, $r = 3.70$, $x_0 = 0.75$.

In an applied sense, the individual would have to make a change to either or both of the model parameters by increasing adaptive capacity, decreasing the environmental turbulence through adaptation or external intervention, or increasing the rate of adaptive change. To the extent that the individual cannot adapt, the system begins to dissipate.

Hypotheses Associated with Research Questions

Based on review of the literature and the empirical studies associated with incidental learning, for RQ1, hypothesis H1A was developed: *Participants will utilize incidental learning to increase adaptiveness in the moment in a purpose driven context.* Specifically, this hypothesis was developed based on studies by Silva (2007), Taber et al. (1999) and Harner (2013). All these studies emphasize the use of incidental learning in the moment to address novel contexts. In all of these studies, incidental learning is identified as being the source of action and direction when the sense of the context does not align with prior training, learning or knowledge.

Hypotheses H2A and H2B are based on analysis of Marsick and Watkins (1990) dimension of reflection as a source of meaning making and knowledge fused with the role of uncertainty as identified in adaptive processes from environmental science (Adger & Vincent, 2005; Vincent, 2007). Based on interpretation of Marsick and Watkins (1990) and the theorized role of uncertainty in adaptive processes and adaptive capacity, H2A is that *uncertainty will negatively influence adaptiveness* and H2B is that *uncertainty will be inversely related to incidental learning*.

The third research question is formed based on applied principles of complexity science in using the fractal dimension of a time series shape to measure the complexity associated with the activities associated with creating the shape. Building on the empirical studies by Skjeltorp (2000) and Guo (2017) that calculated the fractal dimension of a time series based on human activities, this study proposed to use the same method to calculate the fractal dimension associated with various aspects of game play. H3A is based directly on the work of Skjeltorp (2000) and Guo (2017). H3A is *there is a roughness of learning effect that can be estimated as a measure of complexity in game play*.

Three additional hypotheses were developed based on the methodology used by both Skjeltorp (2000) and Guo. (2017) combined with interpretation of Marsick and Watkins (1990). H3B is that the *roughness of learning will reduce over time as a player adapts to the game using informal and incidental learning*. H3C is that *the roughness of learning will be less steep for experienced players*. H3D is that *the roughness of learning trajectory will be steeper for novice players.*

Definitions

Individual adaptive capacity is defined as the range within which a unit of interest may *change* its behavior to respond to a stimulus in pursuit of an objective, either to improve an outcome or avoid adverse consequences (Smit & Wandel, 2006; Yohe & Tol, 2002). Included in this range is the ability of the unit of interest to use warehoused *rules* from prior learning. The unit of interest may be a human, an ant, an organization, or an economy. To increase individual adaptive capacity, the effective adaptive range must be increased by some means (Smit & Wandel, 2006; Yohe & Tol, 2002).

For this study, maximum *adaptive capacity* is defined as a function of the dynamic interactions of individual adaptive capacity of a collection of units operating within a system. For both individual and maximum adaptive capacity, *environment (context)* and *time* provide boundaries to an adaptive range (Holland, 1995; Mitchell, 2009), also called coping range (Yohe & Tol, 2002). Complexity theorists describe adaptive capacity as a latent trait embedded in specific complex systems, distinguished as complex *adaptive* systems (Holland, 1995; Manson, 2001; Mitchell, 2009).

The *roughness of learning* is a function of the complexity of learning in a given context.

Conceptually this can be defined as: Roughness of learning = interaction of (environment, human learning, time, adaptive capacity, and rate of adaptiveness). Fractal dimensionality is a measure of roughness which is a proxy for complexity (the lack of "smoothness" or fit).

Informal and incidental learning is defined by Marsick and Watkins (1990) as "not typically classroom-based or highly structured, and control of learning rests primarily in the hands of the learner" (p. 12). Conscious awareness and the role of reflection distinguish the broader category of informal learning from incidental learning. The greater the learner's clarity on a learning objective, the more direct the learning process and the more specific the learning methods used. This is contrasted with incidental learning where the learner is less aware of knowledge being acquired in a given context and likely is only attuned to the learning when it is applied in a different context.

Incidental learning is distinguished in the proposed study and based on description from Marsick and Watkins (1990), who define incidental learning as a subcategory of informal learning and as learning derived from a process that "takes place on a continuum of conscious awareness":

> Incidental learning includes learning from mistakes (including how people frame experiences as mistakes), learning by doing (including trial-and-error experimentation), and learning through a series of covert interpersonal experiments…. The degree of conscious awareness of one's learning plays an important role in the clarity of learning…. Many times [incidental] learnings are unintentional consequences. (pp. 13–14)

CHAPTER 3

METHODOLOGY

This chapter includes (a) the description of the purpose of the study, (b) research questions and hypotheses, (c) theoretical and methodological framework of the study, (d) instruments, data assembly, table creation and model development methods for structural equation modeling (SEM), and an overview of the development of the roughness of learning variable using a rescaled fractal.

Purpose of the Study

The purpose of the CraftDawg study was to identify, develop and analyze a new variable associated with the informal and incidental learning process as conceptualized by Marsick and Watkins (1990, 2017). The learning variable of interest was described as the *roughness of learning (RoL)*. At its core, the roughness of learning variable was conceptualized to measure the complexity of the learning challenge based on context and allow assessment of how this complexity changes (if at all) over time. As Holland (1995, 1998) noted, complexity is defined by its nonlinear behavior and potentially erratic behavior over time. The RoL variable was developed to capture the complexity of the learning effort *at points in time*.

Research Questions and Hypotheses

To develop the roughness of learning variable, the researcher used an interdisciplinary approach to conceptualizing the data collection and model creation. The research questions and hypotheses provided the basis for the data collection and analysis methods used in this study. The study relied on data collected from participants in a repeated-measures longitudinal study.

The data collected was analyzed using dimensions from informal and incidental learning theory (IIL) of Marsick and Watkins (1990). In addition, data was collected based on theories founded in complexity science as used in environmental studies to examine adaptiveness and uncertainty (Adger & Vincent, 2005; Vincent, 2007). The research questions were developed to align with the primary research purpose. Table 1.1 (repeated below as Table 3.1) summarizes the research questions examined in this study.

Table 3.1

CraftDawg Study Research Questions

Number	Question
RQ 1	To what extent does incidental learning affect adaptiveness in a novel situation?
RQ 2	What is the relationship between uncertainty and adaptiveness in a novel situation?
RQ 3	Is there a roughness of learning variable that measures complexity in adaptiveness?

The first research question was: "*To what extent does incidental learning positively affect adaptiveness in a novel situation?"* To answer this question, adult participants with minimal game playing experience were asked to play the serious game of *Minecraft: Survival Edition version 1.17*. To contrast the play of novice players, more Advanced players were included in the study. All groups of players were asked to play a minimum of five times for a minimum of 10 minutes per play. After each play session, players completed a post-play survey.

The second research question was: *"What is the relationship between uncertainty and adaptiveness in a novel situation?"* To answer this question, the study related *reflection* as defined by Marsick and Watkins (1990) as a partial offset to *uncertainty*. *The assumption underlying this was reflection and uncertainty are inversely related on some basis*. According to Marsick and Watkins (1990), reflection is necessary for meaning making. The implication of the assumption was meaning making *reduced* uncertainty and was replaced by knowledge. Therefore, meaning making was requisite in knowledge creation. *Incidental learning* according to Marsick and Watkins (1990), had no tangible meaning making path, until there was a *purpose* for the previously acquired tacit knowledge. Basic to this assertion was that *time of reflection* to create meaning making was a variable.

A third research question was *"Is there a roughness of learning variable that measures complexity in adaptiveness?"* To answer this question, the study collected, and the researcher scored various 'health measures' at time of each death in the game on a longitudinal basis for the entire population as well as based on the experience level as originally self-reported (Novice, Intermediate, Advanced). The data was plotted as a time series and the boxcounting method was used to calculate the fractal dimension of the series. The researcher compared the fractal dimension for each play session to the previous play session as well as the change in the fractal dimension for the entire series to examine the change in complexity as measure by the fractal from the beginning to the end. The researcher also calculated the fractal based on experience groups as well as for the entire population of participants. The full methodology for parsing, scoring, and creating tables used in the study is shown in as Appendix A.

Study Hypotheses by Research Question

To address Research question 1, "*To what extent does incidental learning positively affect adaptiveness in a novel situation?*", the researcher proposed the following hypothesis based on literature review and previously reported empirical studies (Guo, 2017; Harner, 2013; Silva, 1999; Skjeltorp, 2000; Taber, 2004):

- H1A: Participants will utilize incidental learning to increase adaptiveness in the moment in purpose driven context.

Research question 2 was *"What is the relationship between uncertainty and adaptiveness in a novel situation?"* The researcher posed the following hypotheses for this question:

- H2A: Uncertainty will negatively influence adaptiveness.
- H2B: Uncertainty will be inversely related to incidental learning.

The final research question was "*Is there a roughness of learning variable that measures complexity in an adaptive process?"* To answer this question four hypotheses were posed:

- H3A: There is a roughness of learning effect that can be estimated as a measure of complexity in game play.
- H3B: The roughness of learning will be different for experienced players compared to novice players.
- H3C: The roughness of learning trajectory will be less steep for experienced players.
- H3D: The roughness of learning trajectory will be steeper for novice players.

Theoretical and Methodological Framework of the Study

Robert May's (1975) logistic model provided the theoretical framework for this study. The logistic model is defined mathematically as:

$$x_{n+1} = rx_n(1 - x_n)$$

According to Wikipedia (2022), in this equation,

x_n is a number between zero and one. This represents the ratio of the existing population to maximum population capacity. This nonlinear difference equation is intended to capture two effects:

- *reproduction* where the population will increase at a rate proportional to the current population when the population size is small (rx_n)
- *starvation* (density-dependent mortality) where the growth rate will decrease at a rate proportional to the value obtained by taking the theoretical "carrying capacity" of the environment less the current population ($1-x_n$).

The usual values of interest for the parameter, r, are those in the interval [0,4], so that x_n remains bounded by [0,1].

The essence of May's model was that systems move through various states based on *adaptive ability and resources* in response to environmental complexity. To the extent external forces (context) moved the system into an edge of chaos state (evidenced by more erratic and seemingly random movements and responses by the system), the ability to adapt became stressed and, if adaptive capacity were not adequate and/or could not be increased adequately (amount and timeliness) to reduce complexity then the system dissipated (May, 1975).

May's model showed there was a threshold of complexity where the system exceeded its ability to adapt, and the system dissipated (perhaps to reform in a modified state or completed vanish). Using repeated-measures methodology, this process and effect was shown quantitatively as the loss of predictive patterns as complexity variable (r) approached a threshold (3.56995) (May, 1975). This lack of patterns in system behavior was the definition of chaos (Mitchell,

2009). The CraftDawg study applied this theoretical framework in a repeated-measures longitudinal study to examine human adaptive capacity as influenced by individual incidental learning and uncertainty to predict a given outcome in a serious game.

The researcher, relying on dimensions of incidental learning defined by Marsick and Watkins (1990, 2017), remapped May's equation based on Figure 2.2:

$$adaptiveness_{n+1} = learning_context * adaptiveness_n (1 - adaptiveness_n)$$

- x_n represents *current* adaptiveness as a percentage of maximum adaptive capacity. (All models used $x_0 = 0.75$ for presentation purposes.)
- x_{n+1} represents *new* level of adaptiveness as percent of maximum adaptive capacity.
- $(1 - x_n)$ represents *the inefficiency in trial-and-error effort* (*unlearning*) – effectively inefficiency in marginal learning.
- r represents the complexity in the learning context as measured by the rescaled fractal dimension.

The researcher sorted the data on the basis of play session and calculated the fractal dimension based on the health of the player at time of death using the boxcounting method.

Data Analysis Approach

To answer the research questions and assess the validity of the hypotheses, data was collected using a variety of methods in a repeated-measures, longitudinal study. Data was collected, scrubbed, and parsed as described in Appendix A. Tables were created using MySQL as described in Appendix A. Data from the tables created was used to derive a quantitative model using exploratory factor analysis (EFA) and SEM through confirmatory factor analysis (CFA) to

identify significant latent variables and a structured equation path diagram with parameter estimates that related latent variables and exogenous variables.

Summary of Latent Variables Examined in CraftDawg Study

To capture certain of these specific dimensions (incidental learning, reflection, and adaptiveness) the study examined them as latent variables which manifested in observed variables.

- *Incidental learning* was measured using a self-reported instrument completed prior to participation in the game and using a separate self-reported instrument completed after each game play session. The instrument was developed based on previously developed scales and input from experts.
- *Reflection* was measured directly before participants began play and indirectly as the latent variable of *uncertainty* during the play sessions. The assumption underlying this treatment of reflection and uncertainty was they are opposite sides of the coin. According to Marsick and Watkins (1990), reflection was necessary for meaning making. The logic used in this study was meaning making reduced uncertainty as it was replaced by knowledge. The implication was meaning making was requisite in knowledge creation. Incidental learning according to Marsick and Watkins (1990) had no tangible meaning making path, until there was a purpose for the previously acquired tacit knowledge. The scale for *reflection* was developed based on input from experts. The scale for *uncertainty* was developed using similar scales from environmental science (Adger & Vincent, 2005; Vincent, 2007). .
- *Adaptiveness* was measured using a post-play, self-reported instrument. The instrument was developed using similar scales from environmental science (Adger &

Vincent, 2005; Vincent, 2007). Each participant completed the instrument after each play session up to five times during the study.

Observed variables were captured through self-reporting responses to the various scales developed for the study as well as analysis of observed behavior as manifest in actual game play activities in a simulated complex environment. All self-reported scales are included as Appendix B.

Study Design

Holland (1998) used serious games to simulate the behavior of complex adaptive systems which interact in *nonlinear ways*. According to Lanning (2019), "Serious games are games that have another purpose besides entertainment. They are used to promote learning and behavior change" (para. 1) The CraftDawg study used the serious game, Minecraft: Survival, to simulate a complex environment. Minecraft was considered a serious game and thus was appropriate for the proposed study (Moro et al., 2020).

Branding and Automation of the Study

The overall design of the study relied on methodologies and approaches typically found in new product development and promotion. To create an inviting and safe feel for the study, the researcher branded it as the *CraftDawg Study*. Part of the branding included creating a variety of logos using the Minecraft block method of creating CraftDawgs in various poses and positions. Figure 3.2 shows one of the CraftDawg logos. A fully automated support platform was created with the branding embedded throughout both in language and look and feel of communications. In addition to automated support, payment for participation was designed on an increasing scale.

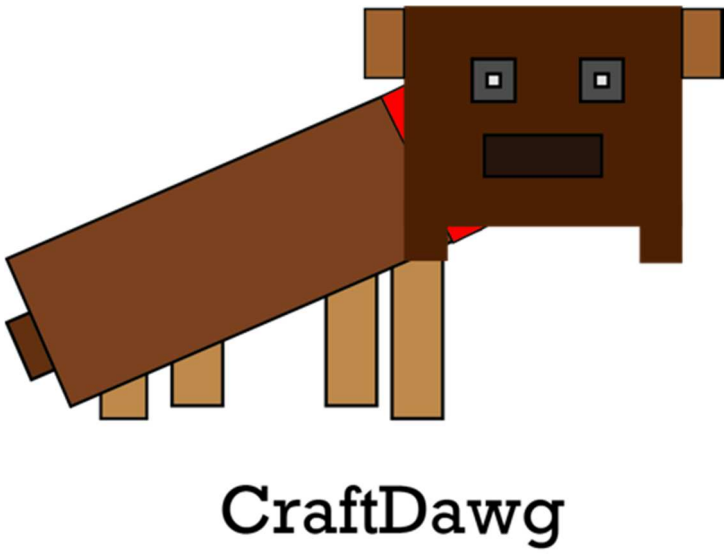


Figure 3.2. Example of CraftDawg logo.

Multiple technologies were used to create the platform for the study. Table 3.2 shows the technologies used for the study platform.

Table 3.2

Technology Platforms Integrated for CraftDawg Study

Technology	Description
Google Forms	Study enrollment
Google Forms	Self-reported demographic data and Pre-Play 1 responses
Google Forms	Self-reported Pre-Play 2 responses
Google Forms	Self-reported Post-Play 1–5 responses
Zapier	Integration software between Google Forms and Salesforce Main Study Platform. Google Forms were designed with a completion trigger that "alerted" Zapier "scripts" to harvest the data and then map it to Salesforce.

Salesforce	This was the primary platform for the Craftdawg Study. All data harvested from Google Forms, data associated with completed plays, follow up dates, reminder emails, instructional emails, and Minecraft license procurement. Minecraft Figure x shows the administrative flow of the study. Server assignment, post-play survey completion status, study completion status, participation payment and study closing status were all housed in Salesforce.
Minecraft Servers	Four Bukkit Minecraft servers housed on Amazon Web Services (AWS)
MySQL	Provided directly written database for Minecraft Plugins (Inventory Rollback and Plan)
R	Multiple R statistical packages (including Lavaan and Psych) housed on AWS. R was used to scrub and parse .log data from game play logs extracted from Minecraft game play. Scrubbed game play files were ported to MySQL and written to appropriate tables using R scripts

The design required a reliable technology platform that would allow the researcher to automatically collect accurate data on a variety of variables based on the input from the participant as well as triggering timing or accomplishments. The study targeted a participant population of older adults, and specifically encouraged non "digital natives" to join the study. Novice and beginner players were also actively encouraged to join the study. Indeed, the study was promoted to participants with the tag line of "How Old Dawgs Learn New Tricks" when it was introduced in the primary organization for recruiting participants.

Because the nature of the study involved installing, configuring, and engaging with potentially unfamiliar technology, the researcher created a comprehensive technology support system for both study administration and game administration. This system included a website hosting instructional manuals and videos of how to download and install the Minecraft client and sign on to the assigned server. Automated emails that included links to customized videos were created by the researcher to provide installation details specific to the study. In addition, the

researcher provided links to various support sites on how to play the game and encouraged participants to use all means they were comfortable with for engaging with the game, including friends, relatives (children and grandchildren), colleagues, web-based forums, and social networking platforms. A series of automated emails was created on a variety of subjects to support the communication and engagement needs of the study. Based on the nature of the trigger, a specific email was triggered and sent to the game email address of the participant.

Study and Game Administration

Study administration was automated based on triggers developed by the researcher using methods available in Salesforce. For instance, when a participant completed the second pre-play survey in Google Forms, the Zapier integration software "alerted" the CraftDawg Salesforce platform, and a researcher-created automated alert was sent to the study administrator requesting a Gamer email account be set up. Once this was done, the study administrator would add the Gamer email to the Salesforce record for the participant. This triggered a researcher created automated email to the participant requesting them to sign into the Study email address and to send a reply to the study administrator. Once the reply was received, the study administrator updated the Salesforce record to reflect that, and an automated request was sent to the study administrator to set up the Minecraft account and procure the Minecraft credentials for the participant. The details of these administrative activities were included in the Salesforce record, triggering an automated email to the Gamer email address advising the participant to download the Minecraft game and which server address to sign into for playing the game. This email included links to download support and videos created for the study. Consistent with institutional review board (IRB) protocols of confidentiality, the gamer name became the primary key for the

participant and was used to integrate the various tables used for analysis. The creation of some analysis and administration tables required the use of secondary keys for sorting purposes.

Game administration used MySQL databases to monitor game play and length of play. The Minecraft plugin, Plan, was used to write data to a table in a CraftDawg MySQL database. The researcher wrote several MySQL scripts to calculate the date and time of play as well as the length of play. This data would be used later to create tables for analysis. This allowed the game administrator to check the play tables multiple times during the day and update the participant record in Salesforce for each play of adequate length. The update of the Salesforce record would trigger an automated email to the participant with a link to a post-play survey. Participants understood compensation for the study was triggered by completion of the post-play surveys. While some participants continued to play without completing the post-play surveys, the play record was not updated until an outstanding post-play survey was completed. As each post-play survey was completed, an automated email was sent thanking the participant and reminding them of how much compensation had been earned and what additional compensation could be earned by continuing to fully participate in the study.

In addition to using the Salesforce platform to automate various tasks, the researcher created various reports in Salesforce to allow for individual follow up with participants on status or errors in the spelling of the gamer name which would cause a fault in the integration software. The ability to efficiently continue to encourage play and to remind participants of how compensation was earned likely produced a higher completion rate of the full target of five plays for a minimum of 10 minutes. In addition, the participation compensation was designed on an increasing basis, so each additional play earned more than the prior play up to a full payout of $150 for completion of all five plays.

Sample

To test the study design, technology and administration protocols, the researcher recruited a pilot group of ten participants to complete the entire study. Eight pilot participants completed the entire study. The pilot participants met the study criteria, and their results were included in the full study as completers. Full study participants were recruited by the researcher from a small, private liberal arts university and its sister law school. IRB approval was received from the primary research site. IRB approval was also requested and received by an onsite principal investigator who helped facilitate support from the human resources director at the school. All nonstudents (faculty, support, and administrative staff (salaried and hourly) were invited to participate in the study with a cap on participation at 200 participants. Overall, 900 prospective participants were identified to receive the announcement and recruitment email. One hundred fifty-six respondents completed PrePlay_Survey1. One hundred forty-three respondents completed PrePlay_Survey 2. Ninety-five respondents completed the entire study which required competition of PrePlay surveys, five play sessions of more than 8 minutes and competition of five post play surveys. Table 3.3 shows the age demographics of respondents completing the entire study (n=95).

Table 3.3

Study Participant Completer Age Demographics

Group	N	Min	1st Quartile	Median	Mean	3rd Quartile	Max
All	95	21	31	39	41.85	51.50	75
Female	65	21	31	39	42.35	54.00	70
Male	30	25	32	36	40.77	45.75	75
Novice	47	21	34	39	43.81	56	75
Experienced	48	24	30.75	37.50	39.94	47.50	69

Data Collection

Data was collected from self-selected participants using two methods: completion of self-reported surveys and directly from game play associated with each participant, either in the form of *.log* data from the game or from databases associated with plug-ins included in the game. Appendix A shows the data collection process used for the self-reported data. Three surveys were created for use with the study: PrePlay1, PrePlay 2 and PostPlay. Appendix B shows these surveys. All surveys were created in and hosted on Google Forms. All data was harvested from Google forms in *.cvs* format. Self-reported data was merged with game play data using the unique participant gamer name. A full participation data set was created for each participant that included enrollment data, PrePlay surveys, and post play surveys mapped to the specific play session associated with the post play survey.

Development of Study Instruments

The researcher used the MEASURE approach to create the self-reported instruments (Kalkbrenner, 2021). Kalkbrenner's (2021) MEASURE approach to instrument development includes seven steps: make the purpose and rationale clear; establish empirical framework; articulate theoretical blueprint; synthesize content and scale development; use expert reviewers; recruit participants; and evaluate validity and reliability (pg. 2).

Scale Development

CraftDawg Pre-Play 1 Scale

IIL theory holds that this type of learning exists along a continuum (Marsick & Watkins, 1990). The researcher hypothesized that incidental learning as theorized by Marsick and Watkins (1990) (tacit knowledge and prior learning from experience) would provide the initial reservoir of knowledge for the study participants. To determine the reliance on this, CraftDawg Pre-Play 1

scale was developed to assess how incidental learning is developed and deployed by the respondent in a perceived novel context. This was a generalized assessment as it was completed prior to game play and after admission into the study.

Working in collaboration with an expert in incidental learning theory, the researcher developed questions to reflect certain dimensions identified by Marsick and Watkins (1990). The scale was refined after testing with a pilot group and questions were removed based on the reliability as measured by Cronbach's alpha [items were removed when standardized alpha was less than 0.60 to improve reliability] (Nunnally & Bernstein, 1994) . Ultimately, self-reported responses to thirteen questions were used for analysis. The final scale is presented in Appendix B.

CraftDawg Pre-Play 2 Scale

Complexity science holds that edge of chaos situations inspire and require adaptive responses to return the system to a stable state (Mitchell, 2009). IIL emphasizes the role of reflection and numerous studies have note the significant influence of reflection in meaning making to create new knowledge. (Eraut, 2007, 2011; Livingstone, 1999; Marsick & Watkins, 1990). Other studies (Harner, 2013; Silva, 2017; Taber et al., 2004) have examined the influence of reflection in edge of chaos contexts where unfamiliarity was paramount and *in the moment* application of previously created knowledge from prior learning was needed to adapt *in the moment*.

Two implied assumptions associated with reflection and confirmed in other empirical studies are the *availability of time* and a *propensity to reflect* (Harner, 2013; Silva, 2017; Taber et al., 2004).Yet in novel circumstances time for reflection was not assured (Goldman et al., 2009; Harner, 2013; Taber et al., 2008). Adaptive practice must rely on tools available *in the moment*,

such as prior experience and tacit knowledge combined with the ability to apply this warehoused knowledge in some manner in the moment to either quell the edge of chaos moment or to deflect or mitigate the most pressing challenge and use the learning process informed by feedback loops to move to a more stable (Harner, 2013; Silva, 2017; Taber et al., 2004). Modest reflection in the moment using feedback loops to revise previous acquired knowledge and/or repurpose tacit knowledge becomes a sustaining approach. This is consistent with Schön's (1984) "reflection in action" process.

The CraftDawg Pre-Play 2 scale was designed to assess the relationship between meaning making through reflection and its expected influence on game play. In IIL as described by Marsick and Watkins (1990), reflection was an integral element of learning as it contributed to the meaning making. The researcher hypothesized that reflection in action would be used on some basis to reduce uncertainty in an effort to increase adaptiveness. This hypothesis was consistent with the study findings by Silva (2017), Taber et al. (2004) and Harner (2013). The implications of this hypothesis would suggest a participant's reservoir of prior learning and knowledge – inclusive of experiential and tacit knowledge would provide the initial base for adaptive response. As additional plays occurred and time elapsed, reflection might influence the game play overall, but not as powerfully as incidental learning in the moment of ambiguity and crisis from novel in-game situations.

To the extent the participants separated reflection and meaning making from game play, the researcher hypothesize that adaptiveness was more influenced by applied incidental learning approaches where reflection was less influential in adaptiveness. To assess the *prospective* influence of meaning making and reflection in the study, the researcher worked with an expert in informal and incidental learning to craft questions that would measure the importance of

meaning making and reflection to a given participant. The researcher also added questions related to how the participant expected to respond to the game environment to the extent the game revealed gaps in knowledge. Questions were culled based on review by an expert in the field. A pilot group completed the refined survey and reliability was assessed using Cronbach's Alpha. Questions that were deemed not reliable (where Cronbach's Alpha was less than 0.60) were removed (Nunnally & Bernstein, 1994). The final instrument is shown in Appendix B.

CraftDawg Post-Play Scale

The post-play scale for Play 1 through 4 was developed using individual incidental learning dimensions as identified by Marsick and Watkins (1990) and scales associated with environmental and political science based on the study of uncertainty and adaptiveness. The constructs of *uncertainty* and *adaptiveness* were included based on the process used by complex adaptive systems (Adger & Vincent, 2005; Vincent, 2007).

As with the development of the pre-play scales, post play scale questions were developed by the researcher. An expert reviewed and culled the questions. A pilot group was used to develop measures of internal consistency. Using Cronbach's alpha as a measure, questions were retained if the measure of internal reliability was greater than 0.60. The final instrument is presented in Appendix B.

Instrument Validation

Measure of Internal Consistency – Cronbach's Alpha Analysis

Cronbach's alpha was run to determine internal consistency as a measure of reliablity for each of the latent variables identified based on the exogenous variables. Table 3.4 shows Cronbach's alpha by instrument and latent variable. A score > = 0.60 is accepted as a providing

"reasonable internal consistency" (Tavakol & Dennick, 2011, pg 54). All factors had standardized alpha greater than 0.60 and were deemed to have reasonable internal consistency.

Table 3.4

Cronbach's Alpha Results for Instrument Latent Variables

					95% Confidence Boundaries	
Instrument	Latent Variable	*n*	Items	Std Alpha	Lower	Upper
Pre-Play 1	Social Incidental Learning	156	7	0.71	0.64	0.78
	Individual Incidental Learning	156	6	0.82	0.78	0.86
Pre-Play 2	Reflection	143	5	0.77	0.70	0.82
	Reflection in Action	143	4	0.80	0.75	0.85
Post Play	Individual Incidental Learning	369	13	0.83	0.81	0.86
	Adaptiveness	369	5	0.85	0.83	0.88
	Uncertainty	369	8	0.76	0.72	0.79

Participant Recruitment

The researcher identified a small United States based liberal arts school for hosting the study. The researcher limited participation to adult staff employed by the school. To recruit prospective participants to join the study an announcement email was sent through the organization email system announcing the study a week before by study administrators and the local principal investigator. The following week a recruitment email with an invitation to participate with a link to a Google Form participation questionnaire was sent. The completed participation link was electronically scored using an embedded algorithm for acceptability. If the

applicant was qualified to participate based on their answers regarding access to technology, a record was automatically created in Salesforce and several emails followed including human subjects' agreement, details of the study in terms of timing and how to earn payments, and the Pre-Play 1 survey.

In the Pre-Play Survey 1 (n=156), self-reported responses to survey questions and limited demographic data were collected. Once Pre-Play 1 was completed in Google Forms, it was automatically submitted through Zapier, the integration bridge from Google Forms to Salesforce, which updated the previously created Salesforce with demographic data and an automated email was sent with Pre-Play Survey 2. This was a fully integrated and automated process with no intervention by the study administrator.

Upon completion of Pre-Play Survey 2 (n=143), study administrators were notified, and the study administration commenced. This cycle continued through each of the five play sessions. Upon completion of the fifth post-play survey, an automated email was produced to notify the study administrator to close the study for the participant and provide payment.

Model Development Methods

The latent variables of *incidental learning* and *reflection* were created from responses to the pre-play surveys using EFA and CFA methods described by Loehlin (2004), Bollen (1989), and Kline (2016). The pre-play surveys were used to assess certain dimensions of Marsick and Watkins' (1990, 2017) IIL. Specifically, *incidental learning* was examined in Pre-Play 1 and *reflection* was captured in Pre-Play 2. Data was collected from two sources: the post play survey and directly from game play. Using EFA and CFA methods, the data was examined for latent variables based on matrix correlation analysis as described by Bollen (1989), Loehlin (2004) and Kline (2016).

CraftDawg Model Development

Loehlin (1989), Bollen (2004) and Kline (2016) describe methods for extracting latent variables from scale data using matrix correlation methods. EFA and CFA are methods to determine the existence of latent variables and the correlation and covariance among the exogenous variables. SEM methods were used to provide data for analysis in answering the research questions and assessing the validity of associated hypotheses. Using EFA to identify latent variables and CFA to identify relationships amongst the variables, latent variables of individual incidental learning and uncertainty (as proxy for reflection to meaning making to inform uncertainty) were estimated and included as predictor variables of the latent variable of adaptiveness. Regression analysis was used as part of model development to create a predictive model for the dependent latent variable of adaptiveness and the dependent observed variable of deaths. Two models were created: (a) context specific, CraftDawg Model 1, i.e., the Crafting Model; and (b) generalized learning model, CraftDawg Model 2, i.e., the Learning Model. CraftDawg Model 1 included scored play from the *crafting* latent predictor variable. CraftDawg Model 2 simplified Model 1 by removing crafting to create a more generalized model.

To answer the research questions and assess the hypotheses associated with those questions, the CraftDawg study used four self-reported scales and collected game play data from individual play sessions in Minecraft: Survival (version 1.17). Two self-reported scales were used before play began. A post-play self-reported scale was used after plays one through four. A final post-play scale was used after play five.

CraftDawg Pre-Play Survey 1 – Latent Variable Extraction Method

For CraftDawg Pre-Play Survey 1, a scale was created to measure Incidental Learning based on Incidental Learning as theorized by Marsick and Watkins (1990). Respondents

provided self-reported responses to demographic questions and a series of questions designed to measure dimensions of incidental learning. The complete questionnaire is included as Appendix B. Only fully completed responses were included in the analysis. A total of 156 respondents completed 29 questions. The R packages psych (version 2.2.5) and lavaan (version 0.6-12) were used for statistical analysis.

Factorability of Data

Correlation analysis was used to examine correlations amongst responses and indentify clustering within the data. This indicated potential factorability of the data and voided the notion of unidimensionality.

Data was tested for nomality using mshapiro test. Test statistic = 0.879, p = 6.04526e-10. If the mshapiro test is significant at p <= 0.05, the variance data is considered to have a non-normal distritution Based on this test, the variance data was determined to be non-normal. SEM is a robust method that can produce useful output on non-normal data (Yuan and Bentler, 2007). As the study used SEM for analysis, non normality did not influence the study methods or findings.

Kaiser-Meyer-Olkin (KMO) was used to determine factorability of the response data. The correlation matrix was used as its input. If the result of the test is > = 0.60 the data is likely factorable. Overall KMO score = 0.77 which indicates the data is likely not unidimensional and thus factorable.

A second test was run to confirm factorability of the data using the Bartlett test for sphericity of the data. If the result is significant (p < = 0.05), the data is likely factorable. Results of the Bartlett test on the correlation matrix of reponses was significant (p = 1.428425e-104)

Though nonnormal, the data was determined to be factorable, thus EFA was run to determine the number of factors evident in the data. "Generalized least squares (GLS) regression extends ordinary least squares (OLS) estimation of normal linear model by providing for possibly unequal error variances and for correlations with different errors. A common application of GLS estimation is to time-series regression in which it is generally implausible to assume that errors are independent" (Fox & Weisberg, 2018, p. 1).

Two factors were identified using the GLS factor extraction matrix. The two factors explained 40% of the variance. Table 3.5 shows various measures of variance explained by the factors.

Table 3.5

Variance Explained by Factors From Pre-Play Survey 1

	GLS1	GLS2
SS Loadings	3.59	1.62
Proportion of Variance Explained	0.28	0.12
Cumulative Variance Explained	0.28	0.40

To better identify the communality amongst the factors, factor analysis was run using the extraction method of GLS with oblimin rotation. Table 3.6 shows the sorted factor loadings by variable.

Table 3.6

Sorted Factor Loadings From Pre-Play Survey 1

Variable	Item	GLS1	GLS2
I do things I can't explain where I learned	12	0.91	-0.10
I surprise myself with stuff I know	11	0.82	0.10
I learn stuff when not trying	13	0.82	-0.01
Sometimes I just know what to do	9	0.66	0.05
Learn from trying and seeing what happens	8	0.40	0.40
ask people so I can learn	3	-0.13	0.62
Seekout other sources of info	5	0.09	0.60
watchothers consider different way	2	0.00	0.57
Think about situation after to learn	6	0.05	0.53
Comfortable learning by watching	1	-0.16	0.53
Try different things	4	0.24	0.47
If I don't know I search for sources	10	-0.02	0.34
Rely on what I already know	7	0.04	0.21

Figure 3.2 shows the relationship of the factors relative to each other. Variable 8 is confounded and not included in the model. Variables that are less than 50% are not included in the model.

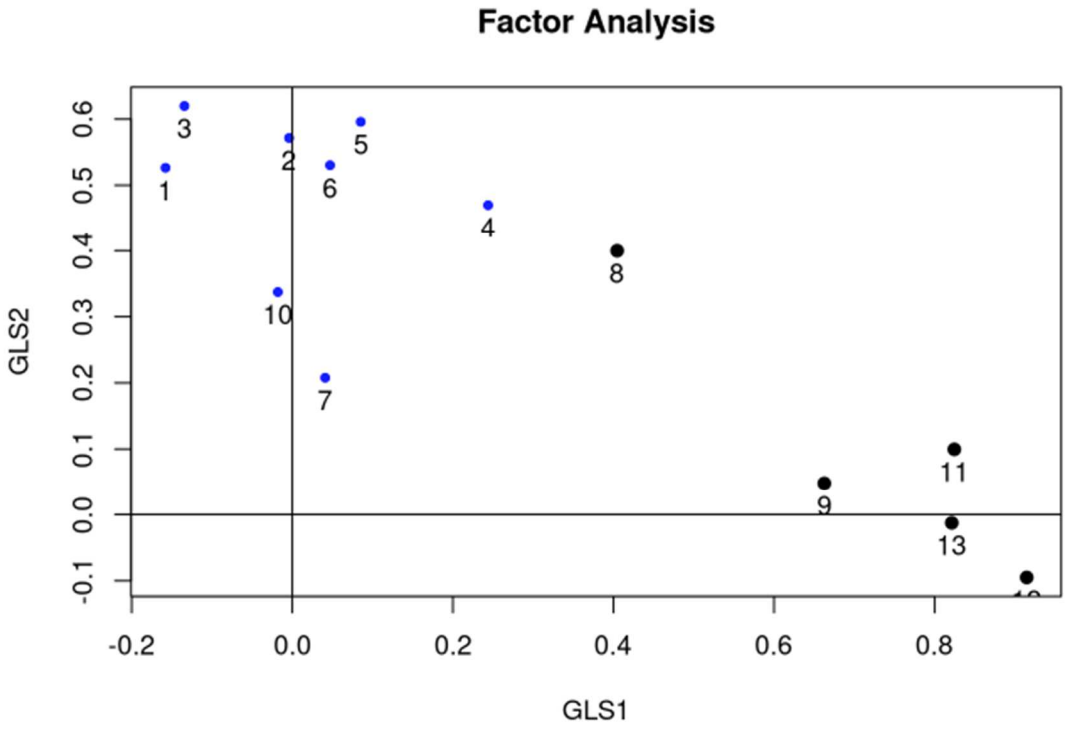


Figure 3.2. Pre-Play 1 cluster analysis of relationship of exogenous variables with latent factors.

The researcher followed the methods described by Bollen (1989), Loehlin (2004) and Kline (2016) to perform EFA and CFA analysis. Based on the result of the EFA, confirmatory factor analysis (CFA) was performed. Two latent factors were identified and described as: *social incidental learning and individual incidental learning*.

Model Identification

Factors that loaded at less than 50% were not included in the model. Confounded variables were not included in the model. Covariances were added to the model to improve the fit of the model. Significant covariances were included in the model to improve model identification.

Model Fit Indices

The model converged after 51 iterations. Model fit indices were calculated and are shown in Table 3.7. All model indices indicate the model is a good fit to the data.

Table 3.7

Model Fit Indices for Pre-Play 1

CFI (>=0.90)	TLI (>=0.90)	RMSEA (<=0.08)	SRMR (<= 0.08)
0.946	0.918	0.074	0.057

Table 3.8 shows the loadings of the observed variables from the latent variables. Standardized parameters are shown. Examination of P(>|z|) shows all parameters are significant at p < = 0.05.

Table 3.8

Loadings of Observed Variables From the Latent Variables for Pre-Play Survey 1

	Estimate	Std. Err	z-value	P(>|z|)	Std.lv	Std.all
Social Incidental Learning =~						
Ask people so I can learn	1.000				0.421	0.370
Seek out other sources of info	1.512	0.409	3.701	0.000	0.637	0.731
Watch others consider different way	1.282	0.322	3.983	0.000	0.539	0.466

	Estimate	Std. Err	z-value	P(>|z|)	Std.lv	Std.all
Think about situation after to learn	1.214	0.346	3.511	0.000	0.511	0.558
Comfortable learning by watching	0.960	0.294	3.264	0.001	0.404	0.303
Try different things	1.433	0.405	3.536	0.000	0.603	0.571
If I don't know I search for sources	0.747	0.250	2.986	0.003	0.314	0.330
Individual Incidental Learning =~						
I do things I can't explain where I learned	1.000					0.902
I surprise myself with stuff I know	1.249	0.274	4.566	0.000	1.126	0.646
I learn stuff when not trying	0.966	0.211	4.587	0.000	0.872	0.752
Sometimes I just know what to do	0.945	0.219	4.325	0.000	0.853	0.705

The covariance between the latent variables social incidental learning and individual incidental learning is shown in Table 3.9. Examination of P(>|z|) shows the covariance is significant.

Table 3.9

Covariance Between Latent Variables From Pre-Play Survey 1

	Estimate	Std. Err	z-value	P(>|z|)	Std.lv	Std.all
Social incidental learning ~~ individual incidental learning	0.155	0.067	2.315	0.021	0.409	0.409

Individual incidental learning latent variable explains 28% of the variance and *social incidental learning* latent variable explains an additional 12% of the variance. Both latent variables are significant at p < = 0.05.

CraftDawg Pre-Play Survey 2

Pre-play Survey 2 was designed to assess the relationship between meaning making through reflection and its influence on game play. *The purpose of this analysis was to support the theoretical and hypothetical development of the model based on the post-play analysis.*

The specific purpose of measuring reflection before the game play commenced was to assess the relationship between *reflective practice* to create meaning amongst the participants (defined as a willingness and an ability to reflect, make meaning, and adapt) and how the game might influence the *reflective practice* in each (game) context.

Pre-Play Survey 2 is shown as Appendix B.

Tests for Normality and Factorability of Data

Correlation analysis with significance testing was used to examine correlations amongst responses and to identify clustering within the data. This would indicate potential factorability of the data and void the notion of unidimensionality. Data was tested for nomality using M-Shapiro test. A significant value would indicate non-normality. The statistic is *0.876, p = 1.323146e-09.* If the M-Shapiro test is significant at p <= 0.05, the variance data is considered to have a non-normal distritution Based on this test, the variance data was determined to be non-normal. SEM is a robust method that can produce useful output on non-normal data (Yuan and Bentler, 2007). As the study used SEM for analysis, non normality did not influence the study methods or findings.

KMO was used to determine factorability of the response data. The correlation matrix was used as its input. If the result of the test is > = 0.60 the data is likely factorable. Overall KMO score = 0.74 which indicates the data is likely not unidimensional and thus factorable.

A second test was run to confirm factorability of the data. The Bartlett test for sphericity of the data was used. If the result is significant ($p <= 0.05$), the data is likely factorable. Result of Bartlett test on the correlation matrix of reponses is significant (26, n = 143, df = 45)

Though nonnormal, the data was determined to be factorable, thus EFA was run to determine the number of factors evident in the data. Generalized least squares is a recommended method for extracting latent variables in nonnormal data (Fox & Weisberg, 2018). Factor analysis using the generalized least squares (GLS) extraction method was performed to determine the number of factors. Parallel analysis identified two factors with three or more exogenous variables loading. The parallel analysis scree plot for Pre-Play 2 is shown in Figure 3.5.

GLS and oblique rotation using oblimin was performed to better identify the loading of exogenous variables on one of the two latent factors. EFA was run to assess the loadings by the exogenous variables to the two factors. The two factors described 45% of the variance in the data. Factor 1 accounted for 24% of the variance and factor 2 accounted for 21% of the variance. Standardized loadings (pattern matrix) based on correlation matrix are presented in Table 3.10.

Table 3.10

Standardized Loadings Based on Correlation Matrix for Pre-Play 2

Variable	Item Number	GLS1	GLS2
My life is meaningful	6	0.79	-0.02
I understand what is meaningful to me	2	0.75	-0.03
Self-reflection makes meaning	4	0.67	0.08
I understand meaning when things are hard	3	0.51	-0.03
I take time to reflect	1	0.51	0.01
I focus on valuable activities	5	0.44	0.02
Game changes affect my feelings	8	-0.03	0.86
Game changes affect my quality of life	7	0.08	0.74
Game change effect 1	9	0.01	0.66
Game change effect 2	10	-0.06	0.64

Bollen (1989) recommends removal of variables with non-significant loadings, thus loadings less than 0.50 were not included in developing the model. This removed Item 5, “I focus on valuable activities”. Based on the theory used to develop the scales, the researcher identified and described the factors as *reflection* (GLS1) and *reflection in action* (GLS2). Figure 3.3 shows the relationship of the exogenous variables as clusters.

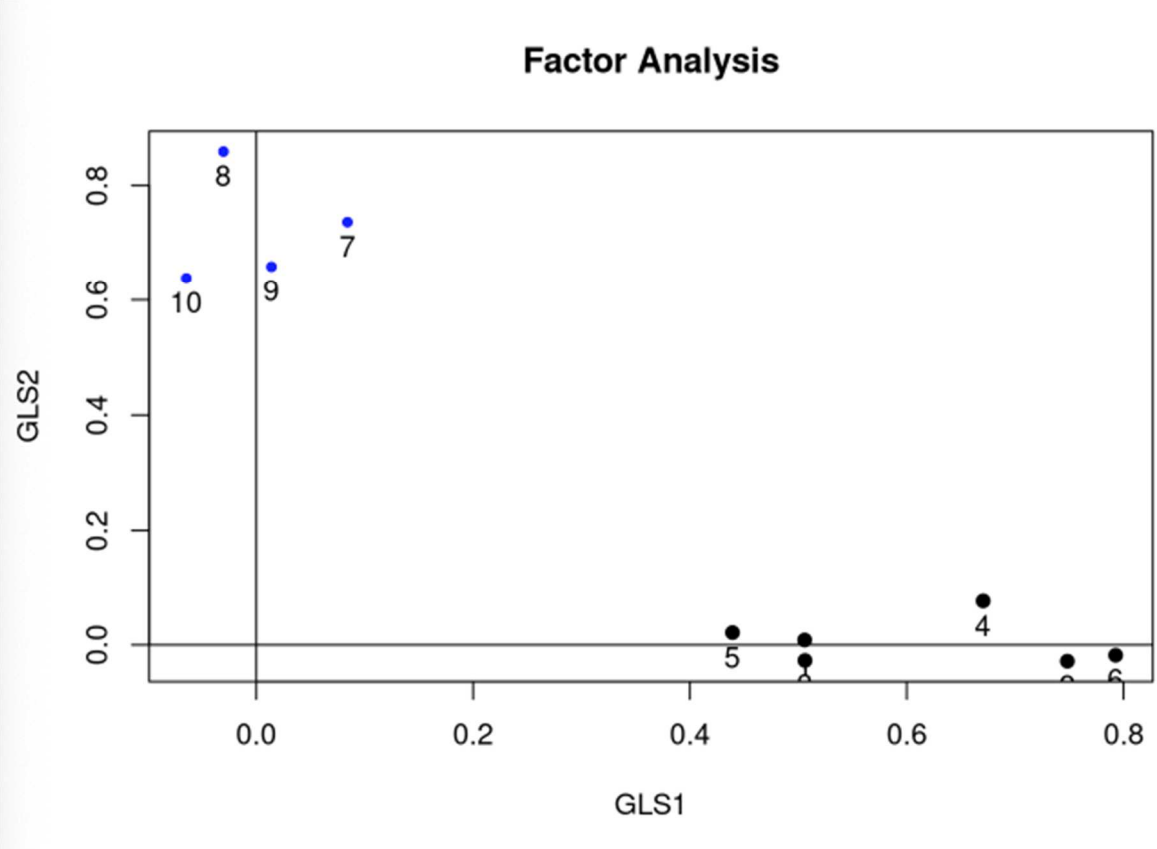


Figure 3.3. Pre-Play 2 cluster analysis of relationship of exogenous variables with latent factors.

Table 3.11 shows the variance explained by the factors.

Table 3.11

Variance Explained by Factors From Pre-Play Survey 2

	GLS1	GLS2
SS Loadings	2.36	2.13
Proportion of Variance	0.24	0.21
Cumulative Variance	0.24	0.45

Model Identification

The researcher developed a model based on theory and the findings from the EFA analysis. Model fit indices are shown in Table 3.12 and indicate the model fits the data well. The model converged after 32 iterations. Thresholds use for model fit indices are noted in the table. These are based on guidance from Bollen (1989) and Kline (2016).

Table 3.12

Model Fit Indices Pre-Play 2

CFI (>=0.90)	TLI (>=0 .90)	RMSEA (<= 0.08)	SRMR (<=0.08)
0.987	0.982	0.038	0.043

Table 3.13 shows the standardized parameter for each exogenous variable associated with a given latent variable. Examination of P(>|z|) shows all loadings are significant at p <= 0.05.

Table 3.13

Loadings of Observed Variables From Latent Variables for Pre-Play 2

Variables	Estimate	Std. Eff	z-value	P(>|z|)	Std. lv	Std.all
Reflection =~						
My life is meaningful	1.00				0.438	0.587
I understand what is meaningful to me	0.808	0.111	7.295	0.000	0.354	0.507
Self-reflection makes meaning	1.471	0.259	5.681	0.000	0.644	0.849

Variables	Estimate	Std. Eff	z-value	P(>|z|)	Std. lv	Std.all
I understand meaning when things are hard	1.165	0.237	4.916	0.000	0.510	0.529
I take time to reflect	0.949	0.185	5.133	0.000	0.415	0.561
Reflection in action =~						
Game changes affect my feelings	1.00				0.623	0.853
Game changes affect my quality of life	0.984	0.111	8.825	0.000	0.613	0.770
Game change effect 1	0.851	0.114	7.465	0.000	0.530	0.641
Game change effect 2	0.961	0.135	7.127	0.000	0.598	0.614

The covariance of the latent variables is shown in Table 3.14. Examination of P(>|z|) shows the covariance is significant at p <= 0.05.

Table 3.14

Covariance of Latent Variables in Pre-Play 2

	Estimate	Std. Err	z-value	P(>|z|)	Std.lv
Reflection ~~ reflection in action	0.062	0.030	2.091	0.037	.228

Recoding Data

To examine the relationships and create predictive models of specific game events, the researcher examined the data from self-reported post-play surveys and associated actual game play data. The purpose of this was to create structured equation models based on the relationship

of latent variables and the game event of "deaths." Deaths was an exogenous variable extracted from the game logs and summarized for each play session per player.

Creating the Data Used in CraftDawg Models

CraftDawg game play data was extracted from actual game play for participants who completed all five game play sessions and completed all five post-play surveys. For this analysis, only the play data from four plays is used. The data was scored using a method designed for this study by the researcher. A review of the literature found no suitable scoring algorithm for play based on the activities of the participant. The researcher examined gaming literature and Minecraft user guides to develop the scoring algorithm ultimated used (Milton, 2019, 2020) .

Data Sources and Types

Raw log data was extracted directly from the Minecraft server using WorldGuard plugin. The Minecraft server collected all data and created a daily log of the data using a 24-hour cycle. Plugin data from the Inventory Rollback plugin and Plan plugin were written directly from the game to MySQL databases. Over 2,000,000 records were captured during the study.

Scrubbing and Parsing of Game Play (Log) Data

.log is the data format used by WorldGuard (the game play data capture plugin) and Minecraft to write data to the log files. For analysis purposes, the *.log* data for each day's play for each server was converted initially to *.txt* files using Atom. A preliminary scrub was done in the *.txt* files to remove server information and other extraneous data. After this scrub, the data was imported into Excel and converted to *.csv* file. A total of 100 daily files from the four game servers were scrubbed using this method. Each of the *.csv* formatted files was exported to the AWS hosted R server using FileZilla Pro.

Parsing the Data Using R

R scripts were created to parse each day's game log for each server. Parsing is a process of bifurcating raw data into raw variables based on delimiters used in the raw data file. A variety of delimiters are used, including spaces, commas, semi-colons, poles, brackets, braces, and parentheses. A script was created using R to parse the data into its component parts to allow for analysis. A separate R script was created to write the parsed data to MySQL database as a table. A total of 80 tables were created from the four servers and the scrubbed log data. MySQL (Oracle) is used as the database for the study as it provides more capacity and flexibility in managing data tables.

Organizing and Scoring the Game Play Data for Analysis Based on the Research Questions

Daily game play data for each game server was aggregated using MySQL script (all_craftdawg1.sql). Four tables were created from this process. The tables were then combined to create a full table of all game play on all servers using MySQL script (create_craftdawg_all_table.sql). Due to the size of the file, this script was run in terminal mode. *Total records for all play are 1,646,117*.

From the full data set, data representing only the game play actions of the player was selected from the full game play log using a MySQL script that selected data associated with Craft Entity = Craft Player. The reasoning for this selection was the research questions were focused on the decisions, priorities, adaptive capacity, rate of adaptiveness and learning of the Player. *For this study, interactions amongst non-Players (i.e., Craft Creepers, Craft Spiders, etc.) were deemed to not be directly relevant to researching the interactions of the player with the game directly.*

Iterative Table Creation to Organize, Categorize, Score and Select Data by Play Session, By Player

An iterative process was used to manipulate the scrubbed, parsed, and relevant data for analysis. Table 3.15 documents the iterative steps used to create the primary analysis table. Beginning with a record count of 1,646,117, the data manipulation, scoring, and consolidation effort created a consolidated table of 510 records and 35 variables which reflects the summary session game play of N=95 participants. Table 3.15 is a summary of the steps used to create the table used for analysis and model building purposes.

Table 3.15

Summary of Steps Used to Recode Data for Analysis and Model Building

Table	Name	Purpose	Script Name	Records
1	craftdawg_raw	Combine all the individual play tables into a master table	Create_craftdawg_raw_table.sql	1,646,117
2	craftdawg_step2	Select only records where craft_entity_character = "CraftPlayer"	create_craftdawg_step2.sql	1,170,464
3	craftdawg_step3	Combine date and server time into single variable. Create the variable of location by coalescing event_placement_location and player_location. Create variable of event_category by coalescing player_block_place_event and player_event_category. Then ALTER table to drop redundant variables and reformat play_datetime to class of datetime	Create_craftdawg_step3.sql Alter_craftdawg_step3.sql	1,170,464
4	Craftdawg_step4	Substring index to segment location variable into loc_x, loc_y, loc_z. This allows the player movement to be measured.	Create_craftdawg_step4.sql	1,170,464

Table	Name	Purpose	Script Name	Records
5	Craftdawg_step5	Substring index to segment craft_events into player_action and action_object. This allows scoring of each action with each object based on scoring algorithm.	Create_craftdawg_step5.sql	1,170,464
6**	Craftdawg_step6	A ***scoring dictionary*** is created for the 7 possible player actions (verbs). The score assigned to each action is relative to other weights for other actions and is based on the research hypothesis that learning will allow more sophisticated actions by the player. For example, DESTROY is an action that is routine in the game and is essentially what happens when a player picks up an item to inventory for later use, if any. USE on the other hand requires the player to be intentional about an item and use a recipe formula from the game. It is not intuitive within the game and requires prior knowledge or new learning from some source.	Create_craftdawg_step6.sql	1,170,464
7##	Craftdawg_step7	Classifies the action_object variable into generalized categories defined by the researcher. The researcher has cataloged over 500 action-objects used by the players in the game. Each object is assigned to one of the generalized categories based on the characteristics of the object and the generalized game objective of Survival (which is based on the notion of Health – each action object affects Health – either *maintaining, replenishing or depleting)* is accomplished by not dying in the game. There are various ways to avoid or escape death and survive, including	Create_craftdawg_step7 which currently has 500 action objects classified. To find additional action object for classification from new data tables, run find_distinct_action_object.sql	1,170,464

Table	Name	Purpose	Script Name	Records
		using weapons to defeat adversaries, regaining, or maintaining health by avoiding hunger, creating structures to avoid adversaries and player damage, etc.		
8^^	Craftdawg_step8	Assigns values to the generalized action_object classes created in Table 7. The value is established by the researcher based an assessment of the complexity associated with the object AND the game objective of Survival. The classes are scored relative to each other, and collectively add to 1.00 The table is then *ALTERed to add a transaction_score column. This column is calculated as action_score + action_object = transaction_score.*	Create_craftdawg_step8.sql Followed by Alter_craftdawg_step8_add_trans_score.sql	1,170,464
9	Craftdawg_step9	Creates a player_transaction column that combines the player_action and the action_object_class columns into a single column for reference purposes. Whitespace is trimmed from the player_name column to allow for matching with other tables.	Create_craftdawg_step9.sql Followed by Trimwhitespace_craftdawg_step9.sql	1,170,464
10	Craftdawg_step10	Add additional data from other tables created independently during game play. A logic matching algorithm is used to add play_start_datetime and play_end_datetime for each record. A session number is also added to allow analysis at the session level for each player. Session length is calculated by subtracting play_end_datetime from play_start_datetime. This is converted from UNIX time to human readable format. Records	Create_craftdawg_step10.sql	1,164,783

Table	Name	Purpose	Script Name	Records
		are removed with NULL is present for Start or End time.		
11	Craftdawg_movement_x	This table calculates the change in loc_x position for each activity in the session. It is partitioned by session_number and ordered by session_start.	xMovementTable.sql	1,164,783
12	Craftdawg_movement_y	This table calculates the change in loc_y position for each activity in the session. It is partitioned by session_number and ordered by session_start	yMovementtTable.sql	1,164,783
13	Craftdawg_movement_z	This table calculates the change in loc_z position for each activity in the session. It is partitioned by session_number and ordered by session_start. Blank and 'world' records are set to NULL to allow for analysis	zMovementTable.sql Followed by Setstringsandblankstonull.sql	1,164,783
14	Total_craftdawg_movement	Total movement is created by calculating the difference between the session movement for each coordidnate (x,y,z) as the absolute value and then adding the absolute values together to create the total movement for a given action	Total_craftdawg_movement_revised.sql	1,164,783
14B	Session_movement	Extracts session number, player_name, and sums total movement (x+y+z) from Total-craftdawg_movement	Session_movment	1117
15	Craftdawg_play_pivot	To create the table that will be used for analysis, the composite table, craftdawg_step10 is pivoted to create a table that makes each session a record (row) in a new table	pivotGameScoreByPlayer	1117
16	Craftdawg_play_summary	This table is created by left-joining Table 15 with Table 14B. This adds the variables associated with session movement, including minutes of play, and movement per minute to the other variables associated with a given session	Craftdawg_play_summary.sql	1117

Table	Name	Purpose	Script Name	Records
17	Plan_players_cd_v2	This table provides data on session level 'mob kills' and 'actor deaths' using the Plan database. This table is ultimately joined with Table 16 to create Table 18.	createPlanPlayCDv2.sql	1413
18	Craftdawg_play_complete_pivot	This table adds the variables of mob kills and deaths to the session data table (Table16). These are two outcome variables that result from player decisions, skills, and actions. They will be used in the analysis phase to create a play model for player adaptive capacity and change in adaptive capacity.	Create_craftdawg_complete_pivot.sql	1117
19	Modification to Table 18	This modification calculates and adds play count to Table 18. Adding play count allows for partitioning play by player, by the which play session the player was engaged in to produce the outcomes in the Table.	addPlayCountertо_craftdawg_play_C_P -THEN - addPlayCounterToPivot_Cd	1117
20	Craftdawg_play_complete_pivot_2	This table tidies up Table 19 by removing redundant data and positioning of columns for readability.	Alter_p_c_pivot_2table.sql	374

6**

WHEN player_action = ' DAMAGE' THEN .25

WHEN player_action = ' DESTROY' THEN .025

WHEN player_action = ' DIG' THEN .15

WHEN player_action = ' INTERACT' THEN .10

WHEN player_action = ' PLACE' THEN .075

WHEN player_action = ' SPAWN' THEN .25

WHEN player_action = ' USE' THEN .15

7##

- *BASIC,*
- *FOOD,*
- *WEAPON,*
- *CRAFTING,*
- *ADVERSARY,*
- *PLAYER*
- *ENCHANTMENT,*
- *OCEAN, and*
- *MINING.*

8^^

WHEN action_object_class = "ADVERSARY" THEN .25

WHEN action_object_class = "BASIC" THEN .025

WHEN action_object_class = "CRAFTING" THEN .075

WHEN action_object_class = "ENCHANTMENT" THEN .10

WHEN action_object_class = "FOOD" THEN .10

WHEN action_object_class = "PLAYER" THEN .25

WHEN action_object_class = "WEAPON" THEN .05

WHEN action_object_class = "OCEAN" THEN .075

WHEN action_object_class = "MINING" THEN .075

The resulting table included 35 variables associated with each play session. The table included the field(column) names in Table 3.16. These were the variables used in the analysis phase to develop the models suggested by the research questions and hypotheses.

Table 3.16

Analytical Variables for Model Development

#	Field Name	Table Name	Type
1	session_number	craftdawg_play_complete_pivot_2	INT
2	play_start_datetime	craftdawg_play_complete_pivot_2	DATETIME
3	play_end_datetime	craftdawg_play_complete_pivot_2	DATETIME
4	player_name	craftdawg_play_complete_pivot_2	TEXT
5	play_count_tot	craftdawg_play_complete_pivot_2	INT
6	play_minutes	craftdawg_play_complete_pivot_2	DOUBLE
7	session_movement	craftdawg_play_complete_pivot_2	DOUBLE
8	survival_score	craftdawg_play_complete_pivot_2	INT
9	movement_per_minute	craftdawg_play_complete_pivot_2	DOUBLE
10	mob_kills	craftdawg_play_complete_pivot_2	INT
11	deaths	craftdawg_play_complete_pivot_2	INT
12	damage_adversary	craftdawg_play_complete_pivot_2	DOUBLE
13	damage_player	craftdawg_play_complete_pivot_2	DOUBLE
14	damage_basic	craftdawg_play_complete_pivot_2	DOUBLE
15	damage_food	craftdawg_play_complete_pivot_2	DOUBLE
16	destroy_basic	craftdawg_play_complete_pivot_2	DOUBLE
17	dig_basic	craftdawg_play_complete_pivot_2	DOUBLE
18	dig_crafting	craftdawg_play_complete_pivot_2	DOUBLE
19	dig_food	craftdawg_play_complete_pivot_2	DOUBLE
20	dig_mining	craftdawg_play_complete_pivot_2	DOUBLE
21	dig_ocean	craftdawg_play_complete_pivot_2	DOUBLE
22	interact_adversary	craftdawg_play_complete_pivot_2	DOUBLE
23	interact_basic	craftdawg_play_complete_pivot_2	DOUBLE
24	interact_crafting	craftdawg_play_complete_pivot_2	DOUBLE
25	interact_food	craftdawg_play_complete_pivot_2	DOUBLE
26	interact_mining	craftdawg_play_complete_pivot_2	DOUBLE
27	interact_ocean	craftdawg_play_complete_pivot_2	DOUBLE
28	place_basic	craftdawg_play_complete_pivot_2	DOUBLE
29	place_crafting	craftdawg_play_complete_pivot_2	DOUBLE
30	spawn_basic	craftdawg_play_complete_pivot_2	DOUBLE
31	spawn_enchantment	craftdawg_play_complete_pivot_2	DOUBLE
32	use_basic	craftdawg_play_complete_pivot_2	DOUBLE
33	use_crafting	craftdawg_play_complete_pivot_2	DOUBLE
34	use_food	craftdawg_play_complete_pivot_2	DOUBLE
35	use_weapon	craftdawg_play_complete_pivot_2	DOUBLE

The mapping of the action_objects to generalized object is presented in Appendix A.

Creating Master Table for Analysis of Play

To create the master table for analysis, data was extracted from the Salesforce database and imported into MySQL. A report was created in Salesforce to include player name, gender, age, play experience and role. Only players who had completed all five post-play surveys were included in the report. A total of 96 participants were identified. Data was imported into MySQL and recoded to simplify analysis. Demographic data was inner joined using create_craftdawg_complete.sql script to create the master table craftdawg_full. The table was created to include up to seven play sessions for each participant when play is greater than five minutes. This reduced the total number of plays from 886 to 510 play sessions for 95 participants.

This reduction was done to better match the number of post-play surveys completed after a given session in support of the matching the time series analysis. Post-play surveys were provided electronically by the researcher after a given play session of at least 10 minutes was completed. The researcher monitored the play data by player two to three times a day during the study. When a player had completed an appropriate play session AND no previously provided post-play surveys were incomplete, the researcher would provide a post-play survey link. Participants were compensated for completed post-play surveys at an increasing rate.

Because of the lag between completing post-play surveys and the ability to continue to play, some participants played additional sessions so there is not an exact matching of a play session and a post-play survey.

Developing and Scoring Post-Play Instruments

Ninety-five participants completed all five post-play surveys. For analysis purposes, only post-play surveys from these participants are included. Only play data from these participants is

included in the analysis. Only matching variable data from Post-Play 5 is included for this analysis.

Post-Play Survey Data Extraction

Post-play survey data was extracted for only participants who completed all five post-play surveys. The post-play scale is included as Appendix B. Ninety-five participants completed all five play sessions and post-play surveys. In this analysis, only game data from the first four plays is included. Only data from the first four post-play surveys is included. As the fifth post-play survey used different questions, the researcher omitted both the associated play and the responses from that survey. The researcher also omitted play and responses from incomplete post-play surveys. This eliminated 11 sessions. Ultimately, $n = 369$ post-play responses and game sessions were used for analysis. The full data set, inclusive of game play aggregated variables and scale data, included 58 variables.

Tests for Normality and Factorability of Data

Normality of the data was assessed using MShapiro test. A significant finding ($p <= 0.05$) would indicate the data is not normally distributed. The MShapiro statistic was 0.892, p = 1.85e-15. The data was determined to be nonnormal. As the study used SEM for analysis, the lack of normality in the data was not considered to be detrimental for analysis purposes (Yuan & Bentler, 2016).

To assess factorability of data, KMO factor analysis was run. A KMO statistic of 0.89 indicated the data was likely factorable. A second test was conducted using Bartlett's test of sphericity. A significant finding would indicate the data was likely factorable and not unidimensional. The results of the Bartlett test showed X^2 of 5434.207, p = 0 and df = 435. This was interpreted to indicate the data was likely factorable.

EFA

As the data was deemed factorable, EFA was performed. Consistent with Bollen (1989) and Kline (2016)for use of EFA when there is no a priori model, EFA was run using the correlation matrix to determine the number of factors present in the data using maximum likelihood (ml) as the factor extraction model. To better identify the factors, "oblimin" rotation was used. Using all 10 factors accounted for 54% of the cumulative variation in the data. Table 3.17 shows the contribution of each factor to explaining the overall variance in results.

Table 3.17

Contribution of Each Factor in Explaining Overall Variance in Game Play Results

	ML4	ML7	ML10	ML9	ML3	ML8	ML1	ML5	ML6	ML2
SS loadings	5.36	5.30	3.72	3.16	2.56	2.51	2.48	2.18	2.16	1.98
Proportion of Variance Explained	0.09	0.09	0.06	0.05	0.04	0.04	0.04	0.04	0.04	0.03
Cumulative Variance Explained	0.09	0.18	0.25	0.30	0.35	0.39	0.43	0.47	0.51	0.54

Table 3.18 shows the factor correlations for game play results that include both post-play survey data and game play data.

Table 3.18

Factor Correlations From Game Play Results

	ML4	ML7	ML10	ML9	ML3	ML8	ML1	ML5	ML6	ML2
ML4	1.00									
ML7	0.14	1.00								
ML10	0.21	0.49	1.00							
ML9	-0.10	-0.15	-0.29	1.00						
ML3	0.38	0.14	0.19	-0.12	1.00					
ML8	0.56	0.07	0.24	-0.10	0.36	1.00				
ML1	0.27	0.08	0.18	-0.13	0.12	0.29	1.00			
ML5	0.00	-0.05	-0.17	0.03	-0.10	-0.06	0.37	1.00		
ML6	0.31	0.10	0.19	-0.10	0.14	0.30	0.37	0.05	1.00	
ML2	0.03	0.06	0.04	0.08	-0.03	-0.06	0.06	0.080	0.02	1.00

To create the most parsimonious model factors were removed based on analysis described by Bollen (1989), Loehlin (2004) and Kline (2016). Thus, the factor correlation matrix as shown in Table 3.17 was examined to determine those factors that are highly correlated which could be interpreted as measuring the same latent variable. Using guidance from Kline (2016), factors were removed if less than three variables loaded on a given factor. Factors were removed if the loading of a given variable was less than 50%. This initial cut resulted in ML4, ML7, ML10, ML9, ML8, and ML6 being retained. These factors explained 41% of the variance. Factor correlations were examined for multi-collinearity. To the extent two factors were deemed to measure the same latent variable, one factor was dropped to allow for analysis of a more parsimonious model.

Factors were described based on the independent variables that loaded on them. ML4 and ML6 were included in the initial development of the CraftDawg 1 Model – Crafting Model. ML4 was described as “Basic Game Play” and ML 6 was described as “Player Aggression” based on

the nature of the loadings for each. These variables were removed to provide for a better fitting model. One of the limitations of the study is the method used by the researcher to develop the scores for game play activities. A search of the literature found no study where game play had been scored, thus no methods were found to use a standardized method for scoring. Future studies using this methodology may benefit from having the scoring method validated by a collective of experienced and expert players.

Four factors were ultimately retained: ML7, ML9, ML10, ML8. These factors were identified based on theories associated with the development of the scales (Adger & Vincent, 2005; Marsick & Watkins, 1990). Table 3.19 shows the factors retained and the researcher description. ML8 was retained as a broad measure of game play as scored by the researcher. Future studies may use a different method of scoring this variable.

Table 3.19

Factors Retained and Description for CraftDawg Model 1

Extracted Factor Label	Factor Description Based on Theory
ML7	Individual incidental learning
ML9	Uncertainty
ML10	Adaptiveness
ML8	Crafting (from game play data)

Analysis was performed to examine *adaptability* as a function of incidental learning and uncertainty in predicting death during the game. The latent variables of incidental learning, uncertainty and adaptability were measured from the responses to post-play surveys. These latent

variables were used to predict the exogenous variable of the number of deaths for each player for a given play session.

Overview of Development of Roughness of Learning Variable

To develop the roughness of learning (RoL) variable, the researcher sorted data by play number and combined measures of player health at time of death to create a "health score at death." This score was plotted for each death to create the *shape of the context*. Using the shape of the context, the boxcounting method to calculate fractal dimensionality of a data series was used to estimate the fractal dimension of learning.

Fractals are a recognized measure of complexity based on scale (Guo, 2017; McCauley, 1994; Skjeltorp, 2000). In this study, the researcher used the fractal dimension calculated from the plot of health score at death as plotted against the number of deaths to create the measure of complexity. The fractal dimension was created based on play session [1:5] to allow comparison between play sessions. It was calculated based on experience grouping to allow comparison between experience levels [Novice, Intermediate, Advanced], [Novice, Experienced]. It was calculated for all play over all sessions to determine the overall complexity of the full study. These measures were used to potentially identify and analyze significant differences in learning process to allow the dimension of *learning complexity* to be included with prior modeling to assess the learning experience.

This allowed the researcher to add a quantitative measure of complexity to the study and provided better context for the relative effort of the player. This was consistent with the logic used in prior studies of Skjeltorp (2000) and Guo (2017).

Fractal as the RoL Variable

This study used fractal dimensions as measures of *contextual complexity*. The fractal is a recognized measure of complexity (Zuo et al., 2020). The fractal is used to measure the complexity in the *shape of figure* (Zuo et al., 2020). Prior studies [Skjeltorp; Guo] have used time series plots to create the *shape of the context*. The boxcounting method "is a method of gathering data for analyzing complex patterns by breaking a dataset, object, image, etc. into smaller and smaller pieces, typically box-shaped and analyzing the pieces at each smaller scale"(Liu et al., 2003, p. 4041). The goal is to find and quantify dimensionally the self-similarity [patterns within] aspect of the object (Fernández-Martínez, 2015; Mandelbrot & Wheeler, 1998).

As the shape of the context provides the data used in the determining the fractal dimension of the shape, the *length of the shape* must be considered. In this study, time series plots were used to create the shape of the context. The time series represents the health score at time of death with the y-axis measuring the health score and the x-axis measuring the death number. Figure 3.8 is an example of the type of plots used to calculate the various fractals examined in this study. The *length* of the plot was the number of deaths (n = 675 in the example).

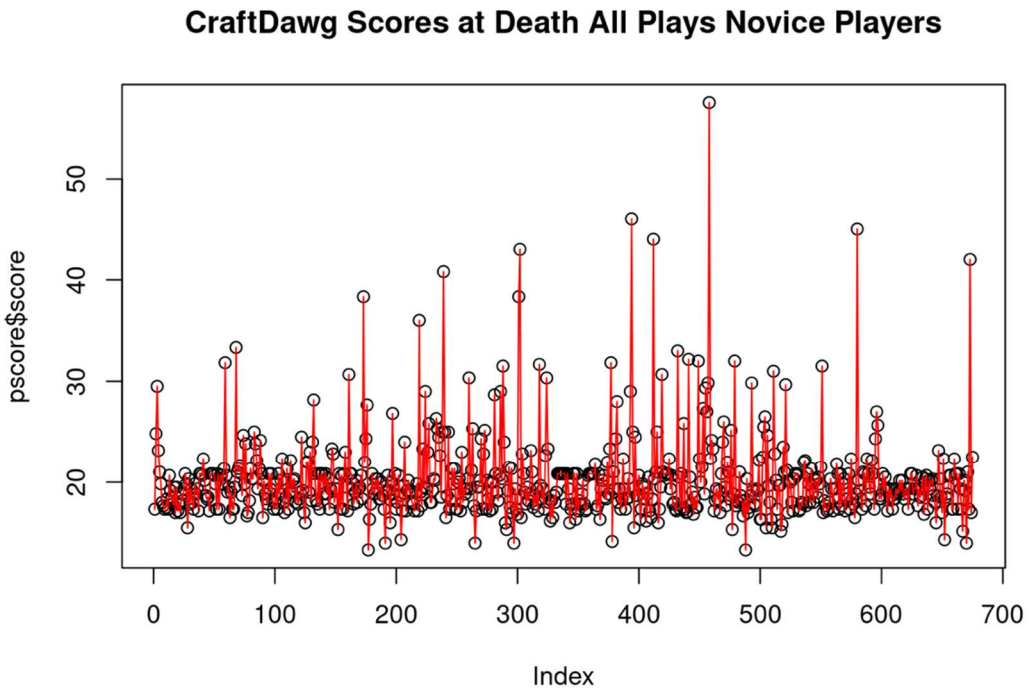


Figure 3.4. Example of CraftDawg health scores at death plot.

The box counting method for measuring a fractal is strongly influenced by the number of data points used to create the plot (Zuo et al., 2020). *The method creates a different fractal based on the shape and length used to create the shape of the context being measured.* Thus, each *tranche* selected as the shape of the context in a continuous time series may have a different fractal dimension. *Until the length of the shape is long enough to capture the self-similarity, the fractal may vary from its theoretical value.* The literature is inconclusive in offering guidance on 'adequate length' [sample size] in determining the fractal. Thus, each fractal is a "pie slice" of the theoretical fractal for the full sample.

Zuo, et al. (2020) note that

> the computing results show that the fractal dimension cannot be accurately calculated because of the fluctuation and narrow scaling region in the case of insufficient data points. This fluctuation tends to be weakened, and the linearity of the scaling region is improved with the increase of sampling length. The estimated fractal dimension increases with the sampling length, and eventually maintains at its theoretical value. Therefore, the sampling length should be more than the minimum length where the stable value can be achieved. Moreover, the sampling length should be appropriately increased for the smooth surface. (p. 1)

For this study, the ultimate sample lengths were novice = 675, experienced = 645, and all = 1320.

Scaling the Fractal to Align With Robert May's Logistic Map

As the shape of the time series plot was two dimensional, the scale for the fractal was 1:2. To align with Robert May's (1975, 1976) logistic map, the theoretical model for this study, the fractals measured for the various shapes, were rescaled using R *scale*s package (version 1.2.1) from 1:2 to 0:4. Table 3.20 shows the fractal of a given tranche on a scale of 1:2 and Table 3.21 shows it rescaled to a scale of 0:4.

Table 3.20

Fractal Dimensions by Player Group (Novice, Intermediate, Advanced) by Play (Scale 1:2)

Play Session	Novice	Intermediate	Advanced	All Players
1	1.691878	1.530515	1.722466	1.353637
2	1.621488	1.584963	1.347923	1.750022
3	1.736966	1.618910	1.378512	1.160964
4	1.415037	1.540568	1.347923	1.247928
5	1.502500	1.369230	1.530515	1.222392

Play Session	Novice	Intermediate	Advanced	All Players
All	1.772590	1.544321	1.643856	1.280009
N	675	319	326	1320

Table 3.21

Rescale of BoxCount Fractal From 1:2 to 0:4 to Match Robert May's Logistic Map Scale

Play Session	Novice	Intermediate	Advanced	All Players
1	2.767512	2.122060	2.889864	1.414548
2	2.485952	2.339852	1.391692	3.000088
3	2.947864	2.475640	1.514048	0.643856
4	1.660148	2.162272	1.391692	0.991712
5	2.010000	1.476920	2.122060	0.889568
All	3.090360	2.177284	2.575424	1.120360
N	675	319	326	1320

To increase the *length* of the sample for the analysis of the fractal using Robert May's Logistic map, the researcher combined the Intermediate and Advanced groups into a single Experienced Group. Table 3.22 shows the fractal derived from this.

Table 3.22

BoxCount Fractal Calculation Based on Plot of Health Score at Death (Scale 1:2) for Novice and Experienced Groups

Play Session	*n* Deaths	Novice	*N* Deaths	Experienced	*N* Deaths	All Players
1	187	1.691878	158	1.321928	345	1.353637

2	150	1.621488	137	1.621488	287	1.750022
3	155	1.736966	117	1.137504	272	1.160964
4	86	1.415037	106	1.184425	192	1.247928
5	97	1.502500	127	1.415037	224	1.222392
All	675	1.772590	645	1.314016	1320	1.280009

Table 3.23 shows the rescaled output of the fractal using May's 0:4 scale.

Table 3.23

Rescale of BoxCount Fractal for Two Groups: Novice and Experienced (From 1:2 to 0:4)

Play Session	*n* deaths	Novice	*N* deaths	Experienced	*n* Total Deaths	All Players
1	187	2.767512	158	1.287712	345	1.414548
2	150	2.485952	137	2.485952	287	3.000088
3	155	2.947864	117	0.550016	272	0.643856
4	86	1.660148	106	0.737700	192	0.991712
5	97	2.010000	127	1.660148	224	0.889568
All	675	3.090360	645	1.256064	1320	1.120360

CHAPTER 4

RESEARCH FINDINGS

This chapter presents the results of the statistical analysis used to examine the research questions and associated hypotheses from the CraftDawg Study. This chapter contains these parts: (a) identification and interpretation of latent variables used, (b) identification and interpretation of CraftDawg Model 1 – Crafting Model and CraftDawg Model 2 – Learning Model, (c) identification and interpretation of roughness of learning (RoL) variable, (d) assessment of research questions and hypotheses testing

Identification and Interpretation of Latent Variables

As both CraftDawg Model 1 – Crafting Model and CraftDawg Model – Learning Model were hypothesized based partially on Marsick and Watkins' (1990) theory of informal and incidental learning (IIL) with specific emphasis on incidental learning and reflection, two pre-play surveys were developed to assess the use of theorized dimensions.

Latent Variable Identification and Interpretation: CraftDawg Pre-Play Survey 1

Analysis of the findings from Pre-Play Survey 1 found two latent variables present. These variables explained 40% of the variance. The two variables were described as *individual incidental learning* which accounted for 28% of the variance , and *social incidental learning* which described an additional 12% of the variance. Analysis of the exogenous variables with the largest standardized parameters was consistent with Marsick and Watkins' (1990) theory on the dimensions of incidental learning. "I surprise myself with the stuff I know" had the largest parameter weight of 0.927. To the extent a participant was actively aware of this dimension of

incidental learning, the overall measure *of individual incidental learning* was positively increased. Marsick and Watkins (1990) do not theorize on the demographics (age, gender, occupation, responsibility) associated with individual incidental learning thus this was not included in the preliminary analysis of the data.

The second latent variable identified from Pre-Play 1 was described as *social incidental learning*. This is learning that occurs environmentally and socially. The largest parameter weight was associated with "I seek out other sources of information" at 0.733. This active effort to find information on a "social" level reveals a robust approach to incidental learning.

The covariance between individual and social incidental learning is positive and significant at 0.399. This indicates that the two variables are related yet different enough to be considered distinct constructs of incidental learning.

Latent Variable Identification and Interpretation: CraftDawg Pre-Play Survey 2

Two factors were identified from responses to Pre-Play Survey 2. This instrument was used to assess theoretical constructs included in developing the models. The two factors identified in using SEM analysis were described as *reflection* and *reflection in action*. Marsick and Watkins (1990) hold that reflection is essential to meaning making. This is especially relevant when examining the dimensions associated with incidental learning and tacit knowledge. An obvious question is "When does reflection occur and making meaning emerge that is associated with incidental learning to create tacit knowledge?"

To begin exploring this question, Pre-Play Survey 2 was developed to assess the relationship between reflection and reflection in action. This researcher theorized that in the CraftDawg SEM models reflection would be related to uncertainty, where uncertainty is effectively the *knowledge state* pre-reflection and pre-meaning making. Consistent with Marsick

and Watkins (1990), the researcher hypothesized uncertainty would be highest when there was inadequate time for reflection, such as during in game challenges. The researcher hypothesized that given the opportunity to reflect, the player would apply various forms of knowledge including tacit knowledge acquired through incidental learning in other contexts. Thus, the researcher believed that as the player engaged with the game more, uncertainty would decrease (because of reflection and meaning making) and adaptiveness would increase.

In interpreting the latent variable, *reflection*, the largest standardized parameter was 0.849 for the exogenous variable of "Self-reflection makes meaning." This was interpreted to indicate that the participants used reflection to create meaning which could later be applied as knowledge. This is consistent with Marsick and Watkins (1990).

The second latent variable identified is *reflection in action*. This variable was interpreted based on the researcher's hypothesis that the player would not be able to fully reflect to make meaning *in the moment*. The largest standardized parameter weight of 0.853 was for "Game changes affect my feelings". The researcher interpreted this to mean the participant's interaction with game changes would affect the participant's feelings *for the game*. This would inspire reflection on some basis as the player assessed those feelings. Accepting Marsick and Watkins' (1990) theory of reflection to make meaning, this recognition by the participant that game changes will affect their feelings and inspire reflection becomes a basis for how uncertainty arises and thus how it influences adaptiveness in the game play model. This is also consistent with Schön's (1984) notion of reflection in action summarized as: *consider the situation, decide how to act, act immediately.*

The covariance between the two latent variables, reflection, and reflection in action, is positive at 0.228. This was interpreted to confirm the two latent constructs, while similar, are

measuring different elements of the participant's belief about prospective behavior during the game.

Identification and Interpretation of Latent Variables: CraftDawg Model 1 – Crafting Model

CraftDawg Model 1-Crafting Model was developed based on the fusion of Marsick and Watkins' (1990) IIL and adaptation and the role of uncertainty as described in environmental science (Adger & Vincent, 2005; Refsgaard et al., 2013; Vincent, 2007).

Post-Play Self-Reported Instrument

After each play session, a participant completed a post-play survey. The completion timing of this varied based on when the study administrator released the survey link to the participant. The study did not assess the time between completion of a play session and completion of the post-play survey. The instrument was designed to capture the influence of incidental learning and reflection as manifest in uncertainty on adaptiveness. Using the post-play survey, three latent variables were identified using EFA and CFA: *individual incidental learning, uncertainty, and adaptiveness*.

Crafting Model Latent Variable: Individual Incidental Learning. Interpretation of this variable is enhanced by examining the parameters of the primary exogenous variables associated with the latent variable. Table 4.1 shows the exogenous variables with the most communality with the latent variable, *individual incidental learning*. This is determined by examining the *standardize.all* value for significant variables.

Table 4.1

Individual Incidental Learning Primary Exogenous Variables

Description	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Use_prior_knowledge[1]	1.387	0.137	10.143	0.000	0.957	0.846
try_lots[2]	1.216	0.126	9.615	0.000	0.838	0.751
Confident[3]	1.096	0.116	9.470	0.000	0.756	0.728

[1]"I use what I already know to help me figure out new stuff in the game"; [2]"I try lots of ways to figure out how to do something I am not familiar with in the game"; [3]"I was confident I could figure it out even if I might fail a few times."

The two largest parameters in the individual incidental learning latent variable are consistent with Marsick and Watkins (1990). "Use prior knowledge" and "try lots of different stuff" indicate *how* the participant approached the game play using individual incidental learning. The exogenous variable of *confidence* emerges in this study as a potential moderating variable that is ripe for further study to determine its influence on the use of individual incidental learning. In this study, confidence is a notable parameter as it is more important than some of the other theorized variables measured.

Crafting Model Latent Variable: Uncertainty. *Uncertainty* is a latent variable that is conceptualized for the study based on complexity science and the role of uncertainty on adaptiveness (Adger & Vincent, 2005; Vincent, 2007). This is a measure of the participant's response to the unfamiliar or novel in the game. Two exogenous measures of uncertainty are most influenced by the latent variable and thus exert the most sway on the influence of uncertainty in relation to adaptiveness. These are behavior-based responses to perceived uncertainty. The importance of these behaviors as manifest in the direct effect on adaptiveness is

revealed in regression analysis of uncertainty on adaptiveness. Table 4.2 shows the parameter estimates and direction for the exogenous variables most strongly influenced by uncertainty.

Table 4.2

Uncertainty Primary Exogenous Variables

Description	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
When_uncertain[1]	1.000				0.772	0.829
No_clear_way_forward[2]	1.006	0.079	12.7 51	0.000	0.777	0.628

[1]"When I am uncertain about something in the game, I get uncomfortable"; [2] "When there is no clear way forward in the game, I get a little frustrated."

"When I am uncertain, I get uncomfortable with it all" showed the largest parameter of 0.829 and "When there is no clear way forward, I get frustrated" was the next largest with a parameter of 0.628. These are interpreted to mean the participant recognizes how uncertainty in the moment affects the participant's emotional state.

Crafting Model Latent Variable: Adaptiveness. *Adaptiveness* is a foundational response in complexity science (Holland, 1995; Mitchell, 2009). The ability to adapt is fundamental to responding to edge of chaos moments. Rate of adaptiveness and adaptive capacity are basic elements in Robert May's (1975, 1976) logistic map, which provides the theoretical framework for this study. Those elements were captured collectively in the latent variable of adaptiveness. Adaptiveness was identified using EFA and CFA methods applied to post-play surveys completed by each participant.

Measuring adaptiveness in terms of response during the game revealed parameters that were influenced by the latent variable. Adaptiveness as a composite construct of adaptive capacity and rate of adaptiveness was conceptualized from adaptiveness as identified in environmental science (Adger & Vincent, 2005; Refsgaard et al., 2013; Vincent, 2007). Including this measure in the study of human learning was a novel measure and of note was the importance of the participant's confidence in responding to a novel situation in the game. Four measures of adaptive response in the game are closely associated and shown in Table 4.3.

Table 4.3

Adaptiveness Primary Exogenous Variables

Description	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Confident_c[1]	1.041	0.067	15.544	0.000	0.854	0.791
Drg_game[2]	1.110	0.073	15.289	0.000	0.911	0.780
Drng_game[3]	0.977	0.040	24.525	0.000	0.801	0.779
Drng_game[4]	1.000				0.821	0.770

[1]"I was confident that I can figure out how to do most new things that I encounter in the game"; [2]" During the game, I felt I coped with changes in the way I did the game tasks"; [3] "During the game, I felt I adapted well to changes in the game"; [4] "During the game, I learned new skills that allowed me to adapt to changes in the game."

"I was confident I could figure out how to do new things" has the largest parameter at 0.791. This was interpreted as confidence being the most important 'mindset' variable in establishing the adaptiveness of a participant. The parameter is positive indicating as confidence

increases, adaptiveness will increase all other variables unchanged. Secondary exogenous variables were closely associated with each other:

- "During the game I coped with changes" was 0.780.
- "During the game, I adapted well to changes" was 0.779.
- "During the game, I learned new skills to adapt to in-game changes" was 0.770.

All were positively related to adaptiveness. Of note was the difference in the parameters between the statement most directly related to "learned new skills to adapt to in-game changes" and "I coped with changes" and "I adapted well to changes". This was interpreted to mean the participant distinguished learning from coping and from adapting. Coping and adapting were then interpreted to be broader constructs that included other methods used by the participant to engage in the game.

Crafting Model Latent Variable: Crafting. Crafting is a game play latent variable derived from the scoring of various in game efforts. The scoring of the game activities is described in Table 3.15. In summary, the scoring method used five generalized activities that a participant could engage (damage, destroy, dig, interact, place, spawn, or use) associated with nine categories of engagement (adversary, basic, crafting, enchantment, food, (other) player, weapon, ocean, or mining). This categorization allowed the game data to be reduced for analysis.

In this model the latent variable of *crafting* was used. This was developed as a composite variable based on the exogenous play activities that were identified in EFA and CFA analysis on all the scored play data. The two primary measures of crafting were *interact-crafting* and *place-crafting*. Both were considered more advanced game play activities by the researcher. The researcher also considered these activities to be fundamental to a participant's ability to sustain

in the game. To the extent a player could not develop these skills, the player could not advance in the game.

Table 4.4 shows the standardized parameters for the two largest variables. These were interpreted more generally as they are game play activities. Both were positive. To the extent crafting as a latent variable had an influence (positive or negative) on adaptiveness, then the level of interact_crafting and place_crafting activities a player engaged in would have the same indirect effect on predicting deaths.

Table 4.4

Crafting Primary Exogenous Variables

Description	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Interact_crafting	6.503	0.502	12.960	0.000	11.816	0.947
Place-crafting	2.324	0.302	7.706	0.000	4.222	0.858

A generalized model was run using the initial set of factors and factors were removed if they were not significant in identifying the model (Bollen, 1989; Kline, 2016; Loehlin, 2004). The basic model structure used the exogenous variable of "deaths" as the dependent variable. This was chosen based on the nature of the game, "survival." The researcher assumed that one of the objectives of the player was to survive [persist: not die]. For the player to persist, he must learn to avoid death and the sources of death (hunger in the form of starvation, and health in the form of damage inflicted by a game adversary, another player, or self-inflicted in the form of a fall).

The model was refined based on model fit indices. The latent variables of individual incidental learning, uncertainty, adaptability, and crafting were developed based on the loadings associated with each latent variable. Consistent with Bollen (1989) insignificant loadings were removed in the final model.

CraftDawg SEM – Model 2, Learning Model

The same data set was used to develop CraftDawg Model 2. The study relied on the same validity, measure of internal consistency, and factorability statistics used to develop CraftDawg Model 1. The purpose for creating Model two was to simplify the model and eliminate the study limitation associated with the scoring of the actual game data.

Parsimony is an accepted principle in model development (Ledolter & Abraham, 1981). In developing a parsimonious model, model fit is examined as well as the explanatory power of the model. In general, the more variables that are included in the model the greater the explanatory power (defined as variance explained by the model) and model fit (Bollen, 1989). Kline (2016) notes " the parsimony principle: given two models with similar fit to the data, the simpler model is preferred, assuming that the simpler model is theoretically plausible" (pg. 128). However, to the extent that included variables are not well understood or poorly developed (the theoretically plausible test), the inclusion of such variables should be avoided. As the use of the Crafting variable in the CraftDawg SEM – Model 1, Crafting Model was developed using a proprietary scoring method that has not be fully tested, the researcher developed a second model that includes only the self-reported data. This resulted in a loss of explanatory power however, model fit improved.

In the second CraftDawg SEM, the researcher removed the latent variable of *Crafting*. As in the first model, the researcher analyzed the self-reported data from the post-play surveys to

identify latent variables. Following the same protocols as used in the creation of Model 1, three latent variables were identified. In creating this model, the researcher removed indicator variables that loaded at less than 50% on the latent variable.

Table 4.5 shows the various measures of variance explained by factor for CraftDawg Model 2 – Learning.

Table 4.5

Variance Explained by Factors in CraftDawg Model 2

	ML4	ML7	ML10	ML9	ML3	ML8	ML1	ML5	ML6	ML2
SS loadings	5.37	5.29	3.73	3.16	2.57	2.52	2.49	2.19	2.16	1.98
Proportion of Variance Explained	0.09	0.09	0.06	0.05	0.04	0.04	0.04	0.04	0.04	0.03
Cumulative Variance Explained	0.09	0.18	0.25	0.30	0.35	0.39	0.43	0.47	0.51	0.54

As with Model 1, a factor correlation matrix was examined for multicollinearity among factors. Consistent with Bollen (2989) factors with high correlation were removed in favor of one. Table 4.6 shows the intercorrelations of the latent variables.

Table 4.6

Factor Correlations From Game Play Survey as Used in CraftDawg Model 2

	ML4	ML7	ML10	ML9	ML3	ML8	ML1	ML5	ML6	ML2
ML4	1.00									
ML7	0.14	1.00								
ML10	0.21	0.49	1.00							
ML9	-0.10	-0.15	-0.29	1.00						
ML3	0.38	0.14	0.19	-0.12	1.00					
ML8	0.56	0.07	0.24	-0.10	0.36	1.00				
ML1	0.27	0.08	0.18	-0.13	0.12	0.29	1.00			
ML5	0.00	-0.05	-0.17	0.03	-0.10	-0.06	0.37	1.00		
ML6	0.31	0.10	0.19	-0.10	0.14	0.30	0.37	0.05	1.00	
ML2	0.03	0.06	0.04	0.08	-0.03	-0.06	0.06	0.080	0.02	1.00

To simplify the model and isolate the latent variables associated with adaptability as measured by the self-reported post-play scales, only ML7, ML9, and ML10 are retained in Model 2. These variables explain 18% of the variance, compared to Model 1 where an additional variable is retained, ML8, which explains an additional 4% of the variance and the model explains a total of 22% of the variance.

The model was simplified by removing variables that loaded at less than 50% communality and variables that were not significant were removed.

Model Identification – CraftDawg Model 1

To create a predictive model, regressions were added to the model. To better define the model, additional covariances were included in the final model. This allowed the model to include communalities amongst exogenous variables that are shared with the latent variable.

The final model represented the direction and strength of the latent learning variables of *incidental learning, uncertainty,* and the game play variable of *crafting* on the latent variable of

adaptability. Adaptability was used to predict 'deaths' in the game. Incidental learning and uncertainty have an indirect effect on deaths through the direct effect on adaptability.

The model converged after 110 iterations using 109 model parameters and 369 observations. The final CraftDawg Model 1-Crafting fit statistics are shown in Table 4.7.

Table 4.7

Fit Statistics for CraftDawg Model 1 - Crafting

CFI > = 0.90	TLI > = 0.90	RMSEA < = 0.08	SRMR < = 0.08
0.914	0.902	0.059	0.069

The parameters for each exogenous variable associated with a given latent variable are shown in Table 4.8.

Table 4.8

Standardized Loadings of Observed Variables From Latent Variables for Game Play Data

Variables	Est	SE	Z value	P(>|z|)	Std.lv	Std.all
Individual incidental learning =~						
Use_other_experiences_to_figure_out something	1.000				0.690	0.517
Try_stuff_if_it_doesnt_work_try_other_stuff	0.706	0.076	9.293	0.000	0.487	0.612
Experiment_with_diff_ideas	0.752	0.091	8.230	0.000	0.518	0.573
Leverage_how_I_play_other_games	1.004	0.085	11.797	0.000	0.692	0.480
Try_different_ideas_already_have	0.917	0.098	9.337	0.000	0.632	0.602

Variables	Est	SE	Z value	P(>|z|)	Std.lv	Std.all
Try_lots_of_different_stuff_to_figure_out_unfamiliar_stuff	1.216	0.126	9.615	0.000	0.838	0.751
Used_prior_knowledge_to_figure_out_new_stuff	1.387	0.137	10.143	0.000	0.957	0.846
Confident_I_could_figure_it_out_even_if_i_failed_some	1.096	0.116	9.470	0.000	0.756	0.728
If_i_dont_know_something_i_try_to_learn_it	0.909	0.102	8.867	0.000	0.627	0.644
Learned_from_other_games_could_meet_challenges	0.911	0.104	8.743	0.000	0.628	0.523
Uncertainty =~						
When_uncertain_get_uncomfortable_with_it_all	1.000			0.000	0.772	0.829
Kept_worrying_something_going_wrong	0.964	0.079	12.751	0.000	0.745	0.553
No_clear_way_forward_get_frustrated	1.006	0.079	12.751	0.000	0.777	0.698
Lots_of_different_things_at_once_freeze_up	0.635	0.058	10.851	0.000	0.490	0.595
Worried_about_consequences	0.707	0.097	7.319	0.000	0.546	0.411
Learning_new_stuff_in_game_is_hard	0.661	0.072	9.221	0.000	0.510	0.510
Somethings_i_cant_figure_out_so_i_dont_try	0.324	0.050	6.477	0.000	0.250	0.363
Uncertain_about_what_to_do	0.624	0.081	7.724	0.000	0.482	0.431
Adaptiveness						
During_the_game_i_coped_with_changes	1.000			0.000	0.821	0.770
During_the_game_i_adapted_well_to_changes	0.977	0.040	24.525	0.000	0.801	0.779
During_the_game,_i_learned_new_skills_to_adapt_to_ingame_changes	1.110	0.073	15.289	0.000	0.911	0.780
Confident_can_figure_out_how_to_do_new_things	1.041	0.067	15.544	0.000	0.854	0.791
Usually_alright_when_not_right_game_answer	0.625	0.071	8.850	0.000	0.513	0.473
Just_knew_what_to_do_cant_explain_it	0.773	0.075	10.274	0.000	0.635	0.544
Crafting =~						
Dig crafting	1.000				1.817	0.572
Interact crafting	6.503	0.502	12.960	0.000	11.816	0.947
Place crafting	2.324	0.302	7.706	0.000	4.222	0.858
Place basic	2.699	0.417	6.481	0.000	4.905	0.610

Table 4.9 shows the regression parameters by latent variable.

Table 4.9

Regression Parameters by Latent Variable for CraftDawg Model 1 - Crafting

	Est	SE	z-value	P(>|z|)	Std.lv	Std.all
Adaptiveness ~						
Individual Incidental Learning	0.970	0.107	9.080	0.000	0.816	0.816
Uncertainty	-0.130	0.043	-2.994	0.003	-0.122	-0.122
Crafting	0.066	0.019	3.529	0.000	0.147	0.147
Deaths ~						
Adaptiveness	-0.639	0.234	-2.726	0.006	-0.524	-0.149

Table 4.10 shows the covariances of the latent variables. Covariances were examined for significance.

Table 4.10

Covariances of Latent Variables in CraftDawg Model 1

	Est	SE	z-value	P(>|z|)	Std.lv	Std.all
Individual incidental learning ~~						
Uncertainty	-0.142	0.036	-3.934	0.000	-0.266	-0.266
Crafting	0.323	0.084	3.865	0.000	0.258	0.258
Uncertainty ~~						
crafting	-0.200	0.085	-2.364	0.018	-0.143	-0.143

Analysis of the covariance associated with the latent variables finds the latent variables have relatively small communality as measured by the covariance. Individual incidental learning had a negative, significant covariance with uncertainty (-0.142, p = 0.000). Crafting had a positive, significant covariance with individual incidental learning (0.323, p = 0.000). Uncertainty and crafting had a negative, significant covariance with each other (-0.200, p = 0.018). In summarizing these relationships, uncertainty had a statistically significant negative relationship with crafting and individual incidental learning.

Except for the scored composite exogenous variable*, interact_crafting*, variances were significant at p <= 0.05. R^2 was used to examine the interact_crafting variable. R^2 for interact_crafting = 0.897 and thus the variable was retained.

Model Invariance

The researcher assessed CraftDawg Model 1 for model invariance using group analysis based on play session. A comparison of fit found the model was not invariant based on play session. Figure 4.1 provides the structural SEM path diagram for CraftDawg Model.

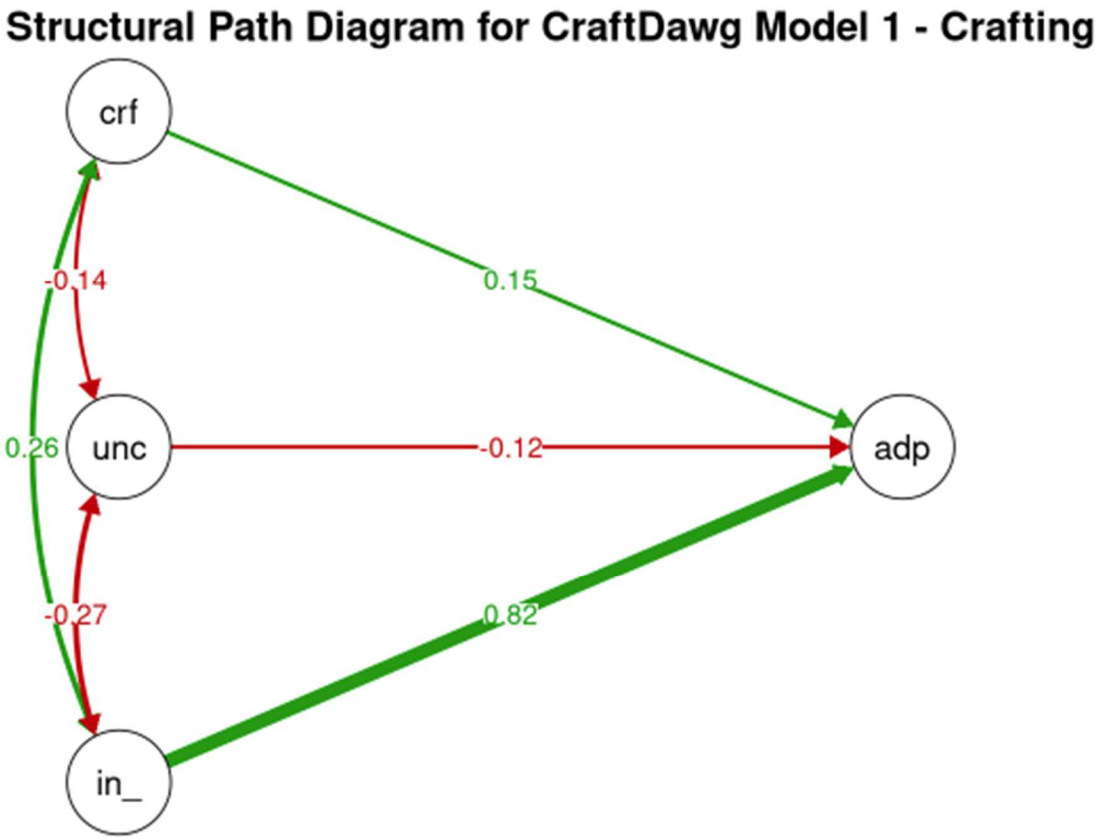


Figure 4.1. Structural SEM path diagram for CraftDawg Model 1 – Crafting.

Figure 4.2 shows the full path diagram for CraftDawg Model 1 – Crafting.

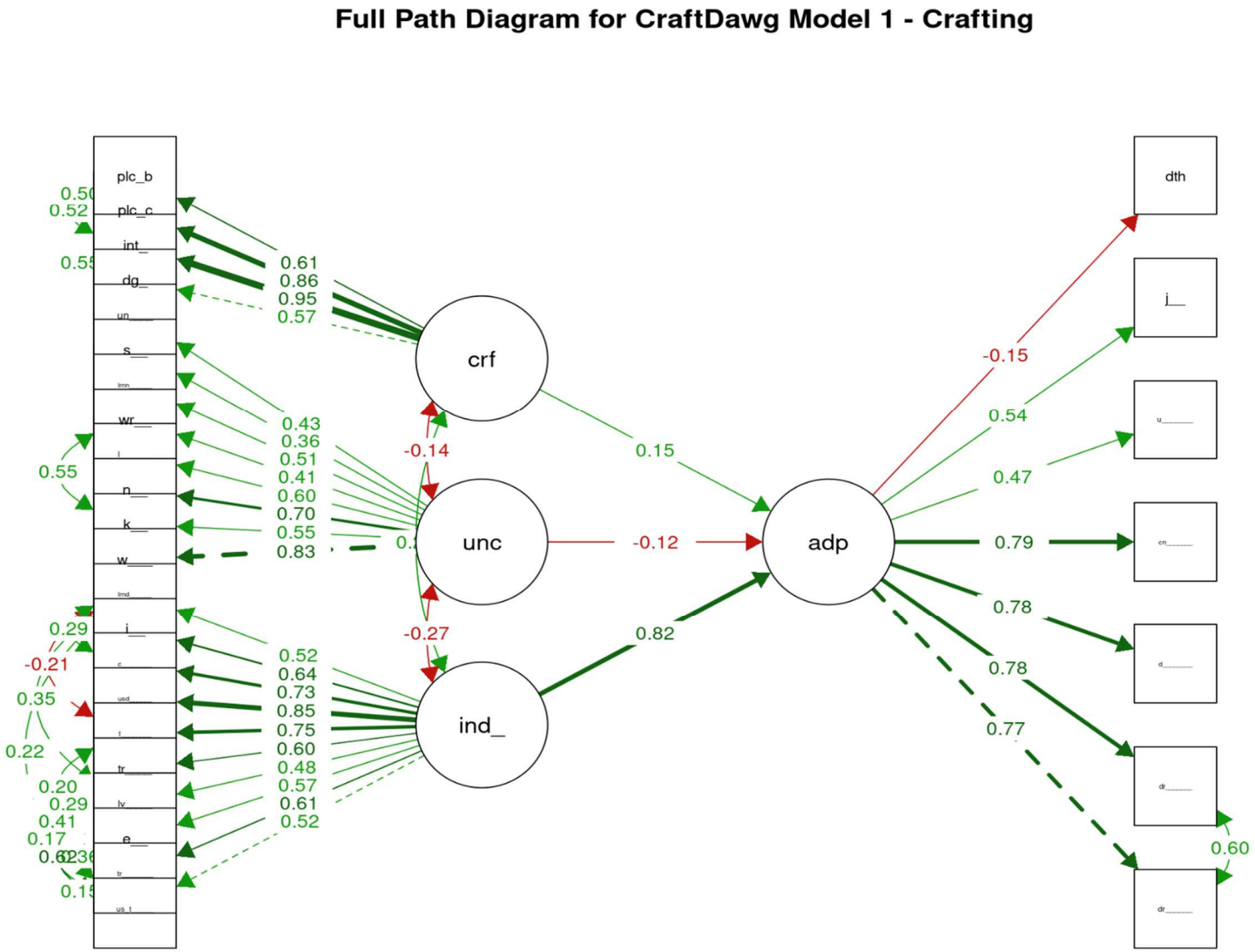


Figure 4.2. Full path diagram for CraftDawg Model 1 – Crafting.

Interpretation of CraftDawg Model 1 – Crafting

Analysis and interpretation of the relationships of the latent variables provided a more detailed insight into the relationships of the various latent variables amongst themselves. These relationships were used to create regression equations that allowed the dependent variable of 'deaths' to be predicted. Through model identification development, the researcher developed an SEM that defined the relationships using regression analysis.

Adaptiveness Regression

The initial regression used the latent variables of *individual incidental learning, uncertainty and crafting* to predict the latent variable of *adaptiveness*. The standardized model was defined as follows:

Adaptiveness = 0.816(individual_incidental_learning) - 0.122(uncertainty) + 0.147(crafting) + *residual.*

The largest influence on adaptiveness is individual_incidental_learning at 0.816. This is interpreted as a one standard deviation increase in individual_incidental_learning will result in a 0.816 increase in adaptiveness. Uncertainty had a negative impact on adaptiveness of -0.122. For a one standard deviation increase in uncertainty, adaptiveness would decrease by 0.122 standard deviations. Lastly, crafting had a positive influence on adaptiveness at 0.147. For each standard deviation increase in crafting, adaptiveness would increase by 0.147 standard deviation. Clearly the influence on adaptiveness from individual_incidental_learning was the most important influence. Combining uncertainty and crafting were interpreted as being offsets to each other. That is as the crafting skill increased, player uncertainty decreased at a similar rate.

A second regression was included in the crafting model. The latent variable of adaptiveness was used to predict the dependent variable, deaths. Deaths was an exogenous

variable that was extracted directly from play data for each participant for each play session. The regression analysis produced the equation:

Deaths = -0.149 (adaptiveness) + residual.

This was a negative relationship interpreted as adaptiveness increases, deaths decrease. Similarly, as adaptiveness decreases perhaps because of uncertainty, deaths increase. The researcher analyzed the indirect relationship between individual incidental learning based on the strength and direction of its direct effect with adaptiveness.

Model Identification – CraftDawg Model 2

The final model was identified using the loadings as shown in Table 4.11. Crafting was removed.

Table 4.11

Standardized Loadings of Observed Variables From Latent Variables in CraftDawg Model 2

Variables	Est	SE	Z value	P(>|z|)	Std.lv	Std.all
Individual incidental learning =~						
Use_other_experiences_to_figure_out something	1.000				0.690	0.521
Try_stuff_if_it_doesnt_work_try_other_stuff	0.735	0.078	9.373	0.000	0.507	0.633
Experiment_with_diff_ideas	0.766	0.088	8.657	0.000	0.529	0.585
Leverage_how_I_play_other_games	1.032	0.091	11.303	0.000	0.712	0.494
Try_different_ideas_already_have	0.924	0.100	9.248	0.000	0.638	0.604
Try_lots_of_different_stuff_to_figure_out_unfamiliar_stuff	1.209	0.125	9.651	0.000	0.834	0.747
Used_prior_knowledge_to_figure_out_new_stuff	1.387	0.144	9.668	0.000	0.957	0.846
Uncertainty =~						
When_uncertain_get_uncomfortable_with_it_all	1.000			0.000	0.735	0.789

Variables	Est	SE	Z value	P(>|z|)	Std.lv	Std.all
Kept_worrying_something_going_wrong	0.978	0.107	9.178	0.000	0.719	0.534
No_clear_way_forward_get_frustrated	1.098	0.092	11.957	0.000	0.807	0.725
Lots_of_different_things_at_once_freeze_up	0.591	0.059	9.990	0.000	0.434	0.528
Worried_about_consequences	0.724	0.105	6.877	0.000	0.532	0.401
Learning_new_stuff_in_game_is_hard	0.734	0.079	9.266	0.000	0.539	0.539
Somethings_i_cant_figure_out_so_i_dont_try	0.350	0.054	6.456	0.000	0.257	0.374
Uncertain_about_what_to_do	0.675	0.088	7.650	0.000	0.496	0.443
Adaptiveness						
During_the_game_i_coped_with_changes	1.000			0.000	0.856	0.804
During_the_game_i_adapted_well_to_changes	0.969	0.040	24.381	0.000	0.829	0.806
During_the_game,_i_learned_new_skills_to_adapt_to_ingame_changes	1.137	0.074	15.457	0.000	0.974	0.833
Usually_alright_when_not_right_game_answer	0.601	0.069	8.734	0.000	0.515	0.475

A regression was used with the latent variable of adaptiveness as the predictor variable and deaths as the dependent (predicted) variable. Individual incidental learning and uncertainty were used to predict adaptiveness. The model provided an indirect effect of individual incidental learning and uncertainty on deaths. Regression parameters and significance is shown in Table 4.12. Uncertainty has a negative relationship with adaptiveness. Individual incidental learning has a positive relationship with adaptiveness. Adaptiveness has a negative relationship with deaths.

Table 4.12

Regression Parameters by Latent Variable in CraftDawg Model 2

	Est	SE	z-value	P(>|z|)	Std.lv	Std.all
Adaptiveness ~						
Individual Incidental Learning	0.926	0.109	8.468	0.000	0.746	0.746
Uncertainty	-0.240	0.059	-4.102	0.000	-0.206	-0.206
Deaths ~						
Adaptiveness	-0.636	0.229	-2.782	0.005	-0.545	-0.155

Covariances were included in the model to improve model fit. The covariances represents the communality between the exogenous variables and the latent variable. Table 4.11 shows the covariance of the latent variables with each other. Covariances were examined for significance by examining the value of P(>|z|) .

Table 4.13

Covariance of Latent Variables in CraftDawg Model 2

	Est	SE	z-value	P(>|z|)	Std.lv	Std.all
Individual incidental learning ~~						
Uncertainty	-0.120	0.035	-3.427	0.000	-0.236	-0.236

Goodness-of-fit analysis was run to determine quality of the model and to allow the "Learning Model" to be compared to the "Crafting Model". Table 4.14 shows variance explained and model fit indices for both models.

Table 4.14

Comparison of Model Fit Indices and Variance Explained for Each Model

Model Desc.	Variance Explained	CFI <= 0.90	TLI <= 0.90	RMSEA <= 0.08	SRMR <= 0.08
Crafting Model 1	22%	0.914	0.902	0.059	0.069
Learning Model 2	18%	0.941	0.927	0.057	0.059

Both models have acceptable fit.

The SEM path diagram showing the structural relationships is shown in Figure 4.3. Standardized parameters are used in the diagram.

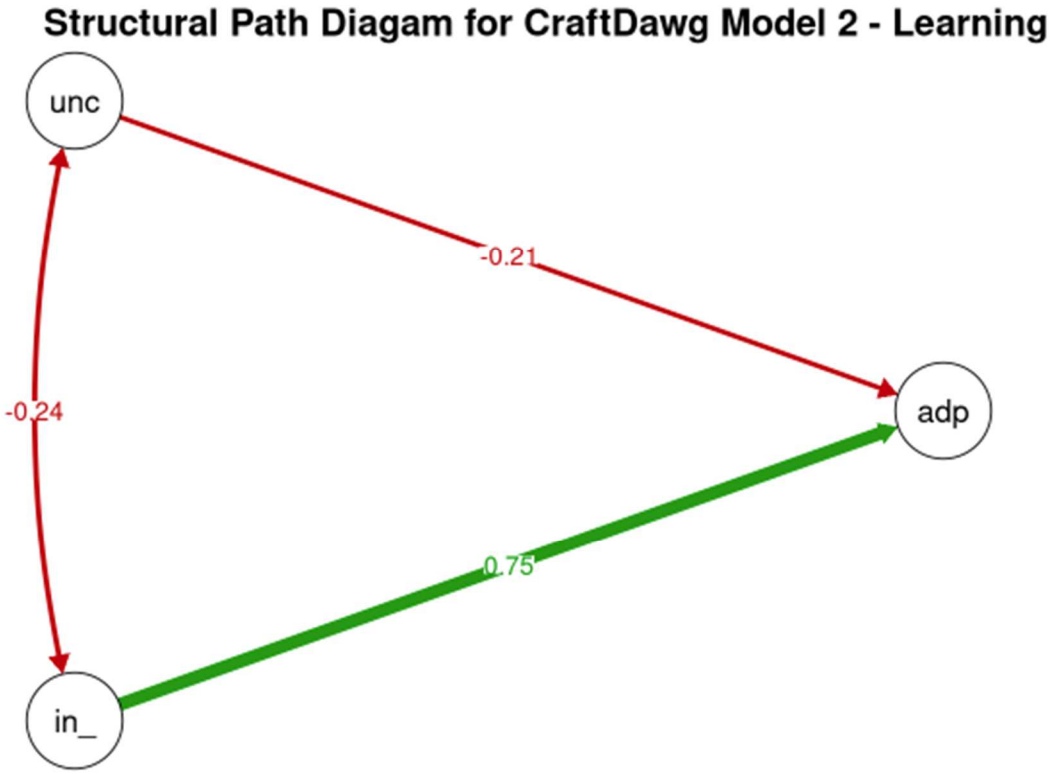


Figure 4.3. Structural SEM path diagram for CraftDawg Model 2 – Learning.

Figure 4.4 is the full path diagram for the CraftDawg Model 2 – Learning.

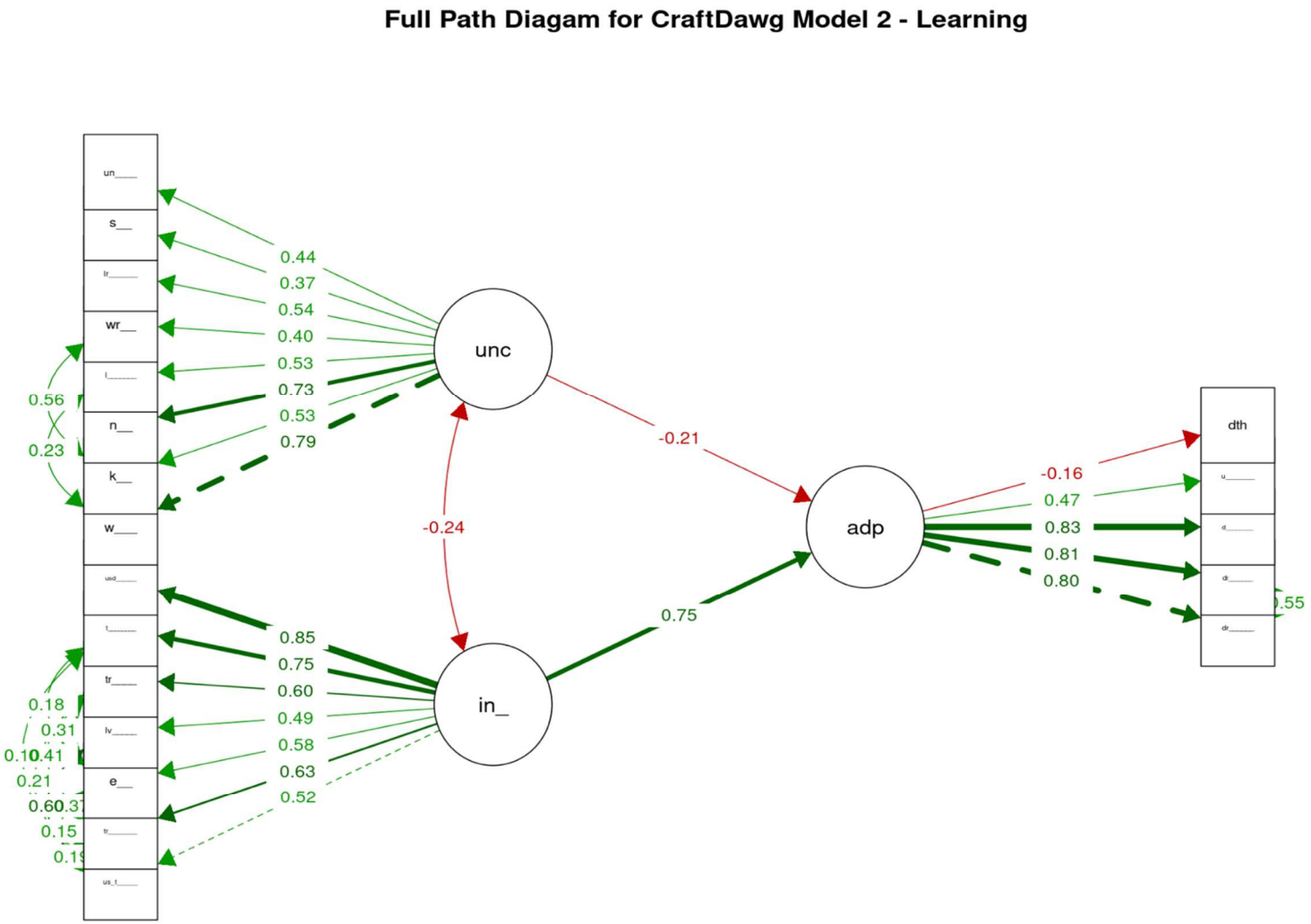


Figure 4.4. Full path diagram for CraftDawg Model 2 – Learning.

Model Invariance

Model invariance analysis was used to examine Model 2 when group based on experience. Three levels (fit, weak, and strong) of invariance were tested with change in model fit statistics used to determine invariance. If the between group models was significant, the model would not be considered invariant. Analysis of variance (ANOVA) was used to compare the four variants of the model. Table 4.15 shows the nested model comparison using the chi-squared difference test.

Table 4.15

Model Invariance Statistics for CraftDawg Model 2 – Learning

	Df	AIC	BIC	Chisq	Chisq Diff	Df diff	Pr(>chisq)
Dawg.exp_fit	576	21033	22007	920.69			
Dawg_exp_weak	614	21065	21890	1029.13	108.44	38	1.072e-08***
Dawg_exp_strong	652	21110	21787	1150.32	121.19	38	1.290e-10***

Significance codes: *** 0.000

As the change between the models is significant, the model is not invariant across groups based on experience. Simply stated, the groups have different factorial structures. The researcher did not examine the factorial structures at the group level as the sample size for each group was deemed inadequate.

Interpretation of CraftDawg Model 2 – Learning

To remove the study limitation associated with the scoring of the in-game play activities, the researcher eliminated the game play exogenous variables from the data. EFA and CFA were used to identify and examine theorized latent variables from the self-reported post-play data. Comparative analysis of model fit data showed that Model 2, identified as the learning model, is a better fit to the data than Model 1 (the crafting model) as shown in Table 4.12.

By removing the latent variable, *crafting*, from the model, the variance explained *decreased* from 22% to 18%. There was also a change in the parameter values associated with the model as shown in Table 4.16. Table 4.16 compares the parameters for the largest exogenous variables for the common latent variables in Model 1 and Model 2.

Comparison of Select Measures for Model 1 and Model 2

Table 4.16

Comparison of Exogenous Variable Weights by Model

Latent Variable	Exogenous Variable	Model 1 Parameter	Model 2 Parameter
Individual_Incidental Learning	Use prior knowledge	0.846	0.846
	Try_lots of different things	0.751	0.747
	confident	0.728	omitted
Uncertainty	When uncertain	0.829	0.789
	No_clear_way	0.628	0.725
Adaptiveness	confident	0.791	omitted
	During the game I coped	0.780	0.804
	During the game I adapted	0.779	0.806

Table 4.17 compares the effect of parameters included in the adaptiveness regression. When removing crafting, the strength of uncertainty in predicting adaptiveness increases and the strength of individual incidental learning decreases. This can be interpreted to reflect a skill-based aspect of the game. By removing this variable, some of the variance explained is reduced and uncertainty is the variable that explains more of the variance while individual incidental learning explains less of the variance explained by the Learning Model. Of note in comparing these models, the variance explained may not be the same variance in the models. Further analysis would be appropriate to find the communality in the variance explained.

Table 4.17

Comparison of Model Latent Variable Parameter Strength and Direction

Model	Dependent Variable	Individual Incidental Learning	Uncertainty	Crafting
Crafting Model	Adaptiveness	+0.816*	-0.122*	0.147*
Learning Model	Adaptiveness	+0.746*	-0.206*	deleted
Change		-0.07	+0.084	

*p < = 0.05

Table 4.18 compares the adaptiveness effect on deaths. The learning model shows adaptiveness explaining more of the variance in deaths.

Table 4.18

Model Comparison of Strength and Direction of Latent Variable Adaptiveness on Dependent Variable Deaths

Model	Dependent Variable	Adaptiveness
Crafting Model	Deaths	-0.149*
Learning Model	Deaths	-0.155*

*p <= 0.05

The generalized interpretation of the learning model was consistent with the interpretation of the crafting model. Individual incidental learning remained positive and the predominant effect on adaptability. Uncertainty remained negative and its effect increased modestly on adaptability. While the model fit statistics indicate the learning model is a better fit, removing the crafting variable reduced the variance explained by the model and increased the effect of the uncertainty latent variable.

Identification and Interpretation of RoL Variable

In this study, one-dimensional measures (i.e., linear measures) were used to build the SEM crafting and learning models. In interpreting these models, it was noted, not unexpectedly, that the parameter weights for the common latent variable were different based on the removal of the game play latent variable. When the crafting variable was removed from the model to create the learning model, the strength of the uncertainty variable increased (+0.084) and the strength of the individual incidental learning variable decreased (-0.070). To add more insight to this change, the researcher examined the fractal dimension of the game play and the change in the fractal dimension from play session to play session and group to group.

Using a linear model to *fully* explain a learning process is not consistent with IIL, which specifically recognizes the irregularity and roughness of the learning process (Marsick & Watkins, 1990), nor the actual game play statistics from the study. In the context of the game, there is a roughness of learning reflected in the efforts a player used to increase the survival rate (the game objective). There is notable irregularity in the game play statistics (Figure 3.8). To the extent the roughness of learning [complexity in the context] impacts adaptiveness, then measuring the irregularity in the learning is useful in informing new methods for better leveraging individual incidental learning or reducing uncertainty, all to increase adaptiveness.

An Additional Method For Assessing Learning in Complexity

Complexity science uses fractals to measure complexity (Fernández-Martínez, 2015; Kenkel, 2013). Applying Holland (1998) and Mitchell (2009) in measuring the roughness of learning in terms of complexity, the researcher envisioned a multitude of interactions absorbed and managed in the human learning process: a process gifted to humans that enables the pursuit of predictability and certainty (knowledge or truth) from chaos (the unknown or wrongly known). Acknowledging the importance and implications of these interactions enabled a more realistic understanding and acknowledgment of the weight of time, the role of incidental (native) learning, the influence of uncertainty and fear, and the latent ability to adapt. To add a measure that represents complexity in human learning, the researcher developed a measure of complexity based on the health score at each time of death from a series of play sessions in the CraftDawg study. To add the roughness of learning (from whatever source) to the analysis of learning as theorized by Marsick and Watkins (1990), the researcher used a common measure of complexity, fractal dimensionality, to reflect the roughness of learning during the game play.

Today fractals are used to measure complexity in various disciplines (Fernández-Martínez, 2015; McCauley, 1994; Skjeltorp, 2000). Likewise, the researcher applied similar logic and reasoning to develop a measure of the roughness of learning using fractal dimensionality associated with certain game play measures. Conceptually, the roughness of learning is a composite variable that measures the overall complexity in the adaptive process at a given moment. By measuring the same transaction (game play) over time and comparing the change in the fractal dimension, the researcher applies Marsick and Watkins' (1990) theory that learning, reflection and meaning making through experience are primary sources of the changed measure of complexity. For this study, roughness of learning was measured in relation to incidental learning, uncertainty and adaptiveness used to survive in the game of Minecraft.

This study attempts to quantify the "roughness and brittleness" Marsick and Watkins (1990, p. 13) describe in their theory. Quantifying this aspect of the theory provides insights into incidental learning, uncertainty, and adaptability to better understand the process learners use to muddle through the roughness of learning to accomplish a task or achieve a desired outcome.

Development of RoL Variable

Play data was collected from the play of the game for the state of the player at time of death. Experience, health, hunger, and saturation are all measured by the game. The values of these variables were added together at time of death to create a score variable.

As death is the variable of interest in the SEM, it was also used to calculate the fractal dimension of play. The *health at time of death score* was plotted for each death. The boxcounting method was used to calculate the overall fractal dimension of the study as 1.28009.

To examine this in more detail, the fractal dimension was calculated by bifurcating the data based on the play number as shown in the "All Players" column of Table 3.20. In addition,

the fractal dimension was calculated for each group of players based on their self-reported experience as Novice, Intermediate or Advanced. Table 3.21 shows the number of "deaths" for each group for all plays in the *n* row. Overall, the "health at time of death score" was calculated and plotted for 1320 death events.

ANOVA was used to determine if there was a significant ($p <= .05$) difference in the fractal dimension between groups and overall. Table 4.19 shows ANOVA results. A significant difference ($p = 0.00446$) was found between groups based on *experience*. There was no significant difference in the roughness of learning based on *play*.

Table 4.19

ANOVA Table for Novice, Intermediate, Advanced, All

Analysis Basis	df	Sum Sq	F value	Pr(>F)
Play	1	0.0181	0.801	0.381
Play:Experience	1	0.0003	0.12	0.913
Experience	1	0.2313	10.263	**0.00446
Experience:Play	1	0.0003	0.12	0.91343

**p <= 0.01

To create a larger sample for fractal analysis on the basis of experience, the researcher combined the intermediate and advanced groups to create the experienced group. The fractal dimension was then calculated for the combined group. Table 3.23 shows the results. ANOVA was run to determine if there was a significant difference between the two groups. ANOVA results are shown in Table 4.20.

Table 4.20

ANOVA of Fractals for Novice, Experienced, All

Analysis Basis	df	Sum Sq	F value	Pr(>F)
Play	1	0.0360	0.995	0.336
Play:Experience	1	0.0180	0.497	0.682
Experience	1	0.2481	6.846	*0.0203
Experience:Play	1	0.0180	0.497	0.4922

*p < =0.05

Figures 4.5, 4.7 and 4.9 show the plot of the *health score at death* for each of the groups: novice, experienced, and all. The plot is the actual data (health score at time of death) from the time series used to calculate the fractal on a scale of 1:2. The researcher rescaled the fractal to 0:4 using May's scale as shown in Table 3.22. Figures 4.6, 4.8, and 4.10 show the behavior of the non-linear logistic map for each of the groups using the rescaled fractal. These plots were created using R package *nonlinearTseries* (version 0.2.12).

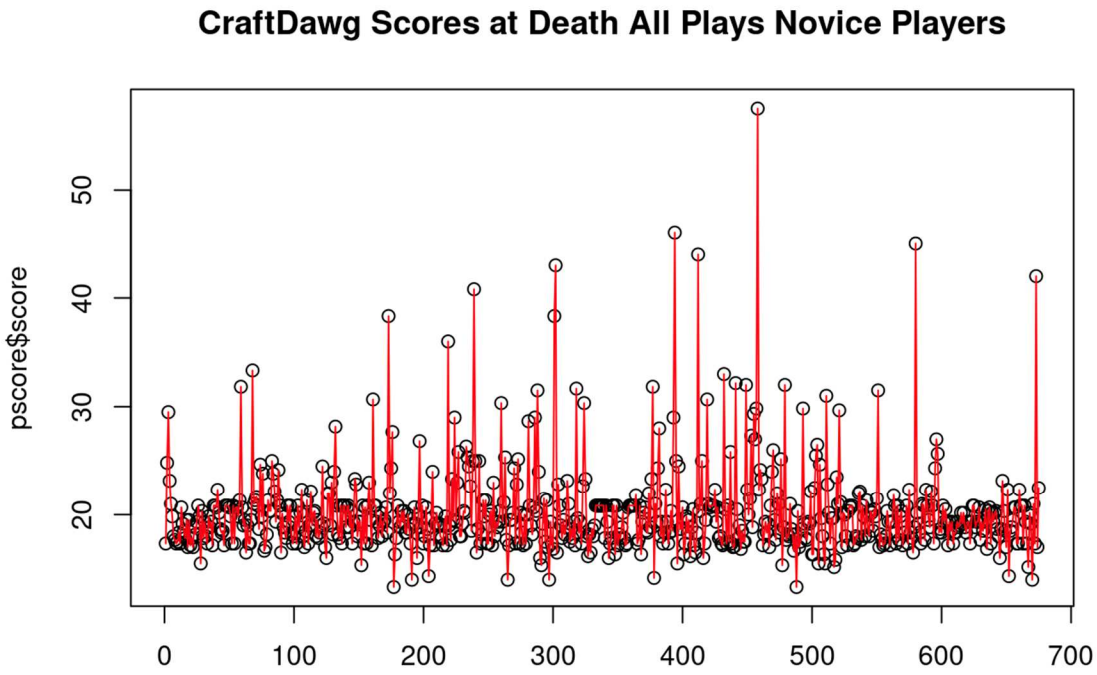


Figure 4.5. CraftDawg health scores at death: all plays, novice players.

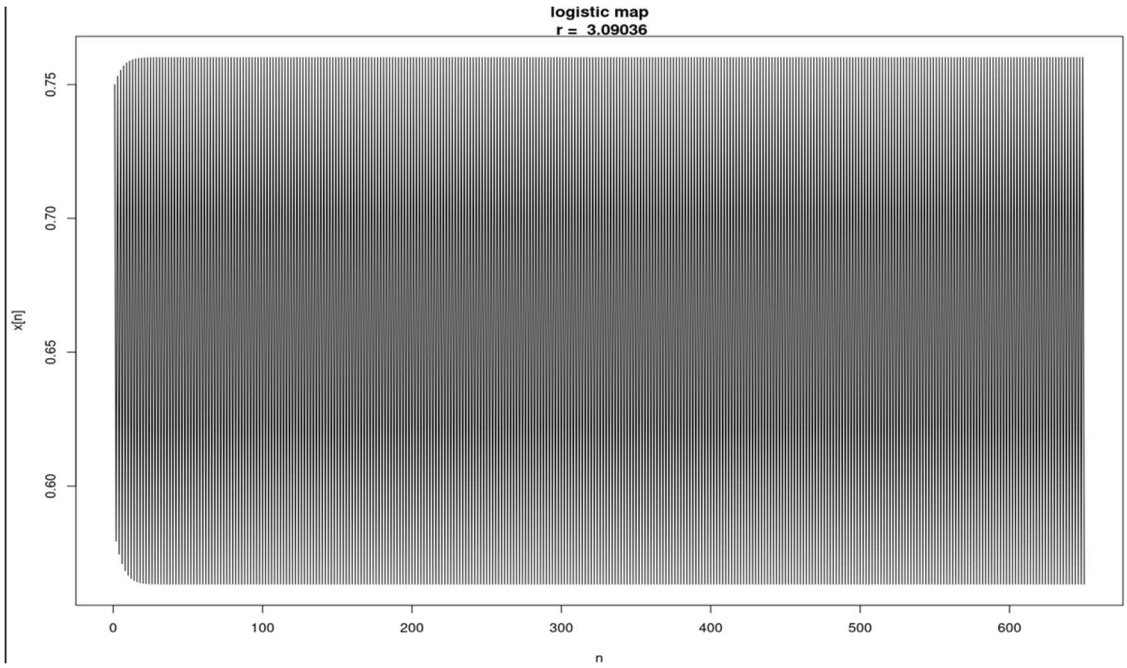


Figure 4.6. Novice group plot using Robert May's logistic map and $r = 3.09036$ and $x_0 = 0.75$.

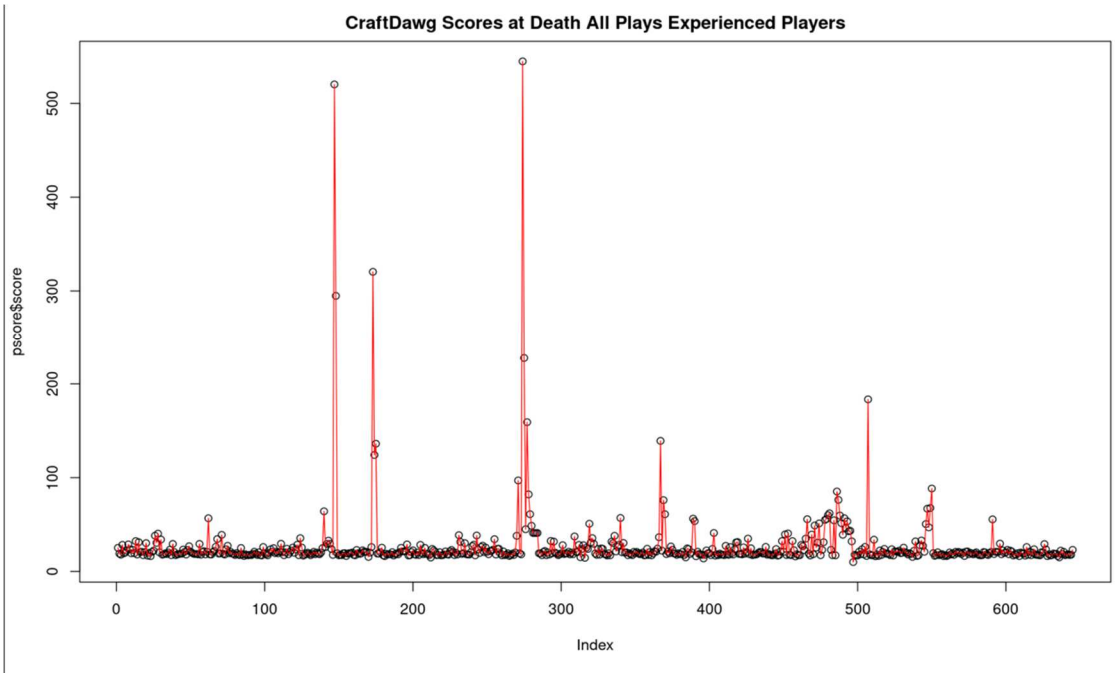


Figure 4.7. CraftDawg health scores at death: all plays, experienced players.

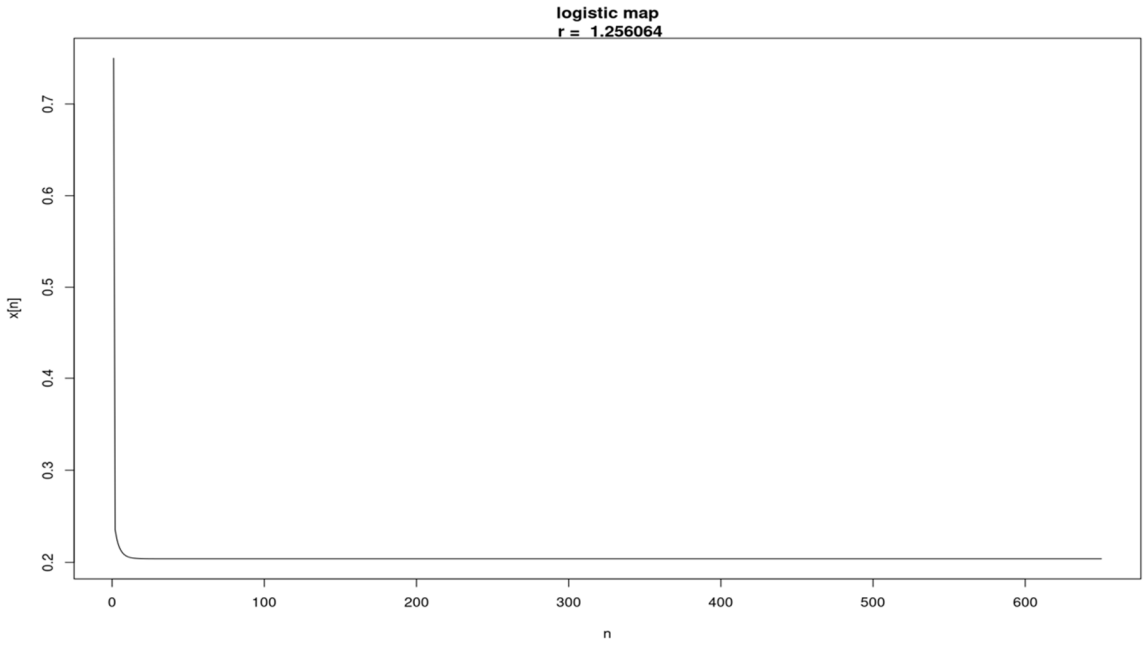


Figure 4.8. Logistic map for experienced group *r=1.256064* and initial x_0 = .75.

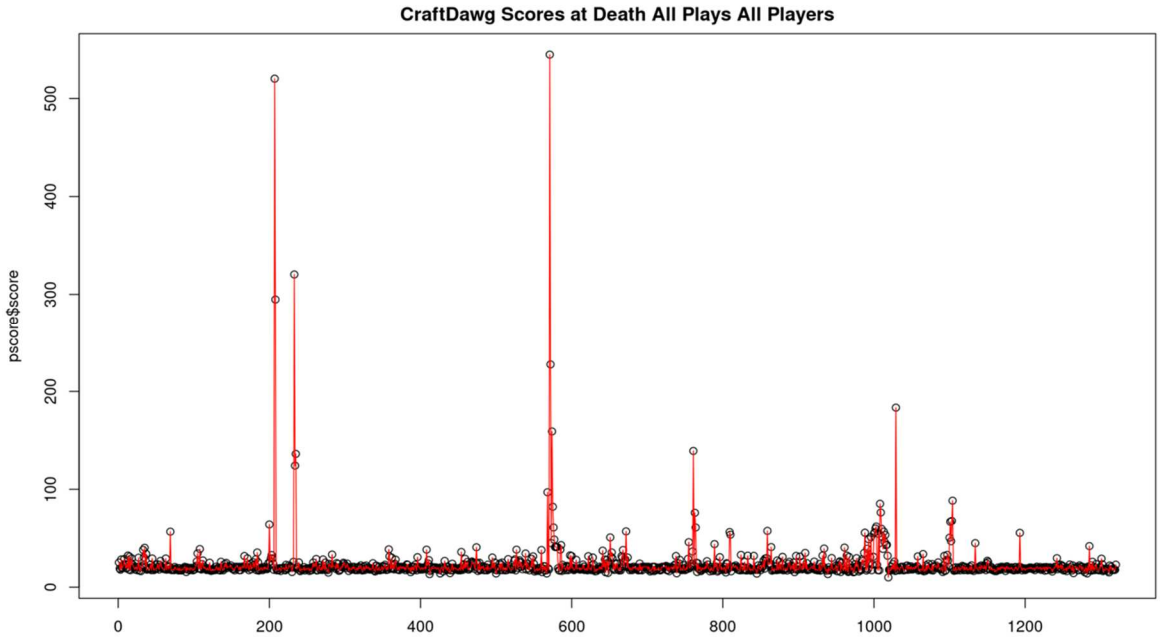


Figure 4.9. CraftDawg health scores at death: all plays, all players.

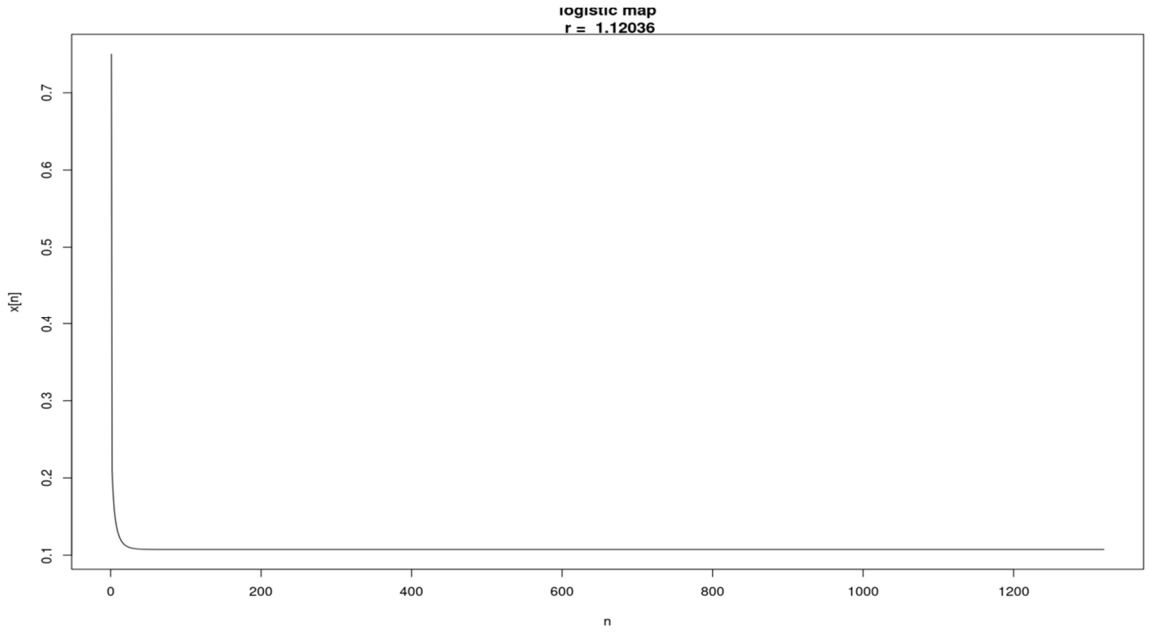


Figure 4.10. Logistic map of all players and all plays $r = 1.12036$ and $x_0 = .75$.

Fractal Dimensionality of Learning – The RoL Variable

The overall purpose of the study was to identify, measure and interpret the RoL variable in the game. This was accomplished by calculating the fractal dimension of play using data extracted directly from the game. The irregularity and roughness of scored play activities were plotted against death to create a *shape* that allowed a fractal dimension to be measured. Figures 4.5, 4.7 and 4.9 are the actual plots from the game data. The horizontal axis in these each of the plots shows the play number while the vertical axis shows the players health score at time of death. This creates the time series view of the game play that allows the fractal to be calculated using the boxcounting method.

Visual examination of the CraftDawg scores at death for all plays (Figure 4.9) emphasized the jagged and irregular nature of the health of individual players at time of their

death in the game The researcher deemed the effort to preserve health and avoid death to be the primary objective for participants in the game. As *health* was required to persist in the game, it was necessary for the player to *learn* how to preserve health and avoid death. This learning would be part of the participants adaptiveness to persist in the game over multiple plays and within the changing context of the game space.

Interpreting Fractal Dimension as a Measure of RoL

The fractal dimension calculated for the various groups (novice, experienced and all players) was rescaled from a 1:2 scale to a 0:4 scale and then used as the *r value* in May's logistic map. May effectively created an index based on r and the behavior of the logistic map when plotted over a time series. *Of note is the model behaves this way no matter what the initial value of x is. This means that adaptive capacity is of limited use in a complex environment. Adaptive capacity can affect the level of the attractors, it cannot change the complexity. Complexity science holds that other interactions and interventions are needed to change the complexity in the system* (Holland, 1995, 1998; Mitchell, 2009).

The CraftDawg *r* values, attractor points, and when the system converges to stability are shown in Table 4.21. Figures 4.6, 4.8 and 4.10 show the *shape* of the behavior for each of the groups. By looking at the attractor level and when the system converges to stability, the RoL variable can be assessed for each group.

The novice group shows the highest RoL. The model converges to predictability after 57 steps and oscillates between two attractors (0.7601560 and 0.5634309). The level of the attractors is a function of the initial value of x_0. Of note is the range of the attractor from the initial value of 0.75. The system moves from creating adaptive capacity on the lower range and expending adaptive capacity on the higher range.

The researcher concluded that without intervention on some basis, the novice system will remain in this state of oscillation. Analysis of the SEM findings suggest that increasing individual incidental learning and/or reducing uncertainty on some basis would be useful in reducing the complexity as measured by a change in deaths.

The experienced group shows a lower RoL, *r*. The model converges to stability after 48 steps and has a single attractor (0.2038622). The experienced group shows a stable pattern and intervention would be produce minimal change in the outcome. Interventions to decrease the initial value of x_0 would result in a lower attractor. *The single attractor is notably less than the initial value of 0.75 and suggest that the system "creates adaptive capacity" over time.*

Similar to the experienced group, the all-participant RoL is low. The model converges to stability after 104 steps at a value of 0.1074298. The overall pattern is stable and intervention would produce minimal change in the outcome. Interventions to decrease the initial value of x_0 would result in a lower attractor. Analysis of the difference between the initial value of .75 and the stable value of 0.1074298 is interpreted as the system is *creating adaptive capacity*.

Table 4.21

R Values From CraftDawg Study by Group, Initial $x_0 = 0.75$

Group	Length	*R*	Attractor(s)	Steps to Predictability
Novice	675	3.090360	0.7601560 and 0.5634309	57
Experienced	645	1.256064	0.2038622	48
All	1320	1.120360	0.1074298	104

As shown in Figure 4.6, the novice group shows oscillation between two attractor values: 0.7601560 and 0.5634309. It achieves predictability after 57 steps. Figure 4.8 shows the experienced group converges to stability after 48 steps at an attractor value of 0.2038622. The all-participant group (Figure 4.10) converges to stability after 104 steps at an attractor value of 0.1074298.

Table 4.22 combines May's complexity index (Wikipedia, 2019) with the researcher's analysis and interpretation of the study findings.

Table 4.22

May's Table as Interpreted and Applied in the CraftDawg Study

r value range	May's Interpretation	CraftDawg Translation to Human Learning	CraftDawg Group and Study Analysis Roughness of Learning Variable (RoL)
0–1	The population will eventually die, independent of initial population	Learning ceases and the game is routine and predictable	None of the groups had a value in this range
1 to 2	The population will quickly approach the value *(r-1)/r*, independent of the initial population	Learning is continuing at a granular level with the players exploring new ideas and new methods. Outcome is predictable. Learning increases adaptive capacity.	Overall (*RoL = 1.120360, x_{48} = 0.2038622*) and the experienced group (*RoL = 1.256064, x_{104} = 0.1074298*) showed this characteristic. (See Figure 4.10 for all players; and Figure 4.8: experienced players.)
2 to 3	The population will eventually approach the same value *(r-1)*/r, but first will fluctuate around that value for some time. The rate of convergence is *linear*,	This range was not found in the CraftDawg study for the overall group populations. The novice group had measures in this range	The novice group had measures in this range for individual play sessions as shown in Table 3.20 – Plays 1, 2, 3 and 5. No analysis was done on this

r value range	May's Interpretation	CraftDawg Translation to Human Learning	CraftDawg Group and Study Analysis Roughness of Learning Variable (RoL)
	except for $r = 3$, when it is dramatically slow, less than linear	but were not plotted because of sample size. There is enough adaptive capacity to learn through the roughness and adaptive capacity increases overtime.	play level fractals because of limited sample length.
3 to ~ 3.44949	The population will approach *permanent oscillations* [italics added] between two values.	Learning is happening but not at a pace that reduces the complexity below 3. Adaptive capacity fluctuates through experiential learning (trial and error). This can be considered an edge of chaos state. *External intervention is needed to add adaptive capacity to overcome the RoL in the context.*	The novice group showed a *RoL = 3.09036.* The plot of the overall play of the novice group shows the irregularity and roughness of the game play (Figure 4.5). The oscillation between two values ($x_{57} = 0.7601560$ *and* $x_{58} = 0.5634309$) does not change no matter what the adaptive capacity ratio (Figure 4.6). The primary influence is the complexity level, *r*.
3.44949 to 3.54409	From almost all initial conditions (adaptive capacity ratio) the population *will approach permanent oscillation among 4 values* [italics added].	Learning is happening but more irregular and jagged with four attractors. Adaptive capacity fluctuates through experiential learning (trial and error). This can be considered an edge of chaos state. *External intervention is needed to add adaptive capacity to overcome the RoL in the context.*	This level was not identified in the study for any of the groups.
3.54409 to ~ 3.56995	From almost all initial conditions (adaptive capacity ratio) the population will	Learning is happening but the context is creating more irregularity in the	This level was not identified in the study for any of the groups.

r value range	May's Interpretation	CraftDawg Translation to Human Learning	CraftDawg Group and Study Analysis Roughness of Learning Variable (RoL)
	approach oscillations among 8 values, then 16, then 32, etc. The lengths of the parameter intervals that yield oscillations of a given length decrease rapidly.	effort. Adaptive capacity fluctuates through experiential learning (trial and error). This can be considered an edge of chaos state. *External intervention is needed to add adaptive capacity to overcome the RoL in the context.*	
~ 3.56995	This is the *onset of chaos* [italics added], at the end of the period-doubling cascade. From almost all initial conditions, we no longer see oscillations of a finite length. Slight variations in the initial population yield dramatically different results over time, a prime characteristic of chaos.	Without external intervention, learning cannot overcome the complexity in the context and the system begins dissipation.	This level was not identified in the study for any of the groups.
> 3.56995	Most values beyond 3.56995 exhibit chaotic behavior, but there are still certain isolated ranges of *r* that show non-chaotic behavior; these are sometimes call *islands of stability.*	Without external intervention, learning cannot overcome the complexity and system dissipation begins with moments where there is some stability (*the eye of the hurricane*)	This level was not identified in the study for any of the groups.

Analysis of Both Measures: SEM Models and RoL Variable

Combining the findings of the SEM analysis with the RoL analysis gives a more holistic perspective of the study. Both SEM models have the same directional relationships between the latent variables of individual incidental learning and uncertainty (negative covariance) ; individual incidental learning and adaptiveness (positive) and uncertainty and adaptiveness (negative); adaptiveness to deaths (negative). Neither SEM model was model invariant which the researcher interpreted as there being a different factor structure for each group.

The researcher's interpretation of the RoL variable for each of the groups supports this. Novice participants have a $RoL = 3.096$ which is characterized in May's logistic map by oscillation between two attractors when $x_0 = 0.75$: 0.7601560 and 0.5634309, which is achieved at x_{57}, x_{58} respectively. The direction of the relationships between the latent variables is the same, but the effort needed by the Novice players is different and at times additional adaptive capacity is needed to sustain the player in the game as reflected by $x_n > x_0\ (0.75)$. The oscillation between the two values is interpreted to mean that the players are continuing to use learning to reduce uncertainty and increase adaptive capacity, however, the players cannot learn their way out of the oscillation using their current reservoir of prior knowledge and experiential learning; and additional intervention is needed.

For the experienced players $RoL = 1.256064$. This population of players uses its current reservoir of prior knowledge to move to a single attractor of $x_{48} = 0.2038622$. The attractor falls to a value much less ($x_{48} = 0.2038622$) than the initial value ($x_0 = 0.75$) which is interpreted as excess adaptive capacity in this group of players. There is less uncertainty and greater adaptiveness warehoused in the prior knowledge collected from past play in the game. These

players engage with the game and are able to persist and prosper in the game more efficiently and effectively.

The analysis for the game overall is similar to that of the experienced players ($RoL_{all} = 1.120360$). However, the steps needed to stabilize the environment is 104. $x_{104} = 0.1074298$ from a starting value of $x_0 = 0.75$. Both SEM models are based on the overall play in the game and the strength and direction of the parameters can be interpreted in conjunction with the RoL variable as there is adequate adaptive capacity to learn the game through experience.

Research Questions and Hypotheses

Research Question 1: To What Extent Does Incidental Learning Positively Affect Adaptiveness in a Novel Situation?

This research question examines the relationship between the latent variables of incidental learning and adaptiveness. A variety of studies identify learning as a critical component of adaptive capacity (de Groot et al., 2020; Pelling et al., 2008). This study again examines that relationship. Analysis of the parameter data in both the crafting and the learning models shows strong, positive relationship between individual incidental learning and adaptiveness. Table 4.23 shows the parameter weights and direction. Figures 4.1 and 4.3 show the relationships within the structural path diagram and Figures 4.2 and 4.4 show the full path diagram for each model.

Based on analysis of *both* the crafting model and the learning model 1, individual incidental learning *positively* effects adaptive capacity in a novel context. The strength of the relationship between individual incidental learning and adaptiveness is large and supports H1A as this is the largest parameter in the model in predicting adaptiveness.

Table 4.23

Adaptiveness Regression Parameters for Incidental Learning, Uncertainty and Crafting as Established in the CraftDawg Models

Model	Incidental Learning	Uncertainty	Crafting
CraftDawg Model 1	0.816 *	-0.122 *	0.147 *
CraftDawg Model 2	0.746 *	-0.206 *	deleted

* p < = 0.05

Research Question 2: What Is the Relationship Between Uncertainty in a Novel Situation and Adaptiveness?

This research question is also answered by analysis of Table 4.11. In both CraftDawg models, uncertainty is negative. As shown in Table 4.11, H2A is confirmed based on the negative parameter associated with uncertainty in predicting adaptiveness. The greater the uncertainty of a participant, the lower the adaptability.

H2B is supported by analyzing the covariance between incidental learning and uncertainty. Analysis of the covariance between individual incidental learning and uncertainty showed a negative relationship. Interpretation of this relationship was that as incidental learning was higher, uncertainty was lower. Table 4.24 shows the covariance for each model.

Table 4.24

Covariance Between Incidental Learning and Uncertainty for Each Model

Model	Estimate	Standard Error	Z value	P(>|z|)	Std.lv	Std.all
CraftDawg 1 – Crafting Incidental Learning ~~ Uncertainty	-0.142	0.036	-3.934	0.000	-0.266	-0.266
CraftDawg 2 – Learning Incidental Learning ~~ Uncertainty	-0.012	0.035	-3.427	0.001	-0.236	-0.236

Research Question 3: Is There a Roughness of Learning Variable That Measures Complexity in Adaptiveness?

To answer this research question, the researcher used a common measure of complexity in analyzing time series data, fractal dimension.

The roughness of learning describes how that complexity influences learning and thus adaptiveness. To establish roughness, change in the fractal dimension between play and between groups was analyzed. In addition, change in the fractal trajectory based on group experience was analyzed. Table 3.21 shows the fractal analysis used. Observation of the data shows that the fractal dimension trajectory decreases for all groups from Play 1 to Play 5. It also decreases for all players combined.

To determine if the observed change is significant, ANOVA analysis was performed to determine if the observed difference in the RoL between plays and between groups was significant. The observed difference was significant at $p <= 0.01$ between groups based on experience. Based on analysis of the ANOVA results as shown in Table 4.17, H3A was

supported. As ANOVA (Table 4.17) did not show the change based on plays was significant at the group level (novice, intermediate, experienced), H3C and H3D were not supported.

To examine the RoL variable as measured by the fractal dimension, the researcher merged two groups (intermediate and advanced) to create an experienced group. ANOVA analysis was performed and the fractal dimension was significantly different between the two groups. All data was sorted by play session. Table 4.20 shows this analysis.

Based on the ANOVA (Table 4.20) analysis and the theoretical model, the researcher rescaled the fractal data from a 1:2 scale to a 0:4 scale. To provide the longest length of context, the researcher assessed the fractal dimension for all play for novice (3.09036, length = 675 deaths); experienced (1.256064, length = 645 deaths); and all participants (1.120360, length = 1320 deaths). The researcher used the rescaled fractal to create a plot using Robert May's (1975, 1976) logistic map. Figure 4.6 shows the novice group plot with $r = 3.09036$ and $x_0 = .75$. The figure shows the group oscillates between two attractors: 0.7601560 and 0.5634309. Based on the theoretical model, the researcher interpreted this as learning and knowledge creation is occurring, but not a rate great enough to reduce complexity in the game.

Figure 4.8 shows the plot of the experienced group where $r = 1.256064$ and initial $x_0 = .75$. The figure shows the group quickly adapts to the game and a single attractor point is 0.2038622 achieved. The researcher interpreted this as showing prior learning and knowledge are applied quickly to minimize the complexity in the game and stabilize the context.

Figure 4.10 shows the all-participant plot using May's model. The researcher interpreted the plot to show the game quickly finds a single attractor 0.1074298 and interpreted this to show the play of the game stabilized at level of complexity that allowed prior experience and knowledge to be used stabilize the game results.

Summary of the Results

Research questions RQ1 and RQ2 were answered by data analysis associated with the CraftDawg crafting model and the CraftDawg learning model. RQ3 was answered by the analysis of the fractal dimension of the game play data. Hypothesis testing of H1A and H2A was done through statistical analysis of concurrent and comparative analysis of both CraftDawg SEMs. Hypothesis testing of H3A, H3B, H3C and H3D was done using the ANOVA analysis of the fractal dimension of game play and the analysis of the fractal dimension based on May's (1975) complexity index. Table 4.25 summarizes the findings.

Table 4.25

Summary of Hypothesis Analysis by Research Question

Research Question	Hypothesis	Results
RQ1	H1A: Participants will utilize incidental learning to increase adaptiveness in the moment in purpose driven context.	Supported
RQ2	H2A: Uncertainty will negatively influence adaptiveness.	Supported
	H2B: Uncertainty and incidental learning will be inversely related.	Supported
RQ3	H3A: There is a roughness of learning effect that can be estimated as a measure of complexity in the game.	Supported
	H3B: The roughness of learning will be different for experienced players compared to novice players.	Supported
	H3C: The roughness of learning trajectory will be less steep for experienced players.	Not supported
	H3D: The roughness of learning trajectory will be steeper for novice players.	Not supported

CHAPTER 5

SUMMARY, CONCLUSIONS, AND IMPLICATIONS

This chapter includes (a) a summary of findings, (b) conclusions, (c) implications for theory and research, (d) limitations of the CraftDawg study, and (e) recommendations for future research.

Summary of Findings

The purpose of the CraftDawg study was to identify and measure a new variable that measures complexity in human learning. To demonstrate the usefulness of adding another insight to the study of human learning, the study was designed to observe human learning in a complex context. This was accomplished by designing, building, and using an integrated, technology-based platform to allow a minimally invasive method for collecting a large quantitative selection of data from a remote, self-directed participant pool over an extended time-period. Data extraction and data scrubbing methods were developed to harvest, scrub, parse and organize the data for use to support the statistical analysis used in the study to answer the research questions. Combining actual play data with self-reported instruments allowed the researcher to develop statistical analysis methods to answer the guiding research questions and assess the hypotheses associated with those questions. Two CraftDawg structural equation models (SEMs) were created and used for analysis of RQ1 and RQ2. Directly harvested quantitative data was used to develop fractal dimensionality of play to answer RQ3 and assess the associated hypotheses. The fractal dimension of play was rescaled to use in Robert May's (1975, 1976) logistic map to

assess RoL using a reimagining of May's index to reflect human learning capacity and the need for external interventions in contexts that are too complex for current adaptive capacity limits.

Interpretation of the two CraftDawg models (crafting and learning) produced consistent results, noting the negative relationship between adaptiveness and uncertainty ($\beta = -0.122, p = 0.003;\ \beta = -0.206, p = 0.000$) and the positive relationship between informal learning and adaptiveness ($\beta = 0.816, p = 0.000;\ \beta = 0.746, p = 0.000$) This was not a surprise. Perhaps somewhat surprising was the difference in the importance of individual incidental learning on adaptiveness relative to uncertainty. The covariance between individual incidental learning and uncertainty indicated the negative relationship between these two latent variables ($\sigma_{iil,unc} = -0.266, p = 0.00;\ \sigma_{iil,unc} = -0.236, p = 0.000$). In the crafting model, where the exogenous variable of confidence was included in both the individual incidental learning latent variable and the adaptiveness latent variable ($\beta = 0.728, p = 0.000;\ \beta = 0.791, p = 0.000$), deeper insight into the sources of uncertainty appeared. When confidence was removed along with the crafting variable, the influence of uncertainty on adaptiveness increased ($\beta = -0.206, p = 0.000$). While the uncertainty parameter is much smaller than the individual incidental learning parameter ($\beta_{iil} = 0.816, p = 0.000, \beta_{unc} = -0.122, p = 0.000;\ \beta_{iil} = 0.746, p = 0.000, \beta_{unc} = -0.206, p = 0.000$), the influence of uncertainty could not be overlooked. The relationship between confidence and uncertainty was an ancillary observation that was not expected in this study.

The relationship between adaptiveness and deaths was also expected and was consistent in both models (β = -0.149, p = 0.006; β = -0.155, p = 0.005) A deeper look at the relationship must acknowledge the large amount of variance that remains unexplained by either model

(Model 1 = 0.78; Model 2 = 0.82). Simply stated, there was more going on than just adaptation in the game.

This is an appealing finding, but it does not fully evaluate *the cost (roughness) of learning in terms of other factors, such as time and effort and consequences*. This is the dimensionality of the adaptation process that the researcher sought in conceptualizing the roughness of learning (RoL) variable as a supplement to the SEMs of the crafting model and learning model.

In examining the game play through the lens of complexity science and measuring the conceptual RoL variable using a fractal dimension, a more holistic analysis was suggested. When looking at the overall fractal for all players and the measured play, the fractal dimension is *1.28009*. May's theoretical framework suggests there is a dynamical relationship involved. To include a measure of the dynamical relationship, a fractal was used to measure *the shape of a plot of the learning* effort using measures created in the game (health at time of death). The fractal was then *rescaled* to allow use in May's logistic map. Marsick and Watkins's (1990) theory of informal and incidental learning (IIL) includes the complexity-based dimension of RoL. This study presented a methodology for quantifying, indexing, and interpreting it.

Combining the CraftDawg models and the RoL variable, the research questions and associated hypotheses were evaluated. As presented in Table 4.23, analysis of the CraftDawg crafting model and CraftDawg learning model supports H1A, participants rely on incidental learning to increase adaptiveness in the moment in a purpose driven context. Analysis of the same models supported H2A that uncertainty negatively influences adaptiveness and H2B, uncertainty and incidental learning are inversely related. Using analysis of the fractal dimension of a summary game play activity, H3A was supported, the RoL effect can be estimated as a

measure of complexity in the game. Analysis of the change in the fractal dimension over game play sessions supported H3B, the RoL was less based on prior experience with the game.

Conclusions

Based on these findings and previous research in the literature, five conclusions can be drawn: (a) May's (1976) logistic model is useful as a theoretical framework for studying dynamics of human learning in a complex context; (b) Marsick and Watkins' (1990) IIL theory has been further supported empirically; (c) RoL is a variable that quantifies complexity based dimensions identified qualitatively by Marsick and Watkins (1990); (d) capturing a human learning effort using a minimally-invasive technology platform enabled richer research into the granularity and patternization of the learning process; and (e) the efficacy of Minecraft: Survival edition was a useful platform for studying adult learning in a simulated complex environment is confirmed.

Conclusion 1: Adaptation of Robert May's Logistic Model Creates an Index for Complexity in Learning Contexts

Robert May's logistic map (1975) provided the theoretical framework for this study. The essence of May's formula is there is a *limit [a ceiling] to adaptiveness in a complex adaptive system.* Once the system exceeds this threshold, chaotic behaviors manifest. Without external intervention to reduce complexity, the system will begin to dissipate. *A system that is overwhelmed by complexity cannot adapt its way out.* May (1975) created an index to describe the behavior of the system quantitatively. Using the logistic map, the system exhibits a range of behaviors depending on the level of complexity in the systems as represented by *r.* The CraftDawg study adapted May's index to a learning environment using the output from the game of Minecraft: Survival. Table 4.22 represents that table as a finding of the study.

Conclusion 2: Marsick and Watkins' (1990) Theory of Informal and Incidental Learning Has Been Further Supported Empirically

Prior empirical studies examined incidental learning in complex contexts (Cheng and van de Ven, 1996; Harner, 2013; Silva, 2007; Taber et al., 2008; Thietart & Forgues, 1997). Analysis of the CraftDawg SEM and the RoL variable supported the analysis of these prior studies by quantifying and modeling a form of learning that occurs in a complex context. The CraftDawg SEM analysis shows the effect of individual incidental learning and uncertainty on adaptiveness. Coupling May's index to the fractal developed from the play data with the relationship of identified in the CraftDawg SEM models quantifies the relationship amongst dimensions identified by Marsick and Watkins (1990).

Harner (2013) notes that

> insufficiencies in knowledge will force incidental learning to occur as employees look for solutions to unanticipated problems. Rapid and instant responses required by time constraints result in incidental learning and subsequent unintended behavior that may or may not be desirable. (p. 43)

Analysis of the change in the RoL variable as a measure of complexity as shown in Table 3.23 showed the participants responded initially to the novelty of the game with "insufficiencies in knowledge," which forced "incidental learning to occur as [players looked] for solutions to unanticipated problems" (Harner, 2013, p. 43). The game environment simulated the environment described by Harner (2013) where the threat of death or damage from game monsters resulted in "incidental learning and subsequent unintended behavior that may or may not be desirable" (p. 43). As the game provided a safe, simulated environment, the players were

able to use dimensions identified by Marsick and Watkins (1990) to reduce complexity (increase adaptiveness) in the game as revealed by the decrease in RoL over the course of the game play.

Marsick and Watkins (1990; 2017) identify *reflection* as fundamental in meaning making to create knowledge. Silva's (2007) study supported this and found "that most incidental learning in the workplace is validated in a manner akin to Schön's (1984) notion of reflection-in-action" (p. 5). Taber et al. (2008) similarly identify the role of incidental learning and reflection in action in describing how firefighters respond, "when all things anticipated or thought known dissolve, and when a firefighter or paramedic stands alone or with a comrade needing to make the right decision, another kind of active, creative, fast-as-lightening learning must be deployed" (p. 284).

Both Silva (2007) and Taber (2008) embrace the *in-the-moment* nature of incidental learning and tacit knowledge as being triggered by uncertainty in the moment. The CraftDawg study measured *uncertainty* as a latent variable and found it had a negative covariance ($\alpha = -0.266, p = 0.00;\ \alpha = -0.236, p = 0.000$) with incidental learning and a negative relationship with adaptiveness ($\beta = -0.122, p = 0.003;\ \beta = -0.206, p = 0.000$). Where knowledge (measured as incidental learning) replaced uncertainty, analysis of the CraftDawg models shows that adaptiveness increased.

Analyzing the decrease in the RoL variable over the study and integrating that analysis with the strength and direction of the relationships between incidental learning, uncertainty, adaptiveness, and deaths also supports analysis by Silva and Taber in support of Marsick and Watkins (1990).

Conclusion 3: Roughness of Learning is a Variable That Quantifies Complexity-Based Dimensions Identified Qualitatively by Marsick and Watkins (1990)

Marsick and Watkins (1990) are consistent in noting the complexity of the learning process and use a continuum based on the level of awareness the learner uses in engaging in the learning effort. Marsick & Watkins (1990) describe the irregular, turbulent and asymmetrical nature of the process. The CraftDawg study quantifies this description with a composite variable that measures the complexity of a learning experience. This variable allows learning to be observed from data by advancing the work of Mandelbrot and Wheeler (1998) and others (Gell-Mann, 1994; Holland, 1995; Mitchell, 2009)

According to Mandelbrot (1983, 1998) "Clouds are not spheres, mountains are not cones, and lightning does not travel in a straight line. The complexity *of nature's shapes* [italics added] differs in kind, not merely degree, from that of the shapes of ordinary geometry, the geometry of fractal shapes" (p. 286). To append Mandelbrot with Marsick and Watkins' (1990) theory of informal and incidental learning, *nor does learning happen as a learning curve*.

The CraftDawg study created a geometric object of learning by capturing and plotting certain game activities. Applying Mandelbrot's use of fractals to measure the complexity in a geometric shape, the study used the boxcounting method to measure the fractal of the shape. Examining the *fractal shape of learning* creates a more insightful and useful measure of the complexity of the learning as evidenced in the 'shape of the learning'. The CraftDawg study describes this as "the roughness of learning." As described by Marsick and Watkins (1990), learning is irregular. It is not a learning "curve." It can be plotted to create a geometric shape that can be measured and the complexity of the learning effort can be measured. Changes in the learning effort can be assessed in terms of the change in the complexity measured by the fractal

shape of the learning. By rescaling the fractal, the complexity of the learning environment can be assessed using May's (1975, 1976) complexity index as adapted in the CraftDawg study.

Understanding the behavior of the learning environment provides greater clarity to the learning challenges. Specifically, the CraftDawg study identified individual incidental learning and uncertainty as influencing adaptiveness. Combining that insight with the RoL index, the analysis shows complexity in the game for all groups can be managed through adaptive processes (learning based): reduce uncertainty, increase individual incidental learning. Further analysis shows there is no need for external intervention to overcome inadequate adaptive capacity for either of the groups: novice ($RoL_{novice} = 3.09036$) or experienced ($RoL_{experienced} = 1.256064$). Neither group has an $RoL >= 3.56996$. Similarly, analysis of the $RoL_{overall} = 1.120360$ finds that the game is *learnable* with no need for external intervention.

Conclusion 4: Capturing a Human Learning Effort With a Minimally Invasive Method Based on an Integrated Technology Platform Enabled Richer Research Into the Granularity and Patternization of the Learning Process

The CraftDawg study relied on an integrated technology platform that can be described as a mosaic of disparate technologies. From capturing over 1,700,000 data points directly from the game to seamlessly populating participant records and triggering notifications with minimal intervention by the study administrators, the CraftDawg study platform provided for a much larger participation level and allowed the study to be conducted remotely and expeditiously. It also allowed the scale needed to perform the level of analysis used. The platform allowed a minimally invasive methodology to engage novice participants by allowing them to engage with the study on their terms.

The design of the methodology and the supporting technology was intended to provide a simulated complex context that allowed multiple participants to complete the number of play sessions and the length of the play sessions. One hundred fifty-three participants were admitted to the study as measured by Minecraft credentials. Ninety-five participants were included in data used in the study as they completed all five play sessions and all pre and post-play surveys. All the data was created and collected over a 40-day period, including the inclusion of pilot participants. By allowing the participants to pick the time and place for their engagement both in playing the game and completing the post-play surveys, the administrative need for managing the study was reduced. By automating feedback to the participants to encourage their continued participation based on certain triggers facilitated the continuous engagement and enthusiasm needed for the study.

The study scale can easily be increased to include substantially more participants and in a variety of locations. The ability to extract quantitative and qualitative data at a much larger scale allows engagement in future research more broadly without the need for dedicated technology infrastructure or support.

Conclusion 5: The Efficacy of Using Minecraft as a Platform for Studying Adult Learning in a Simulated Complex Environment is Confirmed

The literature is plentiful with examples of Minecraft as a base for the study of human learning. A review of the literature finds a wide range of studies that use various features of Minecraft as inputs, predictors, or outcomes in analysis. Riordan and Scharf (2017) recognize the breadth of research associated with Minecraft, noting that

> [b]eyond social applications, Minecraft actively promotes the problem-solving skills, creativity, planning and persistence skills necessary for future success. [The Minecraft

> environment] requires player[s] to interact with unfamiliar environments, experiment, calculate, plan, and develop complex mental representations to understand the world. (p. 2)

As stated by Riordan and Scharf, Minecraft provides a ripe context and platform for studying human learning as was done in the CraftDawg study. Lane, Yi, Guerrero and Comins (2017) agree with the usefulness of Minecraft in studying learning, noting that "[the] interactions in Minecraft involve a broad range of educationally relevant content, *and how one learns to play the game is entirely compatible with classical and modern theories of learning* [italics added]" (p. 389).

The CraftDawg study adds to the literature of using Minecraft to study human learning. The methodology used in this study of extracting actual play data and scoring the data for use in a mixed method study was not found in a review of the literature. Most of the studies reviewed used Minecraft to measure how certain traits were applied through the game and how to use the game to support learning of certain skills.

CraftDawg was effectively a "blind" study in that the participants were given no guidance on the nature of the game, objectives, etc. Thus, the data collected was wholly created by the individual participant's initiative, priorities, and methods. The data created by this method was then scored by the researcher. An extensive review of the literature found no scoring method for in game activities, combinations of activities, or results of activities or combinations. To address this, a basic scoring method was created by the researcher for the study. This allowed scored activities to be included in the development of the CraftDawg models and used in analysis. As noted, the inclusion of the crafting variable in the CraftDawg – crafting model increased the variance explained by the model from 18% to 22%.

Implications for Theory and Practice

The findings of the CraftDawg study add a new learning variable: RoL. The relationships between individual incidental learning, uncertainty and adaptiveness add useful insights that can be applied to develop more thoughtful learning interventions. This section presents three implications (a) exploration of social incidental learning and the emergence of hybrid work models and methods; (b) relationships between individual incidental learning, uncertainty, and adaptability; and (c) use of the RoL to examine organizational development activities by using a *complexity index* based on Robert May's (1975, 1976) logistic map.

Social Incidental Learning and the Emergence of Hybrid Work Models and Methods

One of the surprising findings in the CraftDawg study was significant ($p <= 0.05$) evidence of *social incidental learning* explaining 12% of cumulative variance in the Pre-Play survey results. While *individual incidental learning* was the predominant latent variable explaining 28% of the variance in the Pre-Play 1 results, prior research had not revealed the influence on social incidental learning on *total incidental learning*. The implications of this are notable as organizations consider and adopt hybrid operating models where personnel operate remotely. The questions become what is lost and what is gained? This has the potential for changing how social incidental learning occurs, and the type and amount of social incidental learning that occurs. Imagine a hybrid work model that allows work in a coffee shop where overheard conversations and casually observed behaviors are very different from those had in-person in an enclosed organization setting (i.e., a central office) (Dixon, 1997). The importance of exploring and better understanding the influence of the over-heard conversations, the one-off questions, the individual "ways" of doing things and getting things done that are captured incidentally and become tacit knowledge increases with the recognition of social incidental

learning. The influence of organizational culture is transferred to new personnel through observations and casual conversations. How does this occur in a hybrid model where the social incidental learning is through scheduled interactions, is task specific, and does not provide for learning through other senses?

Does *social* incidental learning change the roughness of learning? In the CraftDawg study, though not captured quantitatively, participants created and used social media platforms to form a community of participants, encourage each other, ask questions, share frustrations, and offer hope and ideas. Analysis of these social interactions would provide more insight into the nature and purpose of these as the networking of information provides a platform for the *networking (spread) of incidental learning and tacit knowledge*.

Relationships Between Individual Incidental Learning, Uncertainty, and Adaptability

Both CraftDawg SEMs revealed the relationships between individual incidental learning, uncertainty, and adaptability. Adaptability emerged as a composite latent variable that is significantly influenced by both individual incidental learning and uncertainty. Individual incidental learning is positively related to adaptability and uncertainty is negatively related to adaptability. This relationship suggests the organizational "management" of incidental learning (likely both individual and social) would be beneficial in increasing both an individual's ability to adapt in edge of chaos situations, as well as collectively increasing organizational adaptability.

Complexity science shows that volatile times require high levels of adaptive capacity for a system to sustain itself. The theoretical framework (Robert May's [1975, 1976] logistic model) underlying this study mathematically confirms this fundamental relationship. Understanding the sources of adaptive capacity organizationally is integral for understanding how to utilize those sources in times of crisis. Incidental learning emerged in this study as being a vital part of

adaptive capacity. To the extent an organization embraces this finding and harnesses it in beneficial ways, the organization will be better for it.

Similarly, individual levels of uncertainty should also be recognized as a drain of adaptive capacity. This is likely better understood by organizations and is typically addressed by "communication" instruments. However, 'incidental uncertainty' that arises from incidental learning is likely not addressed through organizational communication. This type of uncertainty is likely addressed socially through employee-to-employee communication. Better understanding of the primary sources of uncertainty at the individual level would inform more systematic approaches to quelling latent uncertainty at the individual and thus organizational level.

To the extent there is a high level of uncertainty in the organization, from whatever source, the findings in this study hold that adaptive capacity is diminished. A logical assessment of this would be that diminished adaptive capacity weakens an organization. Symptoms of increased uncertainty and diminished adaptive capacity might be found in increased turnover, increased internal performance issues, and reduced quality of output.

Use of Roughness of Learning to Examine Organizational Development Activities in Terms of Complexity as Defined by the Fractal Dimension

Can organizational development efforts be redesigned to reduce the RoL associated with it? The fractal dimension of learning as manifest in the RoL variable adds a new quantified variable to the study and assessment of learning effort.

There was a significant difference based on the beginning experience of the player. This is not surprising as the experienced player improved more rapidly than the novice player. This finding supports a typical organizational practice of having different development paths for difference experience levels. The implication for practice from this methodology is to understand

how the participant is developing over the course of development. Are the development efforts designed to reduce complexity more rapidly and allow the novice participant to become competent more quickly? Are the advanced development activities leveraging the already reduced complexity of the task for the advanced participant?

The CraftDawg study introduced a new learning variable that adds insight to organizational development efforts. By measuring the complexity of the learning context and applying May's (1975) index as reimagined in the CraftDawg Study, organizations can assess at a fundamental level whether the learning context allows adaptiveness to be used to *adapt [learn] the way out of complexity.* Similarly, using the same approach, an organization can better determine when an intervention is needed to reduce complexity and allow adaptiveness to increase and thus reduce complexity in the system, i.e., move the system away from the edge of chaos.

Organizations can also use analysis of the plots associated with May's logistic map (1975, 1976) and the RoL variable to assess how much time and effort are needed to stabilize the system and at what level of adaptiveness the system stabilize, assuming no external interventions.

Development efforts are expensive for organizations: both formal and informal efforts. To the extent these efforts can be better informed and thus better designed to address the RoL, the organization would likely benefit by having faster ramp-up times and less error from training gaps. Both outcomes have beneficial organizational impact.

Limitations of the Study

In examining the study limitations associated with the CraftDawg study, the researcher identified the following areas:

1. sample size associated with the SEM analysis and the development of the group level and play level fractal dimensions to measure the RoL variable;
2. the method used to score the in-game activities as extracted from the game logs;
3. sample size associated with fractal development and trend analysis; and
4. definition of *adaptiveness* as a latent variable.

Adequate Sample Size For Assessing Model Invariance

According to Soper, calculating sample size for SEM has "no single correct or universally accepted calculation or method" (para. 2). Soper explains,

> For instance, some statistics scholars have recommended using the ratio of observations to estimate parameters as a guide. Specifically, Kline (2015) recommended that ratio should be 20 to 1, or 20 observations (participants) for each estimated parameter in the model. Others have suggested that the ratio can be as low as 10 to 1 (Schreiber et al., 2006) or 5 to 1 (Bentler & Chou, 1987). Clearly, there is a lot of variance and uncertainty even in guidelines proposed by SEM scholars. (Soper, n.d., paras. 2–3)

Other guidance suggests a minimum sample size of 300 before considering SEM (Wolf et al., 2013). In the CraftDawg study, the sample was 95 participants using repeated measures over four play sessions. Incomplete post-play surveys and corresponding play session were removed. A total of 369 plays and post-play responses were used for analysis. While this was adequate to develop the model, it was not adequate for assessing model invariance using play session or experience grouping. The group sizes for these two grouping variables were inadequate for analysis.

The researcher adopted the rule of thumb based on review of the literature and used ratio of 20 responses per latent variable. For the CraftDawg crafting model, four latent variables were

estimated. Using the rule of thumb this would require a minimum of 80 participants in the full study (80 * 4 = 320 responses). A total of 369 responses were used for the full model. However, variation in the group response did not allow the model to be assessed for model invariance.

The researcher inadvertently weakened the design of the post-play surveys by linking them to 'the next play'. This resulted in the fifth play and post-play survey not being available for use in the development of the SEMs for the study. This would have increased the sample size by 95 and added to each of the groups.

Scoring Method

Minecraft is a well-known and widely used game in education. Research using the game to measure learning has predominantly focused on use of the game in educational contexts to scaffold learning with younger learners. The CraftDawg study adds to the literature by using a methodology that scores in game activities and transactions. The method for quantifying these game activities was subjectively developed based on the researchers understanding of the game and how it was designed.

The researcher used a judgement-based method to classify the in-game activities and actions. The researcher was not an expert player and relied on analysis of the literature from game playing sites and forums to assign values to each activity and action. The methodology used to calculate the value for each action was additive.

This limitation was removed in the learning SEM model by removing the game-based latent variable. This reduced the variance explained by the resulting model.

Having a group of Minecraft experts score the activities and develop a full scoring methodology based on better understanding of the strategic nuances of the game would reduce the impact of this limitation and allow other game-based activities to be included in the models.

Sample Size Associated with Fractal Development and Trend Analysis

In developing the fractal dimension as a measure of RoL, the researcher consulted a variety of studies in various disciplines. This review found many studies use fractals to estimate complexity in time series data. Most of the studies report the scales used to create the time series and thus the number of data points plotted. This was the method used in the CraftDawg study. What was missing from these studies was a method for determining the validity of the fractal. The CraftDawg study does not provide an estimate for validity and is considered a limitation of the study.

The literature is conflicted on sample size in calculating fractals using the boxcounting method. As with most statistical approaches, larger is better. Kenkel (2013) highlights the challenge of sample size and fractal estimation. Kenkel uses a theoretical probability-based model to examine the relationship between sample size and the reliability of the dimension estimates based on box counting and demonstrates "that very large sample sizes – typically, one to many orders of magnitude greater than those used in most empirical studies – are required for reliable dimension estimation" (p. 144).

Other scholars note that the fractal is not a sample size-based measurement, but rather a measurement that is defined by sampling length. "The estimated fractal dimension increases with the sampling length, *and eventually maintains its theoretical value* [italics added]. Therefore, the sampling length should be more than the minimum length where the stable value can be achieved" (Zuo et al., 2020, p 3.).

The CraftDawg study used different sampling lengths (all data for Plays 1 through 5 and all data for each participant group: novice, intermediate, and advanced). The R package *fractaldim* (version 0.8-5) was used to calculate the fractal for each segment of interest. The

package is appropriate for estimating the fractal dimension of time series and two-dimensional data. As the literature does not provide strong guidance on sample size or sample length, the study did not attempt to determine validity on this basis.

Definition of Adaptiveness as a Latent Variable

Adaptiveness scales are distinguished based on the adaptive behaviors being explored as defined by the purpose of the research associated with the scale (Adger & Vincent, 2005; Harrison, 2016; Vincent, 2007). The CraftDawg study developed its adaptiveness scale based on study of environmental adaptation to align with Robert May's (1975, 1976) logistic model. Dimensions associated with adaptive capacity as identified in environmental studies literature and dimensions identified by Marsick and Watkins (1990) were combined to create the post-play scale in this study.

As the adaptiveness variable is integral to the SEMs created in the study, having the scale validated over more studies to confirm its reliability would strengthen confidence in the findings of this study.

Future Research

The CraftDawg study addressed its research questions, and the findings of the study raised more research questions that can inspire future research. New research avenues include the following:

- Examine dynamics of learning and application of tacit knowledge using quantitative methods associated with complexity science.
- Nonlinearity of human-learning rate
- Nonlinearity of reflection process and methods
- Social incidental learning

- Change in use of tacit knowledge and incidental learning based on age in novel situations
- Examine the accessibility of learning with larger RoL measures (i.e., measures above 3.56995).

Examine Dynamics of Learning and Application of Tacit Knowledge Using Quantitative Methods Associated With Complexity Science

Measuring the quantitative dynamics of learning and the application of tacit knowledge is essential to the efforts of developing artificial intelligence and deep learning. Capturing the *en passant* (Reischmann, 1986) learning in ways that can be quantified and used in more expansive algorithms is a growing area of both cognitive science and computer science. As the paths of these areas begin to merge, the ability to better understand human learning becomes central to these efforts.

What are the adaptive processes used by humans to capture and harvest previously captured tacit knowledge? How are these processes influenced by demographics? Why does a human retain *en passant* knowledge? We have learned from this study that tacit knowledge is utilized in novel contexts. We learned it used as incidental learning to increase adaptive capacity. We learned tangentially there is a social component that is significant. We learned uncertainty is significant in defining adaptive capacity. These findings coupled with new research will accelerate our understanding of all forms learning.

Nonlinearity of Human Learning Rate

For some time, the learning curve has been used as the model for the rate of learning. The symmetrical, smooth downward trajectory of the curve on a plotted scale that begins with ineptitude and ends with mastery has been the visual expectation of how learning happens and how development should be designed and typically assumes external control of the learning

process. We have embraced concepts such as "it's a steep learning curve" and "where are we on the learning curve?"

The CraftDawg study was based on the principles of complexity science and the core assumptions that learning is a complex, rough and irregular process that is best defined by *patterns of development*. Studying human learning as a multi-dimensional process explored the human-learning rate as non-linear. It acknowledged other inputs to the learning process that created the non-linear interactions. In this study for example, learners spontaneously created a Facebook page to share ideas and collaborate – a nonlinear, unanticipated intervention that can affect the learning outcomes.

Humans know they do not learn on a curve. Marsick and Watkins (1990) and others consistently note the trial-and-error nature of learning. Other disciplines in the natural sciences also accept trial and error as a primary source of learning and adaptive practices (Adger & Vincent, 2005; Refsgaard et al., 2013; Vincent, 2007). Future research that explores the trial-and-error process and the nonlinearity of human learning will likely produce approaches to human learning that are much more individualized and better supported by quantification of the learning process. What would individualized development that captures the trial-and-error of human learning look like? What would the development timing be with such a developmental approach? How is experiential knowledge captured? How is experiential knowledge aligned with an individual's prior learning? How is "unlearning" (Burnes, 2004; Lewin, 1935, 1943/2014) developed and implemented (i.e., correction)?

Nonlinearity of Reflection Process and Methods

The CraftDawg study revealed new insights into the reflection process that Marsick and Watkins (1990) deemed essential in knowledge creation though meaning making. Marsick and

Watkins do not address the timing of the reflection process to meaning making. This gap was noted in the pre-play survey analysis and findings. In particular, the gap is notable when examining incidental learning and the development of tacit knowledge. When does the reflection effort occur? Analysis of the findings showed that respondents understood the relationship between reflection and meaning making. Yet, analysis of responses to "some things I just know what to do and I don't know why" was not a large parameter. This is curious and provides an area for future research. Is there some other source of meaning-making other than reflection? Does the reflection to meaning making process follow a non-linear path? Is the development of tacit knowledge more associated with an adaptive process such as coping or resilience? What do the process of creativity, imagination and curiosity play in informing the reflection to meaning making effort? Is tacit knowledge more a creative process than a reflective process?

These questions gain new importance as we study incidental learning in the context of artificial intelligence and deep learning. How is the creative process captured in these technology-based efforts?

Social Incidental Learning

The finding of social incidental learning as a significant component of "total" incidental learning was provocative. Future research from the perspective of organizational development would yield insights on the nature of the incidental learning that occurs in the traditional office environment. How is organizational culture influenced by social incidental learning?

How does the organization leverage social incidental learning through designed activities and interactions? How is social incidental learning perpetuated through effective mentoring programs? Research around these types of questions would greatly benefit organizations as they develop deeper understanding of the impact of hybrid and fully remote organization models.

Examine the Accessibility of Learning (as a Function of Adaptive Capacity) with Larger RoL Measures (i.e., Measures Above 3.56995)

The CraftDawg study introduced the concept of RoL and offered complexity-based method for measuring it using fractal dimensionality. By rescaling the fractal measure of complexity to match the scale used in Robert May's (1975) logistic map, an index was created to represent levels of complexity on a continuum from 0:4, with chaos being represented at 3.56995, and edge of chaos states beginning at 3.00000.

Future research to advance our understanding of the relationship between RoL and accessibility (defined as the adaptive capacity to engage in learning activities) to learning support is a ripe area to advance this concept. To the extent a development process is 'too complex' (*r >= 3.56995*) then it essentially become inaccessible (adaptive capacity is inadequate) for a learner without an external intervention.

Research questions become:

- What level of learning complexity as measured by the roughness of learning indicates an inaccessible (unlearnable) task?
- How is the roughness of learning decreased through increases in adaptive capacity?
- How is the roughness of learning changed through changes in the development effort?
- When does the learning/adaptiveness challenge reach a chaotic state that precludes the ability to adapt a way out of chaos?

Future research that advances our understanding of the relationship between complexity and learning will allow us to imagine and design learning interventions that reduce the

complexity of certain learning scenarios and increase the accessibility of knowledge creation that previously may have been difficult to access because of the level of complexity embedded in learning process.

Overall, the CraftDawg study presented a proof-of-concept methodology for examining human learning, specifically incidental learning, in a novel context. By using Robert May's (1975, 1976) theoretical framework with a rescaled fractal dimension developed directly from game play data, the study created an index that can be used to determine the level of complexity in a learning context and provide insight into the need for an external intervention to reduce the complexity being encountered by a learner. The study presented a more holistic approach to examining basic learning variables (incidental learning and uncertainty) as predictor variables of adaptiveness. Combining adaptiveness with the complexity of learning index as developed in the study provides richer insights into the learning needs associated with the context and the timing of external interventions (if available).

At the most fundamental level, the CraftDawg study accepts the limits to adaptive capacity as a function of the complexity of the context. There is a level of contextual complexity that cannot be overcome through adaptiveness, however developed. According to complexity science, contexts that are (or become) chaotic (as a function of adaptive capacity) result in dissipation of the systems that create the chaotic environment (Holland, 1995, 1998, 2012; Mitchell, 2009). Combining Holland's notion of the interaction of simple rules with May's logistic map reminds us there are adaptive limits and the interaction of simple rules can create contexts that exceed adaptive capacity. According to Mitchell (2009) and Holland (1995, 1998) system dissipation is the result of this chaos producing interaction.

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APPENDICES

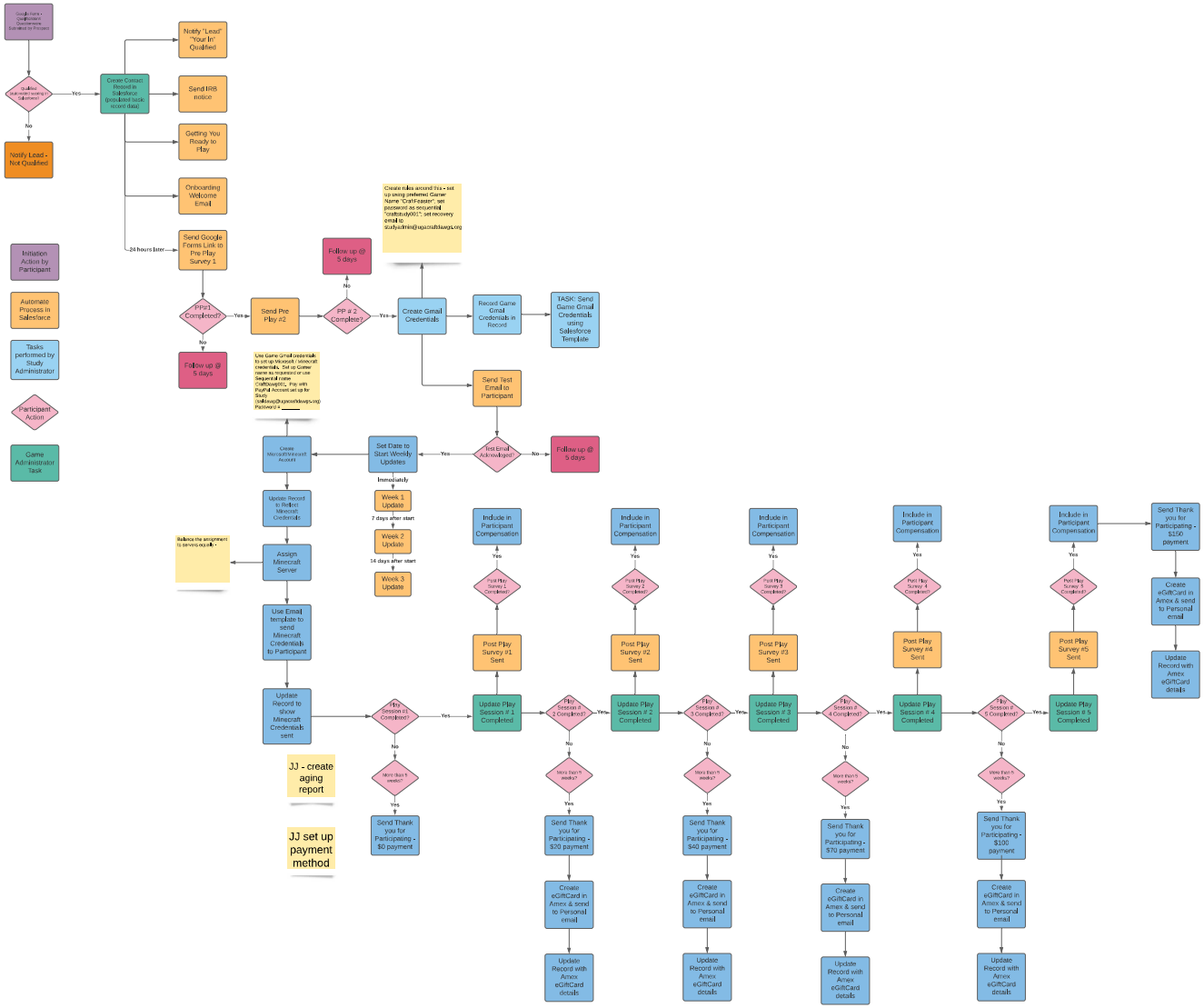
APPENDIX A

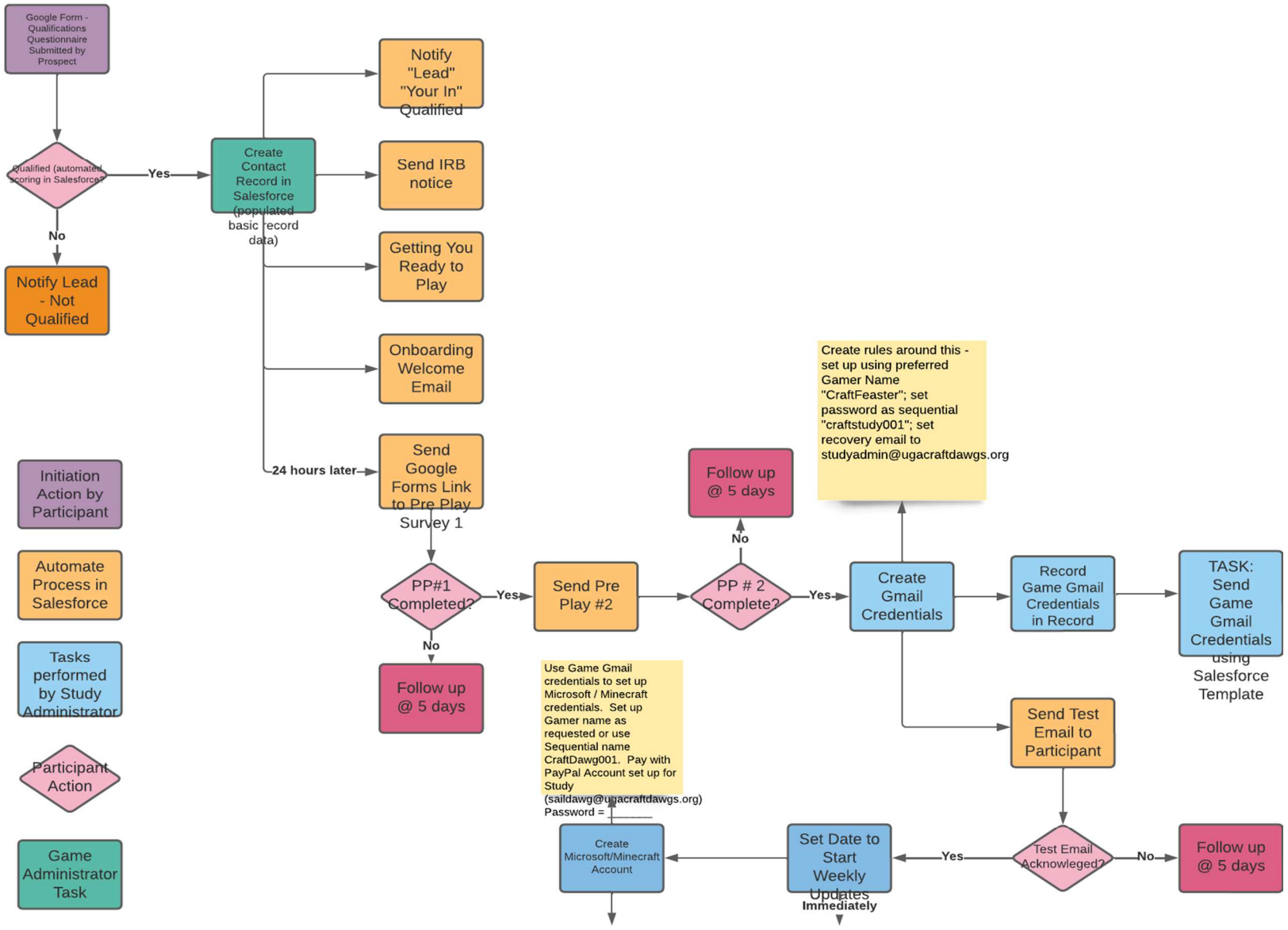
TECHNOLOGY PLATFORM FOR COLLECTING AND STORING DATA

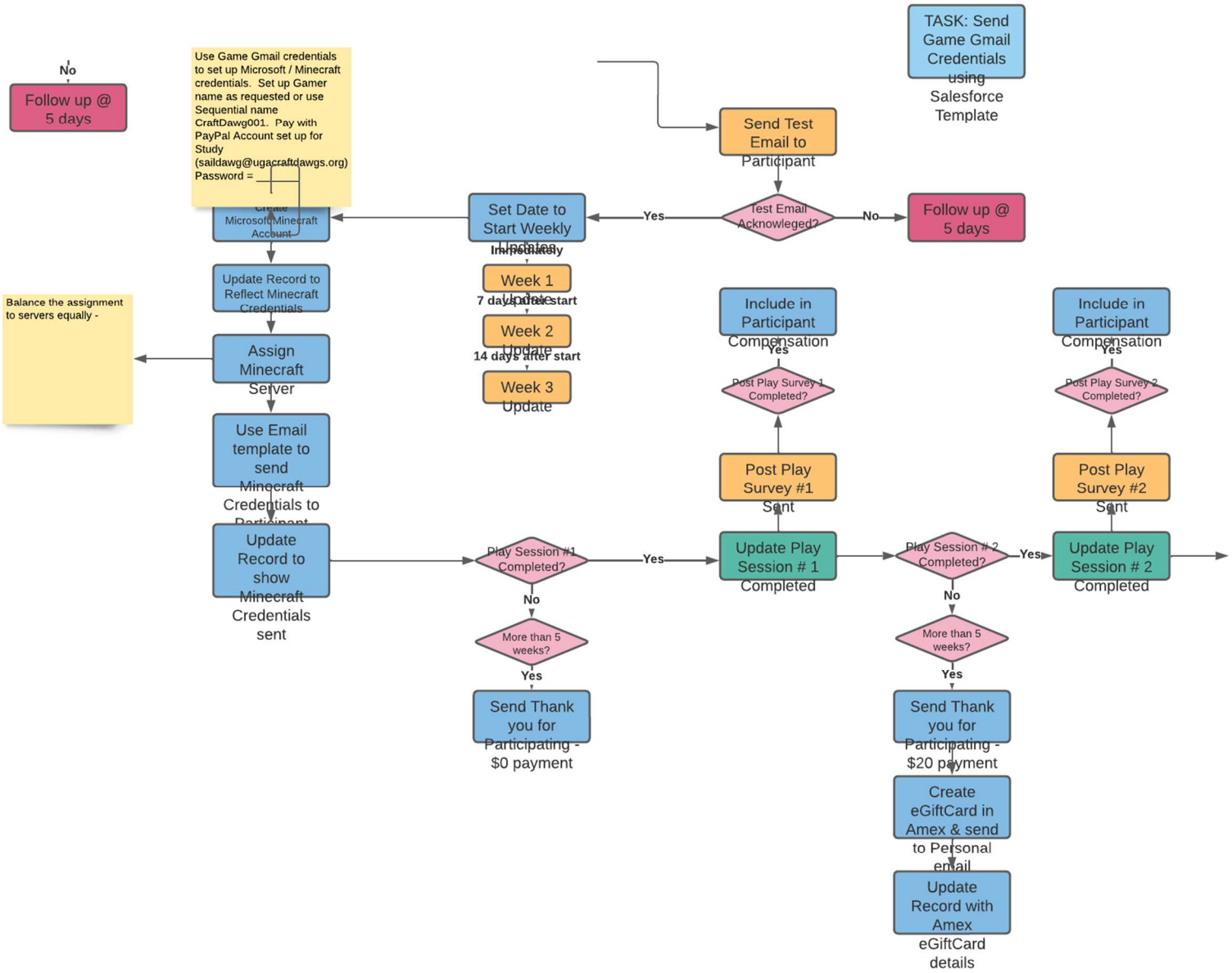
Four Amazon Web Services (AWS) instances were built to run four Minecraft servers. R, MySQL, and Jupiter Notebook (Python) servers were built and hosted on AWS instances to provide database and analysis facilities for the study. In addition, 8 Amazon S3 buckets were created to backup data from the game and data analysis servers (R, MySQL, and Python).

Data Collection Process

Figure A.1 shows the data collection process used.


Google Forms - Completed & Overwritten Submitted to Project
Qualified (automated) scores if Submitted
Yes
No
Notify "Lead" "Your In" Qualified
Create Contact Record in Salesforce (pre-Linked basic record data)
Send IRB notice
Getting You Ready to Play
Onboarding Welcome Email
Send Google Forms Link to Pre Play Survey 1
24 hours later
Notify Lead - Not Qualified
Initiation Action by Participant
Automate Process in Salesforce
Tasks performed by Study Administrator
Participant Action
Game Administrator Task
PPS1 Completed?
Yes
No
Follow up @ 5 days
Send Pre Play #2
PP # 2 Complete?
Yes
No
Follow up @ 5 days
Create Gmail Credentials
Create rules around this - set up using preferred Gamer Name "CraftFeaster"; set password as sequential "craftstudy0001"; set recovery email to studyadmin@upacraftideaxgs.org
Record Game Gmail Credentials in Record
TASK: Send Game Gmail Credentials using Salesforce Template
Send Test Email to Participant
Test Email Acknowledged?
Yes
No
Follow up @ 5 days
Use Game Gmail credentials to set up Minecraft / Minecraft credentials. Set up Gamer name as required or use Regional Native (Pittsburgh/PE). Pay with PayPal. Account set up for Study (sdlikeup@upacraftideaxgs.org) Password: z
Set Date to Start Weekly Updates
Immediately
Week 1 Update
7 days after start
Week 2 Update
14 days after start
Week 3 Update
Create Minecraft/Minecraft Account
Update Record to Reflect Minecraft Credentials
Assign Minecraft Server
Balance the assignment to servers equally -
Use Email template to send Minecraft Credentials to Participant
Update Record to show Minecraft Credentials sent
JJ - create aging report
JJ set up payment method
Play Session #1 Completed?
Yes
No
More than 5 weeks?
Yes
Send Thank you for Participating - $0 payment
Include in Participant Compensation
Yes
Post Play Survey 1 Completed?
Post Play Survey #1 Sent
Update Play Session # 1 Completed
Play Session # 2 Completed?
Yes
No
More than 5 weeks?
Yes
Send Thank you for Participating - $20 payment
Create eGiftCard in Amex & send to Personal email
Update Record with Amex eGiftCard details
Include in Participant Compensation
Yes
Post Play Survey 2 Completed?
Post Play Survey #2 Sent
Update Play Session # 2 Completed
Play Session # 3 Completed?
Yes
No
More than 5 weeks?
Yes
Send Thank you for Participating - $40 payment
Create eGiftCard in Amex & send to Personal email
Update Record with Amex eGiftCard details
Include in Participant Compensation
Yes
Post Play Survey 3 Completed?
Post Play Survey #3 Sent
Update Play Session # 3 Completed
Play Session # 4 Completed?
Yes
No
More than 5 weeks?
Yes
Send Thank you for Participating - $70 payment
Create eGiftCard in Amex & send to Personal email
Update Record with Amex eGiftCard details
Include in Participant Compensation
Yes
Post Play Survey 4 Completed?
Post Play Survey #4 Sent
Update Play Session # 4 Completed
Play Session # 5 Completed?
Yes
No
More than 5 weeks?
Yes
Send Thank you for Participating - $100 payment
Create eGiftCard in Amex & send to Personal email
Update Record with Amex eGiftCard details
Include in Participant Compensation
Yes
Post Play Survey 5 Completed?
Post Play Survey #5 Sent
Update Play Session # 5 Completed
Include in Participant Compensation
Send Thank you for Participating - $150 payment
Create eGiftCard in Amex & send to Personal email
Update Record with Amex eGiftCard details


Google Form - Qualifications Questionnaire Submitted by Prospect
Qualified (automated scoring in Salesforce?
Yes
No
Notify Lead - Not Qualified
Create Contact Record in Salesforce (populated basic record data)
Notify "Lead" "Your In" Qualified
Send IRB notice
Getting You Ready to Play
Onboarding Welcome Email
24 hours later
Send Google Forms Link to Pre Play Survey 1
PP#1 Completed?
Yes
No
Follow up @ 5 days
Send Pre Play #2
PP # 2 Complete?
No
Follow up @ 5 days
Yes
Create rules around this - set up using preferred Gamer Name "CraftFeaster"; set password as sequential "craftstudy001"; set recovery email to studyadmin@ugacraftdawgs.org
Create Gmail Credentials
Record Game Gmail Credentials in Record
TASK: Send Game Gmail Credentials using Salesforce Template
Send Test Email to Participant
Test Email Acknowleged?
Yes
No
Follow up @ 5 days
Set Date to Start Weekly Updates
Immediately
Create Microsoft/Minecraft Account
Use Game Gmail credentials to set up Microsoft / Minecraft credentials. Set up Gamer name as requested or use Sequential name CraftDawg001. Pay with PayPal Account set up for Study (saildawg@ugacraftdawgs.org) Password = _____
Initiation Action by Participant
Automate Process in Salesforce
Tasks performed by Study Administrator
Participant Action
Game Administrator Task


No
Follow up @ 5 days
Use Game Gmail credentials to set up Microsoft / Minecraft credentials. Set up Gamer name as requested or use Sequential name CraftDawg001. Pay with PayPal Account set up for Study (saildawg@ugacraftdawgs.org) Password =
Create MicrosofMinecraft Account
Update Record to Reflect Minecraft Credentials
Balance the assignment to servers equally -
Assign Minecraft Server
Use Email template to send Minecraft Credentials to Participant
Update Record to show Minecraft Credentials sent
Set Date to Start Weekly Updates
Immediately
Week 1 Update
7 days after start
Week 2 Update
14 days after start
Week 3 Update
Send Test Email to Participant
Test Email Acknowleged?
Yes
No
Follow up @ 5 days
TASK: Send Game Gmail Credentials using Salesforce Template
Play Session #1 Completed?
Yes
No
More than 5 weeks?
Yes
Send Thank you for Participating - $0 payment
Include in Participant Compensation
Yes
Post Play Survey 1 Completed?
Post Play Survey #1 Sent
Update Play Session # 1 Completed
Play Session # 2 Completed?
Yes
No
More than 5 weeks?
Yes
Send Thank you for Participating - $20 payment
Create eGiftCard in Amex & send to Personal email
Update Record with Amex eGiftCard details
Include in Participant Compensation
Yes
Post Play Survey 2 Completed?
Post Play Survey #2 Sent
Update Play Session # 2 Completed

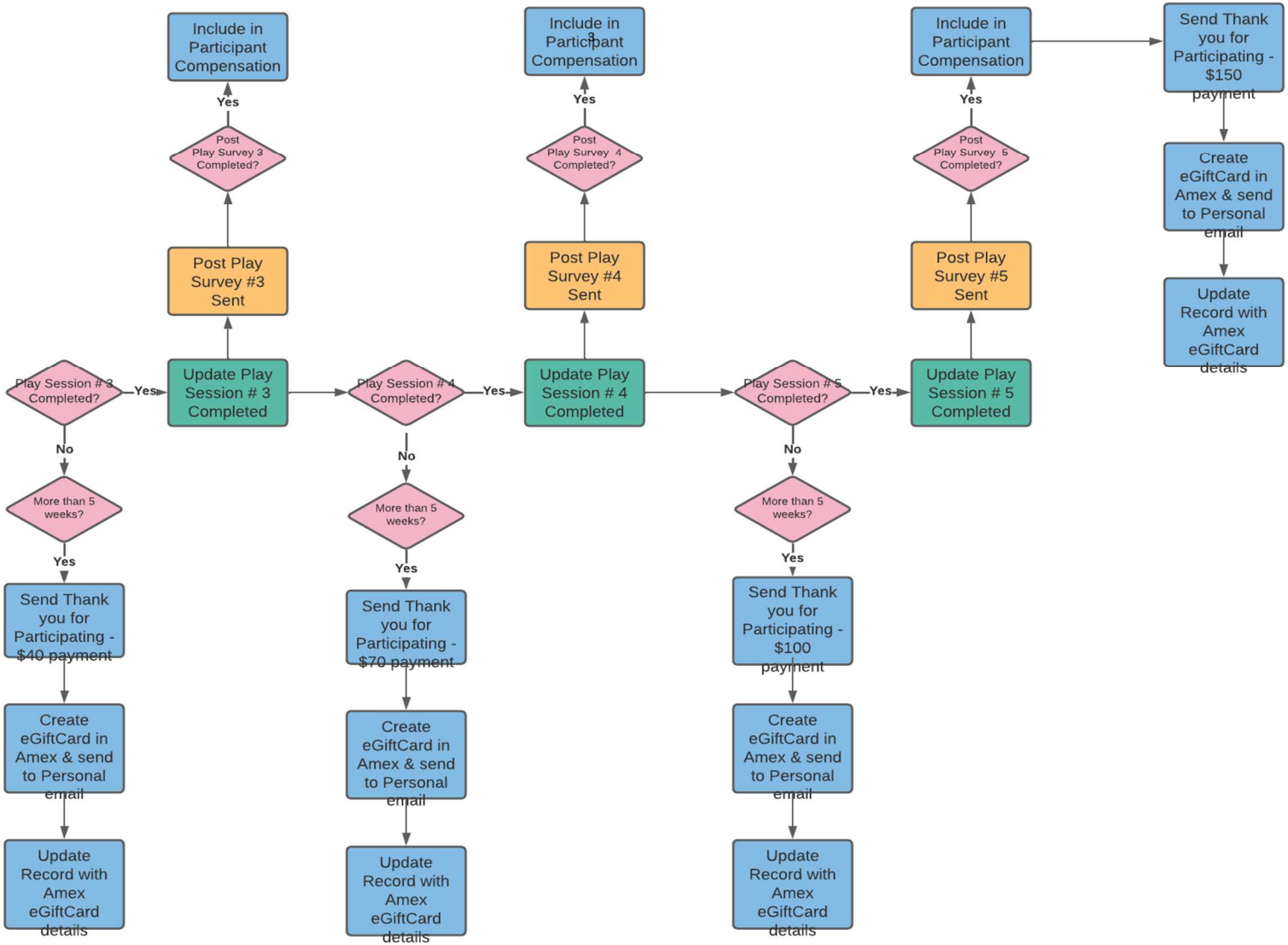


Figure A.1. Visualization of Data Collection Process.

Table A.3

Action Object Mapping

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	CREEPER	THEN	ADVERSARY
WHEN action_object =	SKELETON	THEN	ADVERSARY
WHEN action_object =	SPIDER	THEN	ADVERSARY
WHEN action_object =	ZOMBIE	THEN	ADVERSARY
WHEN action_object =	ZOMBIE_VILLAGER	THEN	ADVERSARY
WHEN action_object =	ENDERMAN	THEN	ADVERSARY
WHEN action_object =	DROWNED	THEN	ADVERSARY
WHEN action_object =	AXOLOTL	THEN	ADVERSARY
WHEN action_object =	PHANTOM	THEN	ADVERSARY
WHEN action_object =	PILLAGER	THEN	ADVERSARY
WHEN action_object =	TRADER_LLAMA	THEN	ADVERSARY
WHEN action_object =	WANDERING_TRADER	THEN	ADVERSARY
WHEN action_object =	WITCH	THEN	ADVERSARY
WHEN action_object =	WOLF	THEN	ADVERSARY
WHEN action_object =	AIR MOB	THEN	BASIC
WHEN action_object =	AIR	THEN	BASIC
WHEN action_object =	ANDESITE	THEN	BASIC
WHEN action_object =	DIRT	THEN	BASIC
WHEN action_object =	DROPPED_ITEM	THEN	BASIC
WHEN action_object =	FERN	THEN	BASIC

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	GRANITE	THEN	BASIC
WHEN action_object =	GRASS	THEN	BASIC
WHEN action_object =	GRASS_BLOCK	THEN	BASIC
WHEN action_object =	JUNGLE_LEAVES	THEN	BASIC
WHEN action_object =	JUNGLE_LOG	THEN	BASIC
WHEN action_object =	JUNGLE_SAPLING	THEN	BASIC
WHEN action_object =	OAK_LEAVES	THEN	BASIC
WHEN action_object =	OAK_LOG	THEN	BASIC
WHEN action_object =	OAK_SAPLING	THEN	BASIC
WHEN action_object =	SAND	THEN	BASIC
WHEN action_object =	STICK	THEN	BASIC
WHEN action_object =	STONE	THEN	BASIC
WHEN action_object =	VINE	THEN	BASIC
WHEN action_object =	CLAY	THEN	BASIC
WHEN action_object =	COBBLESTONE	THEN	BASIC
WHEN action_object =	DANDELION	THEN	BASIC
WHEN action_object =	FLINT	THEN	BASIC
WHEN action_object =	GRANITE	THEN	BASIC
WHEN action_object =	GRAVEL	THEN	BASIC
WHEN action_object =	JUNGLE_SLAB	THEN	BASIC
WHEN action_object =	POPPY	THEN	BASIC
WHEN action_object =	SANDSTONE	THEN	BASIC

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	WATER	THEN	BASIC
WHEN action_object =	TURTLE	THEN	BASIC
WHEN action_object =	COW	THEN	BASIC
WHEN action_object =	PACKED_ICE	THEN	BASIC
WHEN action_object =	SHEEP	THEN	BASIC
WHEN action_object =	SPIDER_EYE	THEN	BASIC
WHEN action_object =	PIG	THEN	BASIC
WHEN action_object =	BIRCH_LOG	THEN	BASIC
WHEN action_object =	BLUE_ICE	THEN	BASIC
WHEN action_object =	BIRCH_LEAVES	THEN	BASIC
WHEN action_object =	BIRCH_LOG	THEN	BASIC
WHEN action_object =	OAK_WOOD	THEN	BASIC
WHEN action_object =	BAMBOO	THEN	BASIC
WHEN action_object =	SUGAR_CANE	THEN	BASIC
WHEN action_object =	WHEAT_SEEDS	THEN	BASIC
WHEN action_object =	MELON_SEEDS	THEN	BASIC
WHEN action_object =	MELON_STEM	THEN	BASIC
WHEN action_object =	OCELOT	THEN	BASIC
WHEN action_object =	SQUID	THEN	BASIC
WHEN action_object =	ACACIA_LEAVES	THEN	BASIC
WHEN action_object =	ACACIA_LOG	THEN	BASIC
WHEN action_object =	ANDESITE_WALL	THEN	BASIC

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	AZURE_BLUET	THEN	BASIC
WHEN action_object =	BAT	THEN	BASIC
WHEN action_object =	BEDROCK	THEN	BASIC
WHEN action_object =	BEE	THEN	BASIC
WHEN action_object =	BIRCH_WOOD	THEN	BASIC
WHEN action_object =	BLACK_CONCRETE	THEN	BASIC
WHEN action_object =	CACTUS	THEN	BASIC
WHEN action_object =	COARSE_DIRT	THEN	BASIC
WHEN action_object =	CORNFLOWER	THEN	BASIC
WHEN action_object =	DARK_OAK_LOG	THEN	BASIC
WHEN action_object =	DEEPSLATE	THEN	BASIC
WHEN action_object =	DIORITE_SLAB	THEN	BASIC
WHEN action_object =	FEATHER	THEN	BASIC
WHEN action_object =	FIRE	THEN	BASIC
WHEN action_object =	GOAT	THEN	BASIC
WHEN action_object =	GRANITE_WALL	THEN	BASIC
WHEN action_object =	HORSE	THEN	BASIC
WHEN action_object =	JUNGLE_WOOD	THEN	BASIC
WHEN action_object =	LARGE_FERN	THEN	BASIC
WHEN action_object =	LAVA	THEN	BASIC
WHEN action_object =	LILAC	THEN	BASIC
WHEN action_object =	LILY_OF_THE_VALLEY	THEN	BASIC

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	LILY_PAD	THEN	BASIC
WHEN action_object =	MAGMA_BLOCK	THEN	BASIC
WHEN action_object =	MOSSY_COBBLESTONE	THEN	BASIC
WHEN action_object =	ORANGE_TULIP	THEN	BASIC
WHEN action_object =	OXEYE_DAISY	THEN	BASIC
WHEN action_object =	PARROT	THEN	BASIC
WHEN action_object =	PEONY	THEN	BASIC
WHEN action_object =	PINK_TULIP	THEN	BASIC
WHEN action_object =	POLAR_BEAR	THEN	BASIC
WHEN action_object =	RABBIT	THEN	BASIC
WHEN action_object =	RED_TULIP	THEN	BASIC
WHEN action_object =	REDSTONE	THEN	BASIC
WHEN action_object =	ROSE_BUSH	THEN	BASIC
WHEN action_object =	SNOW	THEN	BASIC
WHEN action_object =	SPRUCE_LEAVES	THEN	BASIC
WHEN action_object =	SPRUCE_LOG	THEN	BASIC
WHEN action_object =	STRIPPED_BIRCH_LOG	THEN	BASIC
WHEN action_object =	STRIPPED_JUNGLE_LOG	THEN	BASIC
WHEN action_object =	STRIPPED_OAK_LOG	THEN	BASIC
WHEN action_object =	STRIPPED_OAK_WOOD	THEN	BASIC
WHEN action_object =	TALL_GRASS	THEN	BASIC
WHEN action_object =	VILLAGER	THEN	BASIC

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	WHITE_TERRACOTTA	THEN	BASIC
WHEN action_object =	WHITE_TULIP	THEN	BASIC
WHEN action_object =	CRAFTING_TABLE	THEN	CRAFTING
WHEN action_object =	FARMLAND	THEN	CRAFTING
WHEN action_object =	FISHING_ROD	THEN	CRAFTING
WHEN action_object =	JUNGLE_PLANKS	THEN	CRAFTING
WHEN action_object =	JUNGLE_DOOR	THEN	CRAFTING
WHEN action_object =	JUNGLE_PRESSURE_PLATE	THEN	CRAFTING
WHEN action_object =	WOODEN_PICKAXE	THEN	CRAFTING
WHEN action_object =	COBBLESTONE_WALL	THEN	CRAFTING
WHEN action_object =	FURNACE	THEN	CRAFTING
WHEN action_object =	GLASS_PANE	THEN	CRAFTING
WHEN action_object =	JUNGLE_STAIRS	THEN	CRAFTING
WHEN action_object =	WALL_TORCH	THEN	CRAFTING
WHEN action_object =	TORCH	THEN	CRAFTING
WHEN action_object =	STRING	THEN	CRAFTING
WHEN action_object =	STONE_AXE	THEN	CRAFTING
WHEN action_object =	WHITE_WOOL	THEN	CRAFTING
WHEN action_object =	OAK_BOAT	THEN	CRAFTING
WHEN action_object =	BOAT	THEN	CRAFTING
WHEN action_object =	STONE_PICKAXE	THEN	CRAFTING
WHEN action_object =	STONE_SHOVEL	THEN	CRAFTING

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	CHEST	THEN	CRAFTING
WHEN action_object =	JUNGLE_WALL_SIGN	THEN	CRAFTING
WHEN action_object =	BUCKET	THEN	CRAFTING
WHEN action_object =	WATER_BUCKET	THEN	CRAFTING
WHEN action_object =	STONE_HOE	THEN	CRAFTING
WHEN action_object =	OAK_PLANKS	THEN	CRAFTING
WHEN action_object =	BONE	THEN	CRAFTING
WHEN action_object =	ATTACHED_MELON_STEM	THEN	CRAFTING
WHEN action_object =	BELL	THEN	CRAFTING
WHEN action_object =	BIRCH_BOAT	THEN	CRAFTING
WHEN action_object =	BIRCH_DOOR	THEN	CRAFTING
WHEN action_object =	BIRCH_FENCE	THEN	CRAFTING
WHEN action_object =	BIRCH_PLANKS	THEN	CRAFTING
WHEN action_object =	BIRCH_PRESSURE_PLATE	THEN	CRAFTING
WHEN action_object =	BIRCH_SAPLING	THEN	CRAFTING
WHEN action_object =	BIRCH_SLAB	THEN	CRAFTING
WHEN action_object =	BIRCH_STAIRS	THEN	CRAFTING
WHEN action_object =	BLAST_FURNACE	THEN	CRAFTING
WHEN action_object =	BLUE_BED	THEN	CRAFTING
WHEN action_object =	BOOK	THEN	CRAFTING
WHEN action_object =	BOWL	THEN	CRAFTING
WHEN action_object =	BREWING_STAND	THEN	CRAFTING

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	BROWN_DYE	THEN	CRAFTING
WHEN action_object =	CAMPFIRE	THEN	CRAFTING
WHEN action_object =	CHARCOAL	THEN	CRAFTING
WHEN action_object =	CHISELED_STONE_BRICKS	THEN	CRAFTING
WHEN action_object =	CLAY_BALL	THEN	CRAFTING
WHEN action_object =	CLOCK	THEN	CRAFTING
WHEN action_object =	COBBLED_DEEPSLATE_STAIRS	THEN	CRAFTING
WHEN action_object =	COBBLESTONE_SLAB	THEN	CRAFTING
WHEN action_object =	COBBLESTONE_STAIRS	THEN	CRAFTING
WHEN action_object =	COMPASS	THEN	CRAFTING
WHEN action_object =	COMPOSTER	THEN	CRAFTING
WHEN action_object =	CUT_SANDSTONE	THEN	CRAFTING
WHEN action_object =	DARK_OAK_FENCE	THEN	CRAFTING
WHEN action_object =	DARK_OAK_PLANKS	THEN	CRAFTING
WHEN action_object =	DARK_OAK_STAIRS	THEN	CRAFTING
WHEN action_object =	DIORITE_STAIRS	THEN	CRAFTING
WHEN action_object =	DIORITE_WALL	THEN	CRAFTING
WHEN action_object =	DIRT_PATH	THEN	CRAFTING
WHEN action_object =	DISPENSER	THEN	CRAFTING
WHEN action_object =	DRIPSTONE_BLOCK	THEN	CRAFTING
WHEN action_object =	FILLED_MAP	THEN	CRAFTING
WHEN action_object =	FLETCHING_TABLE	THEN	CRAFTING

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	FLINT_AND_STEEL	THEN	CRAFTING
WHEN action_object =	GLASS	THEN	CRAFTING
WHEN action_object =	GOLDEN_SHOVEL	THEN	CRAFTING
WHEN action_object =	GRINDSTONE	THEN	CRAFTING
WHEN action_object =	HAY_BLOCK	THEN	CRAFTING
WHEN action_object =	ICE	THEN	CRAFTING
WHEN action_object =	IRON_SHOVEL	THEN	CRAFTING
WHEN action_object =	ITEM_FRAME	THEN	CRAFTING
WHEN action_object =	JUNGLE_BOAT	THEN	CRAFTING
WHEN action_object =	JUNGLE_FENCE	THEN	CRAFTING
WHEN action_object =	JUNGLE_FENCE_GATE	THEN	CRAFTING
WHEN action_object =	JUNGLE_SIGN	THEN	CRAFTING
WHEN action_object =	LADDER	THEN	CRAFTING
WHEN action_object =	LAVA_BUCKET	THEN	CRAFTING
WHEN action_object =	LEATHER	THEN	CRAFTING
WHEN action_object =	LEVER	THEN	CRAFTING
WHEN action_object =	LIGHTNING_ROD	THEN	CRAFTING
WHEN action_object =	LOOM	THEN	CRAFTING
WHEN action_object =	OAK_DOOR	THEN	CRAFTING
WHEN action_object =	OAK_FENCE	THEN	CRAFTING
WHEN action_object =	OAK_FENCE_GATE	THEN	CRAFTING
WHEN action_object =	OAK_SIGN	THEN	CRAFTING

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	OAK_SLAB	THEN	CRAFTING
WHEN action_object =	OAK_STAIRS	THEN	CRAFTING
WHEN action_object =	OAK_WALL_SIGN	THEN	CRAFTING
WHEN action_object =	ORANGE_BED	THEN	CRAFTING
WHEN action_object =	PINK_STAINED_GLASS	THEN	CRAFTING
WHEN action_object =	PINK_STAINED_GLASS_PANE	THEN	CRAFTING
WHEN action_object =	POINTED_DRIPSTONE	THEN	CRAFTING
WHEN action_object =	POLISHED_ANDESITE	THEN	CRAFTING
WHEN action_object =	REDSTONE_WIRE	THEN	CRAFTING
WHEN action_object =	SANDSTONE_STAIRS	THEN	CRAFTING
WHEN action_object =	SANDSTONE_WALL	THEN	CRAFTING
WHEN action_object =	SHEARS	THEN	CRAFTING
WHEN action_object =	SMITHING_TABLE	THEN	CRAFTING
WHEN action_object =	SMOKER	THEN	CRAFTING
WHEN action_object =	SPRUCE_BOAT	THEN	CRAFTING
WHEN action_object =	SPRUCE_DOOR	THEN	CRAFTING
WHEN action_object =	SPRUCE_FENCE	THEN	CRAFTING
WHEN action_object =	SPRUCE_FENCE_GATE	THEN	CRAFTING
WHEN action_object =	SPRUCE_PLANKS	THEN	CRAFTING
WHEN action_object =	SPRUCE_SIGN	THEN	CRAFTING
WHEN action_object =	SPRUCE_SLAB	THEN	CRAFTING
WHEN action_object =	SPRUCE_STAIRS	THEN	CRAFTING

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	STONE_BRICK_STAIRS	THEN	CRAFTING
WHEN action_object =	STONE_BRICKS	THEN	CRAFTING
WHEN action_object =	STONECUTTER	THEN	CRAFTING
WHEN action_object =	WHITE_BED	THEN	CRAFTING
WHEN action_object =	WHITE_CONCRETE	THEN	CRAFTING
WHEN action_object =	WHITE_CONCRETE_POWDER	THEN	CRAFTING
WHEN action_object =	WHITE_DYE	THEN	CRAFTING
WHEN action_object =	WOODEN_HOE	THEN	CRAFTING
WHEN action_object =	WOODEN_SHOVEL	THEN	CRAFTING
WHEN action_object =	YELLOW_BED	THEN	CRAFTING
WHEN action_object =	EXPERIENCE_ORB	THEN	ENCHANTMENT
WHEN action_object =	CARTOGRAPHY_TABLE	THEN	ENCHANTMENT
WHEN action_object =	EXPERIENCE_BOTTLE	THEN	ENCHANTMENT
WHEN action_object =	GLOW_INK_SAC	THEN	ENCHANTMENT
WHEN action_object =	GLOW_LICHEN	THEN	ENCHANTMENT
WHEN action_object =	INK_SAC	THEN	ENCHANTMENT
WHEN action_object =	MAP	THEN	ENCHANTMENT
WHEN action_object =	MYCELIUM	THEN	ENCHANTMENT
WHEN action_object =	NETHERRACK	THEN	ENCHANTMENT
WHEN action_object =	SPLASH_POTION	THEN	ENCHANTMENT
WHEN action_object =	TUFF	THEN	ENCHANTMENT
WHEN action_object =	APPLE	THEN	FOOD

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	COCOA	THEN	FOOD
WHEN action_object =	COD	THEN	FOOD
WHEN action_object =	CHICKEN	THEN	FOOD
WHEN action_object =	MELON	THEN	FOOD
WHEN action_object =	MELON_SLICE	THEN	FOOD
WHEN action_object =	SALMON	THEN	FOOD
WHEN action_object =	WHEAT	THEN	FOOD
WHEN action_object =	COCOA_BEANS	THEN	FOOD
WHEN action_object =	ATTACHED_PUMPKIN_STEM	THEN	FOOD
WHEN action_object =	BAKED_POTATO	THEN	FOOD
WHEN action_object =	BEE_NEST	THEN	FOOD
WHEN action_object =	BEEF	THEN	FOOD
WHEN action_object =	BEETROOT	THEN	FOOD
WHEN action_object =	BEETROOT_SEEDS	THEN	FOOD
WHEN action_object =	BEETROOTS	THEN	FOOD
WHEN action_object =	BONE_MEAL	THEN	FOOD
WHEN action_object =	BREAD	THEN	FOOD
WHEN action_object =	BROWN_MUSHROOM	THEN	FOOD
WHEN action_object =	BROWN_MUSHROOM_BLOCK	THEN	FOOD
WHEN action_object =	COOKIE	THEN	FOOD
WHEN action_object =	CARROT	THEN	FOOD
WHEN action_object =	CARROTS	THEN	FOOD

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	CARROTS	THEN	FOOD
WHEN action_object =	COOKED_BEEF	THEN	FOOD
WHEN action_object =	COOKED_CHICKEN	THEN	FOOD
WHEN action_object =	COOKED_COD	THEN	FOOD
WHEN action_object =	COOKED_MUTTON	THEN	FOOD
WHEN action_object =	COOKED_PORKCHOP	THEN	FOOD
WHEN action_object =	COOKED_SALMON	THEN	FOOD
WHEN action_object =	MUSHROOM_COW	THEN	FOOD
WHEN action_object =	MUSHROOM_STEM	THEN	FOOD
WHEN action_object =	MUTTON	THEN	FOOD
WHEN action_object =	PORKCHOP	THEN	FOOD
WHEN action_object =	POTATO	THEN	FOOD
WHEN action_object =	POTATOES	THEN	FOOD
WHEN action_object =	PUFFERFISH	THEN	FOOD
WHEN action_object =	PUMPKIN	THEN	FOOD
WHEN action_object =	PUMPKIN_PIE	THEN	FOOD
WHEN action_object =	PUMPKIN_SEEDS	THEN	FOOD
WHEN action_object =	PUMPKIN_STEM	THEN	FOOD
WHEN action_object =	ROTTEN_FLESH	THEN	FOOD
WHEN action_object =	SUSPICIOUS_STEW	THEN	FOOD
WHEN action_object =	SWEET_BERRY_BUSH	THEN	FOOD
WHEN action_object =	COAL_ORE	THEN	MINING

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	COPPER_ORE	THEN	MINING
WHEN action_object =	DIORITE	THEN	MINING
WHEN action_object =	IRON_ORE	THEN	MINING
WHEN action_object =	RAW_IRON	THEN	MINING
WHEN action_object =	COAL	THEN	MINING
WHEN action_object =	COBBLED_DEEPSLATE	THEN	MINING
WHEN action_object =	COPPER_INGOT	THEN	MINING
WHEN action_object =	DEEPSLATE_COAL_ORE	THEN	MINING
WHEN action_object =	DEEPSLATE_COPPER_ORE	THEN	MINING
WHEN action_object =	DEEPSLATE_DIAMOND_ORE	THEN	MINING
WHEN action_object =	DEEPSLATE_EMERALD_ORE	THEN	MINING
WHEN action_object =	DEEPSLATE_GOLD_ORE	THEN	MINING
WHEN action_object =	DEEPSLATE_IRON_ORE	THEN	MINING
WHEN action_object =	DEEPSLATE_LAPIS_ORE	THEN	MINING
WHEN action_object =	DEEPSLATE_REDSTONE_ORE	THEN	MINING
WHEN action_object =	DIAMOND_ORE	THEN	MINING
WHEN action_object =	DIAMOND_PICKAXE	THEN	MINING
WHEN action_object =	EMERALD	THEN	MINING
WHEN action_object =	EMERALD_ORE	THEN	MINING
WHEN action_object =	ENDER_PEARL	THEN	MINING
WHEN action_object =	GOLD_ORE	THEN	MINING
WHEN action_object =	GOLDEN_PICKAXE	THEN	MINING

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	IRON_INGOT	THEN	MINING
WHEN action_object =	IRON_NUGGET	THEN	MINING
WHEN action_object =	IRON_PICKAXE	THEN	MINING
WHEN action_object =	LAPIS_BLOCK	THEN	MINING
WHEN action_object =	LAPIS_ORE	THEN	MINING
WHEN action_object =	OBSIDIAN	THEN	MINING
WHEN action_object =	RAW_COPPER	THEN	MINING
WHEN action_object =	RAW_GOLD	THEN	MINING
WHEN action_object =	REDSTONE_ORE	THEN	MINING
WHEN action_object =	SNOW_BLOCK	THEN	MINING
WHEN action_object =	BRAIN_CORAL_BLOCK	THEN	OCEAN
WHEN action_object =	BRAIN_CORAL_FAN	THEN	OCEAN
WHEN action_object =	BRAIN_CORAL_WALL_FAN	THEN	OCEAN
WHEN action_object =	BUBBLE_CORAL_BLOCK	THEN	OCEAN
WHEN action_object =	FIRE_CORAL_FAN	THEN	OCEAN
WHEN action_object =	FIRE_CORAL_WALL_FAN	THEN	OCEAN
WHEN action_object =	KELP	THEN	OCEAN
WHEN action_object =	KELP_PLANT	THEN	OCEAN
WHEN action_object =	SEA_PICKLE	THEN	OCEAN
WHEN action_object =	SEAGRASS	THEN	OCEAN
WHEN action_object =	TALL_SEAGRASS	THEN	OCEAN
WHEN action_object =	BRAIN_CORAL	THEN	OCEAN

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	BUBBLE_CORAL_WALL_FAN	THEN	OCEAN
WHEN action_object =	DRIED_KELP	THEN	OCEAN
WHEN action_object =	FIRE_CORAL_BLOCK	THEN	OCEAN
WHEN action_object =	HORN_CORAL_BLOCK	THEN	OCEAN
WHEN action_object =	HORN_CORAL_FAN	THEN	OCEAN
WHEN action_object =	HORN_CORAL_WALL_FAN	THEN	OCEAN
WHEN action_object =	TROPICAL_FISH	THEN	OCEAN
WHEN action_object =	TUBE_CORAL	THEN	OCEAN
WHEN action_object =	TUBE_CORAL_BLOCK	THEN	OCEAN
WHEN action_object =	TUBE_CORAL_WALL_FAN	THEN	OCEAN
WHEN action_object =	PLAYER	THEN	PLAYER
WHEN action_object =	ARROW	THEN	WEAPON
WHEN action_object =	STONE_SWORD	THEN	WEAPON
WHEN action_object =	WOODEN_AXE	THEN	WEAPON
WHEN action_object =	WOODEN_SWORD	THEN	WEAPON
WHEN action_object =	BOW	THEN	WEAPON
WHEN action_object =	CROSSBOW	THEN	WEAPON
WHEN action_object =	DIAMOND_SWORD	THEN	WEAPON
WHEN action_object =	FALLING_BLOCK	THEN	WEAPON
WHEN action_object =	GOLDEN_HORSE_ARMOR	THEN	WEAPON
WHEN action_object =	GOLDEN_SWORD	THEN	WEAPON
WHEN action_object =	GUNPOWDER	THEN	WEAPON

WHEN action_object =	Object	Do	Generalized_Object
WHEN action_object =	IRON_AXE	THEN	WEAPON
WHEN action_object =	IRON_CHESTPLATE	THEN	WEAPON
WHEN action_object =	IRON_GOLEM	THEN	WEAPON
WHEN action_object =	IRON_SWORD	THEN	WEAPON
WHEN action_object =	JUNGLE_TRAPDOOR	THEN	WEAPON
WHEN action_object =	OAK_PRESSURE_PLATE	THEN	WEAPON
WHEN action_object =	OAK_TRAPDOOR	THEN	WEAPON
WHEN action_object =	SHIELD	THEN	WEAPON
WHEN action_object =	SNOWBALL	THEN	WEAPON
WHEN action_object =	SPRUCE_TRAPDOOR	THEN	WEAPON
WHEN action_object =	TRIPWIRE	THEN	WEAPON
WHEN action_object =	TRIPWIRE_HOOK	THEN	WEAPON

Roughness of Learning (RoL) Variable Development

To develop the time series to create the fractal dimension used in developing the roughness of learning (RoL) variable, the researcher created a MySQL table that combined the health-related scores as extracted from the Minecraft plugin plan. Data was imported directly from the game to the Plan plugin so no data manipulation was required. The table was sorted by player. These scores were collected at time of death for each death by player. The scores were then plotted with health score at time of death on the y axis and death count on the x axis. A total of 1,320 records from 95 participants who completed all five were included in the table and plot.

Using the plot of the health score at time of death, the boxcounting method was used to calculate the fractal for all deaths for four groups: Novice, Intermediate, Advanced and All Participants. The researcher combined the Intermediate and Advanced groups to create an Experienced Group. This increased the length of the group plot to better measure the fractal.

The fractal dimension was created using a two-dimensional scale (1:2) since the data was organized as two-dimensional data. To match the scale used in the theoretical framework, the fractals were rescaled using R *rescale* function from 1:2 to 0:4. R package *nonlinearTseries* was used to create Logistic maps to create visualizations of the plotted data used. The logistic map plot was matched to same length as the primary data used to calculate the fractal.

APPENDIX B

SELF REPORTED SCALES USED IN CRAFTDAWG STUDY

Jinks Watkins Informal & Incidental Learning Scale (v2)

Start of Block: Default Question Block

Q2 Hello CraftDawger! Thank you for beginning this study. This brief survey should take you about 5 - 10 minutes to complete. Basically, it is all about you. In the matrix below, select the answer that best represents you.

Q3 Please enter your Gamer Name being used in the study. (You can find it in your Welcome email from the Study Administrator.)

_____

Q5 Please enter your Gamer email address assigned for the Study. It will look something like this: gamedawg@ugacraftdawgs.org.

_____

Q5 Tell us a little about yourself if you will. Slide to your age (at the end of the slide is the actual age).

	20 30 40 50 60 70 80 90
Age ()	

Q6 Which best describes your experience with the game of Minecraft as a player.

- ○ Novice - I have never played this game before (1)
- ○ Somewhat familiar - I have played the game before (2)
- ○ Learned from others - I have watched others play the game (3)
- ○ Played the game alot (4)
- ○ Complete newbie - know nothing about the game (6)

Q1 Please select the response that best represents your answer for each statement.

	Rarely, if ever (1)	Sometimes, but not often (2)	Less than half the time (3)	About half the time (4)	A little more than half the time (5)	Almost always (6)
1. I am comfortable learning by watching others do stuff. (1)	○	○	○	○	○	○
2. I watch people do things and I think about how I would do it differently. (2)	○	○	○	○	○	○
3. I ask people how they do things so I can learn from them. (3)	○	○	○	○	○	○
4. I try different things to learn what works and what doesn't work. (4)	○	○	○	○	○	○
5. I seek out other sources of information when I think I can learn how to do something better. (5)	○	○	○	○	○	○

6. I think about situations afterwards to learn from them (6)	○	○	○	○	○	○
7. I usually rely on what I already know to learn something new. (7)	○	○	○	○	○	○
8. I learn a lot from trying things and seeing what happens. (8)	○	○	○	○	○	○
9. Sometimes I just know how to do something even though I have never done it before. (9)	○	○	○	○	○	○
10. Usually, if I don't know how to do something, I will search out sources for help. (10)	○	○	○	○	○	○
11.Sometimes, I surprise myself with the stuff I know how to do. (11)	○	○	○	○	○	○

12. I can do things that I cannot explain where I learned them. (12)	○	○	○	○	○	○
13. I realize that I learned stuff when I wasn't even trying. (13)	○	○	○	○	○	○

End of Block: Default Question Block

Start of Block: Default Question Block

Jinks Watkins Adaptive Capacity Instrument as adapted for Minecraft Project v2

Start of Block: Purpose

Intro This is the second of two surveys that you will complete before beginning to play the game. Once this survey is submitted, the Study Administrator will set up your Minecraft credentials and send them to you so you can start playing the game.

Q7 Please enter your Gamer Name.

_____

Q8 Please enter your Participant Email Address (it will look like this:

bigdawg@ugacraftdawgs.org)

_____

End of Block: Purpose

Start of Block: Q1

Please select the response that best describes you.

	Strongly Disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
1. I believe I have received adequate information about the game. (1)	○	○	○	○	○
2. The information I have received about the game adequately answers my questions about how the game changes. (2)	○	○	○	○	○
3. The information I received about the game is useful. (3)	○	○	○	○	○
4. The information I received about the game is timely. (4)	○	○	○	○	○

Q2 For each of the statements listed, please select the response that best describes you.

	Strongly Disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
1.I actively take time to reflect on events that happen in my life. (1)	○	○	○	○	○
2.I have an understanding of what makes my life meaningful. (2)	○	○	○	○	○
3. When difficult things happen, I am usually quick to see the meaning of why they happened to me. (3)	○	○	○	○	○
4. Self-reflection helps me to make my life meaningful. (4)	○	○	○	○	○
5. I actively focus on activities and events that I personally find valuable. (5)	○	○	○	○	○

6. I feel my life is meaningful. (6)	○	○	○	○	○

Q3 For the statements below, select the response that describes you best.

	Very negatively (1)	Somewhat negatively (2)	Neither negatively nor positively (3)	Somewhat positively (4)	Very positively (5)
1. How do you expect the changes in the game to affect the quality of your game play? (1)	○	○	○	○	○
2. How do you expect the game changes to effect how you feel about your game play? (2)	○	○	○	○	○

Q4 I believe I will find changes in the game to be

- ○ A big threat (1)
- ○ Somewhat of a threat (2)
- ○ Neither a threat nor an opportunity (3)
- ○ Somewhat of an opportunity (4)
- ○ A big opportunity (5)

Q5 I believe I will find changes in the game to be

- ○ very intimidating (1)
- ○ somewhat intimidating (2)
- ○ neither intimidating nor exciting (3)
- ○ somewhat exciting (4)
- ○ very exciting (5)

End of Block: Q1

Jinks Watkins Project Minecraft Post-Play Questionnaire - Play Session 1

Start of Block: Please enter your Player ID

Player Id, Please enter your Player Gamer Name

_____

Q19 Please enter your Study Email address

_____

Q2 How many times have you played the game, including this play session?

	1 2 3 4 6 7 8 9 10
I have played this many times, including this session. ()	

Q3 In all of your sessions combined, about how many minutes have you played including today?

	0 10 20 30 40 50 60 70 80 90 100110120
Minutes played, including this play session. ()	

Q4 Did you set goals to achieve in today's play session?

- ○ Yes (1)
- ○ No (2)

Display This Question:

If Did you set goals to achieve in today's play session? = Yes

Q5 Which statement best describes your play in today's game?

- ○ I did not achieve any of the goals I had set. (1)
- ○ I achieved less than half the goals I had set. (2)
- ○ I achieved a little more than half the goals I had set. (3)
- ○ I achieved almost all the goals I had set. (4)
- ○ I achieved all the goals I had set. (5)

Display This Question:

If Did you set goals to achieve in today's play session? = Yes

Q6 If you did not achieve all of your goals for today, will you keep the same goals for the next play session?

- ○ Yes (1)
- ○ No (2)

Display This Question:

If you did not achieve all of your goals for today, will you keep the same goals for the next play... = No

Q7 Briefly describe the goal(s) you will change, add, or eliminate

_____

_____

_____

_____

_____

Q8 If you play the game again, will your priorities change in the next game?

- ○ Yes (1)
- ○ No (2)

Q9 If your priorities will change, briefly describe why they will change.

_____

_____

_____

_____

_____

Q10 If your priorities will change, briefly describe how they will change

_____

_____

_____

_____

_____

Q11 If you did achieve all of your goals, will you change your goals for the next play session?

- Yes (1)
- No (2)

Q12 Briefly describe your new goals.

_____

_____

_____

_____

_____

Q13 Briefly describe your new priorities.

_____

_____

_____

_____

Q14 If you were to play the game again, how likely are you to do any of these things?

	Won't do this. (1)	Might do this, but I don't know. (2)	Maybe do this. (3)	Likely will do this. (4)	Will definitely do this. (5)
1. Search the internet for videos. (1)	○	○	○	○	○
2. Ask people who have played the game for ideas. (2)	○	○	○	○	○
3. Watch other players. (3)	○	○	○	○	○
4. Try different ideas I already have. (4)	○	○	○	○	○
5. Try stuff and if it doesn't work, try other stuff. (5)	○	○	○	○	○
6. Think about other games and how I played them. (6)	○	○	○	○	○
7. Think about other experiences and whether I can figure out something from those. (7)	○	○	○	○	○

8. Keep doing what I am doing and see if I figure out what I want. (8)	○	○	○	○	○
9. Experiment with some different ideas and see what happens (9)	○	○	○	○	○
10. If I am in a Facebook group, ask some questions there. (10)	○	○	○	○	○

Q15 If you were to play the game before, would you use ideas and strategies you learned from previous play in this game?

○ Yes (1)

○ No (2)

Q16 If you used ideas or strategies from previous play, briefly describe it and why you used it in this game.

_____

_____

_____

_____

_____

Q17 Please select the response that best describes you for each statement.

	Does not describe me at all (1)	Describes me a little (2)	Somewhat describes me (3)	Describes me mostly (4)	Describes me precisely (5)
1. I was uncertain about what to do. (1)	○	○	○	○	○
2. I was worried about the consequences of some of my choices. (2)	○	○	○	○	○
3. I was confident I had learned from other games and could take on the challenges. (3)	○	○	○	○	○
4. I was confident I could figure it out even if I might fail a few times. (4)	○	○	○	○	○
5. Somehow, I just knew what to do, I really can’t explain it. (5)	○	○	○	○	○
6. There was a lot of anxiety during the game. (6)	○	○	○	○	○

7. I kept worrying that something was going to go wrong. (7)	○	○	○	○	○
8. I really had no clue as to what to do at times. (8)	○	○	○	○	○
9. It was easy to try different things because I knew I could learn from them if they worked. (9)	○	○	○	○	○

Q18 Please select the response that best states your answer for each statement.

	Rarely, if ever (1)	Sometimes, but not that often (2)	A little less than half the time (3)	A little more than half the time (4)	Usually, but not always (5)	Almost always (6)
1. When I am uncertain about something in the game, I get uncomfortable with the whole situation. (1)	○	○	○	○	○	○
2. I do not like being in unfamiliar situations in the game that I don't understand. (2)	○	○	○	○	○	○
3. When there is not a clear way forward in the game, I get a little frustrated. (3)	○	○	○	○	○	○
4. I am usually alright when there is not a right answer in the game. (4)	○	○	○	○	○	○

5. When there are lots of different things happening all around me in the game, I freeze up until I figure out what to do. (5)	○	○	○	○	○	○
6. I have confidence that I can figure out how to do most new things that I encounter in the game. (6)	○	○	○	○	○	○
7. I use what I already know to help me figure out new stuff in the game. (7)	○	○	○	○	○	○
8. I try lots of ways to figure out how do something I am not familiar with in the game. (8)	○	○	○	○	○	○
9. Learning to do something a different way in the game is hard. (9)	○	○	○	○	○	○

10. If I don't know how to do something, I try to learn how to do it. (10)	○	○	○	○	○	○
11. There are some things that I just cannot figure out, so I don't even try. (11)	○	○	○	○	○	○
12. During the game, I felt I adapted well to changes in the game tasks. (12)	○	○	○	○	○	○
13. During the game, I felt I coped with changes in the way I did the game tasks. (13)	○	○	○	○	○	○
14. During the game, I learned new skills that allowed be to adapt to the changes in the game. (14)	○	○	○	○	○	○

End of Block: Please enter your Player ID