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THE IMPACT OF VICARIOUS AND ENACTIVE LEARNING FROM A DIGITAL GAME ON STATISTICS KNOWLEDGE, SELF-EFFICACY, AND SITUATIONAL INTEREST

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by

Huiqing Hu

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The dissertation of Huiqing Hu was reviewed and approved* by the following:

Rayne A. Sperling  
Professor of Education, Educational Psychology  
Dissertation Advisor  
Chair of Committee

Gabriela T. Richard  
Assistant Professor, Learning, Design, and Technology

Crystal M. Ramsay  
Affiliate Assistant Professor, Educational Psychology

Alexandra List  
Assistant Professor of Education, Educational psychology

Puiwa Lei-Ng  
Professor of Education, Educational Psychology  
Professor in Charge

*Signatures are on file in the Graduate School
ABSTRACT

College students often view statistics as challenging and unpleasant to learn (Ben-Zvi et al., 2017). Digital games designed for educational purposes have been found to be effective for promoting statistics learning and motivation to learn statistics (e.g. Boyle et al., 2014). However, research is currently lacking on the best practices for integrating digital games into statistics instruction. It is well known in the entertainment game industry that individuals may gain knowledge and skills from commercial games by merely watching other people play without having to play the game themselves (Sjöblom & Hamari, 2017). Unfortunately, little is known about the effects of observing another person play games designed for learning purposes in an educational context. Therefore, this study investigated the impact of enactive learning (i.e. learning-by-doing) from a digital statistics game, compared to vicarious learning (i.e. learning-by-observing) from the game, and conventional instruction (i.e. a non-game learning activity) on college students’ statistics knowledge, self-efficacy, and situational interest. Eighty-seven college students were randomly assigned to either play Stats Invaders to learn about distribution properties (game playing condition), watch a video of a mastery model play the game (game viewing condition), or complete a conventional learning task (control condition). Results suggest that there were no differences in statistical knowledge between learning enactively and vicariously from the game, but neither game-based learning experiences was more effective at promoting knowledge than conventional instruction. Additionally, no differences in statistical self-efficacy were found across the conditions. However, as anticipated, triggered-situational interest was higher for students who either learned-by-
playing or learned-by-observing the game than those who completed the conventional activity. Furthermore, maintained-situational interest-feeling was greater in the game playing condition compared to the control condition, but no differences were found between the game viewing condition and the control, and between the game conditions. There were also no differences among the conditions in maintained-situational interest-value. Overall, although the game conditions were not as effective as non-game conventional instruction on promoting statistical knowledge, the findings indicate that game-based learning experiences may hold promise for enhancing motivation to learn statistics. Specifically, if the aim is to promote students’ situational interest while learning statistics, game-based instruction would likely be more effective than conventional instruction, and vicarious learning experiences from the game may be a viable alternative to enactive learning experiences. Implications for instructional practice and future research are discussed.
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Chapter 1

INTRODUCTION

In today’s data-rich society, statistical knowledge is essential for us to make decisions in our professional and personal lives (Ben-Zvi et al., 2017; Ben-Zvi & Garfield, 2004; Madigan et al., 2013). A major goal of statistics education at the college level is to promote students’ statistical thinking and their abilities to apply statistical concepts in various decision-making contexts in real life (Ben-Zvi et al., 2017; Carver et al., 2016; Nikiforidou et al., 2010; Tishkovskaya & Lancaster, 2010). However, statistical knowledge is reported to be difficult and unpleasant to learn, as it is not uncommon for college students to adopt negative perceptions about learning this particular subject and to lack motivation to engage in statistical learning activities due to various factors such as the complexity of statistical ideas and the problems students often have with the underlying mathematics (Ben-Zvi & Garfield, 2004; Gal & Ginsburg, 1994; Ramirez et al., 2012; Tishkovskaya & Lancaster, 2012). In turn, students who have low motivation to learn statistics are likely to exert less effort and pay less attention when learning statistics, which will likely have a negative impact on statistical knowledge acquisition.

Statistics educators have recognized the difficulties in learning statistics and have identified the importance of addressing the learning and motivational challenges students face, especially in introductory statistics courses (Ben-Zvi et al., 2017). In particular, the 2016 Guidelines for Assessment and Instruction in Statistics Education (GAISE) college report re-emphasized the importance of leveraging available advanced technologies when
designing effective statistics instruction (Carver et al., 2016). There are many important benefits to adopting advanced technologies in statistics instruction. For instance, such technologies can reduce the amount of instructional time spent on teaching computation procedures, which in turn can free up time for students to focus on statistical concepts and the application of statistical ideas (Ben-Zvi et al., 2017; Garfield et al., 2008b).

Technology also allows students to interact with simulations of data and statistical procedures, which can help students visualize distributions of data and variables (Garfield et al., 2008b). A central goal of this dissertation is to investigate the effects of integrating one type of technology in particular, digital games, into statistics instruction, on three critical factors to college students’ statistics education: statistics knowledge, statistics self-efficacy, and situational interest.

Digital games in education are extremely versatile tools that can be integrated into conventional pedagogies in multiple ways (Wouters & Van Oostendorp, 2013) and have been found to be more effective at promoting college students’ learning and motivation than conventional instruction (e.g. lectures) across various academic subjects, including statistics (e.g. Clark et al., 2016; Mayer, 2014; Wouters et al., 2013; Wouters & Van Oostendorp, 2013). Depending on the design of the game, it can be used as either a standalone product that delivers direct instruction throughout gameplay, or it can serve as an instructional supplement to enhance conventional learning experiences outside of the game environment (e.g. a reading task). Unfortunately, regardless of how games are adopted currently in education, the existing studies in the game-based learning literature have only examined the effects of students playing digital games enactively (i.e. learning-
by-doing). However, there is theoretical and empirical evidence to support that students may also learn academic content vicariously (i.e. learning-by-observing) in a similar manner as those who observe gamers play entertainment games.

In the entertainment game industry, millions of people not only buy and play these games themselves, but many also watch professional gamers play games on live streaming platforms such as Twitch, or through online videos such as YouTube (Hamari & Sjöblom, 2017; Kaytoue et al., 2012; Sjöblom & Hamari, 2017). Empirical research has found that the leading motives for viewers to watch someone play commercial-off-the-shelf games is to acquire knowledge about game content and to learn about game mechanics (Hamari & Sjöblom, 2017; Hoffman & Nadelson, 2010). Grounded in Social Cognitive Theory (SCT; Bandura, 1986), this dissertation examines the educational implication of observing others play digital games. Specifically, this study extends prior research and provides an investigation of the impact of learning-by-observing a game, in comparison to learning-by-playing a game, and conventional instruction that does not include a game.

Games are designed to be inherently interactive and responsive. This study proposes that when students play games, they learn enactively by interacting with various game elements (e.g. available game actions, challenges, levels, and stages) and receiving feedback (e.g. points, correct and incorrect game decisions, etc.) on their performance during the game, which also reflects their learning progress (Garris et al., 2002; Mayer, 2011, 2014). If game actions are successful at improving in-game performance, this
indicates that the student has learned the targeted content, whereas if game actions are unsuccessful, this shows that the student might not have learned the desired content.

Games are also effective at promoting achievement motivation (Habgood et al., 2005; Habgood & Ainsworth, 2011; Malone & Lepper, 1987). In addition to the interactive nature of games, games are designed with stimulating features such as fantasy (e.g. fictional narrative background) and visual (e.g. animations) elements. While players experience the consequences of their in-game actions, the fun and exciting aspects of games may motivate players to continuously pay attention and intrinsically engage in the game (Habgood et al., 2005; Habgood & Ainsworth, 2011; Malone & Lepper, 1987).

However, students might also benefit academically from merely observing a model play the game. Prior research has established that students can gain knowledge and skills through vicarious experiences by observing models demonstrate and verbally explain how to complete an academic task (Schunk, 2003; Zimmerman & Kitsantas, 2002). Models also can exhibit motivational beliefs while engaging in the task by showing their confidence and interest in the academic task. Mastery models, in particular, have been found to be effective at promoting learning and motivation outcomes (Schunk & Hanson, 1985, 1989). Mastery models exhibit exemplar performance and verbalize positive achievement beliefs that demonstrate to viewers how to succeed at the task (Bandura, 1986; Schunk & Hanson, 1985, 1989). A mastery model is employed in this particular investigation to be comparable to professional gamers that individuals watch and learn from in the entertainment game industry. As with professional gamers, the mastery model in this study demonstrates the positive standards of how to successfully
play the game and learn the targeted content. This will mirror the authenticity of the game viewing experiences individuals have with commercial-off-the-shelf games.

Since this is the first known study to examine effects of enactive and vicarious learning experiences from a game, a game with a simplistic design, *Stats Invaders*, was chosen to control for the potential confounding effect of game complexity. *Stats Invaders* is designed as a preparatory activity to expose students to statistical conceptual knowledge about the properties of probability distributions (Arena & Schwartz, 2010, 2014). The game has an arcade-style interface and two core game mechanics: shoot alien spaceships that drop from the top of the screen and identify the pattern of the alien’s attack by clicking on one of the two distributions presented to the player at each level. Designed according to the Preparation for Future Learning framework (PFL; Bransford & Schwartz, 1999), there is no formal statistical instruction on probability distributions delivered within the game. Instead, playing *Stats Invaders* is intended to prepare students to further learn from a subsequent reading task on distributions.

To date, only one previous study empirically examined the effects of *Stats Invaders* on college students’ statistical conceptual knowledge. Arena & Schwartz (2014) found that *Stats Invaders* was indeed more effective at preparing students to learn about distributions from a subsequent reading passage than if students only read the passage or only played the game. Due to the simplicity of the game design used in this study, it was expected that observing a model interacting with game elements and learning from her in-game performance would generate comparable learning and motivational experiences for the viewer as if they played the game themselves.
In this dissertation study, college students either played *Stats Invaders* (game playing condition), observed a mastery model play *Stats Invaders* (game viewing condition), or completed a conventional learning activity (control condition) as the preparatory activity before reading a passage. In each condition, after completing the preparatory activity, college students read a short passage on probability distributions. The following chapter presents a review of the theoretical and empirical research that underpins this study, and the hypotheses tested in this research.
Chapter 2

REVIEW OF LITERATURE

The Importance of Statistics Education

The vast amount of statistical information that we interact with in our data-centered society is astonishing and it is more critical than ever to possess statistical knowledge and skills to make professional and personal decisions. In 2017, IBM reported that “90% of the data in the world today was created in the last two years”. A report from the Future of Statistical Science Workshop (Madigan et al., 2013) highlighted that the most-discussed current trends in statistics were the challenges of analyzing Big Data and the rise of careers in data analysis and data science. Some of the most commonly referenced examples of Big Data include popular commercial databases like those from Google or Facebook that generate more than 500 terabytes of data every day, to lesser known databases in physics and astronomy such as those created from new telescopes that generate a petabyte of data every night (Madigan et al., 2013). This unthinkable amount of data requires significant analysis and management, and this need in the job market created some of the fastest growing and highest paying professions in the coming decade (2018-2028), including information security analysts (31.6% growth; median salary $98,350), statisticians (30.7% growth; median salary $87,780), and data scientists (16.5% growth; median salary $118,370) (Bureau of Labor Statistics, 2018).

On a day to day basis in our personal lives, we also receive and interact with a large amount of data, such as those from our smart devices and the applications that we
have installed on them (Ben-Zvi et al., 2017; Carver et al., 2016; Madigan et al., 2013). For instance, health applications will feed us data points about our daily physical activities and will request us to set goals to adopt healthier lifestyles. Moreover, popular media such as digital news outlets, in particular, are filled with data, statistical information, and graphical displays of current and projected trends of the developments of an event.

To be a critical consumer of statistically-based information, it is necessary to understand each component (e.g. the data source, the data, its analysis) and how to accurately interpret the claims being presented (Carver et al., 2016). For instance, in 2020, many distribution graphs were circulating the news media in the United States of America to show the projected trends of cases diagnosed in the Coronavirus outbreak. Some distributions presented critical information about the changes in the number of cases that would be diagnosed if we adopted protective measures, such as social distancing, as well as predictions about what would happen if we did not (Roberts, 2020). In life-threatening times such as a pandemic, it was utterly important for media consumers to accurately understand these distributions of data and the warnings of health professionals to react appropriately and practice protective strategies.

Given various situations in our lives that require us to interpret data to make important decisions, statistics education is essential (Garfield et al., 2008b; Zieffler et al., 2018). At the college level, introductory statistics courses are critical entry points to the domain of statistics (Carver et al., 2016). Moreover, a recent report highlighted that there was a 34.7% increase in students taking introductory statistics courses from 2005 to 2010.
(Carver et al., 2016). This suggests that more students are recognizing the increasingly important role that data and statistics has on our personal and professional lives and may be choosing to become statistically educated from the onset of their undergraduate studies. Students enrolled in these courses either are pursuing a degree in statistics or a degree in another field and need to take foundational statistics courses as an elective or a requirement (Zieffler et al., 2018). For the latter, the introductory course may be their only chance to be exposed to statistical concepts in college (Gal & Ginsburg, 1994). Therefore, statistics educators have recognized the need to critically examine the goals, content, and instruction in these courses to provide all enrolled students with the most relevant and valuable foundation in statistics (Garfield et al., 2008a).

**Goals in Statistics Education**

Statistics educators have recently identified several core objectives to enhance college students’ foundation in statistics when designing introductory courses. In 2016, the Guidelines for Assessment and Instruction in Statistics Education (GAISE) endorsed the objectives recommended by prior reports (e.g. in 2005) and re-emphasized the importance to teach statistical thinking and focus on conceptual understanding in introductory courses (Carver et al., 2016). The report highlighted that students should not leave the introductory statistics course with the impression that statistics is merely a collection of unrelated mathematical formulas, graphical displays of data, and data analysis methods. Instead, the course should help students understand that statistics represents a problem-solving and decision-making process, and the underlying concepts
and ways of thinking statistically are fundamental to making sound decisions using statistical information.

Students’ beliefs in their capabilities to perform statistical tasks and their motivation to learn statistics have been widely recognized as critical factors in statistics education (Gal & Ginsburg, 1994; Ramirez et al., 2012; Zare et al., 2011). Historically, students find statistics courses unpleasant to learn, leading instructors to also find statistics courses unpleasant to teach (Gal & Ginsburg, 1994; Garfield & Ben-Zvi, 2008a). For instance, students often view statistical ideas as complex, abstract, and counterintuitive (Garfield & Ben-Zvi, 2008a). In comparison to other fields, it is more common for college students to have misconceptions of statistical ideas and make errors when applying statistics in real-world contexts (Castro Sotos et al., 2007). In addition, students often have trouble with the underlying mathematics, which interferes with understanding statistical concepts. These are only a few examples among many identified reasons that cause students to have negative perceptions of statistics courses (Ben-Zvi et al., 2017). Negative perceptions of learning statistics may deter college students from pursuing a degree that applies statistics or even enrolling in statistics courses (Zare et al., 2011).

Statistics educators have long recognized these unpleasant images of statistics courses and have encouraged instructors to motivate students to want to learn the subject. Gal and Ginsburg (1994) advocated for statistics courses to not only facilitate statistical thinking, but to also ensure students are willing to further engage in statistical content after the completion of the course. They strongly recommend instructors to be mindful of
students’ reactions and perceptions about their learning experiences in statistics courses (Gal & Ginsburg, 1994). They believe statistics courses should foster students’ motivation such as interest in learning statistics and confidence in applying statistical knowledge and skills, rather than leaving students with anxiety and negative attitudes toward learning statistics.

In addition to the recommendations of what students should learn in introductory statistics courses, the 2016 GAISE report also highlighted the importance of leveraging modern advanced technology tools to promote students’ learning and motivation in statistics (Carver et al., 2016). Historically, technology has played a central role in facilitating and enhancing statistics instruction. For instance, advanced software helps to reduce instructional time necessary for computational procedures in statistics and frees up time to focus on understanding and applying statistical concepts (Ben-Zvi et al., 2017). Moreover, technology also allow students to better visualize abstract statistical concepts and changes in data (Garfield et al, 2008). Overall, interacting with statistical software such as simulations of data can help students more deeply explore and comprehend statistical ideas. More and better technology options have become widely available for statistics instructors to consider. For instance, applets and applications (e.g. Shiny) are popular programs that help students explore statistical concepts, and alternative online learning environments such as instructional videos and Massive Open Online Courses (MOOCs) have been found to be just as effective as traditional face-to-face instruction for learning statistics (Carver et al., 2016).
In recent years, computer games and other virtual environments have been a popular choice to integrate into statistics classrooms to promote students’ statistics learning and motivation (Boyle et al., 2014). A major goal of this dissertation was to examine the benefits of adopting digital games in statistics instruction on students’ conceptual knowledge of probability distributions, statistics self-efficacy, or one’s perceived competence in completing statistical tasks, and situational interest, which is one’s attentional and affective reactions toward the learning context. The following section overviews the literature on how digital games have been used in educational contexts and alternative designs for adopting games into instruction based on research from the entertainment game industry.

**Digital Games in Education**

Digital games in education are extraordinarily complex and multidimensional instructional tools. Broadly speaking, digital games in academic settings vary based on the original intention of the design (i.e. either designed for learning or entertainment purposes), the game features and elements (e.g. game genre, mechanics, visual elements), the electronic device that delivers the gameplay (e.g. computers, consoles, mobile device), the targeted population (e.g. primary vs. college students), the learning content (e.g. history vs. statistics), and the learning context in which the game is to be integrated (i.e. formal educational settings such as classrooms or informal learning environment such as an afterschool club) (e.g. Ke, 2009, 2015; Mayer, 2014; Prensky, 2001; Wouters et al., 2013). Due to the multifaceted nature in the design and use of educational games,
there are many frameworks in the current literature that define their characteristics and functions (e.g. Garris et al., 2002; Hainey et al., 2011; Ke, 2009).

The present research adopts Mayer’s (2011, 2014) framework for conceptualizing the defining features and functions of games used in academic settings. Based on Mayer’s (2011, 2014) conceptualization, computer games have five core characteristics that are interconnected and serve overlapping functions. These features have also been endorsed by other scholars (e.g. Garris et al., 2002; Hays, 2005; Ke, 2015). First, *games are rule-based*. Games involve a set of clear rules to allow for systematic and meaningful interactions during gameplay (e.g. Garris et al., 2002; Hays, 2005; Ke, 2015; Mayer, 2014). For instance, game rules help define the winning conditions, determine the difficulty level of the game, and impose limits, penalties, and constraints to the gameplay experience. For educational games in particular (e.g. *Cache-17*), game rules consist of the learning goal(s) (e.g. learn how electronmechanical devices work such as a wet cell battery) and the game goal(s) (e.g. recover stolen artwork) (Pilegard & Mayer, 2015).

Game rules also inform players how to engage in the game through executing the game mechanics (Garris et al., 2002; Prensky, 2001). Game mechanics are the choices and actions of the player (or a series of choices and actions) that are allowed in the game that lead to meaningful play experiences (Habgood et al., 2005; Plass et al., 2015; Salen & Zimmerman, 2004). For instance, in *Cache-17* (Pilegard & Mayer, 2015), a 3-D adventure game, a core game mechanic is to create a wet cell battery to open a door panel. To make the battery, the player has to click and collect a variety of metals located in a storage room in the game, place the correct metals in a brine solution, and connect
the metals to the door panel with jumper cables that players must also search for in the game environment (e.g. an underground bunker). There are 30 possible combinations of metals available in the game but only two combinations will generate the correct voltage to open the door. After players have made the correct choices and actions to create the wet cell battery and open the door panel, they can continue to search through the game environment to retrieve the stolen art to complete the game goal.

Second, *games are challenging*. Games provide unique types of challenges and means to overcome those challenges that traditional instruction does not (Garris et al., 2002; Hays, 2005; Mayer, 2011). For instance, challenges can manifest as mini-puzzles, mini-games, quests, levels, and various types of game goals. Challenges motivate learners to exert effort and persistence during the game to defeat obstacles and complete the game’s missions (Malone & Lepper, 1987).

Third, *games are cumulative*. Games allow players to be aware of their current progress in the game. Feedback that players receive throughout gameplay help them assess their current state in the game and plan for the next steps to achieve the goal. Feedback can come in a variety of forms and game experiences. For instance, giving players correct and incorrect indicators is a common way games provide feedback on players’ in-game actions. Other types of feedback can be more informative and provide explanations for why the player made a correct or incorrect game decision (e.g. Cameron & Dwyer, 2005).

Fourth, *games are responsive*. One of the most critical features of games is that they provide interactive hands-on learning experiences that allow people to learn-by-
doing or to learn by manipulating game elements (Gee, 2005, 2007; Prensky, 2001; Shaffer et al., 2005; Squire, 2006). As stated previously, games respond to gameplaying actions by providing consistent and immediate feedback to players about their in-game performance, and many argue that this is a main advantage of games over conventional instruction for engaging learners (Mayer, 2011, 2014). Additionally, digital technology allows games to be built with various game elements and objects that players can interact with, and the responsiveness of game experiences are expected to facilitate learning experiences.

Last, *games are inviting*. A crucial and intriguing aspect of games is that holistically they are enjoyable and exciting to engage (e.g. Shaffer et al., 2005; Steinkuehler & Squire, 2014). Therefore, learners are motivated to continue to play and learn from the game (e.g. Plass et al., 2015). It is proposed that when compared to traditional instruction such as lectures, worksheets, or any type of in-class activities, the advantage of digital games is that they create a learning environment that is more effective at motivating students to learn the content because of the stimulating features of a game. These features include the challenges, game goals, fantasy elements (e.g. narrative back story, characters, etc.), visual features (e.g. graphical displays of the game environment), acoustics (e.g. background music), and gameplaying interactions (e.g. sparkles appear after you click on something) (Garris et al., 2002; Habgood et al., 2005; Malone & Lepper, 1987). These elements are intended to trigger interest, excitement, and motivational experiences among the players, thus keeping the players engaged while learning the academic content.
**Intrinsically Integrated vs. Extrinsic Games**

Inviting and motivating educational games are typically intrinsically integrated games (Habgood et al., 2005; Habgood & Ainsworth, 2011), or endogenous games as referred to in other frameworks (Squire, 2006). These types of games intrinsically combine the fantasy elements from the game environment with the instructional content that is being presented in two major ways (Habgood & Ainsworth, 2011; Malone, 1980; Malone & Lepper, 1987). First, intrinsic games “deliver learning materials through the parts of the game that are most fun to play” (Habgood & Ainsworth, 2011, p. 173). However, by merely embedding the instructional content into the most entertaining aspects of the gameplay does not guarantee that the content is essential to play the game.

The second core component of intrinsic games addresses this potential disconnect by emphasizing that these games should “embody the learning material within the structure of the gaming world and the player’s interactions with it, providing an external representation of the learning content that is explored through the core mechanics of the gameplay” (Habgood & Ainsworth, 2011, p. 173). This design element requires that there is interdependence between the learning material and the game experience, so that the content to be learned depends on the player executing the appropriate game mechanics, and the game mechanics can only be properly executed if players have learned the targeted content (Habgood et al., 2005; Malone, 1980). Interdependence between the learning and game experience is created by requiring the subject matter (e.g. build a wet-cell battery) to be related and essential to the game goals (e.g. open a door to navigate to other parts of the game environment).
When players engage in the gameplay of an intrinsically integrated design, changes in the game experiences are only possible if the player demonstrates learning the content beyond an established performance standard. On the other hand, the instructional content within the game can only be accessed and learned by executing appropriate game actions. When there is a disconnect between the learning goals and the game goals, the learning activity can be replaced by any other content and this disconnect will diminish the intrinsic relationship between the learning and game experiences.

Intrinsically integrated educational games are designed to trigger intrinsic motivation to learn the targeted content and to provide a flow experience throughout the gameplay (Habgood et al., 2005). Intrinsic motivation refers to a person engaging in an activity for the sake of the activity itself and not for external rewards (Ryan & Deci, 2000). A person’s sense of flow can be described as a rewarding, subjective, pleasurable state that is reached when there is an optimal balance between challenges faced and the person’s capacities (Csikszentmihalyi, 2014). When an individual is in flow, he will experience intense and focused task concentration, perceive he is exerting optimal effort, sense a distortion of time, and experience the activity as intrinsically rewarding (Csikszentmihalyi, 2014).

The motivational experiences created by intrinsically integrated educational games will, in turn, initiate an increase in effort, persistence, and subsequent learning gains in the player. Although digital educational games are often designed with external rewards (e.g. points, feedback that indicates success or failure), for players engaged in intrinsically integrated games in particular, these external rewards are not viewed as the
main motivator to continue learning through the gameplay. Instead, those who play an educational game for intrinsic purposes are motivated by gaining the underlying knowledge and skills needed to execute the core game mechanics and complete the game goals.

Research has shown that intrinsic games that trigger flow experiences fuel players’ intrinsic motivation to learn the content encountered throughout game interactions (Bachen et al., 2016; Barab et al., 2012; Chang et al., 2012). For instance, *Plague: Modern Prometheus*, can be characterized as an intrinsically integrated game, in which players can only learn about persuasive writing by completing the game tasks (Barab et al., 2012). Compared to non-game lecture-based writing instruction, students who played *Plague: Modern Prometheus* had significantly more learning gains, higher levels of flow, and experienced greater enjoyment while learning about writing (Barab et al., 2012). Furthermore, 65% of the game-based group stated that they completed the game because they enjoyed the activity itself, while 95% of the lecture-based group stated that they completed the activity to get a good grade or because it was required by their teacher. Barab and colleagues (2012) study demonstrated that when instructional content is seamlessly integrated within game interactions, players are more likely to enter a state of flow, enjoy the learning process, and learn the targeted subject matter by completing the game goals. See Table 1 for a comparison between intrinsically integrated games and extrinsic games on core components and motivational outcomes.
Table 1

Core Components and Motivational Outcomes of Intrinsically Integrated Games Compared to Extrinsic Games

<table>
<thead>
<tr>
<th>Core Components</th>
<th>Intrinsically Integrated Games/Intrinsic Games</th>
<th>Extrinsic Games</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning experiences</td>
<td>Learning experiences occur through the fun parts of the gameplay.</td>
<td>Learning experiences are inserted into the gameplay.</td>
</tr>
<tr>
<td>Instructional content is related and essential to the game goals, and learning the content depends on the player executing the main game mechanics.</td>
<td>Instructional content is not related and essential to the game goals and learning the content does not depend on the player executing the main game mechanics. Instead, learning occurs typically through completing isolated tasks that do not require the core game mechanics.</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Motivational Outcome</th>
<th>Intrinsically Integrated Games/Intrinsic Games</th>
<th>Extrinsic Games</th>
</tr>
</thead>
<tbody>
<tr>
<td>Triggers intrinsic motivation.</td>
<td>Triggers extrinsic motivation.</td>
<td></td>
</tr>
<tr>
<td>Creates a sense of flow.</td>
<td>Disrupts the sense of flow.</td>
<td></td>
</tr>
<tr>
<td>Player is motivated by gaining the underlying knowledge and skills needed to complete the game.</td>
<td>Player is motivated by gaining external rewards throughout the game.</td>
<td></td>
</tr>
</tbody>
</table>

In contrast to intrinsically integrated games, extrinsic games, or exogenous games as referred by other scholars (Squire, 2006), demonstrate a disconnect between the learning content presented in the game and the core game play experiences (Habgood et al., 2005; Habgood & Ainsworth, 2011). These types of games are commonly viewed as sugar-coated games, or ‘chocolate covered broccolis’, in which the instructional material is inserted into the gameplay as discrete and isolated learning experiences (Habgood et
al., 2005; Ke, 2015; Klopfer et al., 2009). Often, the game has isolated quizzes or drill and practice activities embedded between other game experiences, and only if players complete the learning tasks can they progress in the game. Additionally, in extrinsic games, the instructional content is not related or essential to the game goals and can be replaced by any other learning content. In this sense, the gameplay can be viewed as a reward for completing the educational tasks throughout the game. Unfortunately, extrinsic designs lead players to view the game challenges and goals as the fun elements of the experience, and in contrast, they will view the educational tasks as the cognitively demanding and less fun aspects of the game.

Extrinsic games are expected to trigger extrinsic motivation and a lack of, or disrupted, flow experience (Habgood et al., 2005; Habgood & Ainsworth, 2011). Extrinsic motivation refers to being solely motivated by external rewards to the task such as points, performance indicators, prices (Ryan & Deci, 2000). When players are extrinsically motivated to play an educational game, the main motivators that keep them engaged are the external stimuli, such as the points and rewards that players get after completing the isolated learning tasks, and less attention is directed at learning the knowledge and skills delivered through the game. Within these games, players may be compelled to engage in trial and error to complete the learning task or use cheating strategies to take short cuts to gain more rewards. Additionally, in extrinsic games, flow is often disrupted, as players are directed to switch between the game environment and the learning task that lacks relevance to the play experience (Habgood et al., 2005). On one hand, some players may view the game elements as unnecessary or as a barrier to the
learning process. On the other hand, others may view the learning tasks as disruptions to the fun game experience. One of the reasons why early edutainment games (e.g. “Math Blasters”, “Reader Rabbit”) failed to sustain students’ interest in playing and learning from the game is because they were extrinsically designed, and they heavily relied on packaging drill-and-practice activities within fantasy themes, flashy sounds, game points, and animation (Games & Squire, 2011; Ito, 2007).

Intrinsically integrated games have been found to lead to more learning gains and greater intrinsic motivation than extrinsic games. In Habgood and Ainsworth’s (2011) research, 3rd-4th graders either played an intrinsic or extrinsic version of Zombie Division, which is a game that teaches mathematics (i.e. division, prime factors, integers, etc.) by fighting cartoonish skeleton zombies in a castle. The game goal is for the player to escape the castle, and the core game mechanic is to control an avatar to defeat the skeleton zombies that are blocking the way at each level. In the intrinsic version of the game design, each skeleton has a number on its chest that serves as a dividend. The player must fight these skeletons by using attacks represented by different numbers that serve as divisors (e.g. 2 is a stabbing action, 3 is a punch). Skeletons can only be defeated if the dividend on their chest is divided into whole parts, and each successful attack will split the skeleton into equal size portions that represent the quotient. Through the game mechanics, students were expected to learn division by dividing the skeletons into whole numbers with the player’s choice of divisor, and the in-game feedback on whether the divisor selected was appropriate to successfully defeat the skeletons.
In the extrinsic version of the game, the attacks were changed to weapon symbols and were not represented by numbers as divisors. The skeletons had attack symbols on their chests instead of the dividends. Moreover, after each successful attack, the skeletons did not split into the quotient but instead merely disappeared. At the end of each level, players received a multiple-choice quiz with division problems, and students were expected to become familiar with the mathematical content by completing the quiz. If they correctly completed the quiz, they advanced to the next game level.

Across two studies, Habgood & Ainsworth (2011) found that 7-year-old students, who only played for two hours, learned more math from the intrinsic version of the game than the extrinsic version of the game before receiving a teacher-led reflection on the math content targeted in the game. Further, after the posttests in the study were concluded, students were asked to choose the game they wished to continue playing. Those who chose the intrinsic version spent seven times longer playing than those who chose the extrinsic version.

**The Effects of Games in Education**

Several meta-analyses revealed evidence that playing digital educational games is more effective at promoting learning outcomes than conventional non-game instruction (e.g. Clark et al., 2016; Mayer, 2014; Vogel et al., 2006; Wouters et al., 2013; Wouters & Van Oostendorp, 2013). For instance, the meta-analysis conducted by Wouters et al. (2013) included 39 empirical studies with students from all age groups and found that educational games lead to greater learning than conventional instruction (e.g. lectures,
reading, drill and practice) in students’ knowledge \((d = 0.27)\) as well as cognitive skills \((d = 0.29)\). Clark et al. (2016) also compared digital game to non-game conditions (e.g. traditional classroom activities such as problem-solving activities) in 69 studies with K-16 students and found greater cognitive learning in the game conditions \((g = 0.35)\). Cognitive learning was defined as cognitive processes, strategies, knowledge, and creativity (Clark et al., 2016). In Mayer’s (2014; 2019) systematic review of 16 rigorous empirical studies, he also found that computer games designed for learning were more effective at improving learning of academic material than conventional media. Specifically, he reported that the most-studied discipline was science (12 out of 16 experiments, \(d = 0.7\)), however, games that were designed to promote second language learning (4 out of 5 experiments, \(d =1.0\)) had the largest effects on learning outcomes.

Digital games in education have also been found to lead to greater achievement motivation, including intrinsic motivation (Habgood & Ainsworth, 2011), flow (Barab et al., 2009), enjoyment of the game (Barzilai & Blau, 2014), and situational interest (Rodríguez-Aflecht et al., 2018). However, in Wouters et al.’s (2013) meta-analysis, they reported greater motivational gains in games compared to conventional instruction, but the difference was not significant \((d = 0.26, p > .05)\). The researchers raised the concern that the studies included in their meta-analysis did not all adopt games with an intrinsically integrated design, and thus the overall effects of games on motivational outcomes were limited.

A recurring issue in the game-based learning literature is that scholars inconsistently identify whether the game(s) under investigation are intrinsically
integrated games or extrinsic games. Therefore, it is difficult to classify which studies fall under the intrinsic integrated games framework and also to synthesize the findings on intrinsic games. Extrinsic games may be more effective at promoting learning outcomes than conventional instruction. However, in accord with the intrinsically integrated games framework, extrinsic games have an inferior design since the learning content is disconnected from the gameplay, and the gameplay merely serves as digitalized packaging for the learning tasks (Habgood et al., 2005; Habgood & Ainsworth, 2011). When the gameplay in extrinsic games can be replaced by any other digital task, learners will more likely view the game experience as unnecessary and perhaps as a barrier for the learning process, and less likely be motivated to learn the academic content during the game. In contrast, intrinsic games are proposed to have the superior design because they deliver relevant and essential instructional content through core game mechanics. Therefore, when compared to extrinsic games, intrinsically integrated games are more likely to promote learning and motivational outcomes. Hence, it is important for scholars to critically examine the design of the game they are investigating and adjust their claims about the effects of the game based on whether it has an intrinsic or extrinsic design.

**Digital Games as a Preparatory Activity**

Digital games used in education can be integrated into existing instructional practices in three major ways. Games can either be (1) designed to deliver the learning materials solely through the gameplay (e.g. *Cache 17* directly teaches Physics within the game; Pilegard & Mayer, 2015), (2) given after a lesson for students to review or to
practice the learning content (e.g. *Orbis Pictus Bestiais* is given after a lecture on animal learning; Brom et al., 2011), or (3) administered before a lesson to be used as a preparatory activity to help students become familiar with the subject matter and prepare them to learn from subsequent conventional instruction. The statistics game used in this study, *Stats Invaders*, is designed as a preparatory activity that exposes students to concepts of probability distributions before formal instruction and prepares students to learn from subsequent reading materials (Arena & Schwartz, 2010; 2014).

According to the Preparation for Future Learning framework (PFL; Bransford & Schwartz, 1999), preparatory activities such as Stats Invaders are not designed to provide explicit instruction on the targeted concepts. Instead, they are expected to provide pre-instructional experiences to familiarize students with the academic content before engaging in formal instruction. Preparatory games are not intended to replace conventional instruction, rather, they are designed to supplement formal instruction, by providing learners with concrete analogies of abstract concepts via the gameplay before formal learning. In the case of statistics, through the simplistic, yet interactive game mechanics of Stats Invaders, players are expected to become familiar with different types of distributions and their properties from the game, which will help them comprehend statistical concepts from the subsequent reading materials. In Arena & Schwartz’s study (2014), students who played the game before reading a subsequent statistics passage had greater statistical knowledge of distributions than students who only read the passage or only played the game. Their study indicated that playing the game facilitated students’ comprehension of the following passage. However, the effects of Stats Invaders have
only been tested in one study and future investigations into the extent students may benefit academically from this game are warranted.

**Alternative Ways to Learn From Games**

There is ecological evidence from the entertainment game industry to show that individuals learn a great deal from watching others play games. Over the past decade, there has been a dramatic increase in digital media content creation and consumption on platforms such as YouTube & Twitch (Hamari & Sjöblom, 2017), and game videos are one of the most popular types of videos created and consumed (Sjoblom et al., 2019). For instance, Twitch, a live streaming platform that predominantly broadcasts live gameplay of commercial games, attracts more than 2.5 million unique viewers per day (Twitch Tracker, 2020). Studies have found that many Twitch streamers are professional gamers and they often demonstrate exemplar game playing behaviors while verbalizing their thought processes and strategies they use when engaged in the gameplay (e.g. Sjoblom et al., 2019). Recent survey studies that examined why individuals watch others play commercial games reported that the leading motivators are to acquire knowledge about the game mechanics, explore the game content, experience enjoyment, and release tension (Hamari & Sjöblom, 2017; Kaytoue et al., 2012; Sjöblom & Hamari, 2017).

In the academic setting, playing digital educational games has been found to be an effective instructional strategy for promoting achievement outcomes (Wouters et al., 2013). However, instructional practices that solely allow students to play games might not be the only way for students to experience meaningful gains in knowledge and
motivation. There is ecological and empirical evidence to speculate that students might not necessarily need to directly play the game to benefit academically, and that merely observing someone else play might also lead to rewarding outcomes. The main purpose of this dissertation is to investigate whether the effects of watching others play a statistics game will lead to similar or more beneficial outcomes when compared to playing the game directly. The following section provides theoretical support to show that students could learn from games enactively by playing the game as well as vicariously by observing a model play.

**Social Cognitive Theory**

Social Cognitive Theory (SCT) explains how we learn new cognitive processes and behaviors by interacting with the environment (Bandura, 1986, 1997; Schunk, 2012; Schunk & Usher, 2012). The triadic reciprocality framework in SCT highlights one of its fundamental principles, that our personal characteristics (e.g. cognition, motivation, affect), behaviors (e.g. decisions we make, effort, performance), and environment (e.g. physical resources, stimuli, context) constantly interact to influence what we learn (Bandura, 1986, 1997; Schunk, 2012). At any given time, one factor may predominate and be the sole influence on another factor. Much of the time, however, multiple factors jointly shape a person’s learning processes.

To illustrate how this framework operates in a real-world context, the interactions among a statistics student’s knowledge, statistics self-efficacy (i.e. one’s beliefs in implementing actions to meet a certain standard), interest, performance, and achievement
behaviors can be used as an example. A student with high self-efficacy in statistics (personal) and high interest in statistics learning activities (personal) is likely to engage in more difficult problems (behavior), persist longer (behavior), and exert more effort (behavior) to complete statistics tasks in the future. These positive achievement behaviors are likely to result in this student gaining knowledge and skills (personal), which will be reflected in his or her statistics performance (behavior). In turn, high statistics performance is likely to be rewarded with teachers’ or parents’ praise (environment) or a high grade on a statistics test (environment). Positive achievement feedback (environment) will likely lead to this student to feel more confident in learning statistics (personal) and to be more willing to engage in effective achievement behaviors in the future (behavior). As demonstrated, personal, environmental, and behavioral factors impact one another to influence learning outcomes in the context of statistics education.

It is important to note that learning and performance is differentiated within SCT (Bandura, 1986, 1997; Schunk, 2012; Schunk & Usher, 2012). Learning specifically refers to gaining new knowledge or skills, whereas performance refers to demonstrating previously learned behaviors. According to SCT (Bandura, 1986, 1997; Schunk, 2012), learning occurs either enactively from direct personal experiences (learning-by-doing), or vicariously from observing other peoples’ experiences (learning-by-observing). Much of human learning occurs from vicarious experiences, and we do not always perform what we have learned unless we are motivated to do so (e.g. due to factors such as interest, incentives, perceived need to perform, social pressure, etc.). However, our performance most likely will reflect what we have learned, given that the assessment of learning is
valid and reliable. Although SCT highlights the importance of enactive learning, vicarious learning has been a central focus.

**Enactive Learning**

Enactive learning refers to learning from the consequences of one’s actions (Bandura, 1986, 1997; Schunk, 2012; Schunk & Usher, 2012). Successful actions are typically retained and will be performed again in the future, whereas unsuccessful actions are refined or discarded. SCT emphasizes the role personal factors play in processing the behavioral consequences that are experienced from the environment (Bandura, 1986, 1997; Schunk, 2012). The behavioral consequences inform and motivate learners by influencing personal factors such as cognition (e.g. knowledge and skills) and motivation (e.g. self-efficacy and interest). If an action is successful, this tells us that we are doing something accurate and appropriate, we interpret this information as we are learning and performing well according to the given standards, then we will be motivated to continue to perform the same behaviors or more effective behaviors. If an action is unsuccessful, this tells us that we are doing something wrong and we are not learning the targeted content and are performing poorly, so we will be motivated to stop this behavior or correct it until it results in success.

**Enactive Learning From Games.** One of the main arguments made by game researchers regarding the advantages of games over traditional instruction is that they allow for students to learn academic content by interacting with game elements (e.g. learning-by-doing), or through enactive learning from the lens of SCT. Based on SCT
(Bandura, 1986, 1997; Schunk, 2012), gameplaying actions could be either successful or unsuccessful, but regardless, they will lead to feedback on in-game performance, which will inform and motivate the player to either continue with the same game behaviors or discontinue and revise her game strategy. More specifically, successful gameplaying behaviors will result in positive in-game feedback (e.g. more scores, advance to the next level), that will indicate that the player is learning from the game, and this will motivate the player to continue to use the same game mechanics. If a player makes errors in the game, this will result in negative feedback (e.g. reduction in scores, failed a level), this will reflect that the player is not gaining the targeted knowledge or skill as intended from the game, and the player will be motivated to stop using the game mechanic and switch to a different game tactic. See Figure 1 for a visual overview of how players learn from games enactively based on SCT using the game mechanics in Stats Invaders as an example.

**Figure 1**

*Visual Overview of How Players Learn Enactively From Games*
Vicarious Learning

Vicarious learning refers to learning-by-observing the thoughts, beliefs, strategies, and behaviors of others (Bandura, 1986; Schunk, 2012; Schunk & Hanson, 1985; Schunk & Usher, 2012; Schunk & Zimmerman, 2007). According to SCT, humans learn a great amount indirectly through vicarious experiences. Vicarious experiences accelerate our learning, because they relieve us from directly experiencing the consequences of each environmental interaction, and they especially prevent us from engaging in many harmful outcomes. For instance, a student who has observed another student receive punishment for shouting in class is likely to not shout in class to avoid the same punishment.

We learn vicariously mainly by observing models. Similar to the functions of behavioral consequences during enactive learning, the models’ behavioral consequences during vicarious observations serve as a source of information and motivation for the observer (Bandura, 1986; Schunk, 2012; Schunk & Hanson, 1985; Schunk & Usher, 2012; Schunk & Zimmerman, 2007). Information that the model exhibits should be organized and meaningful, so that the observer can accurately attend to and understand it. Models may explain and demonstrate how to complete an academic task. Typically, observers are most likely to remember and imitate behaviors that were seen reinforced, and they are most likely to inhibit reproduction of behaviors that were seen punished.

There are many different types of models that we encounter in our social environments or through virtual platforms, such as physical models (e.g. teachers, parents, peers) and symbolic or nonhuman models (e.g. cartoons, pedagogical agents). Models’ characteristics are a crucial aspect of vicarious learning. The characteristics of
the model can vary based upon many factors, including physical appearance (e.g. age, gender, ethnicity), level of competence (e.g. expert versus novice), type of knowledge or skill being modeled (e.g. conceptual or procedural), who is serving as the model (e.g. a teacher, a student), and the type of performance being demonstrated (i.e. coping or mastery) (Bandura, 1986; Schunk, 2012; Schunk & Hanson, 1985; Schunk & Usher, 2012; Schunk & Zimmerman, 2007). These characteristics could influence observers to perceive the model as either trustworthy, similar to themselves, or prestigious based on expertise. For instance, models that demonstrate high levels of expertise attract more attention because observers think that they can learn more accurate information from competent models than incompetent models (Schunk, 2012). Expertise can be reflected by flawless performance of a mastery model (Schunk & Hanson, 1985, 1989; Schunk et al., 1987).

**Mastery Models.** Mastery models exhibit exemplar performance and express positive perceptions of their learning experiences throughout the task, such as statements reflecting high self-efficacy (e.g. “I am sure I can successfully complete this statistics activity”), high ability (e.g. “I am good at completing this statistics activity”), low task difficulty (e.g. “This statistics activity is easy”), and positive attitudes (e.g. “I like learning from and completing this statistics activity”) (Bandura, 1986; Schunk & Hanson, 1985, 1989; Schunk et al., 1987). Mastery models are often contrasted with coping models. At the beginning of an academic task, coping models struggle, make errors, and express negative achievement beliefs that reflect low self-efficacy (e.g. “I cannot succeed on this statistics activity”), low ability (e.g. “I am bad at this statistics task”), high task
difficulty (e.g. “This statistics activity is too hard for me”), and negative attitudes towards completing the task (e.g. “I do not like learning from and completing this statistics task”). However, as coping models make progress in the task, they improve in their competence and eventually reach flawless performance identical to the mastery models, and state positive achievement beliefs as well.

The advantages of mastery models are that they display high competence and flawless behaviors while demonstrating how to successfully learn from and perform the task (Schunk & Hanson, 1985; Zimmerman & Kitsantas, 2002). Observers are most likely to attend to actions that have functional value, and mastery models’ successful behaviors demonstrate high value for observers to retain, because they will most likely believe that if they produce similar behaviors, they too will succeed on the task. Thus, compared to a coping model, observers are more likely to attend to a mastery model for learning appropriate and accurate knowledge and behaviors if they want to perform well.

**Vicarious Learning From Games.** One of the main questions of this current research is: do students learn more statistics and become more motivated to learn statistics after observing a model play a game in comparison to playing the game themselves and conventional instruction? To answer this question, the present study contrasted the effects of enactive learning to vicarious learning from the game and adopted a peer mastery model to play a digital statistics game in the vicarious learning condition for two primary reasons. First, mastery models most resemble professional gamers that viewers in the entertainment game industry attend to and learn from the most. Second, mastery models will demonstrate successful game behaviors and show viewers
how to accurately learn from the game, and this is likely to help viewers learn from the
game as well.

According to the SCT (Bandura, 1986), humans may learn enactively from their
own behavioral consequences, as well as vicariously from observing models performing
certain behaviors, experiencing the consequences of those behaviors, and verbally
explaining their thought processes. Therefore, it can be expected that models who explain
and demonstrate successful in-game performance will inform and motivate observers as
well. Specifically, models’ successful game playing behaviors that lead to learning of the
targeted content have functional value, and observers will likely attend and retain these
behaviors if they also want to succeed in learning from the game. See Figure 2 for a
visual overview of how viewers learn from games vicariously based on SCT. The game
mechanics in *Stats Invaders* was used in this overview.

**Figure 2**

*Visual Overview of How Viewers Learn Vicariously From Games*
Research on the impact of learning-by-observing others play digital games in education is scarce (Law et al., 2010). To date, only one study attempted to examine the effects of vicarious learning from a game. Specifically, Law and colleagues (2010) examined the effects of watching someone else play a digital game on eye gaze patterns and cognitive outcomes. Twenty-four college students each viewed a video of a 12-year-old play a learning game. However, participants did not see the model’s face or hear the model’s voice. They only viewed a video of the gameplaying behaviors. They were asked to watch the video as if they were playing the game themselves. The researchers reported a significant increase in conceptual learning after students had viewed the recording of someone’s gameplay. However, the instructional video in their study did not explicitly include a model that is visibly present. To directly test the effects of observing a model play a game on achievement outcomes, further research is needed to examine whether showing the model’s face while giving verbal explanations of her in-game behaviors also enhances learning and motivation.

Critical Factors in Statistics Education

The main goal of this dissertation was to examine the impact of vicarious learning from a digital statistics game compared to enactive learning and non-game conventional instruction on factors critical to college students’ statistics education. The three factors that were examined as outcome variables included statistical knowledge, statistics self-efficacy, and situational interest.
**Statistical Knowledge**

Students conceptual knowledge of the properties of probability distributions (e.g. center, spread, shape) was examined in this study, which was also the content delivered through the digital game, *Stats Invaders*. How to accurately interpret a distribution of data is one of the first topics introduced in first-year statistics courses. A solid conceptual understanding of distribution properties is fundamental to learning advanced statistical concepts such as statistical inference (Ben-Zvi et al., 2017). However, many students struggle with learning the basic properties of distributions. For instance, students often fail to see the overall shape of distributions when graphing frequency tables (Garfield et al., 2008c). They also have difficulties understanding how data are aggregated underneath the distribution curve and how data can be represented by different distribution shapes (Garfield et al., 2008c). Therefore, it is important for students in introductory courses to receive effective instruction on identifying and interpreting the components of a distribution.

**The Effects of Games on Learning Statistics.** Prior research has found positive effects on achievement outcomes when adopting games in statistics education. For instance, digital games have been found to enhance college students’ knowledge of factorial design (Stansbury & Munro, 2013), statistical thinking about data collection (Bottino et al., 2007), scientific reasoning and argumentation skills (Strom & Barolo, 2011), understanding of expected value (Chow et al., 2010). As aforementioned, Arena & Schwartz (2014) found that students who played *Stats Invaders* reported more gains in conceptual knowledge of probability distributions than those who did not play but
completed a reading activity. However, other instructional methods for using games (e.g. vicariously learning) were not examined in their study.

Unfortunately, compared to research on the effects of digital games in other disciplines (e.g. science, business, language learning), studies on digital games in statistics education are lacking in terms of quantity as well as rigor. Boyle et al. (2014) conducted a narrative literature review of games, animations, and simulations for teaching statistics. Among the 26 articles that were included in the review, only 10 of the papers investigated the effects of digital games in teaching statistics. Five were quantitative studies (Ancker et al., 2011; Chow et al., 2010; Halpern et al., 2012; Nte & Stephens, 2008; Stansbury & Munro, 2013), three were qualitative studies (Barab et al., 2012; Ramler & Chapman, 2011; Steinkuehler, 2008), and two had a mixed-methods design (Asbell-Clarke et al., 2012; Bottino et al., 2007). The trends in the qualitative studies show that the majority of college students perceive entertainment games (e.g. Dance Dance Revolution, Guitar Hero) and serious games (e.g. Operation Acquiring Research Acumen) as beneficial for their learning in statistics courses (Boyle et al., 2014). According to the quantitative and mixed-methods studies in their review, students who played a game generally had higher learning gains in statistical knowledge and thinking skills than those students in control groups who did not play the game.

Other reviews that had more rigorous inclusion criteria included none or few studies that examined statistics games. For instance, Wouters et al. (2013) included 39 studies in their meta-analyses and none were in the domain of statistics; Connolly et al. (2012) reviewed 129 papers, and only included one study in statistics (Nte & Stephens,
2008); Ke (2009) conducted a qualitative review of 89 papers, none in statistics. Overall, the gaps in the current literature clearly show that more empirical research on the effects of games designed to promote statistics learning is needed.

**Statistics Self-Efficacy**

Statistics self-efficacy can be defined as one’s perceptions of his or her capabilities to successfully solve statistics tasks (i.e. current statistics self-efficacy) or to learn the necessary knowledge and skills to complete statistical problems (i.e. self-efficacy for learning statistics; Finney & Schraw, 2003). Self-efficacy directly impacts a range of factors critical to one’s academic achievement, including motivation (i.e. choices, effort, and persistence), learning outcomes, self-regulation, and academic performance (Bandura, 1997; Schunk & DiBenedetto, 2016; Schunk & Usher, 2012; Pajares, 1996; Usher & Pajares, 2008). Those who have high self-efficacy are likely to choose to engage in challenging tasks, persist longer in the task when faced with obstacles, exert more effort at completing the task, and are more likely to utilize effective self-regulation and strategies to enhance learning (Zimmerman, 2000). Additionally, statistics self-efficacy in particular has been found to be positively related to math self-efficacy, attitudes toward statistics, achievement goals, overall performance in an introductory statistics course, and negatively correlated with statistics test anxiety (Finney & Schraw, 2003; Zare et al., 2011).

Self-efficacy is domain- and task-specific (Bandura, 1977; Pajares, 1996; Usher & Pajares, 2008). Students’ self-efficacy can vary across domains. For instance, a student
might have high confidence in learning biology or performing academic tasks in biology, but not in statistics. Within a domain, self-efficacy can vary across tasks. For instance, in statistics, a student could be efficacious in her competence to calculate a mean but not a t-test statistic. Therefore, when measuring self-efficacy in a particular domain, a range of items tailored to domain-specific tasks (e.g. identify a positively skewed distribution) will lead to more accurate estimates of one’s self-efficacy in that subject, than items that are domain-general (e.g. complete a calculation problem) (Pajares, 1996).

Students gather and process information about their self-efficacy in achievement situations from four sources (Bandura, 1997; Schunk, & DiBenedetto, 2016; Usher & Pajares, 1996; Zimmerman, 2000). The most direct, powerful, and reliable source of self-efficacy is from students’ direct performances in the past. Students interpret their performance after completing an academic task and make judgements about their competence against a pre-set standard. If a student appraises his efforts as successful, then his self-efficacy to succeed on the same or similar tasks in the future rises; if a student believes his efforts did not lead to the desired result, then his self-efficacy in succeeding on this task in the future will diminish. Self-efficacy gained from past mastery experiences has strong effects on future task performance, because past success reflects high competence in learning or performing a specific task. Students who have succeeded in statistics in the past will likely believe that they can succeed in statistics in the future, because they perceive themselves as highly competent in this particular subject.

Another powerful influence on self-efficacy is vicarious experiences that occur by observing others. Students often make social comparisons by judging their capabilities
against the performance outcomes of others, such as their peers. Observing a peer succeed can increase observers’ self-efficacy because they will believe that they too can succeed on the task. Observing a peer fail is likely to decrease the observers’ self-efficacy because they will believe that the task is difficult, and they are likely to fail as well.

Students also acquire information about their perceived competence from social and verbal persuasion. For instance, praise, encouragement, and positive feedback from others whom students trust can influence their confidence in their capabilities, whereas criticism will likely lead to doubts in their confidence. However, such social messages are only effective at impacting self-efficacy if they are believable and show that success is attainable. The final source of self-efficacy beliefs comes from students’ emotional and physiological experiences such as stress, fatigue, anxiety, and other emotional states. If a student experiences fear or high anxiety when performing a task, this indicates that she might have low competence which translates to low confidence in succeeding on the task.

The Effects of Games on Self-Efficacy. Games that are designed for educational purposes have been viewed as highly interactive technological tools that have strong potential to enhance learning outcomes throughout the game, and are hypothesized to lead to an increase in self-efficacy in the targeted subject matter (Hoffman & Nadelson, 2010; Sitzmann, 2011). Specifically, as aforementioned, one of the most advantageous features of educational games over traditional instruction is that all games provide immediate feedback on in-game performance, which usually reflects whether the player is learning the material through the game mechanics (Mayer, 2011, 2014). As players advance in the game, it is expected that they will gain new knowledge and skills, and thus
the gameplay feedback serves as a source of information about their learning and performance.

Studies have found that players perceive an increase in their competence when they experience in-game achievement or gradual progression through difficult tasks during gameplay (Hoffman & Nadelson, 2010). Hoffman & Nadelson (2010) conducted interviews with 25 undergraduate frequent gamers (i.e. played video games for more than 5 hours a week) to explore factors contributing to their motivational engagement when they played commercial video games. A key finding of their qualitative analysis revealed that most participants will gain a heightened sense of self-efficacy in completing the game after they overcome game challenges. Additionally, the increased confidence in their gameplaying abilities is one of the main motivators for them to reengage in the game. These findings could also apply to college students playing an educational game and it can be expected that as students gain more knowledge by advancing through the game obstacles, they will also gain a greater sense of self-efficacy in the learning content.

Previous studies have found gains in self-efficacy, such as in science (Meluso et al., 2012) and math (Bai et al., 2012), after playing a digital educational game. However, when comparing gameplaying experiences with other instructional approaches or conventional instruction, the effects of games on self-efficacy is less clear. A meta-analysis by Sitzmann (2011) found that serious simulation games used in educational and non-educational contexts lead to greater learning outcomes and higher training self-efficacy when compared to conditions that did not receive any game training or received alternative instruction. Training self-efficacy was conceptualized as trainees’ confidence
that they have learned the materials or have successfully performed tasks relevant to the game training. Specifically, the findings showed that trainees in the game group gained more declarative knowledge \((d = 0.28)\) and procedural knowledge \((d = 0.37)\), and performed better on retention measures \((d = 0.22)\). Moreover, trainees’ self-efficacy overall was also 20% higher than those in the comparison group and further, showed a larger effect than for learning outcomes \((d = 0.52)\). In contrast, a study by McLaren et al. (2017) later found gains in middle school students’ math self-efficacy after they played a game to learn decimals, however, the gains were not significantly higher than those in the non-game control group.

The effects of games on promoting statistics self-efficacy is currently understudied. Furthermore, the inconsistent empirical findings from previous research suggestion that it is unclear whether the effects of games on self-efficacy in some academic domains can be applied to all domains. A recent study by Smith (2017) sheds light on the potential of a gamified undergraduate statistics course to promote students’ learning and confidence in their statistics competence. Smith (2017) rigorously gamified three instructional modules within the course using nine game elements (e.g. action language, challenge, control, game fiction, etc.). His study revealed that students enrolled in the gamified course had better homework grades than those in the control course without the gamified instruction. Moreover, those who received the gamified instruction had a moderate increase in their statistics confidence or perceptions of their ability to succeed in the statistics course \((d = 0.37)\). However, due to methodology complications,
no comparisons were made between the gamified and non-gamified courses in statistics
self-efficacy.

**Situational Interest**

Situational interest (SI) is conceptualized as state-like attentional and affective
reactions to elements in the environment (Hidi & Renninger, 2006; Renninger & Hidi,
2011; Renninger & Su, 2012; Renninger et al., 2019). For instance, a student who
engages in the interactive features of a 3D virtual learning environment might experience
heightened enjoyment, excitement, and may attend to the technology-enhanced activity
for a longer period of time than a student who completes a conventional activity that is
paper-based. However, this increased interest is in response to surface features of the
learning context and is short-lived unless more meaningful engagement with the learning
activity is experienced.

Situational interest is often contrasted with individual interest. Individual interest
reflects a trait-like predisposition, in which a person’s level of engagement in certain
objects, activities, and subjects is consistent across contexts (Hidi & Renninger, 2006;
Renninger & Hidi, 2011; Renninger & Su, 2012; Renninger et al., 2019). It also reflects a
willingness to re-engage in certain activities. For instance, a student who is personally
interested in learning statistics will show extra effort in statistics classes compared to
other less interested subjects. Outside of class, this student will likely also show high
levels of engagement with statistical content by watching instructional videos on statistics
topics, for example, and will persist longer and exert more effort on statistics homework.
Individual interest is an enduring and self-driven type of engagement, whereas situational interest is spontaneous, temporary, and triggered by environmental factors.

Situational interest in academic settings influences students’ achievement outcomes in many ways. A student’s interest in the learning context is key to developing individual interest (Linnenbrink-Garcia et al., 2013; Renninger & Hidi, 2011). According to the four-phase model of interest development (Hidi & Renninger, 2006; Renninger & Hidi, 2011; Renninger et al., 2019), interest that is sparked by surface level interactions with the learning environment can later transform into enduring interest in certain subject matter or learning activities that the student carries across academic contexts. For instance, previous research has shown that situational interest in a particular lesson or course predicts individual interest in that subject (Harackiewicz et al., 2008; Linnenbrink-Garcia et al., 2010). Additionally, previous studies have shown that situational interest in learning contexts plays a critical role in influencing what students attend to during the learning processes (Renninger & Hidi, 2011), whether students are motivated to learn (Durik & Harackiewicz, 2003), and whether students are achieving successfully (Rotgans & Schmidt, 2014).

One of the major claims about the advantages of educational games is that they are effective at making the learning experience motivating and engaging (e.g. Mayer, 2014). Specifically, the multifaceted and stimulating design of the game structure and interactions are expected to generate different types of motivation in the learner (e.g. intrinsic motivation, flow, interest, etc.). Therefore, in order to accurately capture the
effects of games on situational interest, it is important to examine how interest is impacted from the gameplay on a finer scale.

A number of theoretical conceptualizations have distinguished between triggered and maintained situational interest (Linnenbrink-Garcia et al., 2010; Linnenbrink-Garcia et al., 2013; Mitchell, 1993). Triggered interest refers to a short-lived increase in attention that is initiated by the learning context, whereas maintained interest refers to learners reacting to the situation with a deeper sense of involvement, affection, and personal connection that leads to more sustained engagement (Linnenbrink-Garcia et al., 2013). A recent instrumentation study further extended this distinction and supported a three-component model of situational interest, consisting of triggered-situational interest (triggered-SI), maintained-situational interest-feeling (maintained-SI-feeling), and maintained-situational interest-value (maintained-SI-value; Linnenbrink-Garcia et al., 2010). Triggered-SI reflects short-lived attentional reactions of learners toward how the learning material is being presented in the instructional environment. This phase of interest does not lead to prolonged engagement with the learning content, and is often initiated by certain instructional design elements (e.g. animated interactions, visuals) that serve as a “hook” to catch learners’ immediate attention (Mitchell, 1993). However, triggered situational interest can lead to maintained interest if the context also allows for more meaningful and personal engagement.

In contrast to triggered interest, when learners’ interest is maintained, they will develop more personal and meaningful connections with the academic content presented through the instructional activity. Linnenbrink-Garcia’s (2010) model distinguished
between maintained interest that centers around affective reactions and interest that is initiated by a sense of value. Specifically, *maintained-SI-feeling* are students’ affective responses, such as fascination, enjoyment, and excitement, toward the academic subject that is delivered through the learning context. Whereas *maintained-SI-value* refers to students’ perception of the subject matter they are learning as useful, important, and applicable to real life. Moreover, it is important to note that their model made a distinction between interest reactions toward the form of instruction, which is reflected by triggered interest, and reactions toward the content of the instructional activity, which is reflected by maintained interest. For instance, according to their model, students could find it interesting to learn from a particular type of instructional practice (e.g. digital games), and not think that it is interesting to learn the subject matter that is being delivered (e.g. statistics).

**The Effects of Games on Situational Interest.** As previously stated, some of the defining features of digital games include challenges, cumulative experiences, game responsiveness, player control, and game fantasy (Mayer, 2011, 2014). These stimulating elements are designed to lead to interactions that will trigger short-term heightened attention toward how the instructional material is presented through the gameplay, which is expected to increase triggered-SI. Furthermore, when students engage in intrinsically integrated games that connect the gaming and learning experiences in meaningful ways, the gameplay is expected to enhance students’ enjoyment in learning the content and lead them to develop a perception that the subject matter is important and valuable to learn. In other words, intrinsic games intend to increase maintained-SI-value and maintained-SI-
feeling beyond interest triggered by contextual factors within the game. It is important for a digital game to not only increase triggered-SI in students, but also maintained-SI-feeling and maintained-SI-value throughout the gameplay. If students experience maintained situational interest when engaged in the game, then they are making personal and meaningful connections with the subject matter and will most likely develop individual interest in learning the subject later.

Unfortunately, previous research has shown that playing games for educational purposes leads to high levels of situational interest as measured on a one-dimensional scale, but it is unclear how games impact interest based on a finer scale and the three-component model in particular (Linnenbrink-Garcia et al., 2010). For instance, Plass and colleagues (2013) adopted the three-component model to examine the impact of different modes of play in a math game on situational interest. They found that competition and collaboration gameplaying modes elicited greater situational interest than an individual gameplaying mode overall but did not, however, differentiate among the influences on triggered-SI, maintained-SI-feeling, and maintained-SI-value. In Rodriguez-Aflechet et al.’s (2018) study, 58% of the students showed maintained situational interest across multiple game sessions as indicated by the high levels of interest reported during each session, while 16% showed triggered but not maintained interest as indicated by high levels of initial interest followed by a decrease in interest. However, the differences between affect-based compared to value-based maintained situational interest was not further distinguished. Nietfeld et al. (2014) asked eighth graders to play one game session of Crystal Island, an adventure narrative game that teaches microbiology knowledge.
Their research found that those who successfully solved the game mystery compared to those who did not were better self-regulated learners and reported higher levels of self-efficacy for science, greater learning gains in microbiology, were less overconfident, and displayed higher levels of situational interest toward the game experience overall. Again, the researchers did not distinguish among different sub-types of situational interest, and it is unclear if gameplaying and learning experiences differentially impacted triggered and maintained interest.

**The Current Research**

The main goal of this dissertation was to examine the impact of learning enactively from a digital statistics game compared to learning vicariously, and to further examine these effects in comparison to conventional instruction on college students’ statistical knowledge, statistics self-efficacy, and situational interest. Statistics education is critical for college students’ personal and professional lives (Ben-Zvi et al., 2017). Digital games in education have been a popular and effective technology integrated into statistics instruction for promoting learning and motivation (Boyle et al., 2014). According to the intrinsically integrated games framework (Habgood & Ainsworth, 2011) and SCT (Bandura, 1986), games that intrinsically connect the learning and game playing experiences allow for students to enactively learn (i.e. learning by playing the game) a subject matter more effectively and to become more motivated to learn than conventional instruction. However, there are multiple ways for students to benefit from
games, and instructional approaches other than having students directly play the game are currently understudied.

This dissertation study filled this gap by investigating the effects of college students observing the gameplay and learning process of a mastery model through an instructional video. There is ecological evidence from the entertainment game industry (Sjöblom & Hamari, 2017) and theoretical support (Bandura, 1986) to suggest that vicarious learning from an educational game (i.e. learning by watching someone else play) will also lead to increased learning and motivation outcomes when compared to enactive learning from the game. Furthermore, to thoroughly examine the effectiveness of vicarious learning from a game (game viewing condition) on critical factors to one’s statistics education, this study compared its effects to learning enactively (game playing condition) and also learning from a non-game conventional activity (control condition).

The following research questions were investigated in this study:

RQ1. Are there differences in college students’ statistical knowledge when they either enactively learn from a game, vicariously learn from a game, or are provided conventional instruction?

Hypothesis #1: It was expected that playing a digital statistics game, Stats Invaders, would lead to higher statistical knowledge than completing a conventional activity. Digital games in education that are designed to intrinsically integrate the gameplaying interactions with the learning content allow for students to process the instructional materials through the game mechanics in more meaningful ways (Habgood & Ainsworth, 2011). Furthermore, as learners encounter content through executing core
game mechanics, they experience rewarding or punishing game consequences that inform and motivate their in-game behaviors (Bandura, 1986). \textit{Stats Invaders} is designed to be an intrinsically integrated educational game, and prior research indicated that enactively learning from intrinsic games leads to better learning outcomes than non-game instructional methods (Boyle et al., 2014). Therefore, this study expected to replicate prior findings of the positive effects of games on learning outcomes over conventional instruction.

Hypothesis #2: It was expected that students observing a model play \textit{Stats Invaders} in the game viewing condition would outperform the control condition in statistical knowledge. Although prior research has yet to compare the impact of learning vicariously from a game with conventional instruction, there is empirical and theoretical support to propose that observing a mastery model play an educational game will yield better learning outcomes. Self-report evidence from prior studies indicates that individuals can learn game mechanics and content from watching professional gamers play commercial games (Hamari & Sjoblom, 2017). Furthermore, based on SCT (Bandura, 1986), students often learn vicariously from models’ behavioral consequences across many academic contexts, and it was expected that the effects of vicarious learning would apply to observing models playing educational games as well. Specifically, it was hypothesized that students who observed a mastery model play \textit{Stats Invaders} would learn the statistical content targeted in the game. Viewers would vicariously experience the model’s in-game behavioral consequences and listen to her verbalize in-game decisions, thus gaining information about how to appropriately execute the game
mechanics to learn the content. Given that intrinsically integrated games are designed to be more effective at promoting learning than conventional instruction, students who observed a mastery model successfully play and gain knowledge from an intrinsic game were expected to vicariously learn the content through the game mechanics.

Hypothesis #3: It was expected that there would be no differences in statistical knowledge between learners in the game viewing and game playing conditions. It was hypothesized that students would learn as much by watching a mastery model play Stats Invaders as directly playing the game themselves. In both conditions, students would experience behavioral consequences from the game, either vicariously, or enactively, and both would inform students’ statistical knowledge. The game mechanics and targeted content in Stats Invaders are straightforward and easy to acquire, thus learning experiences between the two game conditions should not be affected by game complexity. Players are only required a minimal level of engagement to advance in the game (e.g. select an attack-pattern button) and become familiar with properties of probability distributions (e.g. recognize the shape of the distribution that is generating the aliens’ attack). When students viewed a mastery model perform flawless gameplay and gain familiarity with the statistical content, they were expected to easily attend to all the game elements and vicariously have the same learning experience as if they were learning by playing the game themselves.

RQ2. Are there differences in college students’ statistics self-efficacy when they either enactively learn from a game, vicariously learn from a game, or are provided conventional instruction?
Hypothesis #4: It was expected that playing *Stats Invaders* would lead to higher statistics self-efficacy than conventional instruction. Although mixed findings have been reported from the few studies that compared playing a digital game with conventional media for self-efficacy (Bai et al., 2012; McLaren et al., 2017), there is theoretical support to predict that playing a statistics game can increase students’ perceived competence in successfully performing statistics tasks. Based on SCT (Bandura, 1986), in-game feedback can serve as a source of information about players’ in-game performance, which reflects learning experiences, and thus will influence self-efficacy (Usher & Pajares, 2008). Specifically, advances in the game reflect the player’s game performance as well as learning progress, the learning progress in turn will influence the player’s self-efficacy in the content that is being acquired. Therefore, it was expected that the successful gameplaying experiences in a statistics game would promote statistics self-efficacy more than the conventional instruction that does not adopt a source for self-efficacy through feedback on direct performance.

Hypothesis #5: It was expected that viewing a mastery model play *Stats Invaders* would lead to higher statistics self-efficacy than conventional instruction. SCT (Bandura, 1986) predicts that people can become more efficacious in a subject matter after observing a mastery model successfully perform a task and show high self-efficacy in the same domain. Mastery models, in particular, demonstrate and explain how to accurately complete an academic task with the appropriate knowledge and they verbalize positive achievement statements to show confidence in their knowledge and performance. Therefore, a mastery model’s verbalization of successful learning during the game could
serve as a vicarious source of self-efficacy for the observer, which was hypothesized to increase observers’ self-efficacy in learning the game’s content (Usher & Pajares, 2008). Specifically, when the model gains statistical knowledge by playing Stats Invaders and demonstrates confidence in her statistics knowledge, the viewers too believe that they can learn statistics from the game. Therefore, it was hypothesized that students who viewed a mastery model demonstrate high self-efficacy by playing Stats Invaders would experience enhanced statistics self-efficacy compared to those in the control condition who did not vicariously experience a model’s high self-efficacy in statistics.

Hypothesis #6: It was hypothesized that statistics self-efficacy would not differ between the game viewing and game playing conditions. As with hypothesis #2, it was expected that observing a model play Stats Invaders and playing themselves would generate comparable learning and game engagement experiences. Therefore, similar learning experiences between the game conditions would lead to similar gains in statistics self-efficacy.

RQ3. Are there differences in college students’ triggered-SI when they either enactively learn from a game, vicariously learn from a game, or are provided conventional instruction?

Hypothesis #7: It was expected that students who played the game would report greater triggered-SI than students in the control condition. Games are inherently designed with entertaining and motivating elements, such as challenges, responsiveness, just-in-time feedback, and stimulating graphical displays (Mayer, 2014). The multifaceted game
The structure of intrinsically integrated games was expected to create attention catching learning experiences while students executed the game mechanics. Therefore, in contrast to conventional instruction without game elements, it was expected that students who engaged in *Stats Invaders*, an intrinsic game, would experience more short-term triggered interest.

**Hypothesis #8:** It was expected that students who viewed a mastery model play *Stats Invaders* would report greater triggered-SI than those in the control condition. Although students were not playing the game themselves, viewers would vicariously experience a model engage in the motivating game features while executing the play mechanics. Another source of triggered situational interest was present as the mastery model verbalized positive attitude statements, such as “I like this game”, “Interpreting the dot plot and identifying the attack pattern is interesting.” Therefore, it was expected that vicariously experiencing a mastery model show interest in the instructional features of the game and showing a positive attitude while learning from an educational game would lead to greater triggered interest in the viewers when compared to those in the control condition.

**Hypothesis #9:** It was hypothesized that situational interest would not differ between the game viewing and game playing conditions. Consistent with hypotheses #3 and #6, it was expected that students in both game conditions would have similar learning and engagement experiences with *Stats Invaders*. In turn, playing the game was expected to generate similar amounts of interest as watching a model play the game. Thus, the
interest triggered from the experiences between these two game conditions would be comparable.

**RQ4. Are there differences in college students’ maintained-SI-feeling when they either enactively learn from a game, vicariously learn from a game, or are given conventional instruction?**

Hypothesis #10: It was expected that students who played the game would report greater maintained-SI-feeling than those in the control condition. The effects of educational games on different facets of situational interest have not been well tested yet. However, based on the intrinsic integrated games framework (Habgood & Ainsworth, 2011), it was expected that when students engage in learning experiences that are integrated into the game mechanics in meaningful ways, they experience greater positive affect toward the instructional content.

Hypothesis #11: It was expected that the game viewing condition would lead to greater maintained-SI-feeling than the control condition. Those in the game viewing group vicariously experience the model engage in an intrinsically integrated game and learn the targeted content through the game mechanics in meaningful ways. Therefore, it was anticipated that these vicarious experiences of maintained-SI-feeling toward the game would lead to viewers experiencing greater positive perceptions toward the instructional content as well.

Hypothesis 12: It was expected that maintained-SI-feeling would not differ between the game conditions. Similar to arguments made in hypotheses #3, #6, and #9, the comparable game-based learning experiences in the game playing and game viewing
conditions would both lead to students’ positive affective responses toward the content in the game.

RQ5. Are there differences in college students’ maintained-SI-value when they either enactively learn from a game, vicariously learn from a game, or are given conventional instruction?

Hypothesis #13: It was expected that students who played the game would report greater maintained-SI-value than the control. Similar to arguments made in hypothesis #10, students who play an intrinsically integrated game such as Stats Invaders are more likely to perceive the statistical content as important and useful to learn.

Hypothesis #14: It was expected that the game viewing condition would lead to greater maintained-SI-value than the control condition. Similar to arguments made in hypothesis #11, vicarious experiences of a model engaging in the game mechanics of an intrinsically integrated game design likely lead the viewers to perceive the instructional content as important to learn as well.

Hypothesis #15: It was expected that maintained-SI-value would not differ between the game conditions. The same arguments made in hypotheses #3, #6, #9, and #12 apply here as well.
Chapter 3

Method

Pilot Study

Institutional review board approval was obtained for the pilot and the full study (Study: 00010952). A small pilot study was conducted in the spring of 2019 to test the feasibility of the study protocol with the game playing and control conditions, and to examine psychometric properties of the instruments to be used in the full study (Hu & Sperling, 2020). Participants in the pilot were 22 students (Mean Age: 19 years old, $SD = 1.43$) from an undergraduate educational psychology course at a research university. The study was conducted in two computer lab sessions at two separate time points, one session for each condition. Eight students randomly signed up to the game condition (7 females, 1 male), and 14 randomly self-selected the control condition (11 females, 3 males). Upon arrival, each participant was individually assigned a computer. They completed the statistical knowledge pretest, self-efficacy pretest, and those in the game condition played *Stats Invaders*, whereas those in the control were given the conventional activity described in the materials section. Thereafter, students completed the situational interest measures, the reading task, and the statistical knowledge posttest, self-efficacy posttest, and demographic survey. All measures and activities were delivered via the computer.

The pilot study indicated that the overall study protocol was successful. Both the self-efficacy (pretest: $\alpha = .97$, posttest: $\alpha = .98$) and situational interest measures ($\alpha = .81$)
demonstrated high reliability estimates. However, the pilot study also revealed several issues with the study procedures and the knowledge test that were addressed in the subsequent study. First, in the game condition, a few participants did not read the game instructions provided within *Stats Invaders*, and a large portion of their session time was spent on the first level of the practice stage. After the researcher made this observation, she explained the game instructions to these students individually. To ensure that all students fully understood the game instruction in the full study, a simplified and clearer set of game instructions was provided to students via a video before game access. To further ensure the fidelity of the gameplay experience in the full study, students were also asked to record the game level and score that they achieved after gameplay.

Second, in the pilot, participants were given as much time as they needed to complete the game or the conventional activity. This resulted in large variation in the time it took to complete the experimental activities across the two conditions. On average, it took participants longer to complete *Stats Invaders* (Mean = 24.54 minutes, Median = 24.52 minutes, $SD = 3.46$, Range: 19.52 - 30.26 minutes) than the conventional activity (Mean = 18.67 minutes, Median = 22.29 minutes, $SD = 7.03$, Range: 5.26 - 27.47 minutes). The average time used to complete the activities across both groups was 20.81 minutes. To minimize the discrepancy between the time spent on the activities during the full study, students completed each activity within 20 minutes. Third, the reliability estimates of the knowledge pre- ($\alpha = .36$) and post-tests ($\alpha = .59$) from the pilot were too low to be used in the full study. In the pilot, the pre- and post-knowledge tests each had 10 items and were designed as parallel forms. Specifically, the items on the pre- and
posttests were parallel in format and targeted content, but the items were not identical. However, in a separate study with 125 introductory statistics students, when the pre- and post-knowledge tests were combined into a single 20-item test, it demonstrated adequate reliability \((\alpha = .70; \text{Hu et al., 2020})\). Therefore, the full study used the 20-item knowledge test at pre- and posttest instead of the 10-item measure used in the pilot.

It is generally not recommended to conduct inferential statistical analyses with small sample sizes that result in underpowered studies (Lancaster, 2015; Lee et al., 2014). Therefore, the pilot study data were not used to inform the direction of the hypotheses tested in the full study nor was the power analysis used to estimate the sample size needed for the dissertation study. However, descriptive statistics were calculated to examine overall trends in the outcome measures. Table 2 presents the descriptive statistics of the statistical knowledge, self-efficacy, and situational interest outcomes in the game and control condition for the pilot study. Overall, the control condition reported higher knowledge scores on pre- and posttest, slightly higher self-efficacy on pre- and posttest, but lower situational interest scores across all three facets.
Table 2

Descriptive Statistics From the Pilot Study

<table>
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<th>Control Condition (n=14)</th>
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<td>T-SI</td>
<td>5.44</td>
<td>0.59</td>
</tr>
<tr>
<td>M-SI-F</td>
<td>4.31</td>
<td>0.95</td>
</tr>
<tr>
<td>M-SI-V</td>
<td>4.28</td>
<td>1.79</td>
</tr>
</tbody>
</table>

Note. SKPRE= Statistical Knowledge Pretest; SKPOST=Statistical Knowledge Posttest; SSEPRE=Statistics Self-Efficacy Pretest; SSEPOST=Statistics Self-Efficacy Posttest; T-SI=Triggered Situational Interest; M-SI-F=Maintained Situational Interest Feeling; M-SI-V=Maintained Situational Interest Value.

Participants

Participants were 87 college students (28 in the game playing condition, 30 in the game viewing condition, and 29 in the control condition) from an introductory undergraduate educational psychology course at a large research university. The mean age was 19.33 years ($SD = 2.94$). The participants were predominately female (89%), Caucasian (86%), enrolled in either the college of education (56%) or the college of health and human development (29%) and anticipated they would receive an A- (37%) or an A (32%) upon completion of the course. With respect to class standing, 51% of the participants were first-year students, 35% were second-year students, 15% were third-year students. The conditions did not differ significantly in terms of mean age (game playing: $M = 19.07$, $SD = 1.02$; game viewing: $M = 19.77$, $SD = 4.84$; control: $M = 19.14$, $SD = .95$), $F(2, 84) = .50$, $p = .61$; or proportion female (game playing: 89%; game
viewing: 87%; control: 88%), $\chi^2(2) = .15, p = .93$. Participants were offered 1% extra credit upon completion of the study.

Design and Procedure

Participants were recruited across two semesters from the same course through an email. Participants used Sign-up Genius to self-select a study session held in an on-campus computer lab. There were multiple study sessions available for students to choose from in each semester. Each lab session was randomly assigned to one of the experimental conditions. Upon arrival, participants were seated individually at a computer and were given a paper slip with their participant identification number. The materials in this study, other than the game, were delivered through online Qualtrics survey software. All participants read the consent form first, entered their participant ID, and completed the pretest measures, which included the pretest statistical knowledge measure and pretest self-efficacy items.

The subsequent procedures differed based upon the assigned experimental condition. The experimenter assisted each participant during the transition of tasks. In the game playing condition (enactive learning), after finishing the pretest measures, participants were asked to put on headphones and watch a 3-minute video of the game instructions. In the game instructions video, the experimenter used PowerPoint slides to verbally explain the goals of Stats Invaders (e.g. stop the highest level of invasion) and the game mechanics (e.g. destroy alien ships to figure out the attack pattern by shooting bullets toward the invading ships). The PowerPoint slides had pictures of the game
interface (e.g. level 1 and level 6), bulleted text descriptions of the game, and arrows pointing to the relevant game element described by the text. After participants watched the game instruction video, the experimenter asked them if they fully understood the game. All participants indicated that they understood how to play the game. Then they were instructed to play *Stats Invaders* on the computer. The participants were stopped either after 20 minutes of gameplay (approximately half of the participants) or if they reached game over. In the *game viewing condition* (*vicarious learning*), participants were first asked to put on headphones to watch the same game instruction video given to the game playing condition. All participants indicated that they understood how to play the game. Thereafter, they were directed to watch a 17-minute video clip of a mastery model playing *Stats Invaders*. In the *control condition* (*conventional activity*), participants were given instructions in the Qualtrics survey to complete the conventional activity within 20 minutes. The gameplay, mastery model video, and the conventional activities served as the pre-instructional activities and defined each condition.

After the pre-instructional activities, participants completed the rest of the study in the Qualtrics survey. First, they were given the situational interest survey, then they received the reading materials, followed by the posttest measures. The posttest measures included the posttest statistical knowledge measure, posttest statistics self-efficacy items, and the demographic survey. The total duration of the experiment was approximately 40 minutes for each participant.
Materials

Stats Invaders

The participants in the game playing and game viewing conditions were exposed to the educational computer game Stats Invaders (Arena & Schwartz, 2010; 2014). Stats Invaders is an arcade-style game designed as a pre-instructional activity. It prepares students to learn from traditional instruction such as a passage about distribution properties, including the shape, center, and spread of statistical distributions (Arena & Schwartz, 2010; 2014). Specifically, since the game is not intended to replace traditional instruction, it does not incorporate explicit definitions or explanations of distribution properties. Instead, Stats Invaders is used to supplement instruction by exposing learners to examples of different types of distributions and their properties through gameplay. A screen shot of the game interface of level 1 can be found in Figure 3.

Figure 3

Stats Invaders Level 1 Screenshot
Stats Invaders has an intrinsically integrated game design, in which the learning content is delivered through the parts of the game that are most fun to play. These are represented by the two core game mechanics. The game has four learning goals. By playing through the game challenges and stages, players learn how to (1) view data as aggregated and recognize data can be represented by different distributions, (2) recognize different shapes of distributions, specifically, uniform, bimodal, right-skewed, left-skewed, and bell-shaped distributions, (3) identify the center of distributions, and (4) recognize the spread of distributions.

There are two core game mechanics and they both contribute to the four learning goals throughout gameplay. The game interface and mechanics are modified from the classic video game Space Invaders. Similar to the original game, the first core game mechanic is to not let alien spaceships hit the bottom of the game interface by shooting the ships with a cannon as they invade from the top of the screen. Players can use the arrow keys on the keyboard to move the cannon left or right and use the space bar to shoot the descending alien spaceships. Players are awarded points for each alien ship they destroy. In this modified version of Space Invaders, at each level, the alien spaceships descend in a specific pattern that will resemble a distribution curve graph displayed on an attack-pattern button, which is located on the right side of the interface (see Figure 3). For instance, if the pattern of the aliens’ attack resembles a right skewed distribution, most of the ships will invade from the left side of the screen and less from the right. In addition, each time a ship is eliminated, a dot that represents the attack location will appear in the rectangular area at the very bottom of the screen. As players eliminate
spaceships, the dots form into a dot plot based on the attack pattern at each level. Destroying the spaceships is designed to be a fun and entertaining gameplaying action. Additionally, gaining knowledge about properties of distributions through the game depends on properly executing this game mechanic. Specifically, players can only become familiar with how data can be aggregated and is represented by different distributions after hitting the descending spaceships and recognizing the attack patterns.

*Stats Invaders* has seven stages, and each stage has five levels, for a total of 35 levels in the game. The game starts with the practice stage (levels 1 – 5). Players at the practice stage are introduced to the core game mechanics, including why and when to click the attack-pattern button, how to shoot the alien spaceships, and the different types of distributions in the game. At the practice stage, each level only has one attack-pattern button and players must click on it to proceed in the game once they have made an association between that attack pattern and the distribution on the button. Each level in stages 2 – 7 has two attack-pattern buttons, each displaying a different distribution from which players can choose. A screenshot of stage 2 level 8 can be found in Figure 4.
Figure 4

*Stats Invaders Level 8 Screenshot*

*Note.* The player in this screenshot has already missed one alien spaceship as indicated by the red dot and made one incorrect guess on the probability distribution marked by one red cross in the information box at the top right corner of the screen.

The second core game mechanic is that at the end of each level after the practice stage, players must contrast two distributions displayed on the attack-pattern buttons and choose one of the two that best describes the pattern of the descending alien ships. Points are also awarded to players for each correctly identified pattern of the aliens’ attack. The overall goal of the game is to get as many points as possible by shooting alien spaceships and choosing the correct attack-pattern button to advance through the game stages and challenges. Selecting the correct attack-pattern button to advance to the next level is designed to be another entertaining game action. In addition, there is an interdependence between gaining the knowledge about probability distributions and their properties and identifying the correct distribution display that represents the aliens’ attack-pattern. More
specifically, if players cannot recognize the pattern of the attack, they will not be able to accurately select the attack-pattern button to complete that level. On the other hand, choosing the correct button is dependent on the players identifying the pattern.

Each stage in the game has a different challenge for players as they identify the correct pattern of attack. From stages 2 – 4 (levels 6 – 20), the two distributions on the attack-pattern buttons have properties that differ based on the shape, mean, and spread of the distributions. For stages 5 – 7 (levels 21 – 35), one attack-pattern button will be hidden. Challenges are cumulative and each stage incorporates the same challenges as the previous stages. See Table 3 for a description of the stages, levels, and challenges of *Stats Invaders*.

For each alien ship that is successfully destroyed, the player earns points equal to 10 * the current level. For instance, at level 3, the player receives 30 points per alien ship that is hit. At the end of the level, for each correct guess of the attack pattern, the player receives bonus points equal to 1000 * the current level. For instance, at level 14, the player receives 14000 bonus points if the player makes a correct guess. Points are not deducted if players guess incorrectly. If the player misses more than 10 alien spaceships or makes five incorrect guesses of the attack pattern, the game is over. At levels 8, 14, and 19, players are given upgraded laser cannons that move and shoot faster. As the alien attacks speed up later in the game, players who advance to the later levels need to use the upgraded lasers to keep up with the pace of the alien ships.
Table 3

Overview of Stages, Levels, and Challenges of Stats Invaders

<table>
<thead>
<tr>
<th>Stage</th>
<th>Levels</th>
<th>Challenge</th>
</tr>
</thead>
</table>
| 1     | 1-5    | • Each level has one attack-pattern button.  
|       | (Practice) | • Player becomes familiar with making an association between the pattern of alien attack and the distribution displayed on the attack-pattern button. |
| 2     | 6-10   | • Each level has two attack-pattern buttons  
|       |        | • Player must contrast the two distributions that *differ based on the shape, center, and spread*.  
|       |        | • Player chooses the distribution that describes the pattern of attack. |
| 3     | 11-15  | • Each level has two attack-pattern buttons  
|       |        | • Player must contrast the two distributions that have the *same centers but differ by shape and spread*.  
|       |        | • Player chooses the distribution that describes the pattern of attack. |
| 4     | 16-20  | • Each level has two attack-pattern buttons  
|       |        | • Player must contrast the two distributions that have the *same centers and shape but different spread*.  
|       |        | • Player chooses the distribution that describes the pattern of attack. |
| 5     | 21-25  | • Same as stage 2, but one attack-pattern button is hidden |
| 6     | 26-30  | • Same as stage 3, but one attack-pattern button is hidden |
| 7     | 31-35  | • Same as stage 4, but one attack-pattern button is hidden |

*Note.* Adopted from Arena & Schwartz (2010, p. 249).
*Video of Mastery Model Playing Stats Invaders*

Participants in the game viewing condition watched a 17-minute video of a mastery model performing exemplary behaviors while playing *Stats Invaders*. The model was a 28-year-old Asian female. Her face was displayed at the bottom right corner of the video, and the *Stats Invaders* game interface was presented at the left side of the screen. Due to the fairly simple game design of *Stats Invaders*, the model played the game approximately five times until she mastered the game mechanics and was able to successfully pass each level of the game. Therefore, it was expected that students would also perceive the game mechanics to be fairly easy to understand and follow. In turn, the simplistic game design was not expected to interfere with students’ learning of the statistical content by merely watching the model play without playing themselves.

At the beginning of the mastery model video, the model introduced herself and stated that the purpose of the video was for viewers to become familiar with different statistical distributions while watching her play *Stats Invaders*. She then played through the practice stage, while briefly reminding viewers of the game goals and mechanics (i.e. game mechanics statements) before entering stage 2. After she entered stage 2, which is the beginning of the main game, she played until level 20.

In previous studies, mastery models were designed to perform a learning task correctly, think aloud the decision making processes used to complete the task, and also additionally verbalize statements reflecting positive achievement beliefs such as high self-efficacy and positive attitude (Schunk et al., 1987; Schunk & Hanson, 1985). Adopting the design of mastery models in previous studies to the game-based learning
task in this study, the model in this study demonstrated mastery of the game mechanics as well as the learning content in three ways. First, the model accurately performed the game mechanics by not missing any alien ships and correctly selecting all of the attack-pattern buttons. Second, the model verbalized her decision making processes throughout the game (i.e. game decision explanations), specifically, before selecting an attack-pattern button at the end of each level, the model explained her decision by referring to the pattern of the aliens’ attack and its distribution properties (e.g. shape, center, spread) and the given distribution shapes on the buttons. Third, the model verbalized multiple positive achievement beliefs while playing the game (i.e. statements of positive attitude, low task difficulty, and high self-efficacy).

The type and length of statements made in the video were coded using MAXQDA 2020 (VERBI Software, 2020). The model played 20 levels of the game, and therefore most of the statements were game decision explanations. During the practice stage, the model briefly reviewed the game mechanics, which represented approximately 17% of the video. Positive achievement statements represented around 11% of the video, so that viewers’ attention would not be directed away from the models’ gameplay. See Table 4 for the coded percentages and examples of the statements presented in the video. See Figure 5 for a visual display of the coded statements in the MAXQDA software.
### Table 4

*Coded Verbal Statements in The Mastery Model Video*

<table>
<thead>
<tr>
<th>Type of Verbal Statements</th>
<th>Percentage of Entire Video</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game Decision Explanation</td>
<td>54.9%</td>
<td>“From the beginning [of the level], we got a lot of ships concentrated toward the left side of the screen, it’s going to be the first one.” (First distribution: right-skewed, second distribution: uniform)</td>
</tr>
<tr>
<td>Game Mechanics</td>
<td>16.9%</td>
<td>“In this game, we will have to choose an attack-pattern button, and we have to decide which attack-pattern button reflects the alien attack patterns.”</td>
</tr>
<tr>
<td>Positive Attitude</td>
<td>3.6%</td>
<td>“I just like to continuously shoot as many bullets as I can to destroy the alien ships. I just think it's more fun this way.”</td>
</tr>
<tr>
<td>Low Task difficulty</td>
<td>2.5%</td>
<td>“This game is not that hard.”</td>
</tr>
<tr>
<td>High Self-Efficacy</td>
<td>4.9%</td>
<td>“This one (referring to the attack pattern) is definitely the second distribution because none of them (referring to the alien ships) are going toward the very extreme ends of the screen.”</td>
</tr>
</tbody>
</table>
Figure 5

MAXQDA Visual Display of the Coded Statements in the Video

Note. GDE=Game Decision Explanation, GM=Game Mechanics, PA=Positive Attitude, LTD=Low Task Difficult, HSE=High Self-Efficacy.
Conventional Activity

In the conventional activity administered in the control condition, participants compared pairs of statistical distribution graphs (i.e. three pairs of dotplots, and three pairs of histograms) and described the similarities and differences based on the shape, center, and spread. Participants were given a total of six pairs in this activity. For each distribution property, participants were given an open-ended textbox in the Qualtrics survey to write their responses. The conventional compare and contrast activity used in this study is comparable to typical pre-instructional activities used in college level introductory statistics courses (Garfield et al., 2008c). Also, the activity exposed participants to distribution graphs in a similar fashion as Stats Invaders, but without the gameplay elements. Specifically, like Stats Invaders, participants were required to contrast two distribution graphs based on the differences in their properties, similar to the second game mechanic. Importantly, the conventional activity also incorporated formal descriptions and explanations of distribution properties. Participants completed the conventional activity in approximately 15 minutes on average. The activity materials are located in Appendix A.
Reading Materials

The reading materials included two expository texts. The first text contained the “Shape of a Distribution” section in the Describing Data unit from an undergraduate introductory statistics textbook (Lock et al., 2016). This section had approximately 630 words and described dotplots, histograms, skewed and symmetric distributions, and other common shapes of distributions. The text was paired with multiple graphs and charts, including one dotplot, two frequency tables, four histograms, and four line graphs. The second text was a 110-word description of the center and spread of distributions adopted from another introductory statistics textbook (Pagano, 2012). The text was paired with two figures, one showed the measures of central tendency for right-skewed, normal, and left-skewed distributions, while the other showed dotplots and line graphs of distributions with small and large spreads. Participants were instructed to read the text carefully and were informed that their knowledge would be tested later in the study. The reading materials can be found in Appendix B.

Measures

Statistical Knowledge Test

A 15-item multiple choice test was administered to measure participants’ knowledge of probability distributions at pre- and posttest. As aforementioned, the statistical knowledge measure initially had 20 items and demonstrated adequate reliability in a separate study (Hu et al., 2020). After combining the 10 items in the pre- and
posttests of the pilot study, five items were eliminated due to the repeated content. Administration of the items from the final version of the scale were randomized at each pretest and posttest. The questions were adopted from exercise questions from two introductory statistics textbooks (Lock et al., 2016; Pagano, 2012). The items aligned with the instructional content targeted in *Stats Invaders*. Specifically, the items assessed participants’ conceptual understanding of how data can be viewed as aggregated and represented by different distributions, their knowledge of different statistical distribution shapes, and their understanding of how to interpret the center and spread of distributions.

The knowledge test had a mix of conceptual and application items that were either text-or graph-based. Each item was dichotomously scored (minimum score is 0, maximum is 15), and the total number of correct items completed by each participant was calculated. Scores on the knowledge test in this study demonstrated adequate reliability; knowledge pretest Cronbach’s α = .76; knowledge posttest Cronbach’s α = .72. See Appendix C for the instrument, with items coded by category.

**Statistics Self-Efficacy**

A 15-item instrument was used to measure students’ statistics self-efficacy at pre- and posttest. The item content was aligned with instructional content targeted in the game-enhanced learning task, including the content experienced in *Stats Invaders* and presented in the reading materials. The instrument instructions were identical to those used in the Current Statistics Self-Efficacy (CSSE) scale (Finney & Schraw, 2003). Specifically, on a 7-point Likert-type scale (1= no confidence at all, 7= complete
participants rated confidence in their current ability to successfully complete 15 statistics tasks to identify or interpret shapes, the center, and the spread of distributions. The average self-efficacy score was calculated for each participant. An example of the item was: “Identify a left skewed distribution.” Scores across all items were averaged for each participant. Consistent with the high reliability (Cronbach’s $\alpha = .96$) reported by Hu et al. (2020), scores on the self-efficacy instrument in the current study also demonstrated high reliability; statistics self-efficacy pretest Cronbach’s $\alpha = .96$; statistics self-efficacy posttest Cronbach’s $\alpha = .97$. The full instrument is located in Appendix D.

**Situational Interest**

An adapted version of the Situational Interest Survey (SIS) was used to measure students’ situational interest in the pre-instructional statistics activity based on the three-component model (Linnenbrink-Garcia et al., 2010). The scale was given immediately after the pre-instructional activity. On a 7-point Likert scale (1=strongly disagree, 7=strongly agree), participants rated their agreement to 12 statements that reflected their triggered-SI, maintained-SI-feeling, and maintained-SI-value of the activity they were given in each condition, each sub-factor had 4 items. Triggered-SI measured affective and attentional responses to the activity structure with items such as “When I did the statistics activity, it did things that grab my attention.” Maintained-SI-feeling captured affective responses to the instructional content in the pre-instructional activity, and an example item was “What I am learning in this statistics activity is fascinating to me.”
Maintained-SI-value assessed personal value of the content that was learned in the statistics activity, and an example item was “What I am learning in this statistics activity can be applied to real life.” Items for each of the three situational interest facets were averaged for each participant. Previous research established sound psychometric properties for the instrument (Linnenbrink-Garcia et al., 2010). Linnenbrink-Garcia and colleagues (2010) reported high reliability of item scores for each subscale: triggered-SI: α =0.86, maintained-SI-feeling: α = 0.92, and maintained-SI-value: α=0.88. Consistent with prior research, scores on the SIS in this study also demonstrated high reliability; triggered-SI Cronbach’s α = .92; maintained-SI-feeling Cronbach’s α= .90; maintained-SI-value Cronbach’s α = .89. The full scale is located in Appendix E.

Demographic Survey

Participants were asked to report their age, gender, college enrollment, ethnicity, class standing, anticipated course grade, and prior experiences with digital games. For prior experience with digital games, participants reported on average, how many hours per week did they play video games on either a computer, gaming console, or handheld device (phone or tablet), what types of games they mostly play, how many hours per week did they watch others play games, the types of games they watch others play, and their skill level in playing video games. Items are reported in Appendix F.
Chapter 4

RESULTS

Preliminary Analyses

Descriptive statistics of the study variables across conditions are presented in Table 5; bivariate correlations among study variables are presented in Table 6. One-way ANOVAs were conducted to examine differences across conditions in age, statistical knowledge at pretest, statistics self-efficacy at pretest, time (secs) spent on reading task part 1, and time (secs) spent on reading task 2. As assessed by inspection of boxplots for values greater than 1.5*interquartile range, there were no outliers on the knowledge pretests. For self-efficacy pretest scores, there was one outlier in the game playing condition where a student reported statistics self-efficacy score 1.5 times lower than the first quartile ($M=1.13$).

For time on the reading tasks, there were outliers outside of the third quartile of the experimental conditions. For time spent on reading task 1, the game viewing condition had two outliers (345 and 283 secs) and the control also had two outliers (196 and 183 secs); for time on reading task 2, the game viewing condition had two outliers (60 and 46 secs), the control had one outlier (97 secs). However, these outliers were kept in the analysis for a few reasons. First, the reading time outliers indicate that these students spent more time on the reading tasks than the average student, which is a desired outcome for the study, thus the outliers were kept in the test analyses. Second, excluding the outliers from the study using a listwise deletion method did not affect the results of
the preliminary analyses. Third, study sessions were carefully monitored by the experimenter, and there is confidence that these reading time outliers do not represent participant off task behaviors.

The normality assumption was violated for each ANOVA as assessed by Shapiro-Wilk’s test \( p > .05 \); however, each analysis was conducted since group size were fairly equal and were similarly skewed (Maxwell & Delaney, 2004). All ANOVAs met the assumption of equal variance across conditions, as assessed by Levene’s test of homogeneity of variances \( p > .05 \). The findings indicated that the conditions did not significantly differ on self-efficacy pretest scores, \( F(2,84) = 1.73, \ p = .18 \); time spent on reading task part 1, \( F(2,84) = .21, \ p = .81 \); or time spent on reading task part 2, \( F(2,84) = .47, \ p = .62 \). Prior knowledge in statistics assessed on the pretest was significantly different among conditions, \( F(2, 84) =3.80, \ p < .05 \). Tukey HSD post hoc analysis revealed that the control condition prior knowledge scores were higher than the game viewing condition \( M_{\text{difference}} = 1.95, \ p < .05 \). No other group differences were statistically significant. Due to the unbalanced prior knowledge scores on the pretest across conditions, pretest knowledge scores were used as a covariate in the primary analyses.
Table 5

Means and Standard Deviations of Study Variables

<table>
<thead>
<tr>
<th></th>
<th>Game Playing (n=28)</th>
<th>Game Viewing (n=30)</th>
<th>Control (n=29)</th>
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<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
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<tr>
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<tr>
<td></td>
<td>(11.21a)</td>
<td>(SE: .41)</td>
<td>(10.75a)</td>
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<td>(SE: .21)</td>
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<td>M-SI-V</td>
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<tr>
<td>RT1</td>
<td>80.66</td>
<td>57.57</td>
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</tr>
<tr>
<td>RT2</td>
<td>20.81</td>
<td>15.01</td>
<td>17.62</td>
</tr>
</tbody>
</table>

Note. SKPRE= Statistical Knowledge Pretest; SKPOST=Statistical Knowledge Posttest; SSEPRE=Statistics Self-Efficacy Pretest; SSEPOST=Statistics Self-Efficacy Posttest; T-SI=Triggered-Situational Interest; M-SI-F=Maintained-Situational Interest-Feeling; M-SI-V=Maintained-Situational Interest-Value. aAdjusted means based on SKPRE covariate. bReading time was measured in seconds.

Table 6

Bivariate Correlations Among Major Study Variables.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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<td>2. SKPOST</td>
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<tr>
<td>3. SSEPRE</td>
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<td>4. SSEPOST</td>
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<td>.37**</td>
<td>.72**</td>
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<td>5. T-SI</td>
<td>.03</td>
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<td>.13</td>
<td>.18</td>
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<td>6. M-SI-F</td>
<td>.00</td>
<td>-.08</td>
<td>.16</td>
<td>.17</td>
<td>.80**</td>
<td>-</td>
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<td>7. M-SI-V</td>
<td>-.03</td>
<td>-.01</td>
<td>.15</td>
<td>.19</td>
<td>.56**</td>
<td>.68**</td>
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</table>


Further preliminary analyses were conducted to examine participants’ prior experience with digital games. Crosstabulation of prior digital game experience by
condition is presented in Table 7. Across conditions, the majority of participants reported either poor (39%) or fair (39%) digital game playing skills; on average they reported they play 1 – 2 hours (40%) or don’t play games (33%) each week; on average they either don’t watch others play games (54%) or watch 1 – 2 hours (37%) each week. If they do play games, most participants reported they play puzzle (40%) or card games (26%), and if they watch someone else play games, most view others playing sports games (20%) or puzzles (22%). Chi-square tests of independence were conducted to assess whether there was an association between condition and participants’ game playing and game watching experiences. To meet the assumption of having expected cell frequencies greater than five for running an accurate chi-square test, a few categories were collapsed for each variable. Specifically, for game playing skills, “very good” was eliminated and merged into the “good” category; for hours of playing games, “6 – 10 hours” and “more than 10 hours” were eliminated and merged into “3 – 5 hours”; for hours of watching games, “3 – 5 hours”, “6 – 10 hours” and “more than 10 hours” were eliminated and merged into “1 – 2 hours”. After combining the categories, the cell frequency assumption was met.

For the game genre mostly played and watched per week, chi-square tests were only conducted on genres that had cell frequencies greater than five and no categories were collapsed. The findings revealed that there were no statistically significant associations between conditions and game playing skills, $\chi^2(4) = 1.13, p = .89$; average hours of playing games per week, $\chi^2(4) = .32, p = .99$; average hours of watching others play games per week, $\chi^2(2) = 3.10, p = .21$; playing puzzles, $\chi^2(2) = .42, p = .81$; playing card games, $\chi^2(2) = .75, p = .69$; watching sports games, $\chi^2(2) = .95, p = .62$. There was
a significant association between conditions and those who watched others play puzzles, \( \chi^2 (2) = 6.23, p < .05 \). The association was moderate, Cramer’s \( V = .27 \). Based on the adjusted standardized residuals, students in the game viewing condition (\( n=2 \)), as compared to those in the game playing and control conditions, were least likely to watch others play puzzles each week. This disproportionate number of students in the game viewing condition who did not watch puzzles was not a major concern for the primary analysis in this study and was not considered in the analysis. Specifically, students not watching others play puzzle games was not likely to impact their experiences in watching a model play *Stats Invaders*.

**Table 7**

*Crosstabulation of Prior Digital Game Experiences by Condition*

<table>
<thead>
<tr>
<th>Game playing skills</th>
<th>Game Playing (% within condition)</th>
<th>Game Viewing (% within condition)</th>
<th>Control (% within condition)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Game Playing (% within condition)</td>
<td>Game Viewing (% within condition)</td>
<td>Control (% within condition)</td>
<td>Total</td>
</tr>
<tr>
<td><strong>Game playing skills</strong></td>
<td><strong>Game Playing</strong></td>
<td><strong>Game Viewing</strong></td>
<td><strong>Control</strong></td>
<td><strong>Total</strong></td>
</tr>
<tr>
<td>Poor</td>
<td>10 (36%)</td>
<td>12 (40%)</td>
<td>12 (41%)</td>
<td>34 (39%)</td>
</tr>
<tr>
<td>Fair</td>
<td>12 (11%)</td>
<td>10 (33%)</td>
<td>12 (41%)</td>
<td>34 (39%)</td>
</tr>
<tr>
<td>Good</td>
<td>5 (18%)</td>
<td>8 (27%)</td>
<td>4 (14%)</td>
<td>17 (20%)</td>
</tr>
<tr>
<td>Very good</td>
<td>1 (4%)</td>
<td>0</td>
<td>1 (3%)</td>
<td>2 (2%)</td>
</tr>
<tr>
<td>Professional</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Average hours of playing games per week</strong></td>
<td>0</td>
<td>1-2</td>
<td>3-5</td>
<td>6-10</td>
</tr>
<tr>
<td>0</td>
<td>9 (32%)</td>
<td>11 (37%)</td>
<td>9 (31%)</td>
<td>29 (33%)</td>
</tr>
<tr>
<td>1-2</td>
<td>12 (43%)</td>
<td>11 (37%)</td>
<td>12 (41%)</td>
<td>35 (40%)</td>
</tr>
<tr>
<td>3-5</td>
<td>4 (14%)</td>
<td>6 (20%)</td>
<td>5 (17%)</td>
<td>15 (17%)</td>
</tr>
<tr>
<td>6-10</td>
<td>3 (11%)</td>
<td>2 (7%)</td>
<td>1 (3%)</td>
<td>6 (7%)</td>
</tr>
<tr>
<td>More than 10</td>
<td>0</td>
<td>0</td>
<td>2 (7%)</td>
<td>2 (2%)</td>
</tr>
<tr>
<td><strong>Average hours of watching others play game per week</strong></td>
<td>0</td>
<td>1-2</td>
<td>3-5</td>
<td>6-10</td>
</tr>
<tr>
<td>0</td>
<td>14 (50%)</td>
<td>20 (67%)</td>
<td>13 (45%)</td>
<td>47 (54%)</td>
</tr>
</tbody>
</table>
### Game genre mostly played per week

<table>
<thead>
<tr>
<th>Genre</th>
<th>1-2</th>
<th>3-5</th>
<th>6-10</th>
<th>More than 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Action (e.g. First-person shooter)</td>
<td>12 (43%)</td>
<td>9 (30%)</td>
<td>11 (38%)</td>
<td>32 (37%)</td>
</tr>
<tr>
<td>Adventure</td>
<td>2 (7%)</td>
<td>0</td>
<td>5 (17%)</td>
<td>7 (8%)</td>
</tr>
<tr>
<td>Massively multiplayer online games (MMO)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Multiplayer online battle arena (MOBA)</td>
<td>0</td>
<td>1 (3%)</td>
<td>0</td>
<td>1 (1%)</td>
</tr>
<tr>
<td>Simulation</td>
<td>3 (11%)</td>
<td>5 (17%)</td>
<td>3 (10%)</td>
<td>11 (13%)</td>
</tr>
<tr>
<td>Role-playing games (RPG)</td>
<td>4 (14%)</td>
<td>0</td>
<td>2 (7%)</td>
<td>6 (7%)</td>
</tr>
<tr>
<td>Sports</td>
<td>3 (11%)</td>
<td>0</td>
<td>3 (10%)</td>
<td>6 (7%)</td>
</tr>
<tr>
<td>Puzzle</td>
<td>11 (39%)</td>
<td>11 (37%)</td>
<td>13 (45%)</td>
<td>35 (40%)</td>
</tr>
<tr>
<td>Card games</td>
<td>8 (29%)</td>
<td>9 (30%)</td>
<td>6 (21%)</td>
<td>23 (26%)</td>
</tr>
<tr>
<td>Racing games</td>
<td>5 (18%)</td>
<td>3 (10%)</td>
<td>1 (3%)</td>
<td>9 (10%)</td>
</tr>
</tbody>
</table>

### Game genre mostly watched per week

<table>
<thead>
<tr>
<th>Genre</th>
<th>1-2</th>
<th>3-5</th>
<th>6-10</th>
<th>More than 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Action (e.g. First-person shooter)</td>
<td>5 (18%)</td>
<td>6 (20%)</td>
<td>5 (17%)</td>
<td>16 (18%)</td>
</tr>
<tr>
<td>Adventure</td>
<td>5 (18%)</td>
<td>2 (7%)</td>
<td>1 (3%)</td>
<td>8 (9%)</td>
</tr>
<tr>
<td>Massively multiplayer online games (MMO)</td>
<td>1 (4%)</td>
<td>3 (10%)</td>
<td>2 (7%)</td>
<td>6 (7%)</td>
</tr>
<tr>
<td>Multiplayer online battle arena (MOBA)</td>
<td>2 (7%)</td>
<td>2 (7%)</td>
<td>1 (3%)</td>
<td>5 (6%)</td>
</tr>
<tr>
<td>Simulation</td>
<td>5 (18%)</td>
<td>2 (7%)</td>
<td>4 (14%)</td>
<td>11 (13%)</td>
</tr>
<tr>
<td>Role-playing games (RPG)</td>
<td>2 (7%)</td>
<td>2 (7%)</td>
<td>1 (3%)</td>
<td>5 (6%)</td>
</tr>
<tr>
<td>Sports</td>
<td>6 (21%)</td>
<td>7 (23%)</td>
<td>4 (14%)</td>
<td>17 (20%)</td>
</tr>
<tr>
<td>Puzzle</td>
<td>8 (29%)</td>
<td>2 (7%)</td>
<td>9 (31%)</td>
<td>19 (22%)</td>
</tr>
<tr>
<td>Card games</td>
<td>5 (18%)</td>
<td>4 (13%)</td>
<td>6 (21%)</td>
<td>15 (17%)</td>
</tr>
<tr>
<td>Racing games</td>
<td>4 (14%)</td>
<td>3 (10%)</td>
<td>1 (3%)</td>
<td>8 (9%)</td>
</tr>
</tbody>
</table>

*adjusted standardized residuals are over +1.96 or below -1.96.
Primary Analyses

RQ1. Are there differences in college students’ statistical knowledge when they either enactively learn from a game, vicariously learn from a game, or are provided conventional instruction?

A one-way ANCOVA was conducted to test whether playing *Stats Invaders* (hypothesis 1) or merely watching a mastery model play *Stats Invaders* (hypothesis 2) leads to higher statistical knowledge than the conventional activity, and whether exposure to the two game groups results in similar performance on the knowledge posttest (hypothesis 3), after controlling for prior knowledge in statistics as measured on the pretest. All assumptions were met for the one-way ANCOVA. The analysis indicated significant difference in knowledge posttest scores among the conditions, $F(2,83) = 5.75$, $p < .01$, partial $\eta^2 = .12$. *Post hoc* analysis was performed with Bonferroni adjustment.

Contrary to hypothesis 1 and 2, after controlling for prior knowledge, statistical knowledge posttest scores were significantly higher in the control group than the game playing condition ($M_{\text{difference}} = 1.43, p < .05$) and the game viewing condition ($M_{\text{difference}} = 1.90, p < .05$). Aligned with hypothesis 3, there were no differences between the game playing and game viewing conditions ($M_{\text{difference}} = .47, p = 1.00$). These findings demonstrate that playing a statistics game or watching a mastery model play the game as a pre-instructional learning activity had the same effect on learners’ statistical knowledge, however, students who engaged in the non-game conventional activity benefited more in statistical knowledge than both the game conditions.
RQ2. Are there differences in college students’ statistics self-efficacy when they either enactively learn from a game, vicariously learn from a game, or are provided conventional instruction?

A one-way ANCOVA was conducted to test whether playing Stats Invaders (hypothesis 4) or observing a model play (hypothesis 5) leads to higher statistics self-efficacy than the conventional activity, and whether exposure to the two game conditions results in similar ratings in statistics self-efficacy (hypothesis 6), after controlling for prior knowledge in statistics. All assumptions were met for the one-way ANCOVA. The analysis showed no significant difference in statistics self-efficacy among the conditions after controlling for prior knowledge, $F(2,83) = .02, p = .98$. Therefore, contrary to hypothesis 4 and 5, the game playing and game viewing conditions did not lead to higher statistics self-efficacy over the control condition. Aligned with hypothesis 6, there were no differences in participants’ statistics self-efficacy between the game playing and game viewing conditions ($M_{\text{difference}} = .06, p = 1.00$).

RQ3. Are there differences in college students’ triggered-SI when they either enactively learn from a game, vicariously learn from a game, or are provided conventional instruction?

To examine whether playing (hypothesis 7) or watching a model play Stats Invaders (hypothesis 8) leads to higher triggered-SI than engaging in the conventional activity, and whether exposure to the two game groups results in similar ratings in triggered interest (hypothesis 9), a one-way ANCOVA was first conducted with prior knowledge in statistics as the covariate. However, the assumption of homogeneity of
regression slopes was violated, as indicated by a significant interaction between condition and the statistical knowledge pretest scores, $F(2,81) = 3.40, p < .05$, partial $\eta^2 = .08$. Therefore, the pretest knowledge covariate was dropped from the analysis and an analysis of variance (ANOVA) was performed instead.

The ANOVA findings showed that triggered-SI was significantly different across conditions, $F(2,84) = 24.25, p < .05$, partial $\eta^2 = .37$. Post hoc analysis with Bonferroni adjustment indicated that the game playing condition had significantly higher triggered-SI than the game viewing condition ($M_{\text{difference}} = .97, p < .05$) and the control ($M_{\text{difference}} = 2.41, p < .05$). The game viewing condition also rated triggered interest higher than the control condition ($M_{\text{difference}} = 1.44, p < .05$). These findings show that, as expected in hypothesis 7 and 8, students who were exposed to Stats Invaders by either playing the game or watching a model play the game experienced greater interest in the game-based pre-instructional activity than students who were given the non-game conventional activity. Contrary to hypothesis 9, the two game conditions triggered different levels of situational interest for students. Specifically, playing the game triggered higher interest in the statistics learning activity than merely watching a model play the game.

To follow up the significant interaction between condition and prior knowledge in statistics, three linear regression analyses of pretest knowledge scores on triggered-SI were conducted, one for each condition. All assumptions for the regression analyses were met. Results indicated that prior knowledge in statistics significantly predicted triggered-SI in the control condition ($\beta = .43; t = 2.47, p < .05$, Adjusted $R^2 = .15$), but not in the game playing condition ($\beta = -.05; t = -.25, p = .81$), or the game viewing condition ($\beta = -$...
These findings suggest that particularly in the control condition where students were given the non-game conventional activity as the pre-instructional learning task, students prior knowledge in distribution properties had a positive impact on triggered-SI. Specifically, higher prior knowledge lead to higher ratings of triggered-SI.

**RQ4. Are there differences in college students’ maintained-SI-feeling when they either enactively learn from a game, vicariously learn from a game, or are provided conventional instruction?**

To examine whether playing (hypothesis 10) or watching a mastery model play *Stats Invaders* (hypothesis 11) leads to higher maintained-SI-feeling than engaging in the conventional activity, and whether the two game groups resulted in similar student ratings in affective interest in the statistical content itself (hypothesis 12), a one-way ANCOVA was first conducted with prior knowledge in statistics as the covariate. As with triggered-SI, the assumption of homogeneity of regression slopes was also violated. There was a significant interaction between condition and the statistical knowledge pretest scores, \(F(2,81) = 6.79, p < .05\), partial \(\eta^2 = .14\). Therefore, the pretest knowledge covariate was also dropped from the analysis and an analysis of variance (ANOVA) was performed instead.

The ANOVA results indicated differences in maintained-SI-feeling across conditions, \(F(2,84) = 7.94, p < .05\), partial \(\eta^2 = .16\). *Post hoc* analysis with Bonferroni adjustment revealed that the game playing condition reported higher maintained-SI-feeling than the control condition \(M_{\text{difference}} = 1.40, p < .05\), but there were no differences between the game viewing condition and the control \(M_{\text{difference}} = .83, p = .06\),
and between the game viewing and game playing conditions ($M_{\text{difference}} = .57, p = .32$).

These findings show that, as expected in hypothesis 10 and 12, playing *Stats Invaders* lead to more enjoyable and engaging feelings toward the material when presented in the game-based activity than completing the non-game conventional activity. Furthermore, the affective interest experienced by playing the game is comparable to watching a model play the game. Contrary to expectations in hypothesis 11, observing a model play *Stats Invaders* did not lead to higher maintained-SI-feeling when compared to the conventional activity.

To follow up on the significant interaction between the condition and statistical knowledge pretest scores, three linear regression analyses of pretest knowledge scores on maintained-SI-feeling were conducted, one for each condition. All assumptions for the regression analyses were met. Results showed that statistical knowledge pretest scores predicted maintained-SI-feeling in the game viewing condition ($\beta = -.39; t = -2.23, p < .05$, Adjusted $R^2 = .12$) and the control ($\beta = .48; t = 2.84, p < .05$, Adjusted $R^2 = .20$), but not in the game playing condition ($\beta = -.10; t = -.51, p < .05$, Adjusted $R^2 = -.03$). The findings indicated that students’ prior knowledge of distribution properties had a negative influence on their affective reactions toward the statistical activity in the game viewing condition and a positive influence on situational interest in the control condition.

Specifically, after observing a model play *Stats Invaders*, those with higher prior knowledge were more likely to report lower maintained-SI-feeling than those with lower prior knowledge. The opposite was observed in the control condition. After completing
the conventional activity, students with higher prior knowledge were more likely to report higher maintained-SI-feeling.

**RQ5. Are there differences in college students’ maintained-SI-value when they either enactively learn from a game, vicariously learn from a game, or are provided conventional instruction?**

An analysis of covariance (ANCOVA) with students’ prior knowledge as covariate was performed to test if playing (hypothesis 13), or watching a mastery model play, *Stats Invaders* (hypothesis 14) leads to greater maintained-SI-value than the control condition, and whether participants’ perceived importance and value of the material would be similar after exposure to either game condition (hypothesis 15). However, as with triggered-SI and maintained-SI-feeling, the assumption of homogeneity of regression slopes was also violated for maintained-SI-value, as indicated by a significant interaction between condition and the statistical knowledge pretest scores, $F(2,81) = 4.74$, $p < .05$, partial $\eta^2 = .11$. Therefore, the pretest knowledge covariate was dropped from the analysis and an analysis of variance (ANOVA) was performed instead.

Results from the ANOVA showed no significant differences in maintained-SI-value across conditions, $F(2,84) = .85$, $p = .43$. Contrary to hypothesis 13 and 14, neither playing nor watching a model play a digital statistics game in a game-enhanced learning task led to higher maintained-SI-value than engaging in a conventional activity. As expected in hypothesis 15, there were no differences in participants’ interest and value of the materials presented in *Stats Invaders* between the game conditions.
Three separate regression analyses of students’ prior statistical knowledge on maintained-SI-value were conducted, one for each condition, to follow up on the significant interaction between condition and prior knowledge. Regression results showed that prior statistical knowledge significantly predicted maintained-SI-value ratings in the game playing condition \( (\beta = -0.40; t = -2.22, p < .05, \text{Adjusted } R^2 = .13) \) and the control \( (\beta = 0.39; t = 2.22, p < .05, \text{Adjusted } R^2 = .12) \), but not in the game viewing condition \( (\beta = -0.08; t = -0.43, p = .67) \). These findings indicate that students’ prior knowledge of distribution properties had a negative influence on students’ situational interest as in perceived importance of the materials particularly in the game playing condition, but a positive impact on maintained-SI in the control condition. Prior knowledge did not influence maintained-SI-value in the game viewing condition. Specifically, after playing *Stats Invaders* those with higher prior knowledge of distribution properties were more likely to report lower maintained-SI-value than those with lower prior knowledge. The opposite occurred in the control condition. After completing the conventional activity, those with higher prior knowledge were more likely to report higher levels of maintained-SI-value than those with lower prior knowledge.
Chapter 5

DISCUSSION

The purpose of the current study was to investigate the differences in college students’ statistics knowledge and motivation to learn statistics when they were instructed to either learn from a digital statistics game enactively (i.e. learning-by-doing), vicariously (i.e. learning-by-observing), or to complete a non-game conventional activity. Overall, results from this study indicated that the effectiveness of each instructional approach was likely dependent on the outcome variable that was targeted. This chapter presents the summary and implications of the findings. This chapter also discusses the recommendations for practice, limitations of the study, and future directions for research.

Summary and Implications of the Findings

The Impact on Statistics Knowledge

Comparisons of students’ statistical conceptual knowledge among the experimental conditions revealed two important findings. First, contrary to predictions in hypotheses 1 and 2, neither playing nor watching a mastery model play led to more knowledge of distribution properties than a non-game conventional activity. These findings are inconsistent with prior research that indicated the potential of digital games to promote conceptual understanding in statistics (e.g. Boyle et al., 2014). Instead, the current study showed no advantage of either learning vicariously or enactively from a statistics game over a non-game conventional activity.
Although students’ benefited more from the conventional activity in the control condition than the game conditions on knowledge performance, it is important to recognize that a probable explanation for this is that the conventional activity was a more robust method of instruction. Mayer (2019) noted that a major methodology challenge to media comparison studies is to ensure that game condition(s) are provided the same learning material and instructional approach as the conventional group. To make a meaningful comparison between games and other types of instruction, the only difference between the condition(s) should be the medium (e.g. game vs. no game) that is used to deliver the learning content. However, due to the multifaceted nature of games, it is often difficult to perceive all the types and levels of interactions students engage in during a game, and especially when each student who plays the game might have a different game experience. Also, in intrinsically integrated games, the learning process is dependent on executing the game mechanics, which makes it even more difficult to translate the game-based instruction into non-game instruction that does not incorporate game mechanics. Therefore, when comparing games to conventional media, the type and level of interactions provided through the method of instruction in the control group should align with instruction experienced from games.

In the context of the current study, students in the control condition were given a generative conventional activity where they employed self-explanations regarding similarities and the differences in properties of distribution graphs as the main method of instruction. Whereas in the game conditions, students also had to compare distributions and process the differences among their properties. In the game condition, however,
students were not required to explicitly explain differences they had observed. Instead, in the enactive learning condition, students only had to quickly make a game decision by choosing the distribution that was most representative of the aliens’ attack patterns. Similarly, in the vicarious learning condition, the model provided brief explanations as to why she choose a certain distribution, however, the explanations were not further elaborated nor justified. These game experiences may have led players to engage with concepts of distribution properties at a more minimal, surface level.

Self-explanation facilitates deep understanding and critical thinking as students engage in learning (Wylie & Chi, 2014). Studies have found that self-explanation in digital learning environments leads to greater learning outcomes compared to activities that do not allow for self-explanation (Wylie & Chi, 2014). Given that both game conditions were not prompted to engage in explicit self-explanation about the comparisons they made between pairs of probability distributions, it is possible that the design of these game experiences were less effective at helping students gain a more meaningful understanding of distribution properties. Therefore, it is perhaps not surprising that students given the more meaningful and generative conventional activity in the control group were more successful at learning the content.

Another probable explanation for the advantages found in the conventional activity over the game experiences is that the intrinsic integrated game framework has not been extensively tested, and especially has not been tested against robust instructional practices prior to this study. Therefore, the extent of the framework is not well understood. The framework proposes that the power of educational games is generated by
connecting the most entertaining parts of the game with the instructional materials and by embodying the content through the core game mechanics (Habgood & Ainsworth, 2005; 2011). However, there is a lack of research on how learning from games with an intrinsic design compares to learning from other instructional approaches. The findings from the current study suggest that when contrasted with a robust instructional approach, learning from a game with an intrinsic design may not be sufficient to promote greater learning outcomes.

The second important finding on the impact of statistical knowledge is that there were no differences in knowledge outcomes between the two game conditions, as predicted by hypothesis 3. Based on SCT (Bandura, 1986), vicarious learning experiences are essential to how students gain knowledge, because they accelerate learning by relieving students from directly experiencing the behavioral consequences in the environment. Furthermore, learning vicariously has been found to be similarly effective as learning enactivley across many academic contexts (Schunk, 2012). The findings in this study indicated no differences in statistical knowledge of college students who played Stats Invaders and those who merely observed a mastery model play the game while also receiving her verbal explanations of the game actions. These results extend prior findings from other academic settings to a game-based learning environment.

**The Impact on Statistics Self-Efficacy**

Contrary to hypotheses 4 and 5, but consistent with hypothesis 6, there were no significant differences in statistics self-efficacy among students who enactively learned
from the game, vicariously learned from the game, and those who completed the conventional learning activity. Although prior research has found more gains in self-efficacy after playing digital games in education (Meluso et al., 2012), the current study did not find either playing nor viewing a model play a game to be more effective at promoting self-efficacy when compared to conventional instruction without game elements. Nonetheless, as predicted in hypothesis 6, the sources of self-efficacy from direct performance in the game playing condition and vicarious experiences in the game viewing condition had comparable impacts on statistics self-efficacy.

Based on SCT (Bandura, 1986), experiencing successful task performance is expected to lead to a greater sense of confidence in succeeding at similar tasks in the future. Vicariously experiencing a model successfully perform a task is also expected to lead the viewer to believe that she too has can perform well on the task in the future. Students in the game conditions experienced a great amount of in-game success either enactively or vicariously, which was hypothesized to translate to statistics learning, and gains in statistics self-efficacy. For instance, in the game playing condition, the median level participants reached was level 19, which indicates that they experienced success when performing game mechanics (e.g. selected the correct distribution to describe the alien invasion) and may have gained insight into different probability distributions. Although it is possible that players successfully guessed some of the correct attack patterns, there were only 10 opportunities to make incorrect guesses. Reaching levels such as 19 suggest that participants were familiar with different distribution shapes. As for the game viewing condition, all participants vicariously experienced the mastery
model successfully play until level 20 and watched as she learned about probability distributions while making in-game decisions. Both game conditions experienced sources of success in learning about distribution properties that should promote self-efficacy. However, the impact of these sources resulted in similar self-efficacy as those in the control condition, who likely gained efficacy from conventional task completion.

One probable reason to explain why the game experiences did not lead to greater self-efficacy than the conventional learning activity, is that the in-game successes did not lead to a deep learning of distribution properties. In turn, the lack of deep learning did not help students gain much confidence in their statistical competencies. When adopting digital games to supplement instruction, it is important to keep in mind that in-game success is not the best indicator of the quality of in-game learning and self-efficacy in the learning content. Students could be advancing through a game while only gaining familiarity with the learning materials at a surface level. The knowledge students gained might be enough for them to continue through the game levels, but if students perceive that they do not learn a great amount of the content, regardless of their in-game successes, they may not gain self-efficacy for content learning.

The Impact on Situational Interest

The effects of learning enactively from Stats Invaders, learning vicariously, and from engaging in the conventional activity were different across the three facets of situational interest. As predicted by hypotheses 7 and 8, learning statistics by either playing the game or by observing the gameplay resulted in higher triggered-SI than
completing a conventional activity. However, contrary to hypothesis 9, playing *Stats Invaders* elicited more triggered-SI than merely viewing the model play. Overall, these findings suggest that direct engagement with the game elements had the strongest impact on students’ attentional responses to the instructional materials, followed by indirectly watching a model play the game, and conventional instruction with no game elements resulted in the lowest level of triggered-SI.

Intrinsically integrated games such as *Stats Invaders* are designed with various stimulating elements, such as challenges, levels, stages, visual features, and responsive game interactions. Such games are expected to trigger students’ interest in learning from the game-based instruction. Prior research has found that those who play an intrinsic educational game can experience high levels of triggered-SI across multiple gameplay sessions (e.g. Rodríguez-Aflecht et al., 2018). The current study extends prior research by showing that playing intrinsic games will lead to higher levels of triggered-SI when compared to observing someone else play or conventional instruction that does not incorporate stimulating features.

Triggered-SI is often a precursor to maintained interest if subsequent learning experiences allow for more meaningful and personal engagement with the instructional content (Renninger & Hidi, 2011). In turn, maintained interest predicts the level of engagement during learning, individual interest, and achievement outcomes (Linnebrink-Garcia et al., 2010). Although triggered-SI was higher for both game conditions over the control, only the game playing condition resulted in higher maintained-SI, maintained-SI-
feeling in particular, than the control. No other differences among the conditions on the two levels of maintained-SI were found.

The situational interest findings showed that enactive and vicarious learning from games are more effective at triggering students’ situational interest than conventional instruction, but not at maintaining students’ interest. However, it is important to note that the unique design of *Stats Invaders* might have contributed a substantial amount to these findings, these findings may not generalize to other games or game designs. *Stats Invaders* was designed as a pre-instructional game that does not incorporate explicit formal instruction. The pre-instructional design of this game might have naturally led students to perceive the game experience as mainly attention grabbing and stimulating, and not very beneficial for their learning. Moreover, the interest that they had toward the stimulating game elements was not enough for them to also perceive that the statistical content was enjoyable and valuable to learn. Therefore, students in the game conditions experienced comparable levels of maintained-SI to the non-game conventional activity.

Another viable explanation for the situational interest findings is that students might have viewed the game experiences as incompatible with formal learning experiences, which lead them to show less affect and perceive less value toward the content that they engaged with in the game. The majority of participants in this study had very little experience with and knowledge about digital games. Specifically, 78% had poor or fair game playing skills, 70% either play 1 – 2 hours or don’t play games each week, and 91% either watch someone else play for 1 – 2 hours or don’t watch others play each week at all. Games are often perceived to be designed for entertainment purposes.
Given that the participants are not familiar with different types of games and perhaps how games can be used in an educational context, it is possible that they do not associate games with learning. Although participants in the game conditions were informed that they would be either playing a game or watching a model play to learn statistical knowledge, the perception that games are created for entertainment purposes might have created a barrier for participants to experience a deeper affect- and value-based situational interest toward learning statistics.

**The Effects of Prior Statistical Knowledge on Situational Interest.** In this study, prior statistical knowledge of probability distributions played a role in predicting situational interest across the three conditions. Particularly for the control group, students’ scores on the knowledge pretest positively predicted all three facets of situational interest. This supports that students who had higher prior knowledge of distribution properties were likely to experience more triggered-SI, maintained-SI-feeling, and maintained-SI-value after engaging in the conventional activity. Conversely, students with low prior knowledge of distributions found the conventional activity to be less interesting. This might have been due to the nature of the conventional activity, which was a non-game generative task. For students who did not have a great amount of conceptual knowledge about distributions and their properties, comparing and contrasting pairs of distributions could be less enjoyable, difficult, and less meaningful.

In the game playing condition, however, prior statistical knowledge was not related to triggered-SI nor maintained-SI-feeling, but it negatively predicted maintained-SI-value. In other words, those who already had of knowledge about probability
distributions were less likely to find the academic content important and valuable after playing *Stats Invaders*. This is consistent with prior research that has found that knowledge deficits lead to greater situational interest on academic tasks. Specifically, Rotgans & Schmidt’s (2014) study showed that there was a negative relationship between prior knowledge and situational interest in certain learning tasks. In their study, students with little prior knowledge showed the greatest interest in learning, but as soon as students gained knowledge, their interest in learning faded. As in the game playing condition in the current study, when students played the game with high prior knowledge of distributions, they did not find learning more about distributions from the game to be interesting, even if the game was designed to be fun, enjoyable, and entertaining.

As for the game viewing condition, scores on the statistical knowledge pretest positively predicted maintained-SI-feeling but were not related to triggered-SI or maintained-SI-value. Specifically, the more statistical knowledge students started with before viewing a model play *Stats Invaders*, the more they experienced a positive affective reaction toward the content after viewing the mastery model play, and found the vicarious gaming experience as interesting and enjoyable. However, it is also likely that these students did not view the instructional video as a formal learning activity and engaged in the vicarious condition with an entertainment purpose. On the contrary, those who lacked prior knowledge were more likely to find the game viewing experience less interesting. This is likely due to their focused attention on gaining knowledge from the viewing experience, instead of engaging with an entertainment purpose.
Recommendations for Practice

The current research tested the use of games in statistics instruction and the findings suggest several recommendations for future instructional practices. First, if and how games should be adopted into instruction depends on the objective of the instruction. If the goal is to increase student’s statistical knowledge, the findings from this study with the stats invaders game, suggest that the best results will come from implementing traditional activities rather than enactive or vicarious learning sessions using the game. If the instruction intends to focus on enhancing students statistics self-efficacy, administering video recordings of a mastery model play the game, asking students to directly play the game, and providing a non-game conventional activity may lead to the same effects. When the instructional objective is to generate situational interest in students, the findings from the current study show that there are several ways to reach this goal. Triggered-SI will most likely be the highest in students directed to play the game, followed by those watching a video recording of someone else playing the game; while conventional instruction will result in the lowest level of student’s interest. Maintained-SI-feeling can also be expected to be highest in students who play the game. Finally, if the goal is to enhance students maintained-SI-value, enactive learning from the game, vicarious learning from the game, and conventional instruction may lead to similar student perceptions of statistics learning.

Second, regardless of the outcome instructors are targeting, if they ultimately choose to adopt games in their classes, statistics educators should be aware of how the design of the game they have selected will impact students learning and motivation. The
intrinsic integrated game framework (Habgood & Ainsworth, 2011) argues that educational games should connect the game and learning elements in meaningful ways to maximize motivation during gameplay, which should lead students’ learning. Furthermore, it is important that prior to implementation statistics educators recognize whether the game they are considering includes effective instruction. If the existing lesson or learning activity already incorporates a robust instructional approach, such as self-explanation, the benefits of replacing the conventional activity with enactive and vicarious learning experiences from games may be limited to increasing students’ situational interest. In previous research, game-based learning experiences were found to enhance students’ learning more than traditional methods, when compared to less robust learning activities such as reading an expository text (e.g. Arena & Schwartz, 2014) or solving division problems (Habgood & Ainsworth, 2011). To maximize students’ learning and motivational gains from enactive or vicarious game experiences, it is best for instructors to search for and implement digital games that are intrinsically designed and incorporate effective instructional strategies.

Third, the comparable learning experiences between the enactive and vicarious learning conditions suggest that administering video recordings of a model playing a game may replace in-person game playing sessions that are typically adopted in classrooms, which would benefit instructional practices. A major benefit of providing students video of a gameplay to watch and learn from is that it consumes less instructional time in class and preparation time outside of class. Pre-service and in-service teachers typically perceive game playing sessions as more time consuming to
prepare for and to implement than traditional instruction, and this perception hinders adoption of games into their lessons, even if playing the game would benefit students academically (Baek, 2008; Sandford et al., 2006). For instance, instructors are concerned about the time needed to find games, planning the game-based lesson, administering the game, and monitoring gameplaying sessions. When they believe that they can use less time to teach a lesson through conventional instruction, teachers could be less motivated to introduce the labor-intensive gameplaying sessions. Given that this study found no differences in the learning benefits students experienced by either playing or observing a model play a statistics game, these findings suggest that using videos of models playing and learning from an educational game either in class or as an assignment would be more time efficient and equally effective compared to in-person gameplaying sessions.

**Limitations of the Study and Directions for Future Research**

There were several limitations of the study. First, this study only tested the effects of vicarious learning from one particular type of game, a pre-instructional game, on statistics learning and motivation. There are various types of games used in education (Wouters & Van Oostendorp, 2013) and the effects of observing a model play a game designed as an instructional supplement (e.g. Stats Invaders) might be different from games designed as the full lesson (e.g. Cache 17). To fully examine the extent of the effects of vicarious learning from games, future research should test the vicarious learning effects from educational games with other game design structures, such as standalone products (e.g. Crystal Island). Standalone products are more likely to
incorporate an intrinsic design as well as robust instructional strategies than are pre-instructional games that rely more on external resources to impact learning. Modeling the learning processes from standalone games would likely also model learning from effective instructional methods, thus potentially leading to better outcomes than conventional instruction.

Second, the current research examined effects of enactive and vicarious learning from a game on one specific topic, which centers around the properties of probability distributions. Statistics topics are extremely diverse and learning about probability distributions is a very different than learning about the p-value, for instance (Ben-Zvi et al., 2017). Although knowledge about distributions is often considered foundational for later advanced statistical skills, the knowledge tested in this study was conceptual and at a surface level. The effects on knowledge, self-efficacy, and situational interest found in this study might not be generalizable to other statistics topics such as hypothesis testing. Further research should compare and test the effects of vicarious learning, enactive learning, and learning from conventional activities across other statistics topics and academic domains.

Third, this study only tested the effects of vicarious learning when students viewed a mastery model playing Stats Invaders. A mastery model was adopted in this study mainly because the game literature suggests that most viewers of entertainment games watch professional gamers who have expert gameplaying skills (Sjöblom & Hamari, 2017). However, it is not uncommon for entertainment game viewers to watch those with beginner or intermediate gameplaying skills. These gamers often fail and
struggle throughout the game, yet they still attract viewers in different ways. For instance, if these gamers are playing a new game, viewers might want to learn the game alongside the model who is also unfamiliar with the game. Also, viewers with poor gameplaying skills might identify with models who have the same skill level and are more willing to work on their skills with them.

Future studies should extend the vicarious learning condition tested in this study and investigate the effects of observing different types of models on learning and motivation outcomes in education. For instance, observing coping models verbalize the mistakes they make while playing and learning from an educational game but who later increase their performance to a mastery level may provide a different learning experience than observing a mastery model playing the game. The differences in learning experiences might also be influenced by students’ prior knowledge of the content. Those with high prior knowledge might enjoy watching the mastery model more, and those with low prior knowledge might benefit more from the coping model, since the coping model will demonstrate correct and incorrect knowledge and skills.

**Conclusion**

The purpose of this study was to test the effects of vicarious learning from a digital statistics game compared to enactive learning, and to further contrast these game-based learning experiences with conventional instruction. Although students who played the game or observed a model play did not benefit more in knowledge acquisition when compared to a non-game activity, learning-by-playing and learning-by-observing
approaches were found to be similarly effective at promoting statistics self-efficacy, and more effective at enhancing multiple facets of situational interest, such as triggered-SI, than the conventional activity. This study informs statistics educators about the effects of an alternative implementation strategy for adopting games into instruction, which is to use video recordings of a model play and learn from an educational game. Game-based learning experiences in this study were found to be promising at promoting motivational outcomes in statistics, while conventional instruction was more beneficial for enhancing students’ knowledge.
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Appendix A

Conventional Activity

For each pair of graphs, participants were asked to: “Compare and contrast these two histograms (or dotplots). Describe the similarities and differences between these two graphs based on the (1) the shape of the distributions, (2) the centers or the means of the distributions, (3) the spread or the variance in the data of the distributions.”
Appendix B

Reading Task

Part 1.

The Shape of a Distribution

We begin by looking at graphical displays as a way of understanding the shape of a distribution. A common way to visualize the shape of a moderately sized dataset is a dotplot. We create a dotplot by using an axis with a scale appropriate for the numbers in the dataset and placing a dot over the axis for each case in the dataset. If there are multiple data values that are the same, we stack the dots vertically. To illustrate a dotplot, we look at some data on the typical lifespan for several mammals.

Table 2.14 Longevity of mammals

<table>
<thead>
<tr>
<th>Species</th>
<th>Longevity</th>
<th>Species</th>
<th>Longevity</th>
<th>Species</th>
<th>Longevity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baboon</td>
<td>20</td>
<td>Elephant</td>
<td>40</td>
<td>Mouse</td>
<td>3</td>
</tr>
<tr>
<td>Black bear</td>
<td>18</td>
<td>Elk</td>
<td>15</td>
<td>Opossum</td>
<td>1</td>
</tr>
<tr>
<td>Grizzly bear</td>
<td>25</td>
<td>Fox</td>
<td>7</td>
<td>Pig</td>
<td>10</td>
</tr>
<tr>
<td>Polar bear</td>
<td>20</td>
<td>Giraffe</td>
<td>10</td>
<td>Puma</td>
<td>12</td>
</tr>
<tr>
<td>Beaver</td>
<td>5</td>
<td>Goat</td>
<td>8</td>
<td>Rabbit</td>
<td>5</td>
</tr>
<tr>
<td>Buffalo</td>
<td>15</td>
<td>Gorilla</td>
<td>20</td>
<td>Rhinoceros</td>
<td>15</td>
</tr>
<tr>
<td>Camel</td>
<td>12</td>
<td>Guinea pig</td>
<td>4</td>
<td>Sea lion</td>
<td>12</td>
</tr>
<tr>
<td>Cat</td>
<td>12</td>
<td>Hippopotamus</td>
<td>25</td>
<td>Sheep</td>
<td>12</td>
</tr>
<tr>
<td>Chimpanzee</td>
<td>20</td>
<td>Horse</td>
<td>20</td>
<td>Squirrel</td>
<td>10</td>
</tr>
<tr>
<td>Chipmunk</td>
<td>6</td>
<td>Kangaroo</td>
<td>7</td>
<td>Tiger</td>
<td>16</td>
</tr>
<tr>
<td>Cow</td>
<td>15</td>
<td>Leopard</td>
<td>12</td>
<td>Wolf</td>
<td>5</td>
</tr>
<tr>
<td>Deer</td>
<td>8</td>
<td>Lion</td>
<td>15</td>
<td>Zebra</td>
<td>15</td>
</tr>
<tr>
<td>Dog</td>
<td>12</td>
<td>Monkey</td>
<td>15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Donkey</td>
<td>12</td>
<td>Moose</td>
<td>12</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**DATA 2.2**

Longevity of Mammals

The dataset MammalLongevity includes information on longevity (typical lifespan), in years, for 40 species of mammals as well as information on length of gestation for these same mammals. The longevity data are given in Table 2.14.

A dotplot of the longevity data is shown in Figure 2.6. We see a horizontal scale from 0 to 40 to accommodate the range of lifespans. Quite a few mammals have lifespans of 12, 15, and 20 years. All but one typically live between 1 and 25 years, while the elephant's lifespan of 40 years is much higher than the rest. The value of 40 years appears to be an outlier for longevity in this group of mammals.

Figure 2.6 Dotplot of longevity of mammals
**Histograms**

An alternative graph for displaying a distribution of data is a *histogram*. If we group the longevity data into five-year intervals (1–5 years, 6–10 years, and so on), we obtain the frequency table in Table 2.15. We see that, for example, six of the mammals in the sample have longevity between 1 and 5 years.

The histogram for this dataset is shown in Figure 2.7. The frequency count of 6 for values between 1 and 5 in Table 2.15 corresponds to a vertical bar of height 6 over the interval from 1 to 5 in Figure 2.7. Similarly, we draw vertical bars of heights corresponding to all the frequencies in Table 2.15. Histograms are similar to bar charts for a categorical variable, except that a histogram always has a numerical scale on the horizontal axis. The histogram of mammal longevities in Figure 2.7 shows the relatively symmetric nature of most of the data, with an outlier (the elephant) in the class from 36 to 40.

**Table 2.15 Frequency counts for longevity of mammals**

<table>
<thead>
<tr>
<th>Longevity (years)</th>
<th>Frequency Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–5</td>
<td>6</td>
</tr>
<tr>
<td>6–10</td>
<td>8</td>
</tr>
<tr>
<td>11–15</td>
<td>16</td>
</tr>
<tr>
<td>16–20</td>
<td>7</td>
</tr>
<tr>
<td>21–25</td>
<td>2</td>
</tr>
<tr>
<td>26–30</td>
<td>0</td>
</tr>
<tr>
<td>31–35</td>
<td>0</td>
</tr>
<tr>
<td>36–40</td>
<td>1</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>40</strong></td>
</tr>
</tbody>
</table>

*Figure 2.7 Histogram of longevity of mammals*
Symmetric and Skewed Distributions

We are often interested in the general “big picture” shape of a distribution. A distribution is considered symmetric if we can fold the plot (either a histogram or dotplot) over a vertical center line and the two sides match closely. When we consider the shape of a dataset, we ask: Is it approximately symmetric? If not, is the data piled up on one side? If so, which side? Are there outliers? These are all questions that a histogram or dotplot can help us answer.

The histogram in Figure 2.8(a) is called symmetric and bell-shaped. The sort of non-symmetric distributions we see in Figures 2.8(b) and (c) are called skewed. The direction of skewness is determined by the longer tail. In both cases, we see that the right tail of the distribution is longer than the left tail, so we say that these distributions are skewed to the right.

![Histograms of Pulse rate, Exercise hours, and Number of piercings](image)

Figure 2.8 Three histograms for the student survey data

Using a Curve to Represent the Shape of a Histogram

We often draw smooth curves to illustrate the general shape of a distribution. Smoothing a histogram into a curve helps us to see the shape of the distribution with less jagged edges at the corners. When we describe a histogram with a smooth curve, we don’t try to match every bump and dip seen in a particular sample. Rather we
find a relatively simple curve that follows the general pattern in the data. Figure 2.9 gives examples of curves showing several common shapes for distributions.

**Common Shapes for Distributions**

A distribution shown in a histogram or dotplot is called:

- **Symmetric** if the two sides approximately match when folded on a vertical center line
- **Skewed to the right** if the data are piled up on the left and the tail extends relatively far out to the right
- **Skewed to the left** if the data are piled up on the right and the tail extends relatively far out to the left
- **Bell-shaped** if the data are symmetric and, in addition, have the shape shown in Figure 2.9(c)

Of course, many other shapes are also possible.

![Figure 2.9 Common shapes for distributions](image-url)
Part 2.

Center and Spread of a Distribution

One way to describe the center of a distribution is to use the mean. The mean of the distribution is the balancing point of the distribution graph. If the graph is bell-shaped or normally distributed, it is at the middle of the graph, if it is not bell-shaped or normally distributed, the mean is close to the highest point of the graph.

Right-skewed  Normal distribution  Left-skewed

One way to describe the spread of a distribution is to use its variation. Variation describes how widely data values are spread out in a distribution. The variation is smaller when the values are close together, and larger when the values are farther apart.
Appendix C

Statistical Knowledge Test

(Conceptual Text-Based items: CTB; Conceptual Graph-Based items: CGB; Application Text-Based items: ATB; Application Graph-Based items: AGB)

1. What would a distribution that is skewed to the left look like? (CTB; Correct: C)
   a. The data are symmetric, and the two sides approximately match when folded on a vertical center line.
   b. The distribution of data has a large variance.
   c. The data are piled up on the right and the tail extends relatively far out to the left.
   d. The data are piled up on the left and the tail extends relatively far out to the right.

2. How would you describe the shape of the distribution below? (CGB; Correct: B)
   a. Symmetrical
   b. Skewed to the left
   c. Not skewed
   d. Skewed to the right

   ![Distribution Graph]

3. Which of the distribution graphs is bell-shaped? (CBG; Correct: C)

   a. ![Graph A]
   b. ![Graph B]
4. Which distribution has the largest variance? (CGB; Correct: B)

5. Consider a dataset given the adult weight of species of insects. Most species of insects weight less than 5 grams, but there are a few species that weight a great deal, including the largest insect known: the rare and endangered Giant Weta from New Zealand, which can weigh as much as 71 grams. What is the shape of the distribution of the weights of insects? (ATB; Correct: C)
   a. Skewed to the left
   b. Bell-shaped
   c. Skewed to the right
   d. Bimodal
6. What is the approximate mean of the following data set? (CBG; Correct: C)
   a. 115 cm
   b. 119 cm
   c. 124 cm
   d. 129 cm

7. A survey conducted in August 2007 asked 1598 teens to estimate, on average, the number of friends they had made online. While 43% had made less than 5 friends, a small number of teens had made more than 5 friends online. What do you expect the distribution of number of friends made online to be? (ATB; Correct: D)
   a. Skewed to the left
   b. Bell shaped
   c. Symmetrical
   d. Skewed to the right

8. In an experiment, one female and one male restaurant server drew happy faces on the checks to their customers. The figure below is a dotplot comparing tip percentages for the female (22 checks) checks to the tip percentage for the male (23 checks). Compare the two servers with respect to the approximate centers and the variation of their tip percentages. Who do you think benefits most from drawing faces on their checks? (AGB; Correct: C)
   a. both benefits equally
   b. male
   c. female
   d. neither benefits
9. The following frequency table gives you the mean August temperature of 60 U.S. cities. What is approximately the shape of the data set? (ATB; Correct: A)

a. skewed to the right
b. skewed to the left

<table>
<thead>
<tr>
<th>Mean Temperature</th>
<th>City Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>64</td>
<td>2</td>
</tr>
<tr>
<td>65</td>
<td>1</td>
</tr>
<tr>
<td>66</td>
<td>4</td>
</tr>
<tr>
<td>67</td>
<td>5</td>
</tr>
<tr>
<td>68</td>
<td>10</td>
</tr>
<tr>
<td>69</td>
<td>7</td>
</tr>
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<td>70</td>
<td>7</td>
</tr>
<tr>
<td>71</td>
<td>6</td>
</tr>
<tr>
<td>72</td>
<td>3</td>
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<td>73</td>
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<td>79</td>
<td>1</td>
</tr>
<tr>
<td>80</td>
<td>2</td>
</tr>
<tr>
<td>81</td>
<td>1</td>
</tr>
<tr>
<td>82</td>
<td>0</td>
</tr>
<tr>
<td>83</td>
<td>0</td>
</tr>
</tbody>
</table>
10. How would you describe the shape of the distribution below? (CGB; Correct: B)  
   a. Bimodal  
   b. Skewed to the right  
   c. Symmetrical  
   d. Skewed to the left

11. The following figure is a histogram summarizing the responses given by 116 college students to a question asking how much they had slept the previous night. What is one of the most frequently reported hours of sleep they had the previous night? (CGB; Correct: B)  
   a. 4 hours  
   b. 7 hours  
   c. 9 hours  
   d. 11 hours
12. Which distribution has the smallest variance? (CGB; Correct: B)

![Graph A]

![Graph B]

![Graph C]

![Graph D]

13. What is the approximate mean of the following data set? (CGB; Correct: B)
   a. 26
   b. 39
   c. 42
   d. 50

![Histogram of Age of Best Actress Award Winners 1928-2009 (n = 83)]
14. When the distribution is bell-shaped or normally distributed, the mean can be found (CTB; Correct: B)
   a. To the right of the median
   b. At the middle of the distribution
   c. To the left of the mode
   d. At one of the tails of the distribution

15. The variation of a distribution describes (CTB; Correct: B)
   a. The center of the graph
   b. How widely data values are spread out
   c. How high the peak is of the distribution
   d. Where is the tail of the graph
Appendix D

Statistics Self-Efficacy Instrument

Please rate your confidence in your current ability to successfully complete the following tasks. For each task, please mark the one response that represents your confidence in your current ability to successfully complete the task.

1 = No confidence at all, 7 = Complete confidence

1. Identify patterns that can be expressed by distribution graphs
2. Interpret the properties of a bell-shaped or normal distribution
3. Identify the center of a distribution based on its mean
4. Interpret the center of a distribution based on its mean
5. Interpret a dotplot
6. Interpret a histogram
7. Identify a symmetric distribution
8. Interpret patterns that can be expressed by distribution graphs
9. Interpret the properties of a symmetric distribution
10. Interpret the properties of a right skewed distribution
11. Identify a bell-shaped or normal distribution
12. Interpret the spread of a distribution based on its variance
13. Interpret the properties of a left skewed distribution
14. Identify a right skewed distribution
15. Identify a left skewed distribution
Appendix E

Situational Interest Survey (SIS)

Reflect on the statistics activity that you have just completed. Please rate how each statement describes you (1=strongly disagree, 7=strongly agree):

Triggered-SI:

1. The statistics activity is exciting
2. When I did the statistics activity, it did things that grab my attention
3. The statistics activity is entertaining
4. The statistics activity is so exciting it’s easy to pay attention

Maintained-SI-feeling:

5. What I am learning in this statistics activity is fascinating to me
6. I am excited about what I am learning in this statistics activity
7. I like what I am learning from the statistics activity
8. I find the activity interesting

Maintained-SI-value:

9. What I am learning from this statistics activity is useful for me to know
10. The things I am learning in this statistics activity are important to me
11. What I am learning in this statistics activity can be applied to real life
12. I am learning valuable things from this statistics activity
Appendix F

Demographic Questionnaire

What is your age?

__________

What is your current gender identity?

☐ Male
☐ Female
☐ Non-binary/third gender
☐ Prefer to self-describe________
☐ Prefer not to say

Which college(s) are you enrolled in? (select all that apply)

☐ College of Agricultural Sciences
☐ College of Arts and Architecture
☐ Smeal College of Business
☐ College of Communications
☐ College of Earth and Mineral Sciences
☐ College of Education
☐ College of Engineering
☐ College of Health and Human Development
☐ College of Information Sciences and technology
☐ College of the Liberal Arts
☐ College of Nursing
☐ Eberly College of Science
☐ Schreyer Honors College

Which of the following describes you?

☐ Asian
☐ African American
☐ Caucasian
☐ Native Hawaiian or Other Pacific Islander
☐ Latin American
☐ Other/Please specify: ______________________

What is your class standing?

☐ First-year student
☐ Second-year students
☐ Third-year student
☐ Fourth-year student
☐ Fifth-year student
What grade do you anticipate receiving in this course?

- A
- A-
- B+
- B
- B-
- C+
- C
- C-
- D
- Below D

On average, how many hours do you play video games on either a computer, gaming console, or handheld device (phone or tablet) per week?

- 0
- 1-2
- 3-5
- 6-10
- More than 10 hours

What kinds of digital games do you mostly play (select all that apply)?

- Action (e.g. First-person shooter)
- Adventure
- Massively multiplayer online games (MMO)
- Multiplayer online battle arena (MOBA)
- Simulation
- Role-playing games (RPG)
- Sports
- Puzzle
- Card games
- Racing games

How would you describe your skill level in playing video games in general?

- Poor
- Fair
- Good
- Very good
- Professional Gamer

Additional item for study 2:

On average, how many hours do you watch others play video games on either a streaming platform (e.g. Twitch) or a video platform (e.g. YouTube) per week?
❑ 0
❑ 1-2
❑ 3-5
❑ 6-10
❑ More than 10 hours
Helen Huiqing Hu
Vita

Education
M.S., Educational Psychology, 2016, The Pennsylvania State University, University Park, PA
B.S., Psychology, 2013, Juniata College, Huntingdon, PA

Professional Experiences
Instructional Designer, 2020-present, College of Health and Human Development, The Pennsylvania State University
Graduate Assistant, 2018-2020, Teaching and Learning with Technology (TLT), The Pennsylvania State University
Graduate Assistant, 2017-2018, Penn State Learning, The Pennsylvania State University
Academic Consultant for New Student Orientation (NSO), Summer 2017, Division of Undergraduate Studies, The Pennsylvania State University
Research Assistant, 2013-2019, Department of Educational Psychology, Counseling, and Special Education, The Pennsylvania State University
Online Instructor for EDPSY 421: Learning Processes in Relation to Educational Practices, Summer 2018, Department of Educational Psychology, Counseling and Special Education, The Pennsylvania State University
Residence Instructor for EDPSY 10: Individual Differences in Education, Fall 2017, Department of Educational Psychology, Counseling and Special Education, The Pennsylvania State University

Selected Publications Submitted

Selected Conference Presentations