RELATIONSHIP BETWEEN VISUAL ATTENTION AND FLOW EXPERIENCE IN A SERIOUS EDUCATIONAL GAME: AN EYE-TRACKING ANALYSIS

by

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DEDICATION

This dissertation is dedicated to my family: Mom, Dad, Penny, Ivy, Matthew, and my two nieces, whose forgave me for my absence of all major family events in Hong Kong. They wholeheartedly supported my decision to drop everything and fearlessly come to the US to pursue my dream. Their unconditional love and trust give me strength and courage to stay true to myself.

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ABSTRACT

RELATIONSHIP BETWEEN VISUAL ATTENTION AND FLOW EXPERIENCE IN A SERIOUS EDUCATIONAL GAME: AN EYE TRACKING ANALYSIS

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Game-based learning has become a topic of interest in education, especially within the science education community. Although some evidence supporting the effectiveness of digital games for science learning is emerging, the results overall have been largely inconclusive. In order to further advance research on game-based learning, the purpose of this study was to apply an interdisciplinary approach using the cognitive-affective integrated framework, the information-processing model of selective attention (Broadbent, 1958; Lachter et al., 2004), and the dual-process theories of cognition (Kahneman, 2011; Svahn, 2009), to construct a comprehensive view of the mental processes of visual attention during gameplay in relation to the positive affective state of Flow experience. This study utilized a mixed methods design, using a concurrent embedded strategy QUAN/qual (Creswell, 2008) to collect and analyze both quantitative and qualitative data. Thirty-one high-school students (*N*=31) in the mid-Atlantic region of

the United States, between ages 14 and 17, played the Serious Educational Game (SEG) called Neuromatrix. Self-report surveys and an eye tracking method were used to collect quantitative data for statistical analysis. A gaze duration sequence diagram (Raschke, Chen, & Ertl, 2012) was adopted for data visualization and qualitative scanpath analysis. Two Flow scales (FSS-2 and eGameFlow) were used to explore the differences in psychometric properties between the generic and context-specific Flow measures. The results showed a negative linear relationship between visual attention and Flow experience ($p < .001$). Three visual attention variables were identified and served as the indicators of Flow and perceived science learning in an SEG environment: (a) low fixation counts indicated students' focused attention and immersion in an SEG; (b) short total visit duration represented the efficiency of selective visual attention and may serve as an indicator of Flow experience during gameplay; and (c) total fixation duration illustrated the extent to which students looked at specific learning materials that could possibly pass through the selective filter into conscious attention and thus, lead to learning. The interplay between affective and cognitive processes during gameplay played a key role in students' deep engagement and had an impact on their positive science learning in an SEG. An interactive effect of total fixation duration and Flow on perceived science learning was found ($p < .001$, $p\eta^2 = .324$), implying that a well-designed SEG that aligns gameplay and learning objectives may promote synergy between engagement and learning. Moreover, two individual differences factors, science interest and self-efficacy for computer use ($p < .01$) – that predicted Flow were identified by a stepwise regression analysis; these factors were shown to influence the attentional processes and cognitive processes of gameplay. The evidence of a positive relationship between science interest and Flow in an SEG may encourage teachers and parents to take an active role in instilling students' science interest in their early years, and to support students' ongoing development of science interest through exposure to various formal and informal learning contexts.

CHAPTER ONE: INTRODUCTION

Background of the Problem

Game-based learning has become a topic of interest in education, especially with the science education community. Many experts have called for a new approach to spark students' interest in science, technology, engineering, and mathematics (STEM), and immersive, well-designed digital games suggest a promising approach to promoting students' curiosity and engagement in STEM (Annetta, 2008b; de Freitas, 2006; NRC, 2011; Prensky, 2001). Although some evidence for the effectiveness of digital games in supporting science learning is emerging, the results overall have been largely inconclusive (Dondlinger, 2007; NRC, 2011; Young et al., 2012). A growing body of literature has indicated that effective game-based learning relies on three human processing components: affective, motivational, and cognitive processes (see Ke, 2009, for a review). In order to further advance research on game-based learning, there is a need to expand our research attention beyond looking solely at learning outcomes and also consider the engagement component in educational games, which includes learners' cognitive, emotional, and motivational processes in gameplay.

In 2002 Ben Sawyer, cofounder of the Serious Games Initiative, introduced a new genre of computer games (called "Serious Games" to distinguish them from other video games). Serious Games have been used for training and instruction in various domains, such as defense, scientific exploration, health care, city planning, and engineering. As a result of the ongoing interest in using technology to support student learning through completion of complex tasks, a subset of Serious Games, known as SEGs (for Serious Educational Games) has emerged. SEGs are game-based, authentic learning environments that specifically target K-20 teaching and learning (Annetta, 2008a). SEGs have the potential to transform education and promote 21st century skills such as expert problem solving and complex communication (Spires, 2008). Therefore, SEG researchers have begun to examine more deeply the complex learning dynamics that take place during gameplay.

Since SEG is a complex learning environment and game-based learning research is a relatively new area in education, both learning outcomes and gameplay processes should be systematically examined. Cognitive psychology's focus on mental processes provides a new approach for SEG researchers to study gameplay and game-based learning. Understanding player-learner mental processes and the emotional episodes that occur during gameplay can ensure a close match between the learning activities and the desired outcomes. For SEG researchers who study engagement, it is especially critical to apply an interdisciplinary approach in order to understand the influences of positive affective states on individuals' cognitive processes related to gameplay and learning. Therefore, the cognitive-affective integrated framework of cognitive psychology can provide insights and expand our current understanding, enabling us to examine the mental processes that operate while users are playing and learning from SEGs. The resulting knowledge could then be applied to other game-based learning systems.

The concepts of visual perception and attention provide a foundation for studying the cognitive processes of gameplay. Selective attention is especially relevant to game-based learning. Therefore, the information-processing model of selective attention (Broadbent, 1958) has been applied in this study to explain the mechanisms of effective allocation of visual attention in gameplay. Moreover, game-based learning depends on multiple levels of cognitive operations, so the application of dual-process theories of cognition may provide a universal means of interpreting the various levels of cognitive processing underlying the complex learning environment of SEGs.

The role of positive affective states in student engagement is a critical component of the relationship between SEGs and learning. One relevant concept for this purpose is known as Flow theory (Csikszentmihalyi, 1975). Flow is a state of perceived optimal personal experience, and it is composed of distinctive cognitive, perceptual, and emotional domains, all of which are highly related to game-based learning (e.g., Annetta, 2008b; Sweetser and Wyeth, 2005). Existing studies have shown that Flow state is a subjective experience characterized by positive valence and high arousal, and associated with other affective states such as joy, excitement, or ecstasy (Lang, 1995; Mauri et al., 2011; Nacke & Lindley, 2008). Flow is also described as a state of effortless attention that arises through an interaction between positive affect and high attention level (de Manzano et al., 2010). Therefore, attention and Flow are closely associated.

Although Flow can be intuitively linked to SEGs and learning, more rigorous research is needed; specifically, relationships among cognition, emotions, and learning in SEGs should be considered more systematically. Eye tracking is one available objective measure for studying human cognitive and perceptual processes. It records tangible interactions to correlate observed behavior with self-reported information and bridges the gaps between retrospective reports and in-game, real-time behaviors. Eye tracking thus provides a new means of studying gameplay and allows SEG researchers to visualize gamers' experience.

Purpose of the Study

Studies from cognitive psychology have supported the contention that higher-order cognition is affected by the interplay of affect and cognition. The primary goal of this study is to apply an interdisciplinary approach, using the cognitive-affective integrated framework of cognitive psychology and the information-processing model of selective attention, to investigate the following three relationships in a science SEG environment: (a) the relationship between visual attention and Flow experience, (b) the outcomes of visual attention and Flow, and (c) individual differences factors with regard to visual attention and Flow. The theoretical model presented in Figure 1 illustrates the theoretically grounded relationships between the individual differences factors, visual attention, Flow, and their outcomes (perceived science learning and perceived enjoyment) in a science SEG environment.

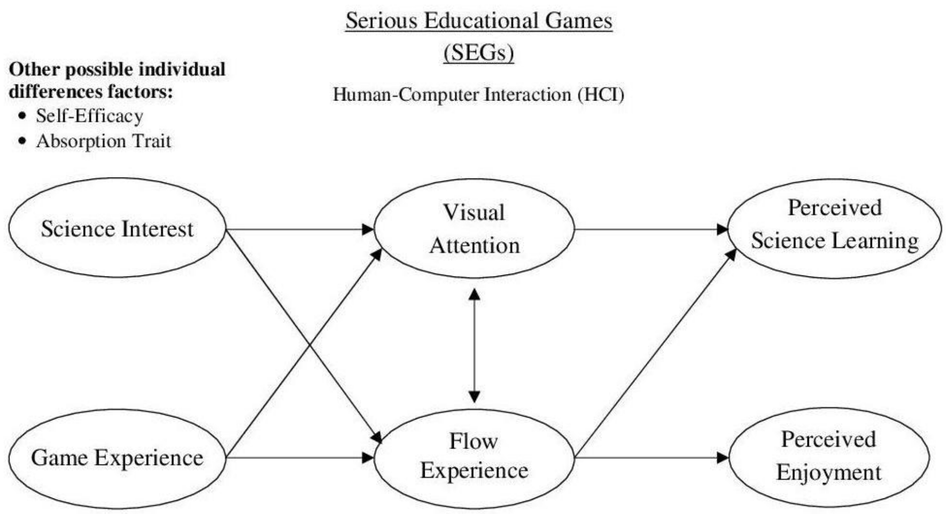


Figure 1 Theoretical model of visual attention and Flow in SEGs.

Research Questions

Three research questions were proposed in order to test the theoretically grounded hypothetical relationships between visual attention and Flow in an SEG; their possible interactive effects to outcomes, and to determine which individual differences factors may relate to visual attention and Flow in a science SEG.

The three research questions are:

1. What are the associations between visual attention and Flow experience during gameplay?
    a. Are there any relationships between the number of fixations and gaze duration on Areas of Interest (AOIs), and Flow experience while playing an SEG?
    b. Are there any differences in scanpaths (length and pattern) while playing an SEG between high Flow and low Flow individuals?

2. What are the associations between visual attention, Flow experience, and their outcomes (perceived science learning and perceived enjoyment) through playing an SEG?
    a. Are there any interactive effects of visual attention and Flow experience (high, medium, and low) on perceived science learning and perceived enjoyment?
    b. Whether students' Flow experience has positive relationship with perceived science learning?
    c. Is there a strong positive relationship between Flow and perceived enjoyment?
    d. Are there any relationships between gaze duration during gameplay and perceived science learning or perceived enjoyment?
3. What individual differences factors related to students' Flow experience and visual attention in an SEG environment?
    a. What individual differences factors are the predictors of Flow experience?
    b. Is there any correlation between science interest and visual attention?
    c. Is there any correlation between science interest and Flow experience?

Significance of the Study

This study aims to apply a cognitive-affective integrated framework from cognitive psychology, specifically the information-processing model of selective attention and the dual-process theories of cognition, to construct a foundation for a comprehensive understanding of the mental operations of visual attention during gameplay, in relation to the positive affective experience of Flow in a science SEG environment. The combination of self-reported data and eye tracking offers a new approach in studying gameplay processes and game-based learning.

Recent research aimed at expanding our understanding of Flow and has begun to generate new ways of recognizing the affective, cognitive, physiological, and behavioral components of this phenomenon (de Manzano et al., 2010; Peifer, 2012). Both visual attention and Flow play a key role in determining students' engagement in an SEG and seem to have an interactive effect in game-based learning. An examination of a science SEG through an integrated and interdisciplinary approach may significantly help educators, learning scientists, SEG researchers, and game designers to better understand how Flow and visual attention are related to students' gameplay and learning experiences. The research results may identify potential benefits of the cognitive-affective integration model in explaining the role of Flow and visual attention in gameplay processes; this information, in turn, could provide guidance for the design of effective SEGs that will facilitate Flow and support science learning.

Little empirical research has examined the individual differences factors that may predict Flow and increase the efficiency of selective attention during gameplay. This study will identify possible predictive factors that could influence Flow and efficiency of visual attention in an SEG. The knowledge gained from this study will assist teachers and school administrators in focusing on relevant individual differences and maximizing the benefits that each individual can receive from game-based learning.

This study applies an interdisciplinary approach to study the cognitive-affective processes of gameplay and perceived science learning in an SEG, drawing from literature in education, psychology, computer sciences, engineering of human-computer interaction (HCI), and management information system (MIS). These fields offer a robust base of scientific evidence to advise teacher educators in making decisions and informing teachers as to the power of SEGs. Better information on the effectiveness of SEGs may encourage in-service and pre-service teachers to shift the focus of traditional science teaching to an interactive, enjoyable way of game-based learning in science education, ultimately increasing students' interest in STEM education and careers.

Moreover, this study employs a visual analysis method, namely a gaze duration sequence diagram, to visualize eye tracking data and qualitatively analyze scanpath patterns in an SEG environment. Unlike the classical static scene analysis, in which heat maps or other aggregated density based representations are used to evaluate eye tracking patterns, this new method enables greater flexibility in the study of extremely interactive and dynamic 3-D game environments and provides an effective way to manage, view, and analyze the recorded eye tracking data. It also allows researchers to transform these data into a spatial-temporal structure and to evaluate the visual diagrams from a user-centered perspective. The qualitative scanpath pattern analysis used in this study demonstrates a creative way to evaluate visualizations and compare eye fixation scanpaths heuristically. It will help SEG researchers to rely less on computer algorithms, which require highly technical and specialized knowledge, and to conduct visual analysis of recorded eye tracking data more efficiently.

Finally, this study examined the measurement perspective of Flow by comparing the results of two different scales: the generic FSS-2 and the context-specific eGameFlow scales. This is a first step toward differentiating the measurement validity of the two Flow scales in the context of game-based learning. The further examination of the sensitivity validity of the context-specific eGameFlow scale may help to transform this instrument into a useful diagnostic measurement tool in predicting Flow in game-based learning; the scale could then serve as a means of assessing the effectiveness of SEGs.

Limitations

Several limitations of this study should be considered. First, the learning theory applied in Neuromatrix, the SEG used in this study, was not explicitly specified by the game developer, who did not claim that this SEG has the best design for science learning.

Second, the perceived science learning measure used in this study does not reflect actual science learning or acquisition of any specific knowledge originally proposed by the game developer. The measure assesses only the students' subjective feeling of how much they have learned after gameplay. Further investigation or different measures would be needed to assess actual science learning in an SEG environment.

Third, self-reported measures collected *immediately after* the activities were used to reflect the latent construct of Flow. Subjective measures are retrospective in nature and may not accurately reflect the entire subjective experience. Triangulation with the eye tracking data applied in this study may help to identify the presence of Flow *during* the activity without interrupting the participants. However, development of a psychophysiological approach to explain the direct association between Flow and eye movement in Serious Games research is still in its infancy. The effort faces challenges in interpreting eye tracking data accurately. In addition, it will require more carefully designed and controlled experiments, large sample sizes, and advanced technology, as well as the use of a variety of psychophysiological measures together with questionnaires, so as to gain a better understanding about the subjective experience of Flow in gameplay.

This study applied a naturalistic perspective to explore the possible interactive effects between cognitive and affective processes in gameplay. A full understanding of users' specific mental processes and how they directly affect gameplay and Flow experience will require carefully designed experimental studies, with a multistage approach, designed to test the precise mental operations that relate to gameplay and learning processes.

The students played this science SEG for only 15 minutes each. It is unknown whether students' Flow experience and perceived science learning might change significantly if they played the game for a longer period of time.

Finally, the sample used in this study constitutes a limitation. There were 31 subjects, all from one school. It was a convenience sample, and the sample size was limited due to the time constraints involved in eye tracking data collection. Therefore, interpretations of the study's results and generalizations to other populations should be made with these considerations in mind to avoid any form of bias.

Future Research Direction

The cognitive-affective integrated framework of cognitive psychology should be further applied in learning sciences and game-based learning research in order to understand the impact of positive affective states on students' thinking, problem solving, and ultimately their deep learning in an SEG environment. SEG researchers should continue to investigate the interactive effect of Flow and visual attention on science learning with larger sample sizes, using creative measures that shift away from traditional assessment instruments, such as multiple-choice tests, to capture students' actual science learning in a highly dynamic and interactive game environment.

Playing computer games is a very personal experience. Studies have shown that personality traits and motivation are strong indicators of game genre preferences, behaviors in gameplay, immersion in a game environment, and effectiveness in game-based learning. This study has identified specific individual differences factors that influence Flow experience and visual attention; future researchers should further investigate precisely how and why these factors affect Flow and selective attention in an SEG. Science educators and researchers interested in fostering science interest may also wish to investigate the relationship between students' science interest or prior science knowledge of students and their experience of Flow and learning in a science SEG.

Flow is a subjective experience; therefore, researchers cannot solely rely on self-reported measures to truly understand it. Eye tracking is a physiological measure that can help researchers to visualize players' in-game experience through eye movement and scanpath patterns. Other psychophysiological measures, such as brain imaging and facial electromyography (EMG), can be equally useful in examining Flow in game research. These psychophysiology approaches to studying Flow can enable physiological and neural data to be collected during gameplay without interrupting the participants. Development of a synthetic theory with cognitive, affective, behavioral, and neurophysiological components to explain Flow phenomena could help us to more fully understand the functions and consequences of Flow and could ultimately offer practical implications on how to produce Flow experiences and impact learning in SEG environments.

The Affective Response Model applied in this study has explanatory power in addressing the various pertinent affective concepts in an HCI context and how they relate to each other. SEG researchers and learning scientists may further apply this model in studying the affective aspects of game-based learning holistically or individually.

There is also an urgent need to test the measurement validity of the currently available Flow scales (generic or context-specific) in game-based learning situations and to, further evaluate their respective psychometric properties – in particular the measures of sensitivity, specificity, and predictive value – with, larger samples. Rigorous examinations of the sensitivity of the context-specific eGameFlow scale may help to transform it into a useful diagnostic measurement tool for predicting Flow in game-based learning and may enable it to serve as an assessment of the effectiveness of SEGs.

Operational Definitions

Serious educational games (SEGs). SEGs are electronic or computer games that are designed to target K-20 audience and educational content instead of purely for entertainment purposes (Annetta, 2008a).

Flow. Flow is defined as a state of personal perceived optimal experience, a holistic sensation that people feel when they act with total involvement

(Csikszentmihalyi, 1975). Recent Flow researchers proposed a working definition of Flow that integrates affective, cognitive, physiological, and behavior components into it; where Flow can be defined as an experience during task performance as a result of an interaction between emotional and attentional systems, that is, both cognitive and physiological processes, enabled by a certain level of expertise (de Manzano, Theorell, Harmat, and Ullén, 2010).

Emotional episode. Emotional episode includes anything starting from the stimulus to the later components or the immediate consequences of the emotion. Examples of components are: (a) cognitive; (b) feeling, referring to emotional experience; (c) motivational, consisting of action tendencies or states of action readiness; (d) somatic, consisting of central and peripheral physiological responses; and (e) motor, consisting of expressive behavior. These components correspond to functions such as (a) stimulus evaluation or appraisal; (b) monitoring; (c) preparation and support of action; and (d) action (Moors, 2010).

The following measure concepts of eye tracking metrics are defined by Jacob and Karn (2003):

Fixation. A relatively stable eye-in-head position within some threshold of dispersion (typically ~ 2°) over some minimum duration (typically 100-200 ms), and with a velocity below some threshold (typically 15-100 degrees per second) (Jacob & Karn, 2003).

Gaze duration. A cumulative duration and average spatial location of a series of consecutive fixations within an area of interest (AOI). Gaze duration typically includes several fixations and may include the relatively small amount of time for the short saccades between these fixations. A fixation occurring outside the area of interest marks the end of the gaze (Jacob & Karn, 2003). Other terms of gaze in eye tracking studies will be dwell and visit. A dwell time is a visit in an AOI from entry to exit.

Area of interest (AOI). Area of display or visual environment that is of interest to the research and thus defined by them (not by the participant).

Scanpath. It is the spatial arrangement of a sequence of fixations. It indicates the efficiency of the arrangement of elements in the user interface (Jacob & Karn, 2003).

Number of gazes on each area of interest. Gazes (the concatenation of successive fixations within the same area of interest) are often more meaningful than counting the number of individual fixations (Jacob & Karn, 2003).

The following interpretations are proposed by Jacob and Karn (2003) and Holmqvist et al. (2011):

Gaze duration mean, on each area of interest. They predicted that gazes on a specific display element would be longer if the participant experiences difficulty extracting or interpreting information from that display element (Jacob & Karn, 2003). The term dwell time is also used in eye tracking studies. It indicates interest in an object or higher informativeness of an object. There is a strong relationship between consecutive fixations on an item and how much you need to mine information from it. High dwell time may also indicate uncertainty and poorer situation awareness (Holmqvist et al., 2011).

Fixation duration mean, overall. Longer fixations (and perhaps even more so, longer gazes) are generally believed to be an indication of a participant's difficulty extracting information from a display (Jacob & Karn, 2003). In usability studies, shorter fixation durations reflect increased experience of a task; whereas out-of-context objects generate fixations than objects which fit the context (Holmqvist et al., 2011).

Number of fixations on each area of interest. This variable is closely related to gaze rate, which is used to study the number of fixations across tasks of differing overall duration. The number of fixations on a particular display element (of interest to the design team) should reflect the importance of that element. More important display elements will be fixated more frequently (Jacob & Karn, 2003). The number of fixations also negatively correlated with search efficiency in the study of assessing usability. A high number of fixations would be an indicative of difficulty in interpreting the fixated information (Holmqvist et al., 2011).

The following operational definitions of eye tracking metrics for calculated values in this study are primarily adopted from the Tobii Studio User manual (2012), version 3.2 Rev A:

Fixation duration. It measures the duration of each individual fixation (seconds) within an AOI (Tobii, 2012). The fixation identification is based on Velocity-Threshold Identification (I-VT), employing a fixation velocity algorithm. It classifies eye movements based on the velocity of the directional shifts of the eye. Data points with angular velocity below the threshold are classified “fixation” and data points above are classified as “saccade,” which the default threshold is set to 30 visual degrees per second (°/s). I-VT has a gap fill-in function to fill in data through linear interpolation where valid data is missing. Data between two data loss scenarios is filled in with a maximum gap length of 75 milliseconds (ms), as the minimum blink duration is 75 ms according to Komogortsev et al. (2010). The default value of I-VT filter for the minimum fixation duration is set to 60 ms. If the duration is shorter than the parameter value; the fixation is reclassified as an unknown eye movement. This filter function is needed so as to remove data points which are too short a time for the visual input to be registered by the brain, according to cognitive processes theory (Olsen, 2012). Total fixation duration is the sum of all AOIs and non-AOIs durations.

Fixation count. It measures the number of times the participant fixates on an AOI (p. 103). Total fixation count is the sum of all AOIs and non-AOIs fixations.

Visit duration. It measures the duration of each individual visit within an AOI (seconds). A visit is defined as the interval of time between the first fixation on the AOI and the next fixation outside the AOI (Tobii, 2012). Total visit duration is the sum of all AOIs and non-AOIs durations.

Visit count. It measures the number of visits within an active AOI. A visit is defined as the time interval between the first fixation on the active AOI and the end of the last fixation within the same active AOI where there have been no fixations outside the AOI (Tobii, 2012). Total visit count is the sum of all AOIs and non-AOIs visits.

CHAPTER TWO: LITERATURE REVIEW

For more than three decades, education researchers have been investigating the potential for the application of computer games to learning (e.g., Gee, 2007; Kafai, 1995; Malone, 1981; Prensky, 2001; Squire, 2003). There is a growing literature about computer games and education which identifies three components of game-based learning: affective, motivational, and cognitive processes (see Ke, 2009, for a review). The unique characteristics of computer game design not only provide challenges and immediate feedback while playing, but also introduce problems that are framed in a situated context, and invoke an intensity of engagement in players, which enable gamers to personalize instruction to their own needs and interests.

Although many experts around the world support the use of computer games for learning due to mounting evidence in its effectiveness (Hinrichs & Wankel, 2011; Kirriemuir & McFarlane, 2004; Mitchell & Savill-Smith, 2004; NRC, 2011), the results are inconsistent and inconclusive (Dondlinger, 2007; Ke, 2009; Young et al., 2012). Ke (2009) argues in a recent meta-analysis of computer games as learning tools that out of the 89 empirical studies that have been systematically reviewed, well over half of the research questions of the studies (65 studies or 73%) were evaluating the effects of computer-based games on learning while only a few (4 studies or 4.5%) were investigating the cognitive and motivational processes during gameplay. Given that a computer game is a complex learning environment and that game-based learning research is a relatively new area in education, both learning outcomes and processes should be systematically investigated. Yet, the majority of empirical studies in game-based learning have focused on learning outcomes instead of on the variety of learning processes. Even among the few studies that examined various game-based learning processes, they only focused on either cognitive or motivational processes rather than the interactive effects between cognition and affect (or emotion) in gameplay. This issue exhibits a lack of systematic and theoretical examination of both affective- and cognitive-related phenomena, concepts, and their relationships in the game-based learning environment. Affect is a fundamental aspect of being human and influences our perceptions, cognition, judgment, and various behaviors consciously or unconsciously. Recent developments in cognitive psychology and affective science have achieved a level of consensus of both the meanings and structures of various mental processes and affective concepts (e.g., Barrett & Russell, 1999; De Houwer & Hermans, 2010; Evans & Frankish, 2009; Reber, 1993; Russell, 2003, 2009; Scherer, 2003). These findings are particularly relevant to game-based learning, but such a lack of research attention in cognitive-affective integration may be a major contributing factor to the inconclusive results. There is a need to expand our current framework by using an interdisciplinary approach to examine how people learn in a game-based learning system.

In this study, a wide-range of literature from different academic fields is examined in order to determine the links between visual attention and Flow experience while playing a Serious Educational Game (SEG). Under the cognitive-affective framework of cognitive psychology, in particular, Broadbent’s filter model of selective attention (Baddeley & Weiskrantz, 1993; Broadbent, 1958; Lachter, Forster, & Ruthruff, 2004), the dual-process theories of cognition (e.g., Evans, 2009; Evans and Over, 1996; Kahneman, 2011; Reber, 1993; Stanovich, 1999; Svahn, 2009), and the affective response model (Zhang, 2013), will be used to integrate cognitive (visual attention) and affective (Flow) components to understand the students' mental processes in a science SEG.

Serious Educational Games: Learning and Engagement

Historical review of computer-based educational games. The educational use of digital games dates back to 1971 when three Carleton College students invented the game *The Oregon Trail* which was later released throughout the state and to the general public via the Minnesota Educational Computer Consortium (MECC). Other classics such as *Lemonade Stand* (1973, 1979), *Snooper Troops* (1982), *Where in the World is Carmen Sandiego* (1985), *Math Blaster* (1986), and *Jumpstart* (1994), offered the alternative means to learning from traditional classroom lectures and laboratory activities. These early computer-based educational games are designed to integrate learning motivation and gameplay, where players must work for knowledge and actively solve challenging tasks, and travel through meaningful game world. The connection between the play experience and the learning experience became stronger than ever (Egenfeldt-Nielsen, 2005).

Early versions of computer-based educational games tend to be based on a behaviorist approach on learning without any uniform pedagogy within the games.

Therefore, the characteristics of these early designed games are usually engaging but not necessarily fun, while learning can be implicit or explicit. For example, the use of operant conditioning techniques helped shape player behavior and allowed players to perform more complex tasks through successive approximations, and ultimately, learning (Salen & Zimmerman, 2004). Later games such as *Quest Atlantis* (2003), *River City* (2004), and *Crystal Island* (2008), tried to incorporate experiential, situated, and socio-cultural pedagogical models to promote effective learning. Based on the accumulation of knowledge in educational game design, Ulicsak and Wright (2010) summarized that any good computer-based educational games are dependent on three elements: pedagogy, game mechanisms, and content. All elements should be integrated into a game so that learning becomes intrinsic during play.

Serious games: A new approach to learning. The term *Serious Games* was first formally discussed by Clark Abt in 1970. In his view, Serious Games "unites the seriousness of thought and problems that require it with the experimental and emotional freedom of active play. Serious Games combine the analytic and questioning concentration of the scientific viewpoint with the intuitive freedom and rewards of imaginative, artistic acts" (Abt, 1970, p. 11). He further states, "Serious games offer us a rich field for a risk-free, active exploration of serious intellectual and social problems… The role-playing that students undertake in games that simulate life is excellent preparation for the real roles they will play in society in later life" (pp. 13-14). Even though his references were primarily based on board and card games, he offered an insightful definition of Serious Games, which is continuously applicable in the Digital Age.

In 2002, Ben Sawyer, co-founder of the *Serious Games Initiative*, initiated a new genre of computer games called *Serious Games* in order to distinguish it from video games. He argues that Serious Games are created for training and instruction while video games are developed primarily for entertainment purposes (Gudmundsen, 2006). Serious Games (including simulations and virtual worlds) provide a safe, relatively cost-effective, and high-level of fidelity for learning complex concepts or training specific skills. Sawyer and Smith (2008) generated a list of terms that describe Serious Games, such as virtual reality, immersive learning, social impact games, and synthetic learning environments, which reflect the nature of this genre.

There are benefits in playing Serious Games. Klopfer, Osterweil, and Salen (2009) state that game players often exhibit persistence, risk-taking, attention to detail, and problem solving skills when engage in play. Klopfer and his team proposed *The Four Freedoms* of play that are fundamental to optimizing the players' experience, which are not commonly found in traditional classroom environments. They are: (a) freedom to experiment, that allows students to direct their own learning process based on their curiosity; (b) freedom to fail, that eliminates the penalty for making mistakes as well as the fear of failure that may shut down students' ability to think creatively; (c) freedom to try on identities, that gives players a chance to decide and customize their avatar that experimenting with different aspects of self and personal identity; and (d) freedom of effort, that allows players to do their best when they are most motivated while taking it easy at other times based on their own pace and interest. Serious Games allow gamers to become another person through actively interact and experimenting the complex systems of a virtual world. Interactivity is considered to be “the key to the emerging supremacy of digital gaming” (Bryant & Fondren, 2009, p. 107). The sense of realism and interactivity are properties of Serious Games that allow communications between individual gamer and the context-rich game system. Freely exploring the gaming environments, interacting with the game elements, actively seeking information or influencing the trajectories of gameplay through decision-making and subsequent actions, are the distinct and crucial features of Serious Games (Ritterfeld, Shen, Wang, Nocera, & Wong, 2009). Therefore, Serious Games is a powerful tool for teaching and learning in complex and social situations like in science and business education (Akilli, 2007). Gamification is another way to apply game design in education; that is using game mechanics, game dynamics, and game design frameworks to promote learning and engagement in a non-game context (Lee & Hammer, 2011).

In a review article, Dalgarno and Lee (2010) identified five learning benefits to education that may be uniquely exhibited in 3-dimensional (3-D) virtual learning environments (VLEs). They are: (a) spatial knowledge representation, (b) experiential learning, (c) engagement, (d) contextual learning, and (e) collaborative learning. For instance, 3-D simulations designed to support training for various medical procedures that facilitate learners to practice skills and undertake embodied learning tasks, which otherwise will be expensive, dangerous, or impossible to undertake in the real world. The high degree of personalization of VLEs and game-based approaches may lead to increased intrinsic motivation and engagement. Moreover, the individualized, interactive, and realistic learning in VLEs provides a unique opportunity for situated learning and improve transfer of knowledge and skills to real situations through contextualization of learning.

The use of Serious Games in *knowing about* the real world is no longer restricted to fields like scientific research, engineering, or business modeling; it is also gaining momentum in education. Therefore, a subset of Serious Games, known as *Serious Educational Games* (SEGs), has emerged. SEGs are game-based, authentic learning environments that specifically target K-20 teaching and learning (Annetta, 2008a). SEGs have the potential to transform education and promote 21st century skills such as expert problem-solving and complex communication (Spires, 2008). These skills can be developed or practiced in the context of real world goals, rules, and situations. Gee (2007, 2009) also suggested that the theories of learning used in designing good digital games is close to the best theories of learning in cognitive science and thus will fit well within the confines of classroom instruction.

SEGs in science learning. Although scientific and technological competence is vital to the nation's future, many students in the United States are losing their interest in science and as a result, a large gap between the science and mathematics competence of young Americans and their counterparts internationally exists (Organisation for Economic Co-operation and Development; OECD, 2011). Therefore, the science education community started to examine the current curriculum that was used in decades and made significant revision to match the new objectives for the 21st century. Some view K-12 science education as a pre-professional form of training for students who will become the scientists of tomorrow, while others view science education as a foundation for students to develop knowledge of science and processes of scientific thinking (Osborne & Hennessy, 2003). The National Academies *Gathering Storm* report concluded that a primary driver of the future economy and concomitant creation of jobs will be innovation, largely derived from advances in science and engineering. While only four percent of the nation's work force is composed of scientists and engineers, this group disproportionately creates jobs for the other 96 percent (National Research Council; NRC, 2007). The National Science Board (NSB) has long been concerned with the state of science, technology, engineering, and mathematics (STEM) education in the United States, and "firmly believe[s] that to ensure the long-term prosperity of our Nation, we must renew our collective commitment to excellence in education and the development of scientific talent" (NSB, 2010, p. 1).

In November, 2009, President Obama launched the *Educate to Innovate* Campaign (White House, 2010), to improve the participation and performance of America's students in STEM. The campaign has invested greatly in the development of immersive, science-related digital games intended to promote students' curiosity and engagement in STEM (Young et al., 2012). Despite the national concerns of STEM education, the NRC committee revisited the issue and found that the overall public school system "has shown little sign of improvement, particularly in mathematics and science" (NRC, 2010, p. 4). Changing the current lack of STEM talents is a long-term battle. It requires significant foresight and early intervention. Mastery of a STEM discipline requires decades of intensive study in college and graduate school, but the interest in STEM may start in K-12, or even in early childhood. In a recent report, *Learning Sciences through Computer Games and Simulations*, many experts call for a new approach to science education that spark students' interest by "engaging them in investigations, helping them to develop understanding of both science concepts and science processes while maintaining motivation for science learning" (NRC, 2011, p. 1). Computer games have the potential to catalyze this new approach and motivate students by designing appropriate challenges, providing immediate feedback, and offering personalized instruction to match their individual needs and interests.

Many Serious Games for science have emerged and are supported by eminent science institutes and universities. For instance, Federation of American Scientists (FAS), as part of their *Learning Technologies Projects Group* has designed various SEGs; *Immune Attack* and *Digital Human* are two examples that relate to science learning. NASA's *Learning Technologies* focuses on several areas of the *NASA eEducation* including games for learning and virtual worlds; *Moonbase Alpha* is a NASA-funded multiplayer 3-D immersive game, which players assume the role of an astronaut working in a hypothetical lunar outpost. The JASON Foundation for Education, a nonprofit subsidiary of the National Geographic Society, with Kauffman Foundation funding, developed a game known as *Operation: Resilient Planet* (ORP) in 2008. ORP combines the scientific exploration with realistic gameplay targeted for middle-school science students on missions to explore the ocean ecosystems. The University of Washington developed a freely available, multiplayer online game called *Foldit* (http://fold.it), which helped research scientists solve a decade old complex scientific problem – the structure of a retrovirus enzyme (Markoff, 2010). More than 57,000 players, all volunteers, contributed extensively to the project since 2008 when this protein-folding computer game was launched online. The results generated by *Foldit* have been published in the leading scientific journal *Nature* (Khatib et al., 2011) and *Nature Biotechnology* (Eiben et al., 2012), marking the first time it has published a paper with over 57,000 authors (Foldit players).

The potential of SEGs is enormous. Dondlinger (2007) reviewed literature in the last 20 years on educational games and concluded that "there is a widespread consensus that games motivate players to spend time on task mastering the skills a game imparts… [A] number of distinct design elements, such as narrative context, rules, goals, rewards, multisensory cues, and interactivity, seem necessary to stimulate desired learning outcomes" (p. 28). New games have been developed to make subjects like world culture, molecular biology, and space exploration more accessible and fun to learn for students (Akilli, 2007; Derryberry, 2007; Gaudiosi, 2009). Young et al. (2012) reviewed the past 30 years of literature about SEGs and argues that there is positive evidence about the increased in student engagement and interest in science, but little support for academic outcomes. Although there is limited evidence for gaming and learning in science, it is important for researchers to recognize that the unique feature of SEGs is to promote learning *and* maintain the game experience.

Since SEGs are virtual experiences centered on problem solving, gamers view learning and mastery of skills as a form of pleasure. Effective educational games provide learning environments that go beyond individual's participation to social collaboration, which supply clear goals, practice, explanation, and feedback for deep learning (Gee, 2009). SEGs potentially improve not only the acquisition of knowledge and cognitive skills, but also the acquisition of fine-grid motor skills and attitudinal change, which students' engagement and motivation are critical to sustained learning (de Freitas, 2006). However, not all SEGs facilitate learning. In order to further advance the game-based learning research, there is a need to shift our research attention from solely learning outcomes to the engagement component in SEGs that includes learners' cognitive, emotional, and motivational processes in gameplay.

SEGs and engagement. In general, many students enjoy computer games. Games are not just playing; students also talk about it, deeply engage in it, and become part of their everyday life (Annetta, 2008b). Bassi and Delle Fave (2004) found that computer and video games became the number one leisure activity of choice in 2000 among adolescents in Italy and were primarily associated with positive experience and engagement. The authors stated that activities, such as computer use for meaningful school activities "provides pleasure, self-expression and intrinsic motivation, at the same time requiring intentional effort toward well-defined goals and competencies" (p. 173). Shute, Ventura, Bauer, and Zapata-Rivera's (2009) study also suggests, "combining school material with games has tremendous potential to increase learning, especially for lower performing, disengaged students" (p. 295). The team used a Bayesian model to illustrate a variety of factors that may indicate student engagement and achievement such as creative problem solving, novelty, and efficiency. They concluded that student engagement is strongly associated with games and academic achievement.

How do educational games promote student engagement? Evidence shows that sense of "immersion" in virtual learning environments as well as the problem-solving environment in games resembles the *Flow* state, which contributes to the deep engagement and is ideal for learning (e.g., Hedley, Billinghurst, Postner, May, & Kato, 2002; Witmer & Singer, 1998). Flow is a state of personal perceived optimal experience (Csikszentmihalyi, 1975). One of the definitions is that Flow is the experience of becoming engaged in activities that bring challenge to a set of skills (Csikszentmihalyi, 1990). Flow theory allows researchers to better measure how computer games influences the level of engagement and students' learning (e.g., Gregory, 2008; Schoenau-Fog, 2011). Therefore, Hoffman and Novak (2009) called to our attention that researchers interested in studying the optimal experience of Flow should shift from traditional Web sites to other new emerging areas in online human-computer interaction (HCI), such as virtual environments. The unique features of virtual worlds and Serious Games create a compelling environment for the study of Flow and engagement.

Current trends in serious games research. With over thirty years of digital game research, the topic of motivation and enjoyment continue to be the focal point in the scientific community. The ideas of learning through Serious Games and virtual worlds are very different from traditional approaches of knowledge transfer because these games more focused on the players' experience and exploration (de Freitas, Rebolledo-Mendez, Liarokapis, Magoulas & Poulovassilis, 2010). As a result, there is a call for more empirical studies of game-based learning research related to gamer experiences.

Mikropoulos and Natsis (2011) conducted a ten-year critical review of empirical studies on educational virtual environments between 1999 and 2009. Fifty-three articles are reviewed and 40 of them (75%) are related to science, technology, and mathematics. Among the reviewed empirical studies, 16 involved the use of immersive educational virtual environments. They found that gamer experience, such as free navigation, first person point of view, natural semantics, autonomy, and a sense of presence, may contribute to learning. The authors suggested that characteristics of virtual environment such as immersion and presence are important factors that contribute to learning and need further exploration. Factors connected with these subjective experiences, such as perceptual features, information-processing, individual differences factors, and content characteristics that seem to be essential to learning, require further exploration and have not be studied extensively. Moreover, Orvis, Horn, and Belanich (2006) empirically examined how gamers' characteristics, such as goal orientation, self-efficacy, and prior exposure to video games, influenced processes and outcomes in the *America's Army* game. Their results suggested that these gamer characteristics had a positive impact on their motivation, satisfaction, ease of use, team cohesion, use of metacognitive strategies, and time spent engaging in the training game.

Summary. Although evidence for the effectiveness of SEGs for supporting science learning is emerging, the results have been largely inconsistent and inconclusive. Current research approaches should be carefully reviewed and evaluated. Through the efforts of many researchers in the past decades, several integrated models between individuals' motivation, emotion, and educational games have been developed, including the application of Flow theory in game design (Sweetser & Wyeth, 2005), and applying Self-Determination Theory in game motivation studies (Ryan, Rigby, & Przybylski, 2006). In order to broaden our understanding of game-based learning, questions including (a) what types of mental processes have been recruited during gameplay, and (b) how affective state plays a role in the cognitive aspects of gameplay, should be systematically investigated. From a cognitive psychological perspective, affective state arises from tackling the cognitive tasks during gameplay. It is necessary to search for cognitive and affective theories for explaining the relationships of various cognitive and affective processes in gameplay.

Cognitive Framework of Emotion

The scientific breakthroughs in the integration of cognition, emotion, and motivation have been influenced by various fields of studies, such as cognitive science, cognitive psychology, neuroscience, affective science, and psychology in general. Although early cognitive science neglects emotion research, recent brain-imaging procedures allow the study of emotion independent of subjective emotional experiences. Inclusion of work on emotion within the cognitive framework becomes a main focus in the 21st century (LeDoux, 2000). A review from Immordino-Yang and Damasio (2007) summarize the neurobiological evidence and suggest that learning, attention, memory, decision-making, and social functioning are significantly affected by and subsumed within the emotional processes. The advances in neuroscience may revolutionize our understanding of the role of affect in education. For learning scientists, there is an urgent need to expand our current framework of learning through interdisciplinary knowledge to inform our theoretical understanding of the interplay between cognition, emotion, and motivation in the learning process. For SEG researchers who study engagement and learning outcomes, it is especially critical to understand the influences of positive affective states on individuals' cognitive processes related to learning, especially attention and memory in the gameplay process.

The term emotion tends to be used to refer a fairly brief but intense experience (Eysenck & Keane, 2000). Affect tends to cover a wide variety of experiences, such as emotions, moods, and preferences. Cognition is the mental representation of reality through perception, attention, learning, memory, and thought (Hilgard, 1980). In a system perspective, the cognitive system detects and interprets the environment in order to increase our understanding and knowledge. Affective system has three functions: (a) transforms information into arousal states, (b) provides judgment, to determine good or bad, safe or dangerous, and (c) controls the muscles of the body and changes the brain functions through chemical neurotransmitters. Therefore, emotion can be defined as the product of the interaction of the cognitive and affective systems (Royce & Diamond, 1980).

One of the most influential findings about emotional processing related to cognition was discovered and theorized by Joseph LeDoux in 1996. Evidence shows that emotional processing has two separate pathways: unconscious (thalamus to amygdala) and conscious (thalamus to neocortex and hippocampus, to amygdala), which lead to representations, behaviors, and actions. (LeDoux, 1996; Masmoudi, 2012). The two routes are leading to amygdala, where the key function of amygdala is to control the expression of certain emotional reactions. LeDoux's model emphasizes the role of amygdala in emotion processing that permit the appraisal of the emotional meaning through both perceptual information and abstract thoughts (LeDoux, 1996; Mermillod, 2012). Therefore, amygdale can influence ongoing perceptions, mental imagery, attention, working memory, and long-term memory, as well as various higher-order thought processes (LeDoux, 1996).

Another well-understood model of cognitive processes was proposed by Baddeley and Hitch in 1974, known as the working memory model. His original models (Baddeley, 2000; Baddeley & Hitch, 1974) suggested that memory comprises three stores: (a) sensory memory (phonological loop and visuospatial sketchpad), (b) short-term or working memory (episodic buffer), and (c) long-term memory. There is a central executive which plays a role in selecting incoming information and makes conscious awareness of it. Later, Baddeley (2007, 2012) modified his memory model and incorporated a new component known as *hedonic detector* in order to address the observed impact of emotions (e.g., anxiety, fear, and depression) on human performance of cognitive tasks. The hedonic detector translates information from physiologically-based emotions into psychologically-based feelings, as well as translates conscious thoughts in the episodic buffer into feelings and into modulation of attentional decisions in the central executive.

The Role of Cognitive Psychology in Game-based Learning

Beginning in the 1970s, a new discipline of education was formed known as learning sciences. Its research base emerged from psychology, computer science, philosophy, socio-cultural studies, cognitive science, and other fields (Sawyer, 2006). The learning sciences is an interdisciplinary domain of study which the main focus is consistently on what is needed to make human learning more successful (Leighton & Gierl, 2011) and centrally concerned with learning processes, that is the study of *what* is going on in a learning environment and *how* it is contributing to improve student performance (Sawyer, 2006). For learning scientists, there are two approaches in studying game-based learning: the gameplay process and the learning outcomes. In this respect, the fields of cognitive psychology and affective science play a pivotal role in understanding the gameplay process. This gameplay process includes human's affective, motivational, and cognitive processes, as well as the mechanisms that enhance or hinder learning.

Cognitive psychology is a study of mental processes. It studies how people perceive, learn, remember, and think (Sternberg, 2009). Affective science, on the other hand, focuses on affective processes and phenomena such as emotions, feelings, attitudes, and temperament. Affective science is linked to cognitive psychology as scientists believe that affective processes are responsible for mobilizing individual's resources to cope with the physical and social environments, as well as our day-to-day decision making and judgment (Davidson, Scherer, & Goldsmith, 2003). Therefore, the cognitive-affective integrated approach of cognitive psychology will provide insights and expand our current framework to examine how people learn in SEGs and other game-based learning systems.

Visual perception and attention. Visual perception and attention sets an important foundation in studying the cognitive processes of gameplay. Perception is our sensory experience of the world and the ability to make sense of the environment and surroundings through organization and interpretation. Attention, on the other hand, is the ability to select and concentrate on any of the perceived stimuli while ignoring others (Chun & Wolfe, 2005; Sternberg, 2009). For instance, at Edgar Rubin's ambiguous figures (the image of two faces or a vase) and Albert Necker's Necker cube: The sensory inputs are the same, however, when we switch attention, one image or the other becomes clear. The study of attention is concerned with how people are able to coordinate perception and action to achieve goals (Johnson & Proctor, 2004). Thus, visual attention is the first step in studying game-based learning.

Attention has been studied for over one hundred years but it remains a concept that psychologists find difficult to define. William James (1890) tried to define attention as: "Everyone knows what attention is. It is the taking possession of mind in clear and vivid form… Focalization, concentration, of consciousness are of its essence it implies withdrawal from some things in order to deal effectively with others…" (p. 403). Nowadays, psychologists generally agree that "attention is characterized by a limited capacity for processing information and that this allocation can be intentionally controlled" (Styles, 2006, p. 1). In the cognitive psychology perspective, the brain processes sensory inputs by concentrating on specific components of the entire sensory realm so that interesting sights, sounds, or smells, may be examined with greater attention to details than peripheral stimuli (Duchowski, 2007; Styles, 2006).

In general, there are two ways of distinguishing attention. The first way which William James (1890) used the terms “active” and “passive” to distinguish the two modes of attention. Attention is active when controlled in a top-down way by individual’s goals or expectation. Attention is passive when controlled in a bottom-up way by external stimuli. The second way of distinguishing attention is focused and divided attention. According to Eysenck and Keane (2010), focused attention (or selective attention) is defined as “a situation in which individuals try to attend to only one source of information while ignoring other stimuli” (p. 153); whereas divided attention is “a situation in which two tasks are performed at the same time” (p. 153). There is a third type of attention which is unique to visual system is called split attention, in which “attention is directed to two or more regions of space not adjacent to each other” (p. 163). It is assumed that split attention (e.g., bimodal distribution of processing) would save processing resources because we would avoid attending to irrelevant regions of visual space lying between two relevant areas (Awh & Pashler, 2000). Alternatively, rather than focusing on the modes of attention, other researchers attempt to expand the cognitive paradigm of attention by employing neural studies to associate with different brain regions. Posner and Peterson (1990) proposed that attention is multidimensional, which is composed of three functional processes: alerting, orienting, and executive processing. Alerting (also known as vigilance or sustained attention) is the ability to maintain attention and alertness over time. Orientating refers to the ability to select incoming sensory information to which to attend. Executive attention (also known as selective or focused attention) is the ability to discriminate and select information that should be processed in priority among all other information surrounds you at a given context. It involves planning or decision making, error detection, regulation of thoughts and feelings, and overcoming of habitual actions (Raz & Buhle, 2006).

Selective attention is especially important in game-based learning. In a game environment, players require self-control, are goal-directed, and consciously focus on target stimuli while ignoring irrelevant stimuli. If the target task is too easy, the spare attentional resources will “spill over” to the distractors and negatively influence target processing. Yet, irrelevant processing can be prevented when there is a subjective balance in challenge and skill (perceived difficulty) between gamers and their target task that all available resources are devoted to the target task, not the distractors (Chun & Wolfe, 2005; Green & Bavelier, 2003). It involves effective allocation of visual attention in order to achieve the goal in any game environments. At the same time, research also suggests that playing digital games, such as action games, improves selective attention (Green & Bavelier, 2003; Prensky, 2001). Hence, it is clear that selective attention and gameplay are highly related; it opens up several promising avenues for SEGs researchers to explore and examine their interactions systematically.

Information-processing model of selective attention. One of the earliest theories of attention dates back to Donald Broadbent’s most famous contribution in *Perception and Communication* in 1958. In Broadbent’s selective filter theory (Figure 2), he proposed that multiple channels of sensory input (stimuli) reach an attentional filter in parallel (at the same time). It permits only one channel of sensory information to proceed through the filter and reach the processes of perception, and assign meaning to our sensations, while the other input remains in the buffer for later processing. Only target stimuli with distinctive sensory characteristics may pass through the attentional systems. The filter prevents overloading of the limited-capacity mechanism of our attentional systems (Eysenck & Keane, 2010; Sternberg, 2009). Broadbent's theory was supported by Cherry's finding that sensory information may be noticed by an unattended ear, which is referred to as the "cocktail party" problem (Cherry, 1953). However, other researchers questioned the utility of Broadbent's theory as they saw his theory as an inflexible system of selective attention which was inconsistent with their findings. Moray (1959), for example, found that powerful, highly salient messages may break through the filter of selective attention to our conscious attention.

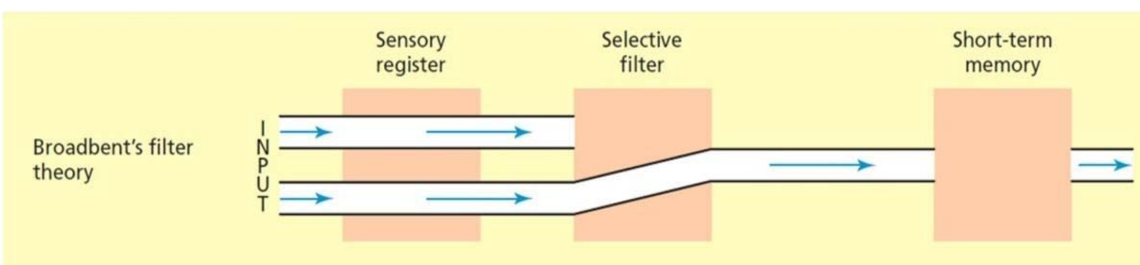


Figure 2 Broadbent's selective filter theory.
The model suggests a means by which incoming sensory information passes through the attentional system to research high-level perceptual processes.
Note. From *Cognitive Psychology*, 6th edition, by M. W. Eysenck & M. T. Keane, 2010, p.155. Copyright 2010 by Taylor & Francis Books (UK). Reprint with permission.

Distractor processing. Even though later theories rejected Broadbent's (1958) filter theory of selective attention on the basis of numerous findings that people identify irrelevant stimuli (e.g., Deutsch & Deutsch, 1963; Johnson & Heinz, 1978; Moray, 1959; Treisman, 1960), many researchers have revived interest and are continuously revisiting his theory (Baddeley & Weiskrantz, 1993). The core architecture of Broadbent's model is still relevant. Recently, Lachter and colleagues (2004, 2008) tested Broadbent's theory using visual stimuli, ushering in a modern version of filter theory of selective attention. They conducted a series of experiments to test the slippage account; that is, attention may be accidently allocated to the irrelevant (or supposedly unattended) stimuli causing these items to be identified, which they called it as "slippage" (Lachter, Forster, & Ruthruff, 2004). They noted that the experimental conditions used in most Stroop paradigms would allow attention to "slip" to the irrelevant word (slippage of attention).

Selective attention is the ability to remain focused on target (or task-relevant) stimuli in the presence of distractors. When ones direct attention to a specific part of the visual field, information processing occurs at attended locations relative to unattended locations. However, we cannot completely prevent unattended stimuli (or distractor) processing. Neuroimaging studies showed that there is still activity in response to unattended visual stimuli or distractors (Wojciulik, Kanwisher, & Driver, 1998). Lavie (2005) proposed two major assumptions that may be important in determining whether we can maintain attentional focus on a target task, which are critical in performing selective attention task. The first assumption is that attention to distractors is greater when the task involves low perceptual load than when it involves high perceptual load.

Perceptual load is based on how complex the task stimulus needs to be perceived or processed. In low perceptual load situations, any capacity not taken up in perception of target stimuli may involuntarily "spill over" to perceiving distractors. Lavie predicted that "high perceptual load that engages full capacity in relevant processing would leave no spare capacity for perception of task-irrelevant stimuli" (Lavie, 2005, p. 75). The second assumption is that attention to distractors is more susceptible when the load on executive cognitive control functions is high. This is because "load on executive cognitive control functions, such as working memory, that renders them unavailable to actively maintain stimulus-processing priorities throughout task performance has the opposite effect to perceptual load: it increases interference by irrelevant low-priority distractors rather than decreases it" (p. 81). This perceptual load theory provides a better understanding of how distractor processing is affected by the capacity limits in our mental processes and influenced our performance.

Processing choices. Emotion also plays a role in the processes of selection attention as they operate together in prioritizing our thoughts and actions (Fenske & Raymond, 2006). William James over a century ago already identified the relationship between attention and interest that: "The things to which we attend are said to *interest* us. Our interest in them is supposed to be the *cause* of our attending. What makes an object interesting we shall see presently; and later inquire in what sense interest may cause attention" (James, 1890, p. 416).

Burnham (1908) suggested that attention depends upon interest. He defined interest in two senses: a temporary affective state and a permanent mental possession (e.g., interest in art or literature or music). When someone has interest in a subject, he or she may have a habit of attending it. Attention and interest seems to be two sides of a coin; that are interconnected and mutually dependent. McDougall (1949) states "interest is latent attention and attention is interest in action" (p. 277). Therefore, each of our interests can become a powerful stimulus to draw our attention. Dobrynin (1958) also proposed that attention is highly influenced by affects and volition, such as needs, drives, and interests. He suggested that there are at least two kinds of interests: "Some interests are directed toward doing a certain activity, while others are directed toward reaching certain goals" (Dormashev, 2010, p. 297). In general, psychologists use the term "interest" in several ways: (a) a transient affective state which commonly associated with positive emotional experience (Silvia, 2001); (b) an aspect of personality, where interests are idiosyncratic & person specific (Silvia, 2001); and (c) a construct which is the synthesis of both affective and cognitive domains (Krapp, 1999, 2002). Despite the differences, the basic assumption of *interest* is that it is a "phenomenon that emerges from an individual's interaction with his or her environment" (Krapp, Hidi, & Renninger, 1992, p. 5).

Evidence suggests that emotionally salient stimuli and affective states can determine the allocation of visual attention; for instance, in an experiment on eye movement behavior, results show that emotional salience can override visual salience and determine the attention allocation in complex scenes (Niu, Todd, Kyan, & Anderson, 2012). Reciprocal effect is also true that attention influences emotional responses as selective attention has the distinct affective consequences for visual stimuli. Therefore, the presence of emotional stimuli may bias our initial attentional orientation and subsequent sustained attention responses to visual stimuli (Compton, 2003; Fenske & Raymond, 2006; Fichtenholtz & Labar, 2012).

Forgas (2001) proposed a view of information-processing consequences of affective states known as Affect Infusion Model (AIM). The AIM assumes that affective states, although distinct from cognitive processes, do interact with and inform cognition and judgments through influencing processing strategies. Therefore, this model argues that people tends to adopt different processing strategies in response to different contextual requirements based on the absence or presence of affect infusion. The model links the informational and processing consequences of affect on cognition and judgments within an integrated framework. Informational effects occur because affect may influence the content of cognition (what people think). Processing effects occur because affect also has an impact on the process of cognition (how people think). Task familiarity, complexity, and novelty, as well as personal relevance, motivation, and cognitive capacity are variables that determine processing choices.

Capacity limits of attention. Affect and cognition are both playing important roles in human's learning processes. However, are they working in parallel without competing with each other for our mental resources? From a neuroscience and cognitive psychology's point of view, cognitive and emotional processes draw on, to varying degrees, a shared pool of mental resources that are highly interrelated. It also coincides with the physiological research from Baumeister's team. In his seminal experimental works, his group shows that nervous system consumes more glucose than most other parts of the body. Effortful mental activities, such as cognitive reasoning and engagement in a task, appear to be expensive in terms of glucose consumption – a limited energy source of human body (Gailliot & Baumeister, 2007; Gailliot et al., 2007; Kahneman, 2011). This limited attention resource may be seen as a cause of selectivity, which processing must be allocated selectively to a sub-set of the available input information but not all (Lambert, 2003). Therefore, the efficiency of visual selection and attention allocation are highly affected by the competitive nature of cognitive and emotional visual processes for our limited mental resources.

Measure of Visual Attention: Eye tracking Method

How can perceptual experience be measured? Two board categories of measuring emotions and experience are: objective and subjective. Subjective measures generally record user's perception through surveys, interviews, or other ethnomethodological techniques. Objective measures, however, are not dependent on user's perception and generally include independent measures such as task completion timing, mouse clicks, screen capture, video capture, eye tracking, as well as more recent use of physiological and neurological measures. According to the user experience evaluation literature, subjective measures offer insight into the user experience directly from the user's point of view and allow users to express the complexity and depth of their interactions with computer on their own terms (Bardzell et al., 2008; Hornbæk, 2006). However, the disadvantages of subjective measures are retrospective in nature, which may not reflect accurately on their experience but depend on the memories of the experience. Therefore, Bardzell et al. (2008) suggested a triangulation approach that using psychophysiological measurements combined with traditional measures of subjective, self-report feedback techniques to identify patterns in the study of Human-Computer Interaction (HCI).

Eye tracking is one of the traditional objective evaluation methods to monitor user behaviors or experience during HCI, including gameplay (Bardzell et al., 2008). It records tangible interactions to correlate observed behavior with self-report information. It is believed that tracking the eye movements of gamers while playing games with a non-invasive eye-tracker may provide insights on how to measure perceptual experience.

Current trends of eye tracking research. As a keynote speaker at the *Eye Tracking Research and Applications Symposium 2000*, John Sender relates eye tracking research to a "Phoenix raising from the ashes again and again with each new generation of engineer designing new eye tracking systems and each new generation of cognitive psychologists tackling new problems" (in Jacob & Karn, 2003, p. 575). In more recent times, as technological advances such as the Internet, virtual environments, and computer gaming, the use of eye tracking in HCI has shown modest growth both as a means of studying the usability of computer interfaces and the interaction with the computer, as well as to serve as a computer input device.

The relationship between visual perception and language has historically interested researchers in reading (Rayner, 1978, 1998) and linguistic processes (Henderson & Ferreira, 2004), for example. Yet, eye movement research can inform the study of more complex behaviors, such as decision-making processes, playing sports, or flying a plane (Richardson & Spivey, 2004). Eye movement study has received little or no attention in the educational assessment literature (Pellegrino, Chudowsky, & Glaser, 2001). However, the application for eye tracking in education has started to gain more attention. For instance, Tai, Loehr, and Brigham (2006) investigated the differences in problem-solving behaviors between experts and non-experts in three science disciplines using eye tracking method. The results showed that gaze patterns can predict individual's levels of expertise and knowledge of a particular science topic. Wiebe and Annetta (2008) studied gaze fixation and saccades (rapid motion of eyes from one fixation to another) to examine how visual attention between text, graphic, and narration was distributed in multimedia instruction and in relations on learning. She and Chen (2009) applied the eye tracking method to tackle the tacit cognitive processes underlying learning. They examined the pattern of eye movement on various multimedia learning materials to understand how students construct science concepts.

Eye tracking in HCI studies is a method for determining where on a computer screen a game player is looking. We move our eyes to bring a particular portion of the visual field into high resolution (foveal vision), so that we may see in fine detail whatever is at the central direction of gaze. Most often we divert our attention to that point so that we can focus our concentration on the object or region of interest. Thus, it can be assumed that tracking a person's eye movements can follow along the path of attention deployed by the observer (Duchowski, 2007; Stark, 1994). Serious Games are usually visually rich, interactive, 3-D virtual environments in which visual cognition has a primary role (Sennersten & Lindley, 2008). Therefore, there is an emerging trend for game researchers using eye tracking methods to understand how visual attention distributes during gameplay and how visual attention leads to variations of player experience and cognitive learning outcomes. For instance, Cairns et al. (2006) aimed to develop a more quantifiable and objective measure of immersion in computer games through eye tracking method; Alkan and Cagiltay (2007) employed an eye tracking method to investigate how novices learn to play a computer game; Kearney and Pivec (2007) examined player immersion with eye tracking method and identify factors how computer games foster the persistent re-engagement of the players; and Renshaw, Stevens, and Denton (2009) used eye tracking technology to understand players' interaction and emotional experience in digital games. Furthermore, Jennett and colleagues conducted a series of studies on immersion and eye movements using eye tracking analysis. One of their studies was comparing individual's eye movement data between non-immersive and immersive game conditions (Jennett et al., 2008). The results (N=41) showed that the mean number of fixations for participants in the non-immersive condition increased over time (Spearman's $\rho = 0.518$, $p < 0.001$) and 26.4 percent of the variability could be accounted for by the regression model. The mean number of fixation in the immersive condition, in contrast, decreased over time (Spearman's $\rho = -0.191$, $p < 0.05$, $R^2 = .043$). They suggest that individual's eye movements decrease in the immersive game condition because their attention becomes more focused on visual components relevant to the game. On the other hand, individual's eye movements increase in a non-immersive game condition because they are more likely to be distracted by other items in the visual display irrelevant to the game.

In order to apply eye tracking methods, researchers are required to understand the visual system, the physiological organization of the vision, as well as the cognitive and behavioral aspects of visions (Duchowski, 2002).

Eye-mind assumption. It is assumed that the eye has close links with the brain and models of perceptual mechanisms. Yarbus's *Eye Movements and Vision* (1967), one of the most cited eye tracking publications ever, wrote about the relation between attention and eye movements. He stated that "[e]ye movements reflect the human thought processes; so the observer's thought may be followed to some extent from records of eye movement" (p. 190). Eye movement research and eye tracking methods flourished in the 1970s due to the great advances in both technology and psychological theory to link eye tracking data to cognitive processes. Just and Carpenter (1980) conducted an experimental study that significantly advances the eye movement research. For a sample of 15 "difficult" to "fairly difficult" scientific articles (excerpts from *Time* and *Newsweek* magazines) read by 14 college students, Just and Carpenter were able to account for 72 percent of the variance in the mean gaze duration data. The conclusion was that cumulative fixation times (or gazes) reflect at least part of the cognitive processing that occurs for each word as it is comprehended in context. They proposed an influential eye-mind assumption that eye movements offer information about higher psychological processes; or the eye remains fixated on a word as long as the word is being processed.

The visual system. The human visual system consists of two parts: the eyes and the visual processing in the brain. The eyes act as image receptors that capture light and convert it into signals, which are then transmitted to image processing centers in the brain. At the rear interior surface of the eye, the retina contains receptors sensitive to light (photoreceptors) which comprise the first stage of visual perception. The photoreceptors effectively convert light energy to electrical impulses and these neural signals further lead to the visual cortex in the brain. Human eye has a visual field of about 200°. The center of the retina is a special spot called the fovea, only 1-5° of visual angle, allowing fine scrutiny and perceiving details. The fovea is the sharpest point of visual acuity. Further away from the fovea will be less focused with less light (Fischer, 2007). Eye movements are fundamental to the operations of the visual system. When visual attention is directed to a new area, fast eye movements (saccades) reposition the fovea. Saccade control is the ability of the eyes to move quickly from one point of interest to the next. Approximately 90 percent of the viewing time is spent in fixation (Duchowski, 2007). Fixation is a relatively stable eye-in-head position within a threshold of dispersion (2° visual angle) over some minimum duration (typically 100 to 300 milliseconds; Jacob & Karn, 2003). According to Fischer (2007), to obtain a complete picture of the visual field a normal adult has to perform between 3-5 saccades per second to bring all the visual field into focus. The brain organizes the serial images in a temporal sequence and fills up the gaps in order to form a complete image. He proposes a hypothesis of optomotor cycle that responsible for the stability of gaze control. The optomotor cycle consists of three components: the reflex (generating saccades), the fixation (suppressing saccades) and the voluntary conscious control. The functional role of visual processing involves to two sub-processes: (a) the reflexive saccades that are scanning the visual field; and (b) the voluntary efforts that control the reflex by fixation. It requires both reflexes and voluntary control to determine the direction of sight based on selective attention and to ignore others. Therefore, there is always a competition between the control of attention and saccades.

Scanpath theory. Scanpath theory was first introduced and defined by David Noton and Lawrence Stark in the early 1970s (1971a, 1971b), and since then it has been influencing research on visual attention and eye movements. Two important definitions of scanpath theory, according to Privitera (2006), are: (a) scanpath sequences are experimentally defined as an idiosyncratic and repetitive alternation of glimpses and rapid jumps of eye position to various regions of interest in the viewed scene; and (b) a top-down internal cognitive representation (or model) controls both visual perception and the active-looking eye movement mechanisms. These internal cognitive models activate perception and interpret, confirmation, or denial of hypothesized models encountered. Experimental studies support the second definition of a top-down concept as it often came from studies of scanpaths of human subjects viewing fragmented figures, ambiguous figures, and Necker cubes. The understanding of eye movements during visual imagery and during visual search offers insights into the top-down model argument (Stark, 1994).

Another mechanism of visual attention is known as bottom-up (or feature-based) processes, which the external world enters the brain and controls visual perception, and eye movements. In brief, bottom-up processes are considered as a lower level vision, which involves both foveal vision and peripheral vision. The foveal vision is where high resolution acquisition of information occurs; whereas peripheral vision covers wide angle but with low resolution, is ideally adapted for motion perception and pre-attentive "pop-up" parallel sensing. The selective attention is controlled by stimulus properties, irrespective of the goals of the observers. This control mode is known as stimulus-driven, exogenous control, involuntary, or bottom-up (Godijn & Theeuwes, 2003; Stark, 1994). Top-down processes, on the other hand, are the higher-level vision includes perception occurring in the mind's eye, which control the selective attention by the observers' goals and expectations (Godijn & Theeuwes, 2003). When eye movements are driven in a top-down fashion, the critical regions-of-interest that determined from the internal cognitive model will be sampled with high-resolution foveal vision (Stark, 1994). This cognitive model of a scene (or a picture) is called the representation, and its operational phase is called the active looking scanpath. This control mode is known as goal-directed, endogenous control, voluntary, or top-down (Godijn & Theeuwes, 2003). This "dichotomy regarding top-down (informativeness) and bottom-up (conspicuity) domination of human vision has continued since the Scanpath Theory was introduced and remains an important source of debate" (Privitera, 2006, p. 3).

Summary. Stark (1994) stated, "seeing is an illusion that hides the actual processes of vision" (p. 7). Understanding visual processes may help to explain those illusions that work well to the real world as well as to the worlds of virtual reality (VR). In game environments, it is more important to consider top-down processes of selective attention because the mode of attention in gameplay is more task-relevant and goal-driven than for free-viewing of natural scenes (Jie & Clark, 2007). Therefore, understanding the gamers' eye movements and their scanpath patterns in gameplay by eye tracking methods may uncover the visual scanning strategies, as well as the control of selective attention (visual target and distractor processing) and other higher cognitive strategies and states between individuals and the game environments (Chisholm & Kingstone, 2012; Goldberg & Helfman, 2010).

Cognitive Architectures: The Dual-Process Theories of Cognition

Study of attention sets a foundation in understanding gameplay processes. However, the research journey does not end here. Game-based learning consists of various types of cognitive operations, including but not limited to: procedural memory that enables smooth navigation in virtual environment; organize and interpret information in the game environment; recognize features, patterns, and rules; and encode meaningful information in order to respond to the real-time feedback. They all depend on different levels of cognitive processes such as visual attention, information processing, memory, as well as problem solving, judgment, and decision making. In order to understand this complex HCI system of game-based learning, a cognitive architectural theory of two minds hypothesis – the dual-process theories of cognition is discussed.

System 1 and System 2. Cognitive scientists proposed that there are two distinct cognitive systems underlying human's reasoning and thinking. Various terms have been associated with these two systems, such as implicit knowledge/explicit knowledge, unconscious/conscious, automatic/controlled, associative/rule-based, fast/slow, and many others (Frankish & Evans, 2009). The neutral terms System 1 and System 2 were first introduced by Stanovich (1999) and are more commonly accepted in the research communities nowadays. Evans (2003) describes that "System 1 is old in evolutionary terms and shared with other animals: it comprises a set of autonomous subsystems that include both innate input modules and domain-specific knowledge acquired by a domain-general learning mechanism. System 2 is evolutionarily recent and distinctively human: it permits abstract reasoning and hypothetical thinking, but is constrained by working memory capacity and correlated with measures of general intelligence" (p. 454). In particular, these two distinct Systems 1 and 2 are responsible for Types 1 and 2 processing respectively. The terms Type 1 and Type 2 processes have been first used over 30 years ago in the study of reasoning (Wason & Evans, 1975); other names, like *heuristic* and *analytic*, are also popular among researchers to indicate these two types of processes (Evans, 1984). A widely used definition of the two processes are: Type 1 processes is fast, automatic, high processing capacity, low effort, and operates in parallel; whereas Type 2 processes is slow, controlled, limited capacity, high effort, operates in sequential, and related to individual differences in cognitive capacity (Evans, 2008).

Dual-process approach to reasoning is evidenced by the wider application to other fields such as judgment, decision making, and social cognition (Evans, 2003; Frankish & Evans, 2009; Kahneman & Frederick, 2002). The advantage of a dual-process approach is it explains human's conscious reflective thought (System 2), and provides the flexibility and foresight that the tacit system (System 1), by its nature, cannot deliver. Most of our decision making is automatic and habitual, but the conscious system gives us the possibility to deal with novelty and hypothetical thinking (Evans & Over, 1996).

Cognitive ease and positive affect. Scientists have been speculating on how these two systems operate dynamically. Reber (1993) argued for the "primacy of the implicit" and suggested that unconscious cognition should be the default and dominant system. Kahneman (2011) also agreed that System 1 runs by default in which System 2 adopts with little or no modification in a comfortable low-effort mode. However, when tasks get more difficult, System 2 takes over and supports a more detailed and specific processing that attempts to solve the immediate problem. The division of labor between the two cognitive systems is highly efficient which minimizes effort and optimizes performance. It also suggests that System 2 is in charge of self-control and needs cognitive efforts to overcome the impulses of System 1. Furthermore, it is well documented that lower animals as well as humans, when given the choice of action, will naturally select one requiring the least effort. This process is known as the "Least Effort Principle" (Zipf, 1949). This principle also applies to cognitive processes (Kahneman, 1973). Hence, constant assessments of the environments are carried out automatically by System 1 and continuously determine whether extra effort is required from System 2. This evaluative process can be measured by a psychological construct called *cognitive ease*, range between "Easy" and "Strained" (Kahneman, 2011). "Easy" is a sign of comfort in which there is no need to redirect attention or mobilize effort, while "Strained" indicates that a problem exists and it requires increased mobilization of System 2. When people are in a state of cognitive ease, they may feel familiar, effortless, and in a good mood. There is growing evidence that good mood, intuition, and creativity are closely related at one end, whereas sadness, vigilance, suspicion, analytic approaches, and increased effort are grouped together at the opposite end of the spectrum (Forgas & East, 2008; Kahneman, 2011). It seems that a happy mood loosens the control of System

2 over performance. When in a good mood, people become more intuitive and creative but also less vigilant and are prone to logical error. Kahneman (2011) concludes that cognitive ease is both a cause and a consequence of pleasant feelings.

The phenomenon associated between cognitive ease and positive emotion is also supported by the study of perceptual fluency. Psychophysiological measures using facial electromyography (fEMG), conducted by Winkielman and Cacioppo (2001), showed that high fluency due to mere-exposure effect (repeated exposures) or familiarity was associated with stronger activity over the zygomaticus regions (cheek muscle) that is an indicator of positive affect, but not associated with the high activity of corrugators region (brow muscle) that is an indicator of negative affect. The findings also suggest that affect generated by processing facilitation is positive and may assume that fluency is hedonically marked and closely linked to the affective system and elicit positive responses; in brief, fluency enhances liking.

Application of dual-process theories in gameplay. Measuring the mental processes of gameplay is notoriously difficult but the dual-process approach of cognition can be useful to understand how gamers think about the play situation and how these two systems or processes operate in action. Svahn (2009) was one of the earliest theorists that applied dual-process theories in social psychology in order to understand how play (or more specifically digital play) is understood, perceived, and processed by the players. He identified the dual-systems as: (a) *Heuristic Route*, where people do pay attention to the situation but perceive it, and pass judgment on it based on the previously stored memory; and (b) *Systematic Route*, where people perceive the situation through systematic processing, then make a decision about what to do, and how to feel. Under the assumption of *Sufficiency Principle* similar to the *Least Effort Principle* discussed earlier, these two systems are not a binary system but a fluid continuum. The human mind by default enjoys the cognitive economy in the heuristic processing but requires systematic processing in decision making (Svahn, 2009). There is always a tension between these processes. When a game is relatively difficult or novel, it requires a player to have an effortful and conscious thought. In order to measure the dynamic of these processes, a construct was introduced and called *subjectively perceived complexity of a game*. It becomes a sliding scale mapping on the Heuristic/Systematic processing over time (Figure 3). If a game is perceived to be easy, the more heuristics will be used by the individual player. In contrast, the more challenging the game is perceived, the more the player is going be driven into systematic processing. Over the course of playing a new game, a player may first go through a heuristic mode of processing, followed by challenges that make the game appear complex which in turn makes the player shift to the systematic mode. After playing for some time, the player recedes to a more heuristic processing, until it reaches equilibrium on the Sufficiency scale. This new dual-process theory of cognition in gameplay proposed by Svahn (2009), increases the explanatory power in describing the play experiences – especially how tasks are perceived and processed, and allows game researchers and game designers additional insight into gameplay.

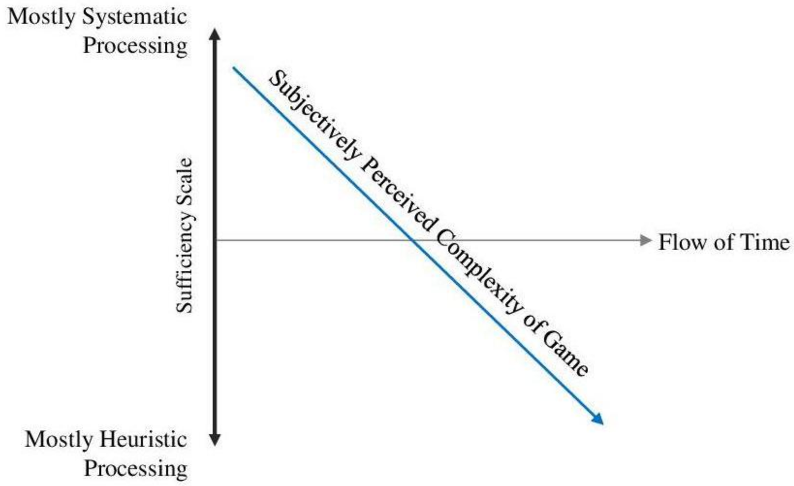


Figure 3 The sufficiency/complexity diagram.
Note. Redrawn from "Processing Play: Perceptions of Persuasion" by M. Svahn, 2009, *Proceedings of DiGRA: Breaking new ground: Innovation in games, play, practice and theory*, p. 4. Copyright 2009 by author. Reprinted with permission.

Affective Concepts in HCI: Affective Response Model

As discussed earlier in details about the new paradigm of cognitive-affective integrated framework of cognitive psychology, there is no doubt that affective state plays a critical role in human decisions and behaviors. There are a growing number of studies that incorporate the affective dimension in HCI research. However, a comprehensive model that provides a systematic categorization of affective concepts in HCI has yet been established. Such a lack of research attention on theorized affective concepts in HCI has been addressed by Zhang (2013) and was published in *MIS Quarterly*. She developed a model called *Affective Response Model* (ARM) based on theoretical reasoning and empirical evidence; and systematically established the relationships of various affective concepts in the information and communication technology (ICT) context. Taxonomy of affective concepts in ICT context with five dimensions was identified (refers to Table 1). They are: (a) the residing dimension, whether it is residing within a person, a stimulus (or an object), or residing between a person and a stimulus; (b) the temporal dimension, whether it is constrained by time; (c) stimulus specificity (object versus behavior), such as anxiety towards computers or using a computer are two different kinds of affective response; (d) stimulus specificity (particular versus general), example as using internet (overall) is enjoyable, or using (this) website is enjoyable; and (e) the process versus outcome dimension, to distinguish process-based affective evaluations from outcome-based evaluations.

Table 1

Taxonomy of Affective Concepts: Super Categories and Categories

<table>
<tr><td colspan="2">Residing within a Person</td><td rowspan="2">Residing within a Stimulus</td><td colspan="5">Residing between a Person and a Stimulus (Affective Responses)</td></tr>
<tr><td>Temporally Constrained (State)</td><td>Temporally Unconstrained (Disposition)</td><td>Temporally Constrained (State)</td><td colspan="4">Temporally Unconstrained (Evaluation / Disposition)</td></tr>
<tr><td rowspan="4">(1)
Free-floating Affective State (e.g., Mood)</td><td rowspan="4">(2)
Affectivity (e.g., Temperament)</td><td rowspan="4">(3)
Affective Characteristics (e.g., Affective Quality, Affective Cue)</td><td rowspan="4">(4)
Induced Affective State (e.g., Emotion)</td><td rowspan="2"></td><td colspan="2">Particular Stimulus</td><td rowspan="2">General Stimulus</td></tr>
<tr><td>Process-Based</td><td>Outcome-Based</td></tr>
<tr><td>Object Stimulus</td><td>(5.1)
Process-Based Affective Evaluation Toward a Particular Object</td><td>(5.2)
Outcome-Based Affective Evaluation Toward a Particular Object</td><td>(7)
Learned Affective Evaluation/ Disposition Toward a Type of Objects</td></tr>
<tr><td>Behavior-Stimulus</td><td>(6.1)
Process-Based Affective Evaluation Toward a Behaviors on a Particular Object</td><td>(6.2)
Outcome-Based Affective Evaluation Toward a Behaviors on a Particular Object</td><td>(8)
Learned Affective Evaluation/ Disposition Toward Behaviors on a Type of Objects</td></tr>
</table>

Note. From "The Affective Response Model: A Theoretical Framework of Affective Concepts and their Relationships in the ICT Context" by P. Zhang, 2013, *MIS Quarterly, 37*(1), p. 259. Copyright 2013 by Regents of the University of Minnesota. Used with permission.

A scenario to illustrate the ARM taxonomy and categories (Zhang, 2013, p. 259) is presented below:

> Imagine a person named Alex. <u>Alex usually does not get over-excited about novel things in his surroundings</u> (*category 2: affectivity – temperament*). <u>He does not like playing computer games in general</u> (*category 8: learned affective*

> *evaluation/disposition toward behaviors on a type of objects – attitude toward behavior*), yet tends to like colorful things (*category 7: learned affective evaluation/disposition toward a type of objects – attitude toward object*). One day, while passing by an electronic store in a calm mood (*category 1: free-floating state – mood*), Alex was attracted to a set of sharp, colorful, and dynamic screen displays of a game (*category 3: affective characteristics – affective quality and affective cues*). He said to himself, "Wow, that is cool!" (*category 5.1: process-based affective evaluation toward a particular object*). He stepped in and started exploring the game. Soon, he felt engaged, stimulated, playful, and overall was having a lot of fun (*category 4: induced affective states – emotions*). Alex was really enjoying himself (*category 4: emotions*) without realizing the passage of time. Once he finished the exploration, he was thinking: "Playing this game was really engaging and enjoyable" (*category 6.1: process-based affective evaluation toward behaviors on a particular object*). As a result of this experience, Alex concluded "This is a really cool game that is well designed (*category 5.2: outcome-based affective evaluation toward a particular object*), and I liked playing it" (*category 6.2: outcome-based affective evaluation toward behaviors on a particular object*). Then he thought, "Maybe playing computer games is not such a bad idea" (*category 8: learned affective evaluation/disposition toward behaviors on a type of objects*).

Furthermore, causal relationships between the affective concepts were proposed. Figure 4 shows that affective antecedents may trigger and influence the three types of affective response in an ICT interaction episode. The induced states may influence affective evaluations, both learned and particular. Learned affective evaluations/dispositions may have an impact on induced states and contribute to the formation of particular affective evaluations.

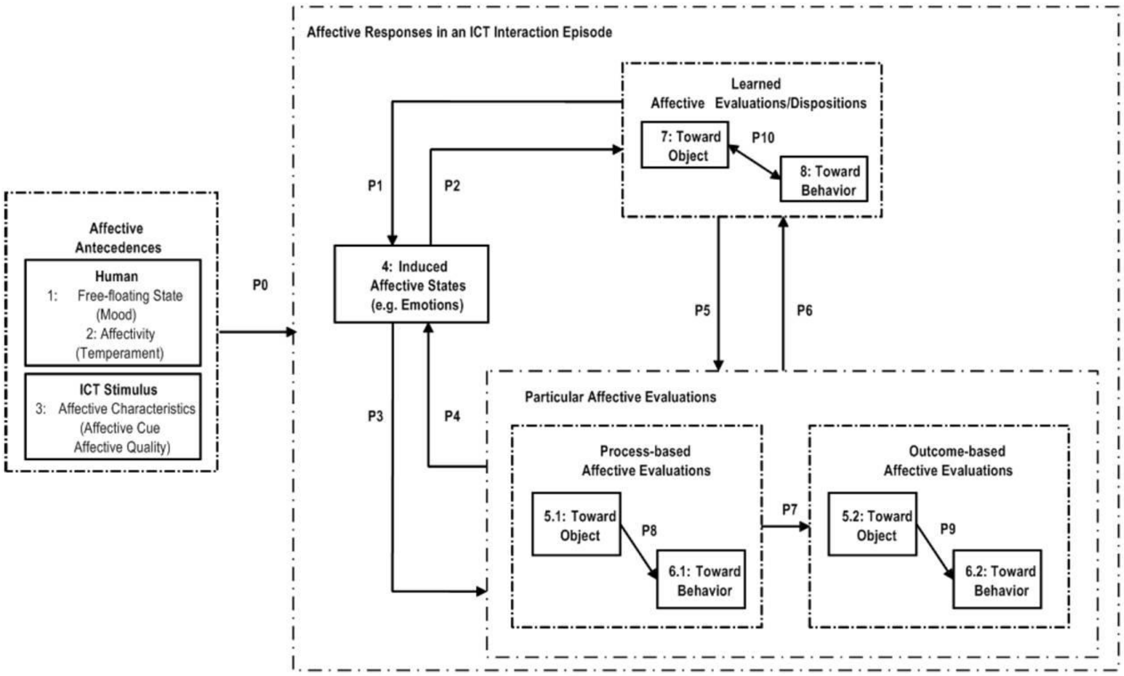


Figure 4 A nomological net for causal relationships.
Note. From "The Affective Response Model: A Theoretical Framework of Affective Concepts and their Relationships in the ICT Context" by P. Zhang, 2013, *MIS Quarterly, 37*(1), p. 263. Copyright 2013 by Regents of the University of Minnesota. Reprinted with permission.
P0 to P10 are the proposition of connecting different affective concepts.

In conclusion, the ARM offers explanatory power in addressing the following three issues: what are the pertinent affective concepts in an ICT context? How are they similar or different from each other? How are these affective concepts related to each other? It is a theoretically bound model which provides researchers a systematic and holistic framework for any ICT or HCI study on affect. Learning scientists may also apply this model in studying the affective aspect of game-based learning holistically or specifically. ARM is also a useful model to be incorporated into the cognitive-affective integrated framework in order to explore possible relationships between specific affective concepts (such as interest and Flow) and processing choice (the visual processing of selective attention) in gameplay, which in turn, may influence performance and outcome.

Flow, the Optimal Experience

Mihaly Csikszentmihalyi first proposed *Flow theory* in 1975 and defined as a state of personal perceived optimal experience. Subjective experience, from the view of cognitive psychology, is composed of cognitive, emotional, and motivational aspects and represents the conscious processing of information coming from the external environment and the inner world of a person (Csikszentmihalyi, 1982; Delle Fave, Massimini, & Bassi, 2012). Csikszentmihalyi has greatly contributed to the investigation of the phenomenology of this subjective experience through the analysis of people's self-reports and descriptions of their quality of experience in diverse situations and contexts, for example, highly creative artists and scholars who reported the experience of Flow when engaged in their best work (Csikszentmihalyi, 1990, 1996).

Flow is characterized by narrowing focus of awareness, loss of self-consciousness, a sense of control over the environment, and a heightened sense of playfulness. Researchers have applied Flow experience to study activities ranging from sports (e.g., Jackson & Csikszentmihalyi, 1999), music (e.g., Wirgley & Emmerson, 2011), hobbies and recreation (e.g., Csikszentmihalyi, 1990), and HCI (e.g., Ghani & Deshpande, 1994; Hoffman & Novak, 1996). The original definition of Flow is "the holistic sensations that people feel when they act with total involvement" (Csikszentmihalyi, 1975, p. 36). Hoffman and Novak (1996) further defined Flow under three different perspectives: (a) experience of Flow (intrinsic enjoyment, loss of self-consciousness), (b) structural properties of the Flow activities (seamless sequence of responses facilitated by interactivity with the computer and self-reinforcement), and (c) antecedents of Flow (skill/challenge balance, focused attention, and telepresence). Csikszentmihalyi (1997) specifies that concentration, interest, and enjoyment in an activity must be experienced simultaneously in order for Flow to occur. It is because Flow experience is characterized by the state of intense concentration and highly focused; interest in an activity is a fundamental aspect of Flow experiences, it sets the foundation for continuing motivation and serves as a bridge to more complex task; and Flow activities are very often enjoyable, provide a feeling of accomplishment and satisfaction (Shernoff et al., 2003).

Engeser and Schiepe-Tiska (2012) argued that the definition of Flow has changed very little since Csikszentmihalyi's original definition in 1975. Yet, recent research studying Flow from a psychophysiological perspective generates a new dimension of this phenomenon: for instance, de Manzano et al. (2010) proposed a physiological definition of Flow and developed a model of emotion, attention, and expertise, which Flow is considered a state of effortless attention and arises through an interaction between positive affect and high attention. Similarly, Peifer (2012) summarized the pervious theoretical approaches and empirical findings and proposed a working definition of Flow that integrates affective, cognitive, physiological, and behavior components, which "Flow is a positive valenced state (affective component), resulting from an activity that has been appraised as an optimal challenge (cognitive component), characterized by optimized physiological activation (physiological component) for full concentration on coping with environmental / task demands (behavioral component)" (p. 149). In summary, Table 2 provides definitions of Flow from a sample of nine different studies.

Table 2

Definitions of Flow

Reference	Conceptual or Operational Definition
Csikszentmihalyi (1975)	"the holistic sensation that people feel when they act with total involvement" (p. 36). "when in the flow state "players shift into a common mode of experience when they become absorbed in their activity. This mode is characterized by a narrowing of the focus of awareness, so that irrelevant perceptions and thoughts are filtered out; by loss of self-consciousness; by a responsiveness to clear goals and unambiguous feedback; and by a sense of control over the environment...it is this common flow experience that people adduce as the main reason for performing the activity" (p. 72).
Csikszentmihalyi and LeFevre (1989)	"experience will be most positive when a person perceives that the environment contains high enough opportunities for action (or challenges), which are matched with the person's own capacities to act (or skill). When both challenges and skills are high, the person is not only enjoying the moment, but is also stretching his or her capabilities with the likelihood of learning new skills and increasing self-esteem and personal complexity. This process of optimal experience has been called flow" (p. 816).
Csikszentmihalyi (1990)	we feel "in control of our actions, masters of our own fate...we feel a sense of exhilaration, a deep sense of enjoyment" (p. 3) "the state in which people are so intensely involved in an activity that nothing else seems to matter; the experience itself is so enjoyable that people will do it even at great cost, for the sheer sake of doing it" (p. 3)

Webster, Trevino and Ryan (1993)	"the flow state is characterized by four dimensions... within the human-computer interaction experience, flow incorporates the extent to which (a) the user perceives a sense of control over the computer interaction, (b) the user perceives that his or her attention is focused on the interaction, (c) the user's curiosity is aroused during the interaction, and (d) the user finds the interaction intrinsically interesting" (p. 413).
Hoffman and Novak (1996)	"the state occurring during network navigation which is (1) characterized by a seamless sequence of responses facilitated by machine interactivity, (2) intrinsically enjoyable, (3) accompanied by a loss of self-consciousness, and (4) self-reinforcing" (p. 57).
Prensky (2001)	"a mental state of intense concentration, often to the point where previously difficult tasks become easy and whatever you are doing becomes enormously pleasurable" (p. 124).
de Manzano, Theorell, Harmat, and Ullén (2010)	"flow is experienced during task performance as a result of an interaction between emotional and attentional systems, that is, both cognitive and physiological processes, enabled by a certain level of expertise" (p. 309)
Jackson (2012)	"Flow is an internal, conscious process that lifts experience from the ordinary to the optimal" (p. 128).
Peifer (2012)	"Flow is a positive valenced state (affective component), resulting from an activity that has been appraised as an optimal challenge (cognitive component), characterized by optimized physiological activation (physiological component) for full concentration on coping with environmental / task demands (behavioral component)" (p. 149).

Physiological component of Flow. There is strong linkage between emotion and attention. But how much stimulation is enough to attract attention, psychologists use the term "arousal level" to describe how excited or bored one feels. Arousal research has become a research interest in psychology since the late 1990s (Steriade, 1996), which experimental studies show that arousal influences cognitive activities and information processing, such as perceptions of time, colors, and heights, as well as high level of arousal fosters the spread of activation within the semantic network (see Gilet & Jallais, 2012, for a review). Several neurotransmitters, such as acetylcholine, glutamate (Steriade, 1996), dopamine, and epinephrine (Coull, 1998), are associated with arousal. Emotion theorists (e.g., Barrett, 2006; Russell, 2003) proposed a dimensional theory of emotion, which sub-emotional variables of valence and arousal are the building blocks of emotions. These variables can be considered as the properties of stimuli, which stimuli vary on the dimensional variables valence and arousal. The combination of both variables is called "affective quality" (Moors, 2009). The affective quality of stimuli can be reflected by the two aspects in a person's affect state, they are: (a) the neurophysiological side, i.e., valence and arousal are associated with distinct neural systems; and (b) the mental side, i.e., the conscious experience of affective quality. Thus emotions involve not only subjective feelings, but also facial expressions, cardiovascular, and hormonal changes. Positive emotions with their neurophysiological changed, broaden attention, perception, thoughts, and actions (Cohn & Fredrickson, 2009), as well as broadens visual search pattern leading to increased attention to peripheral stimuli (Wadlinger & Isaacowitz, 2006). In a seminal work of psychophysiological study conducted by Nacke and Lindley (2008, 2009), Flow experience demonstrated significant high-arousal positive affect emotions and high value for positive valence. The results also agreed with studies of Lang (1995) and Mauri et al. (2011), which Flow state is a subjective experience characterized by positive valence and high arousal, and associated with other affective states such as joy, excitement, or ecstasy. Therefore, both attention and emotion play a key role in determining whether a person is in a Flow state or engaged in a task (Mauri et al., 2011). Attention is generally understood to require effort, but in Flow state, a person experiences less effort while being in a state of high attention and focus, what Bruya (2010) refers to as effortless attention.

Palladino (2007), adopted the Yerkes-Dodson Law developed in 1908, interpreted the inverted-U relationship between arousal and task performance. The horizontal line represents arousal level, whereas the vertical line represents concentration or task performance. She suggests that when one is overstimulated, he/she is in overdrive and feels intense forms of over-excitedness, worry, nervousness, anger, or being afraid. Conversely, when one is understimulated, he/she feels underpowered, sluggish, or unmotivated. When stimulation is just right, one is in a relaxed-alert state, which psychologists refer to as “optimal arousal.” He/she feels motivated, confident, and focused.

Palladino (2007) suggest that the inverted-U relationship serves as a unifying principle to explain findings in biophysics and neuroscience. The horizontal x-axis can be labeled as stimulation, arousal, drive, intensity, or motivation. The vertical y-axis can be labeled as attention, concentration, or performance. At the top of the hill called the “peak.” The closer to the peak, the closer someone gets to an ideal state of stimulation and attention, which is similar to the Csikszentmihalyi’s Flow state. In his book, *Flow*, Csikszentmihalyi (1990) provides a heuristic explanation on how a person is pulled into and out of the Flow state. His Flow model combined with the inverted-U model of arousal and concentration become a conceptual framework in describing the pleasure of play in games (Salen & Zimmerman, 2004). However, the inverted-U model has its deficiencies as multiple brain systems control both cortical arousal and attention and it is difficult to generalize the relationship between the two constructs in a simple fashion. There is still little empirical evidence for the general arousal-concentration association (Matthews et al., 2010).

Conceptualization of Flow. By referring to the model showed in Figure 5, Flow tends to occur when a person's skills are fully involved in overcoming a challenge. It is a fine balance between a person's ability to act and the available opportunities for action. If challenges are too high, one may feel frustrated, worried, and anxious. If challenges are too low, one may feel relaxed, or even bored. If both challenges and skills are low, one may feel apathetic. Flow happens when high challenges are matched with high skills, then the deep involvement flashes in and optimal experience can be achieved. A Flow zone is generated (Figure 6).

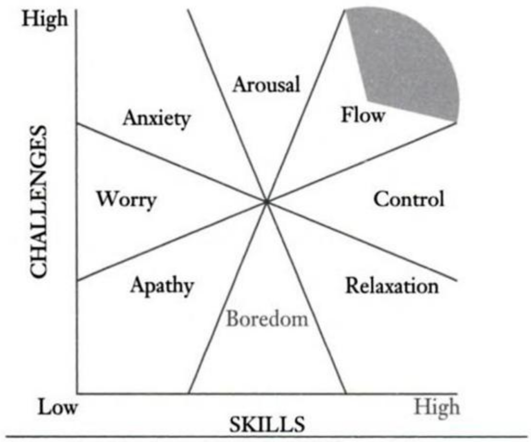


Figure 5 The quality of experience as a function of the relationship between challenge and skills.
Note. From *Finding Flow: The Psychology of Engagement with Everyday Life*, by M. Csikszentmihalyi, 1997, p. 31. Copyright 1997 by Perseus Books Group. Reprinted with permission.

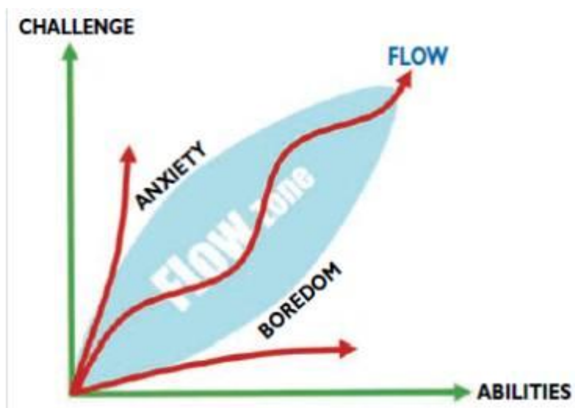


Figure 6 Flow zone.
Note. From "Flow in Games (and Everything Else)," by J. Chen, 2007, *Communications of the ACM, 50*(4), p. 32. Copyright 2007 by ACM (The Association for Computing Machinery). Reprinted with permission.

Csikszentmihalyi (1990) has conceptualized the nine dimensions that signified the conceptual elements of the Flow experience, which is the optimal psychology state. The following descriptions of the nine dimensions of Flow are based on the Flow manuals from Jackson (2010, 2012), with some examples highlighted by Csikszentmihalyi (1975, 1990). They are:

1. ***Challenge-skill balance.*** Challenges can be thought of as opportunities for action whereas skills are the capacities that we possess to produce desired outcomes. Critical to the challenge-skill balance is that the perception of challenge/skill is more important than the objective challenge/skill levels.
2. ***Clear goals.*** Goal setting is a process that helps to move a person toward Flow. Once in this state, individuals know what they are supposed to do while this clarity of purpose occurs on a moment-by-moment basis.
3. ***Unambiguous feedback.*** It is closely associated with clear goals in performing a task. When in Flow, feedback is easier to receive and interpret. Individual receives clear, unambiguous information that one can process them effortlessly.
4. ***Action-awareness merging.*** It relates to the sense of effortlessness and spontaneity of an individual perceived. Feelings of automaticity and total absorption in what one is doing; "You do not see yourself as separate from what you are doing" (Csikszentmihalyi, 1975, p. 39).
5. ***Total concentration on task at hand.*** Individuals are totally focused in the present on a task with no extraneous thoughts and do not feel distractibility;

"When the game is exciting, I don't seem to hear anything – the world seems to be cut off from me and all there is to think about is my game" (Csikszentmihalyi, 1975, p. 40).

6. ***Sense of control.*** A sense of infallibility when performing a task in Flow. One feels empowering and free from feeling the fear of failure. Similar to the challenge-skill relationship, control requires delicately balanced. Challenge does not exist under the conditions of absolute control as it will move an individual away from Flow into relaxation or even boredom; "I get a tyrannical sense of power. I feel immensely strong, as though I have the fate of another human in my grasp" (Csikszentmihalyi, 1975, p. 44).
7. ***Loss of self-consciousness.*** When a person is no longer concerned with what others think of them, self-consciousness has been lost. Flow is an unselfconscious action, which liberating the voice within our head and free from self-doubt and criticism; "You yourself are in an ecstatic state to such a point that you feel as though you almost don't exist…I just sit there watching it in a state of awe and wonderment" (Csikszentmihalyi, 1975, p. 44).
8. ***Transformation of time.*** Deep moments of Flow seem to transform the perception of time. Some may feel time stops, some feel time slow down, while others may feel time move more quickly than expected. There is a close link between the intensity of involvement in Flow and time transformation.
9. ***Autotelic experience.*** This is the intrinsically rewarding experience that Flow brings to the individual. Feelings of great enjoyment may come after a Flow

experience that Csikszentmihalyi (1990) described this dimension as the end result of the other eight Flow dimensions.

Drengner, Sachse, and Furchheim (2009) further categorize the characteristics *challenge-skill balance, clear goals*, and *unambiguous feedback* as antecedents of Flow; characteristics *action-awareness merging, total concentration, sense of control, loss of self-consciousness,* and *transformation of time* as the reflective dimensions or the manifestation of Flow; and characteristic of *autotelic experience* as the consequence of Flow experience. Salen and Zimmerman (2004), identified characteristics of *challenge-skill balance, clear goals*, *unambiguous feedback* and *sense of control* as the four prerequisite elements of Flow when designing games; while characteristics of *action-awareness merging, total concentration, loss of self-consciousness,* and *transformation of time* as the four facets of Flow that can diagnose whether a player has reached the Flow state. Not all of the components are required to give a person the experience of Flow (Chen, 2007). A central consideration to facilitating an environment conductive to Flow is the existence of a challenging situation. There is a critical balance of challenges and skills in a situation (Jackson, 2012). Moreover, how a person perceived the situation as challenge and his/her perceived self-efficacy (i.e., what you believe you can do) are critical to the occurrence of Flow, rather than the actual demands in a situation or an objective level of abilities (Jackson, 2012; Jackson & Csikszentmihalyi, 1999).

Flow experience in HCI. Since Csikszentmihalyi proposed the theory of Flow in 1975, thirty-seven years of Flow research has provided the time to study various contexts and topics. Engeser and Schiepe-Tiska (2012) suggested two major current trends of

Flow research. The first trend is the research on sports and learning in educational settings. Understanding the conditions and consequences of Flow of physical activities and classroom learning would help understand the motivational aspect and the potential high performance outcomes. The study would benefit trainers, athletes, teachers, and students to enjoy and improve the respective activities. The second research trend is on HCI, game-based learning, and media use. It would help understanding the characteristics of computer-mediated environments that generate users' concentration on task and subsequently influence their behavior. Activities that induce Flow are known as "Flow activities" (Csikszentmihalyi, 1997).

Every Flow activity provides a sense of discovery, a creative feeling of being transported into a new reality, which Sweetser and Wyeth (2005) believed, was a familiar sensation for game players. Trevino and Webster (1992) also suggested Flow is an important element in understanding human-technology interactions. Finneran and Zhang (2005) provided a critical review to analyze the promises and challenges of studying Flow in the computer-mediated environments. They focus on Flow models in business and information system (IS) context. In general, the models and other empirical Flow studies in HCI seem to suggest three stages as a Flow framework: Flow antecedents, Flow experience, and Flow consequences. More recent researchers start to highlight the individual differences in the empirical Flow models and include the distinction between task and artifact, as well as applying the models to virtual and game environments (e.g., Kiili, 2005; Pavlas, 2010; Reid, 2004; Takatalo et al., 2004), which help define the Flow antecedent constructs more precisely in diverse contexts of HCI.

Flow experience in Serious Games. The phenomenon of Flow is especially important in game research. Salen and Zimmerman (2004) suggest that Flow theory is extremely useful for conceptualizing the pleasure of play in games. Flow theory specifically looks into the degree of challenge and skills that one perceived in an activity.

Game designers have to consider if players think it was too difficult to learn or play the game, or it was not challenging enough for their skill level. For an ideal game, it should be simple to learn but difficult to master, provide an appropriate challenge for both beginners and advanced players. Moreover, meaningful play is the goal of successful game design, which occurs from the relationships between actions and outcomes in a game. When players take action within the game, the system in the game should responds to the action in an appropriate and meaningful way. Thus, they conclude that "[i]f you want to create flow in a game, meaningful play must be present. If you want to design meaningful play, flow can be a useful diagnostic tool in the process of making your game" (Salen & Zimmerman, 2004, pp. 338-339). Furthermore, Pavlas (2010) compared the requirements of Flow with the "Game Flow" elements in Table 3, which were proposed by Jones (1998), Sweetser and Wyeth (2005), and Cowley et al. (2008). This mapping has been used to show how computer games can be explicitly formulated as Flow-producing activities.

Table 3

Flow Requirements Linked to Game Elements

Flow Requirement	Game Element		
	Jones (1998)	Sweetser & Wyeth (2005)	Cowley et al. (2008)
A task to accomplish	Levels provide sub-tasks that lead to completion of whole task.	The game itself.	The complete gaming experience.
Ability to concentrate on task	Creation of convincing worlds to draw users in.	Game provides interesting stimuli & workload.	Presence; Dedicated gaming environment.
Clear task goals	Survival, collection of points, gathering of items, solving puzzles.	Primary and intermediate goals are presented.	Missions, plot lines, and levels.
Immediate feedback	Actions have immediate consequences. Shooting an NPC causes a result, picking up an item moves in.	Feedback is provided via status, score, and progress indicators.	Rewards and penalties.
Sense of control over actions	Mastering physical inputs such as keyboard or mouse.	Player is able to move their avatar(s) and feel control over input devices.	Familiarity or skill with controls, knowledge of game conventions.
Deep but effortless involvement	Fantastic environments remove suspension of disbelief and engage players.	Game environment should transport player emotionally / viscerally.	High motivation to play, emotional draw to content.

Note. Adapted from *A Model of Flow and Play in Game-Based Learning: The Impact of Game Characteristics, Player Traits, and Player States*, by D. Pavlas, 2010, p. 30.

Flow experience and related constructs in HCI. In many engagement studies on computer-mediated environments, terms have been developed in order to account for experiences, such as Flow, cognitive absorption, telepresence, presence, and immersion. Jennett et al. (2008) have given a comprehensive conceptual overview of immersion, presence, cognitive absorption, and Flow in relation to virtual environments. In game research, particularly, Flow, immersion, and presence are the terms widely used (Mikropoulos & Natsis, 2011; Qin, Rau, & Salvendy, 2007).

Presence. The term presence and immersion are often used without clear distinctions. Traditionally, the sense of presence in a virtual world has been used to refer to user's perception of 'being there.' Slater, Usoh, and Steed (1994) define presence as a psychological sense of being in a virtual environment (VE). Blade and Padgett (2002) refer presence as an illusion of being part of a VE. The more immersive a virtual environment experience, the greater the sense of being part of the experience. Takatalo (2002) and Nunez (2003) define presence as a mental state that generated by the computer (VE) rather than the real environment, so presence is the prerequisite for performance in VE.

Immersion. According to the *Virtual Environments Standards and Terminology*, immersion is defined as the experience of being physically immersed within a virtual environment experience. The term is sometimes subcategorized into external and internal immersion, and sensory and perceptual immersion (Blade & Padgett, 2002).

Clinical studies of phobias suggest that the sense of presence can be enhanced by immersive experiences, as immersive experiences (or presence) heighten physiological arousal. For instance, a person with a fear of flying experience much more physiological arousal when exposed to virtual environment depicting a flight sequence (Wiederhold, Davis, & Wiederhold, 1998).

A qualitative study conducted by Brown and Cairns (2004) evaluated players' feelings towards their favorite game and attempted to understand the dimensions for immersion using grounded theory approaches. Three levels or stages of immersion were revealed: (a) engagement, gamers need to overcome barriers and invest time, effort, and attention in order to enter this level; (b) engrossment, next level after engagement that game features need to combine gamers' emotions to become engrossed; and (c) total immersion, requires the highest level of attention and feel disconnected from reality. Ermi and Mäyrä (2005) further explored the heuristic gameplay experience and immersion. Three forms of gameplay experience were listed: (a) sensory immersion, that is related to the audiovisual execution of games; (b) challenge-based immersion, which is "when one is able to achieve a satisfying balance of challenges and abilities" (p. 7); and (c) imaginative immersion, when the players use their "imagination, empathise with the characters, or just enjoy the fantasy of the game" (p. 8).

Relationship between presence, immersion and Flow. Study from Takatalo (2002) supported the hypothetical relationship that presence is a prerequisite for Flow in virtual environments. His findings (*N*=58) showed that Flow followed presence in VE; there were no groups experiencing high levels of Flow and low levels of presence. He suspected that interaction is the determinant of presence and it also impacts individuals to feel arousal and challenged, which is the essential in creating Flow (refers to the inverted-U relationship in Figure 4). Jennett et al. (2008) argue that presence can be viewed as a state of mind, while immersion is an experience in time. Presence is possible without immersion because one could imagine a person feeling present in a virtual environment but not experience a lost sense of time. Dalgarno and Lee (2010) distinguish between the two constructs as “immersion relies on the technical capabilities of VR technology to render sensory stimuli, whereas presence is context-dependent and draws on the individual’s subjective psychological response to VR” (p. 13). Mikropoulos and Natsis (2011) believe an “immersive virtual environment is one that perceptually surrounds the user, and could increase his or her sense of presence” (p. 777).

It is also clear that immersion, especially the total immersion level and challenge-based immersion, has links to Flow (Jennett et al., 2008; Lindley, Nacke, & Sennersten, 2008). IJsselsteijn et al. (2007) suggest that Flow and immersion are related concepts that emerge from literature on digital gaming and both “appear relevant to characterize and potentially measure the somewhat holistic yet important concept of ‘gameplay’ that both game designers and game reviewers frequently refer to when discussing the interactive experience of a game in relation to its content and interface” (p. 2). Although Flow is associated with positive affects, immersion by itself does not mean that the player feels pleasure as immersion is considered as the sub-optimal experience (Jannett et al. 2008).

A degree of experience is observed while playing computer games based on the relationship between Flow, immersion, and presence. Playing games can produce an optimal experience (Flow) or sub-optimal experience (Immersion); but well-designed games should help individual to reach a state of Presence (the pre-requisite of Flow).

Moreover, a neurobiology study using fMRI during gameplay from Klasen et al. (2012) revealed that inferior parietal lobe down regulations (a decrease in the number of receptors on cell surfaces) were observed during the phases of high presence in the game, as well as that the caudate nucleus is activated during high presence. As a result, they conclude that “virtual presence and Flow experience during video games are related concepts and may share neural correlates. Moreover, the sense of presence may facilitate the emergence of Flow and correspond to the aspect of deep immersion which is characteristic for Flow in games” (p. 491). It is important for game researchers to further differentiate the conceptualization of Flow, immersion, and presence and understand their distinctive characteristics in relation to players, games, and their interactions. A summary table (Table 4) of the related constructs is shown below:

Table 4

Selected Engagement Studies on HCI

Reference	Engaging experience	Application	Dimensions
Csikszentmihalyi (1990)	Flow	Human Psychology	• Focused concentration • Merging of activity and awareness • Perceived control • Time distortion • Loss of self-consciousness
Steuer (1992)	Telepresence	Virtual Reality environments	• Vividness of the experience: • Breadth (number of senses involved) • Depth (degree of involvement) • Responsiveness of the system
Psotka & Davidson (1993)	Immersion	Virtual environments	• Implicit: biological processes and skills • Conscious: attention, self-control, distractibility, expectations, will power
Hoffman & Novak (1996)	Flow	Computer-mediated environments	• Skill/challenge • Focused attention • Telepresence • Interactivity
Witmer & Singer (1998)	Presence & Immersion	Virtual environment	• Presence: control, sensory, distraction, realism • Immersion: tendency to become involved in activities, maintain focus on current activities, tendency to play video games

Draper, Kaber, & Usher (1998)	Telepresence	Computer-mediated environments	• Vividness: sensory richness of displays or the remote environment • Interactivity: degree to which users can modify the remote environment
Schubert, Friedmann, & Regenbrecht (1999)	Presence	Virtual environments	• Spatial presence • Involvement • Judgment of realness
Agarwal & Karahanna (2000)	Cognitive Absorption	Information Technology	• Temporal dissociation • Focused immersion • Heightened enjoyment • Control • Curiosity
Takatalo (2002)	Presence & Flow	Virtual environments	• Presence: transportation, immersion, realness, interactivity, exploration, skill, challenge, control, arousal, valence • Flow: being there, impressed, pleasant, mediarichness
Chou & Ting (2003)	Flow	Online computer game	• Concentration • Playfulness • Distortion in time • Telepresence • Exploratory behavior
Sas & O'Hare (2003)	Presence	Virtual environments	• Being there • Not being here • Reflective consciousness (or awareness of being there)

Huang (2003)	Flow	Website	• Control • Attention focus • Curiosity • Intrinsic interest
Skadberg & Kimmel (2004)	Flow	Website browsing	• Time distortion • Enjoyment
Ermi & Mäyrä (2005)	Immersion	Gameplay experience	• Sensory immersion • Challenge-based immersion • Imaginary immersion
Sweetser & Wyeth (2005)	Flow	Game player experience	• Concentration • Challenge • Skills • Control • Clear goals • Feedback • Immersion • Social interaction
Cowley, Charles, Black & Hickey (2008)	Flow	Gameplay experience	• Focused concentration • Merging of activity and awareness • Perceived control • Time distortion • Loss of self-consciousness
Nacke & Lindley (2008)	Immersion & Flow	Gameplay experience	• Immersion: self-location, possible actions, spatial presence • Flow: tension, challenge, positive affect

Chandra, Srivastava, & Theng (2009)	Cognitive Absorption	Virtual Worlds	• Temporal dissociation • Focused immersion • Heightened enjoyment • Control • Curiosity
Weniger & Loebbecke (2010)	Cognitive Absorption	Information Technology	• Cognitive dimension: control, curiosity, temporal dissociation, focused immersion • Affective dimension: heightened enjoyment • Intrinsic motivator
Plass et al. (2010)	Engagement	Educational Games	• Behavioral • Cognition • Social • Emotional
Hoffman & Nadelson (2010)	Motivational Engagement	Video Games	• Decision to engage: fun (cognitive challenge), socialization, goals, control • Consistent reengagement: challenge, social, Flow (heightened sense of awareness), positive affect, perseverance • Sustained engagement: socialization, physiological satisfaction, achievement motivation, context (appealing gaming environment)
Whitton (2011)	Learning engagement	Computer game in education	• Challenge • Control • Immersion • Interest • Purpose

Measurement of Flow. *Flow* is a subjective, holistic experiential phenomenon. It requires researchers to pay special attention to the measurement of this subjective state of consciousness (Finneran & Zhang, 2002; Jackson, 2012). Jackson (2012) proposed that "a multimodal approach that incorporates both qualitative and quantitative methods of measurement is likely to yield the greatest gains" (p. 133). Several approaches and measures are commonly used. They are: (a) interviews; (b) self-report measures, such as Experience Sampling Method (ESM; Csikszentmihalyi & Larson, 1987) and Flow questionnaires (e.g., Delle Fave & Massimini, 1988; Fu, Su, & Yu, 2009; IJsselsteijn et al. 2008; Jackson, 2010; Jackson & Marsh, 1996); (c) cognitive appraisal of emotional experience; and the more recent approach (d) psychophysiological measures, such as facial electromyography (EMG), electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance (fMRI).

Kivikangas (2006) was probably one of the first game researchers investigating the correlations between psychophysiological measures and the Flow experience during gameplay. Nacke and Lindley (2008, 2009) and their colleagues (Nacke, Lindley, & Stellmach, 2008) further explore the use of experimental psychophysiological study to examine the gameplay experience and Flow experience through high-arousal positive affect emotions. The use of psychophysiological measures "provides an objective, continuous, real-time, non-invasive, precise, and sensitive ways to assess the game experience" (Kivikangas et al., 2010, p. 1). In the review from Kivikangas et al. (2010), several psychophysiological approaches were introduced in relation to the game-related experience. The psychophysiological approach to game research is still in its infancy. It faces challenges in interpreting the quantitative data accurately. However, with more carefully control experiments, large sample sizes, advanced technology, as well as triangulate with other psychological measures, like questionnaires and eye tracking method. This innovative research approach is essential in gaining a better understanding the subjective experience of gameplay and Flow.

Summary

This chapter includes five broad research areas related to game-based learning that are grounded in conceptual frameworks and empirical evidence: features of SEGs, theories related to cognitive-affective integrated framework of cognitive psychology, visual attention, eye tracking method, and Flow theory. There are still doubts about the popularity of digital games and their potential use in education. However, literature shows that SEGs can be a powerful learning tool that encourages active, personalized, and meaningful learning. Along with increasing research interests on engagement, motivation, and learning in education, little empirical research has examined the factors leading to engagement in digital games, especially the genre of SEGs. Flow, a positive psychological state, represents a rich and meaningful engagement with an activity at hand, which is highly linked to game experience. The dynamic nature between Flow, cognitive processing, and affect response, when viewed through the lens of the fields of cognitive psychology and affective science, helps explain student engagement and enjoyment in game-based learning. Conceptualization and measurement of Flow should be carefully examined to help advance our understanding of Flow state, as well as its antecedents and consequences, in game-based learning.

An increased interest in connecting cognition, neuroscience, and educational practices in the past decade improves our knowledge on how people learn. Cognitive neuroscience aims to understand how cognitive functions and their manifestations in behavior and subjective experience arise from the brain's activities. Recent neuropsychological research reinforces that cognition (e.g., attention, representation, and memory) is intricately related to emotion and motivation. A thorough understanding of visual attention and inclusion of work on emotion and affect within the cognitive framework becomes a main focus in the 21st century. Dual-process theories of cognition have been widely applied to studies of higher level cognition such as reasoning, decision making, and judgment; along with the knowledge of visual attention and visual information processing, it will be a valuable framework for learning scientists in understanding the complex world of game-based learning. The advancements of technology have significantly changed the landscape of educational research. The use of eye tracking and fMRI measurements, integrated with traditional self-report questionnaires and observations, permit more reliable analysis of individual differences and aid the study of mental processes, choice behavior, and subjective experience in learning. Eye tracking method has received more attention in the educational assessment literature after Pellegrino, Chudowsky, and Glaser (2001) has criticized the lack of application in 2001. Because eye movement data reflect attention, eye tracking may be very helpful in investigating the underlying mechanisms of visual attention processing so as to explore patterns of attention allocation that varies between gamers with different characteristics in relation to emotion and motivation (such as Flow experience and interest).

CHAPTER THREE: METHOD

To explore the feasibility of the theoretical model of Flow in the SEGs proposed in this study, a pilot study was conducted to explore any possible issues in administrating the instruments and understanding the students' perspective and feedback on the selected SEGs. A preliminary analysis of individual differences factors leading to Flow experience was performed to guide the development of the final study. The final study was focused on a science SEG and examined the following three relationships in an SEG environment: (a) the relationship between the visual attention and Flow experience, (b) the outcomes of visual attention and Flow, and (c) individual differences factors with regard to visual attention and Flow.

Pilot Study

A pilot test was conducted between March 6, and April 23, 2012, during weekly 1.5 hours meetings. The foci of the pilot study were to collect students' feedback on the two science-related SEGs, and test the administration procedure and related measures. A total of 32 high school students, between grades 9 and 11 participated. Of these, 10 students were self-selected to the study and participated in the session after school; whereas 22 students belonged to an environmental science class and participated in the study during their class period. The study was comprised of students between 14 and 18 years of age (M = 16.61, SD = 1.15). More than half of the participants were reported as

White or Caucasian (53.1%) and majority were reported as gamers (87.5%). The sample of participants was chosen because they were similar to the school district's student body that would participate in the final study. Table 5 offers an overview of the students' demographic background. Two SEGs, Neuromatrix and Operation: Resilient Planet (ORP), were used for the pilot study.

Table 5

Demographics of Pilot Study Sample (N = 32)

Characteristic	*n*	*(%)*
Grade		
9	2	6.3
10	5	15.6
11	10	31.2
12	13	40.6
Not Reported	2	6.3
Gender		
Male	20	62.5
Female	12	37.5
Ethnicity		
White or Caucasian	17	53.1
Hispanic or Latino	6	18.8
Black or African American	4	12.5
Indigenous American	2	6.3
Mixed Racial	3	9.3
Game Experience		
Gamer	28	87.5
Non-Gamer	4	12.5

A Flow questionnaire, eGameFlow (eGF; Fu, Su, & Yu, 2009, Appendix D), was used. It is a seven-point Likert-like scale, ranging from 1 (strongly disagree) to 7 (strongly agree) based on their extent of agreement with each statement. The original eGF consists of eight subscales with a total of 42 items. One of the subscales, *Social Interaction*, was removed due to the fact that the selected games were designed to be played by individuals and as a result, was deemed inappropriate for inclusion. Due to the small sample size (*N*=32), a technique of item parcels was used in this study. According to Hau and Marsh (2004), the advantages of item parcel include: increased reliability, less violation of normality assumptions, and more stable parameters estimates, particularly when the sample size is small. Therefore in this study, the items from the remaining seven subscales were parceled into three new subscales. The three original subscales from eGF, *Goal clarity*, *Feedback*, and *Challenge*, were parceled into one subscale called *Perceived Game Quality* (GQ; 13 items). Another three original subscales, *Concentration*, *Autonomy*, and *Immersion*, were parceled into another new subscale called *Flow State* (FS; 16 items). *Knowledge improvement* was used as a consequence of Flow and renamed as *Perceived Science Learning* (SL; 5 items). A statistical package, *Mplus*, was used to compute the estimation of scale reliability (REL). High reliability of the three new latent subscales from the eGF was shown in the pilot study: REL = 0.946 (GQ), REL = 0.935 (FS), and REL= 0.919 (SL).

An outcome survey, Perceived Enjoyment Scale (PE; Venkatesh, 1999, 2000; Appendix E), was used to test if enjoyment would be the consequence of Flow. It consists of three items and was commonly used in HCI research (Agarwal & Karahanna, 2000).

Several individual differences measures were used to test for possible predictor(s) of Flow. They are: (a) Science Interest Survey (SIS; Lamb, Annetta, Meldrum, & Vallett, 2011, Appendix A) with 19 items in a five-point Likert scale; (b) prior experience with games (Cheng, the current study; Appendix B) that consists of 7 closed-ended questions and 1 item called *Perceived Game Experience* (GEx), which was a self-rating of experience with video games ranged between 0 and 100; (c) Self-Efficacy for Technology and Science-Short Form (SETS-SF; modified from the SETS survey from Ketelhut, 2004 and validated by Lamb, Annetta, Vallett, & Cheng, (accepted); Appendix C) that consists of 16-items with three self-efficacy subscales: science process, video games, and computer use. All items are answered on a five-point Likert scale; and (d) Tellegen Absorption Scale (TAS; Copyright by University of Minnesota Press) that consists of 34 true/false items that assess an individual's openness to experience, emotional and cognitive alternations across a variety of situations. Details of the above measures were discussed under the instrumentation section.

In order to explore what individual differences factor(s) may predict students' level of Flow experience in SEG environments, stepwise multiple regression models were computed with perceived game quality (GQ) and Flow State (FS) as criterion variables. A set of possible predictor variables of individual traits (SIS, GEx, SETS-SF, and TAS) was entered in a stepwise fashion to detect the strongest predictor of Flow (GQ & FS). After reviewing the missing data of incomplete surveys, six participants were excluded and the remaining 26 were used in this analysis. A summary of the analysis is shown in Table 6. The regression analysis for GQ demonstrates that the set of two predictor variables model (science interest and perceived game experience) was significant, $F(2,23) = 12.501$, $p < .001$. Since the two predictors has only moderate correlation ($r = .35$), both of them can be considered a unique representation in the model, explaining 52.1 percent of the variance in perceived game quality. Science interest was the strongest predictor explaining 42.5 percent of the variance in perceived game quality. For predicting Flow state, one predictor model resulted. Science interest accounted for 27.8 percent of the variance in Flow state, $F(1,24) = 9.219$, $p < .01$.

Table 6

Stepwise Multiple Regression Analysis of Individual Difference Variables Predicting Flow Experience

Criterion Variable	Predictor Variables	B	SE B	BETA	Unique Variance (%)
eGF-GQ					
R^2 =.521 ; F=12.50, p<.001	SIS	1.481	.297	.769***	42.5
	GEx	-.194	.091	-.331*	9.6
eGF-FS					
R^2 =.278 ; F=9.22, p<.01	SIS	1.385	.456	.527**	27.8

Note. Only significant beta weight are shown (n=26).
GQ = Perceived Game Quality; FS = Flow State
*p < .05. **p < .01. ***p < .001.

After the pilot study, issues were identified and resolved in order to further improve the research design in the final study. For instance, the Flow questionnaire used in the pilot study, eGF (2009), is a relatively new measure and as a consequence, it is necessary to ensure its measurement reliability and validity; that is the degree to which the measure of Flow is accurate, consistent, and replicable. A widely used instrument in Flow research, LONG Flow State Scale (FSS-2; Copyright 2009 by Jackson) that measures the intensity of Flow experience and demonstrates well-established psychometric properties, was used in parallel with eGF in the final study. The eGF is a domain-specific scale, which the items describe respondent's experience in a game context, whereas the FSS-2 is a generic measurement scale, which the items describe the broader nature of an activity. It is often recommended that a generic measure should be used alongside with a domain-specific measure to allow comparisons with other studies (Bowling, 2001).

Moreover, the result from the stepwise regression analysis showed that an individual differences factor of science interest was a strong predictor of Flow, which account for 27 to 42 percent of Flow experience. It became necessary to further investigate how science interest may affect Flow experience under the framework of cognitive psychology and complete the proposed theoretical model that link the individual differences factors to Flow and visual attention. Lastly, through focus group and observation of students' playing in the pilot study, between the two SEGs – Neuromatrix and ORP – Neuromatrix was selected because more students found it engaging, and as a research point of view, it allows meaningful and comparable contexts (or scenes) for eye tracking analysis.

Proposed Theoretical Model

This study adopts four theories and one framework in proposing a theoretical model related to SEGs research. They are: Flow Theory (Csikszentmihalyi, 1975, 1990; Jackson, 2009; Sweetser & Wyeth, 2005), Information-processing model of selective attention (Broadbent, 1958; Lachter et al., 2004), Dual-process theories of cognition (Kahneman, 2011; Svahn, 2009), and Affective response model (Zhang, 2013), which all are examined using the cognitive-affective integrated framework of cognitive psychology.

The proposed model consists of three parts that are theoretically related to the cognitive processes in gameplay. The core part in the middle is to test the relationships between visual attention and Flow experience within the cognitive-affective integrated framework of cognitive psychology. The second part is to test the outcomes whether perceived enjoyment is associated with Flow, as well as to examine any interactive effects of visual attention and Flow on perceived science learning. The final part includes two individual differences variables – science interest and perceived game experience – that serve as affective concepts and might be relevant to Flow experience through the lens of the two theoretical models: the dual-process theories of cognition and the affective response model. Science interest may also have an effect on visual attention during gameplay as proposed by the information-processing model of processing choice in selective attention. The theoretical model showed in Figure 7 demonstrating the hypothetical correlations between the individual differences factors, visual attention, Flow, and their outcomes of perceived science learning and perceived enjoyment.

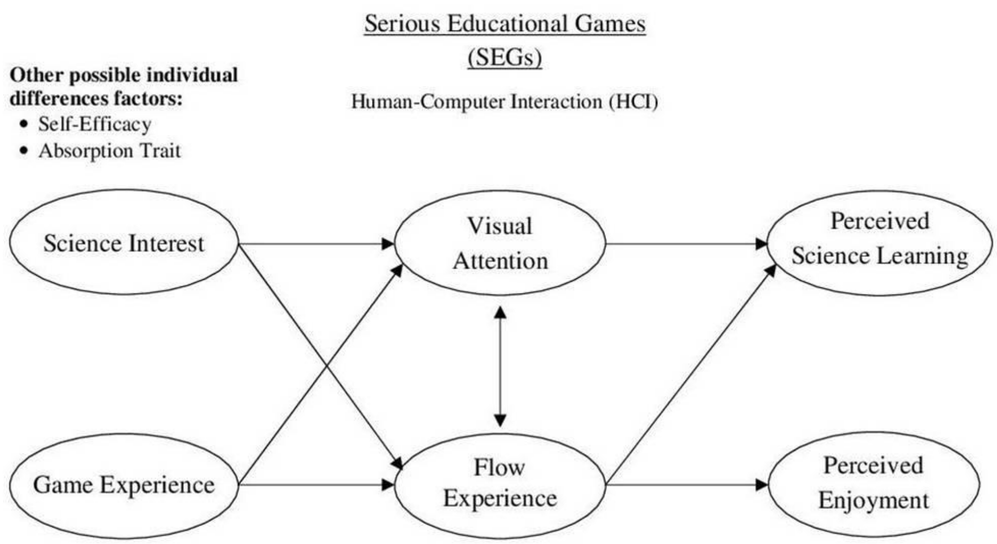


Figure 7 Proposed model of Flow and visual attention in SEGs.

Research Questions

Three research questions were proposed in order to test the hypothetical relationships between Flow and visual attention in an SEG; any interactive effects to outcomes, and to determine which individual differences factors may relate to them.

1. What are the associations between visual attention and Flow experience during gameplay?
   a. Are there any relationships between the number of fixations and gaze duration on Areas of Interest (AOIs), and Flow experience while playing an SEG?
   b. Are there any differences in scanpaths (length and pattern) while playing an SEG between high Flow and low Flow individuals?

2. What are the associations between visual attention, Flow experience, and their outcomes (perceived science learning and perceived enjoyment) through playing an SEG?
    a. Are there any interactive effects of visual attention and Flow experience (high, medium, and low) on perceived science learning and perceived enjoyment?
    b. Whether students' Flow experience has positive relationship with perceived science learning?
    c. Is there a strong positive relationship between Flow and perceived enjoyment?
    d. Are there any relationships between gaze duration during gameplay and perceived science learning or perceived enjoyment?
3. What individual differences factors related to students' Flow experience and visual attention in an SEG environment?
    a. What individual differences factors are the predictors of Flow experience?
    b. Is there any correlation between science interest and visual attention?
    c. Is there any correlation between science interest and Flow experience?

Research Design

A mixed method research design was used in this study, and a concurrent embedded strategy QUAN/qual (Creswell, 2008) was employed. Self-report survey and eye tracking methods were used to collect quantitative data and were treated as the primary and predominant methods that guide the study. The secondary method, qualitative scanpath analysis, was nested within the primary eye tracking data. Eye tracking video of a selected scene was transformed into individuals' qualitative scanpath by using a visualization method known as gaze duration sequence diagram. The visualized scanpaths provide an impression of when and where (time and space) the participants looked, which allow in-depth investigation and interpretation. Concurrent mixed methods procedures are used to converge and merge quantitative and qualitative data in order to provide a comprehensive analysis of the research problem (Creswell, 2008). A research design matrix that outlines the data sources and methods used for each research question is shown in Table 7. Methods for the testing of validity and reliability of instruments are shown in Table 8.

Table 7

Research Design Matrix

	Research Question	Data Source	Method
Q1. What are the associations between visual attention and Flow experience during gameplay?			
1a.	Are there any relationships between the number of fixations and gaze duration on Areas of Interest (AOIs), and Flow experience while playing an SEG?	FSS-2 eGF Eye tracking data	• Simple Linear Regression • Multiple Regression
1b.	Are there any differences in scanpaths (duration and pattern) while playing an SEG between high Flow and low Flow individuals?	FSS-2 eGF Eye tracking data	• Qualitative analysis (Gaze Duration Sequence Diagram)

Q2. What are the associations between visual attention, Flow experience, and their outcomes (perceived science learning and perceived enjoyment) through playing an SEG?			
2a.	Are there any interactive effects of visual attention and Flow experience (high, medium, and low) on perceived science learning and perceived enjoyment?	FSS-2 Eye tracking data SL PE	• 2-factor Analysis of Variance (3 x 3 ANOVA)
2b.	Whether students' Flow experience has positive relationship with perceived science learning?	FSS-2 eGF SL	• Simple Linear Regression • Multiple Regression
2c.	Is there a strong positive relationship between Flow and perceived enjoyment?	FSS-2 eGF PE	• Simple Linear Regression • Multiple Regression
2d.	Are there any relationships between gaze duration during gameplay and perceived science learning or perceived enjoyment?	Eye tracking data SL PE	• Simple Linear Regression
Q3. What individual differences factors related to students' Flow experience and visual attention in an SEG environment?			
3a.	What individual differences factors are the predictors of Flow experience?	FSS-2 eGF SIS GEx TAS, SETS-SF	• Stepwise Multiple Regression
3b.	Is there any correlation between science interest and visual attention?	SIS Eye tracking data	• Simple Linear Regression
3c.	Is there any correlation between science interest and Flow experience?	SIS FSS-2 eGF	• Simple Linear Regression

Table 8

Validity and Reliability Testing of Measurement Data

Measures	**Testing**	
	Validity	**Reliability**
Self-report measures (SIS, FSS-2, eGF)	Exploratory Factor Analysis (EFA)	Latent Variable Modeling (LVM) Approach to Internal Consistency Reliability
Eye Tracking	Validity coding	Calibration

Determine sample size. *A priori* power analysis was performed to identify sample size for the current study. It is an important part of research planning and allows researchers to determine how many cases are needed to detect an effect of a specified size with the desired amount of power. For this study, a stand-alone power analysis software, G*Power (version 3.1.3; Faul, Erdfelder, Buchner, & Lang, 2009; Faul, Erdfelder, Lang, & Buchner, 2007) was used to compute the necessary sample size.

The program was set to the *F*-tests family, which the desirable sample size was estimated for a given power, alpha (α), and population effect size (ES). The Cohen's ES (f^2) in this study was 0.35, considered to be large using Cohen's (1988) and Faul's et al. (2007) criteria. With an alpha = 0.5 and power = 0.80, the projected sample size needed with this effect size (GPower 3.1.3) is approximately $N = 31$ for linear multiple regression with two predictors. For ANOVA: fixed effects, main effects and interactions test, the Cohen's univariate ES $f = 0.40$, considered to be large using Cohen's (1988) and Faul's et al. (2007) criteria was set. With an alpha = 0.5 and power = 0.80, the projected sample size needed with this effect size (GPower 3.1.3) is approximately $N = 64$.

For this study, the sample size was also restricted by the use of eye tracking. One of the most debated questions in eye tracking research is determining the sample size. From the review of 21 usability studies incorporating eye tracking listed by Jacob and Karn (2003), subject numbers ranged between three and 40, depending on the research resources and the required depth of analysis. By and large, researchers in the eye tracking, usability, and user experience fields suggested approximately 20 to 40 users are needed to conduct quantitative testing or understand the visual behavior; but as few as five participants could be used for qualitative testing such as think aloud (Kara & Jakob, 2009). In this study, one eye-tracker was used and lasted for 20 minutes each for calibration and gameplay. Due to the limitation of the three-day workshop (4 hours a day excluding lunch time), this study allowed the maximum of 30 student participants in the eye tracking study. Thus, by considering the estimation from power analysis for linear multiple regression with two predictors, eye tracking participant number recommendation, and the time constraint for this study, the sample size $N = 30$ was determined.

Participants and Setting

Thirty-one high school students from one school in the mid-Atlantic region, between grade 9 and 12 participated in the final study. Students played the SEG Neuromatrix at the school's computer laboratory. All related game software was installed on the school computers by school staff. All students were self-selected to join the workshop outside their regular school day. Consent and assent forms were signed before the workshop began. The final study was comprised of students' ages between 14 and 17 (M = 15.98, SD = 0.861). One third of the participants were reported as White or Caucasian (32.3%), another one third was reported as Mixed Racial (29.0%). Approximately 77 percent were male and more than half were reported as frequent gamers (67.7%). Table 9 offers an overview of the students' demographic background.

Table 9

Demographics of Study Sample (N=31)

Characteristic	*n*	*(%)*
Grade		
9	7	22.6
10	8	25.8
11	14	45.2
12	2	6.5
Gender		
Male	24	77.4
Female	7	22.6
Ethnicity		
White or Caucasian	10	32.3
Black or African American	6	19.4
Asian	4	12.9
Hispanic or Latino	2	6.5
Mixed Racial	9	29.0
Game Experience		
Frequent Gamer	21	67.7
Moderate Gamer	10	32.3
Not Gamer	0	
Science Grade		
A	9	29.0
B	18	58.1
C or below	4	12.9

SEG: Neuromatrix

An SEG, Neuromatrix (Morphonix, http://morphonix.com), was selected for this study. The game takes place in a 3-dimensional virtual space while players interact with non-player characters and virtual objects, and purposefully learn various science concepts through the gameplay. It is suitable for students from ages 9 to 15. In Neuromatrix, players assume the role of a secret agent infiltrating a neuroscience research facility. The mission of this game is to track down and root out Nanobots invading the brains of scientists. Players diagnose the infested parts of the scientists' brains, then shrink down and navigate into the brain to eliminate the Nanobots. The aim of Neuromatrix is to understand the various functions of the brain such as the cerebral cortex, hippocampus, amygdala, and neurotransmitter.

The components and levels of Neuromatrix have been organized and displayed in Figure 2. Through the observation of students' playing the SEG in the pilot study, the most fluent players could only reach the beginning of level three in the set time of 15 minutes. Detailed descriptions are applied to level one and level two only as shown in Figure 8. Diagnostic analysis of Neuromatrix, in terms of its cognitive processes and affective concepts, was discussed later in the chapter.

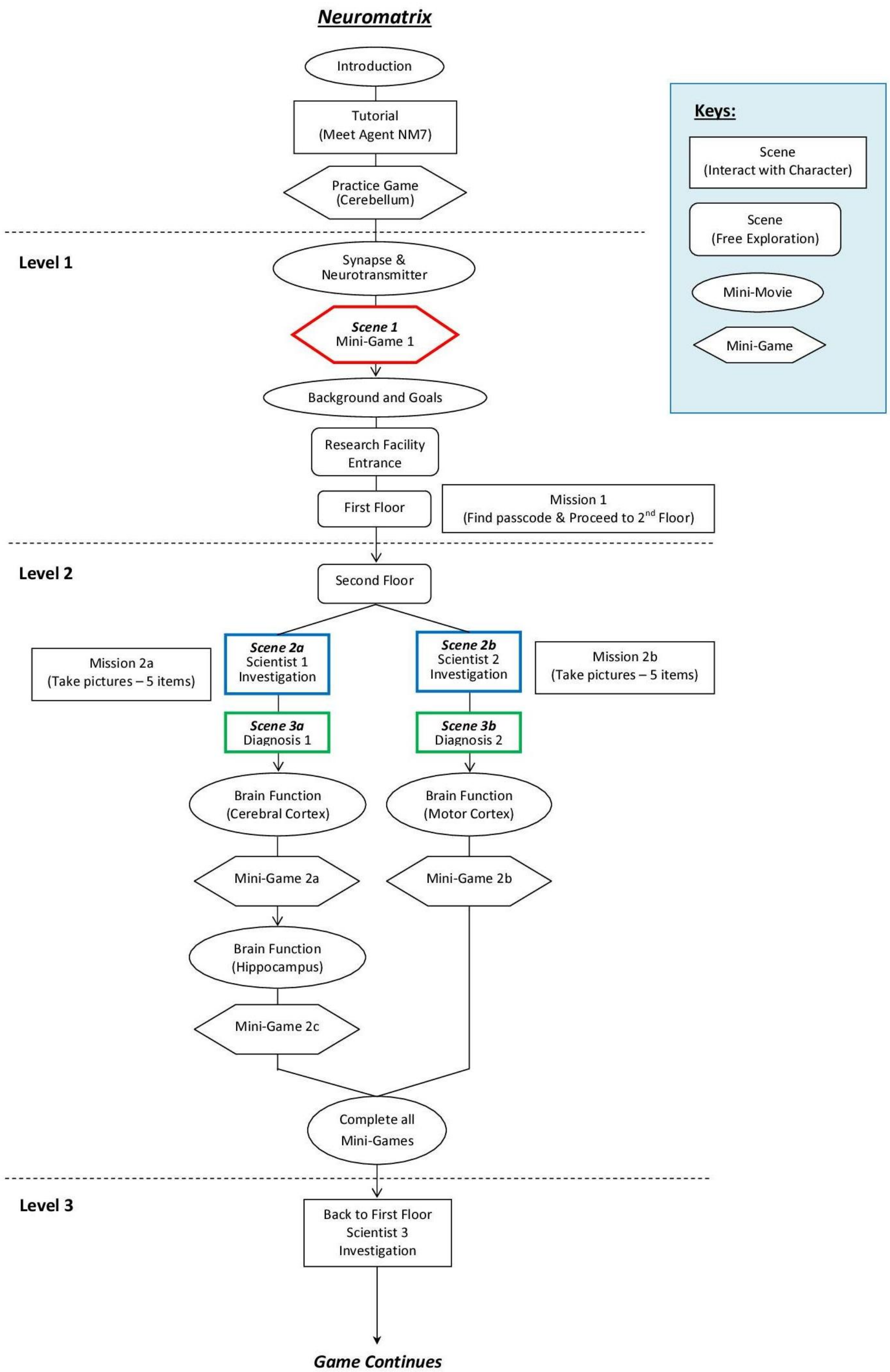


Figure 8 Game structure of Neuromatrix.

Procedure

In the three-day workshop, school teacher provided various activities related to game-based science learning in the computer laboratory while the eye tracking data collection was performed in a separate room inside the computer laboratory. Students who participated in this final study completed a set of surveys on day one (completion of the surveys took approximately 30 minutes). The self-reported surveys include: the demographic data, such as grade, ethnicity, gender, and number of hours playing video games, as well as SIS, SETS-SF, TAS. They were administered before the gameplay. All data (except TAS) were collected online through survey monkey (www.surveymonkey.com). TAS was conducted using a paper-and-pencil method based on the permission guidelines for the use of copyrighted content.

Each student had a desktop with the Neuromatrix game pre-installed. Students first played the Neuromatrix for 15 minutes in order to go through the tutorial and get familiar with the navigational controls. Then, one-by-one, individual participant was invited to a separate room to play the Neuromatrix for another 15 minutes under the eye tracker. Other students remained in the computer room and participated the workshop conducted by the school teacher while the eye tracking session was in progress. During the teacher-led workship, students were instructed not to play Neuromatrix until everyone finished the eye tracking data collection.

Tobii T120 Eye Tracker with the 17-inch display was employed for the real-time eye tracking recording (such as gaze, fixation, and saccades) while playing Neuromatrix. Participants were placed in front of the eye tracker and sitting comfortably at an approximate distance of 65 cm prior to intiating the test. Before recording, participants went through a calibration procedure. The calibration process ensures that the eye tracker learns the characteristics of the participant's eyes and accurately calculates the direction of his/her gaze on the surface of the screen. The researcher then clicked "Start Recording" to record the in-game behaviors and eye tracking data. Each participant had 15 minutes to play the game. Before exit, students filled in a survey form with the combined items from eGF, FSS-2, SL, and PE immediately after playing Neuromatrix.

Instrumentation

Self-report measures were used in the study. The interest and self-efficacy scales were specifically related to science learning. Most items are answered on either a five- or seven-points Likert-type scale. The Absorption scale was scored as True (=1) or False (=0) indicating the agreement or disagreement with the statements. Reliability information reported from previous studies was stated for each measure.

Measures related to individual differences. Students' traits, motivation and beliefs are assessed using the following instruments.

1. Science Interest Survey (SIS; Lamb, Annetta, Meldrum, & Vallett, 2011, Appendix A) contains 19 items with five response categories arranged in a Likert scale describing respondent levels of interest in science (1=strongly; 5=strongly agree) and one overall science interest rating. The 19 items are divided into five subscales: F = Family encouragement, P = Peer attitudes toward science, T = Teacher influence, I = Informal learning Experiences,

and S = Science classroom experiences. It also consists of an “overall science interest” score rating between 0 and 10 at the end of the survey. Lamb et al. (2011) reported the internal reliability of SIS as .72 with the person separation index as 8.75, which is considered an adequate internal reliability of the measure under both Classical Test Theory and Item Response Theory (N = 528). The person item map of the Rasch scaled SIS shows good targeting of the scale with no floor or ceiling effect. They suggested the measure SIS can be used as a unidimensional construct of science interest.

2. Prior experience with games (Cheng, the current study; Appendix B) consists of seven closed-ended items, which focus on their time spent on computers and computer games and game genres which they played most. One item that was used as a measure of *Perceived Game Experience* (GEx) is an overall self-rating of experience with video games ranged between 0 and 100.

3. Tellegen Absorption Scale (TAS; Copyright by University of Minnesota Press) consists of nine content clusters: responsiveness to engaging stimuli, responsiveness to inductive stimuli, thinking in images, a tendency to have cross-modal experiences, an ability to become absorbed in one’s thoughts and imaginings, a tendency to have episodes of expanded awareness, an ability to experience altered states of consciousness, and an ability to re-experience the past. TAS containing 34 true/false self-report items that assesses an individual’s openness to experience, emotional and cognitive alterations across a variety of situations. Summed scores on the instrument

are calculated by identifying *true* responses as 1 and *false* responses as 0, creating a possible range of 0 to 34, with higher scores indicating stronger trait absorption. Tellegen (1982) reported high levels of internal reliability (r = .88) on a study sample of college females (N = 500) and college males (N = 300) and high levels of test–retest reliability (r = .91) on a study sample of college females (N = 111) and college males (N = 62).

4. Self-Efficacy for Technology and Science – Short Form (SETS-SF; modified from the SETS survey from Ketelhut, 2004 and validated by Lamb, Annetta, Vallett, & Cheng (accepted); Appendix C) consists of 16-item, three self-efficacy subscales. They are: science process, video games, and computer use. It is designed to measure the motivational belief in virtual environments. All items are answered on five-point Likert scale (1=strongly disagree; 5= strongly agree). Study from Lamb et al. (accepted) reported the internal reliability of SETS-SF is .95 and the person separation index is 5.69, which confirmed adequate reliability under both Classical Test Theory and Item Response Theory (N = 506). The authors suggest that the SETSSF is a unidimensional measure of self-efficacy within the domains of science process knowledge and technology use.
5. Participant demographic survey (Cheng, the current study; Appendix B) consists of six items, which include the participants' school type, letter grades received in science class, age, gender, and ethnicity.

Measures for Flow experience. Flow experience is measured by two scales, the *eGameFlow* and *Flow State General Scale*.

1. EGameFlow (eGF; Fu, Su, & Yu, 2009; Appendix D). eGF aims to measure the level of Flow experience provided by e-learning games to the users, which the item statements are bounded to game-related contexts. A total of 42 items are answered in a seven-point Likert-like scale, ranging from 1 (strong disagree) to 7 (strongly agree) based on their extent of agreement with each statement. The survey consists of eight subscales (seven-point scale), and an "overall sense of enjoyment" visual analogue rating scale between 0 and 100. The eight subscales are: *Concentration* (6 items), *Goal clarity* (4 items), *Feedback* (5 items), *Challenge* (6 items), *Autonomy* (3 items), *Immersion* (7 items), *Social interaction* (6 items), and *Knowledge improvement* (5 items). The SEG used in this study was designed for individual play, the subscale "social interaction" is not appropriate in this study. Therefore, all items of social interaction were taken out. One item from subscale *Challenge* from the original scale has been removed as there is no "online support" from the games used in the study. The modified version used in this study had 34 items consist of seven subscales. *Knowledge improvement* subscale was used as an outcome variable to measure the perceived science learning gain of students. The Cronbach's alpha estimate for reliability from Fu et al. (2009) was 0.942 (N = 166).

Like in the pilot study, due to the small sample size ($N = 31$), a technique of item parcels was used in the final study. According to Hau and Marsh (2004), the advantages of item parcel include: increased reliability, less violation of normality assumptions, and more stable parameters estimates, particularly when the sample size is small. The three original subscales, *Goal clarity*, *Feedback*, and *Challenge*, were parceled into one subscale called *eGF-Perceived Game Quality* (eGF-GQ; 13 items); whereas *Concentration*, *Autonomy*, and *Immersion*, were parceled into the second subscale called *eGF-Flow State* (eGF-FS; 16 items). *Knowledge improvement* was used outcome renamed as *Perceived Science Learning* (SL; 5 items).

2. LONG Flow State - General Scale (FSS-2; Copyright 2009 by Jackson). The FSS-2 General Scale intends to assess people whose activity does not involve sports or other movement-based performance. It is designed as a post-event assessment of Flow, with instructions worded to ground the respondent in a recently completed activity; that is according to the respondents' experience immediately following a task or activity. FSS-2 contains 36 items with four items for each of the nine dimensions of Flow. Each dimension comprises a subscale of the total scale. The nine subscales are: *Challenge-Skill balance, Action awareness, Clear goals, Unambiguous feedback, Concentration on task, Sense of control, Loss self-consciousness, Transformation of time, and Autotelic experience*. The FSS-2 are rated on a five-point Likert scale,

ranging from 1 (strongly disagree) to 5 (strongly agree). Respondents are asked to indicate their extent of agreement with each of the Flow descriptors in relation to activity that has just been completed. Scores on the FSS-2 can range from 36 to 180, with higher scores indicating higher Flow experiences. The goodness-of-fit for nine-factor model ($\chi^2 = 1332.89$, *df* = 558) and higher-order factor Flow model ($\chi^2 = 1717.60$, *df* = 585) exhibit CFI values exceeding .95 and RMSEA values .05. Factor loadings for the nine dimensions were between .68 and .84. The reliability of the FSS was satisfactory, ranged between .80 and .90.

Similar to eGF, item parcel technique was used. Three Flow dimensions with four-items each: *Challenge-skill balance*, *Clear goals*, and *Unambiguous feedback* were parceled into a subscale called *FSS-Perceived Game Quality* (FSS-GQ; 12 items). The remaining six Flow dimensions: *Merging of action and awareness*, *Concentration on the task at hand*, *Sense of control*, *Loss of self-consciousness*, *Transformation of time*, and *Autotelic experience* were parceled into the second subscale called *FSS-Flow State* (FSS-FS; 24 items).

Measures for outcomes. Two proposed outcomes were measured by the following two scales.

1. Perceived Enjoyment Scale (PE; Venkatesh, 1999, 2000; Appendix E) consists of three items that are commonly used in HCI research (Agarwal & Karahanna, 2000). The statements have been revised to suit the game

context. The Cronbach's alpha estimate for reliability from Venkatesh (2000) was 0.81 (N = 30) and 0.90 (N = 70).

2. Perceived Science Learning (SL; Fu, Su, & Yu, 2009; Appendix F). It is measured by the *Knowledge improvement* (5 items) subscale from the eGF.

Eye tracking instrument (hardware and software). Eye movements were captured by a Tobii T120 Eye Trackers integrated a 17-inch (1280 x 1024 pixels) TFT monitor with built-in eye tracking optics. The eye tracker is binocular, sampling at 120 Hz with an average of 0.5° accuracy. Tobii Studio (3.0) software was installed on Windows desktop computers for recording the eye tracking data and video capturing the game environment during data collection, and an updated version Tobii Studio (3.2) was used to analyze the gaze data after data collection. A Windows desktop computer with Tobii Studio (3.0) software and video capture card was connected to the Tobii T120 Eye Tracker using the VGA cable and Ethernet. A laptop computer running the selected game was connected to the desktop computer via HDMI cable (see Figure 9). The Tobii T120 Eye Tracker has a built in speakers and the eye tracking sensors, located at the front and bottom of the monitor (Figure 10). The illuminator of the Tobii T120 has been tested at ETL SEMKO, Stockholm, according to IEC/EN 60825-1/A1-A2 in 2008. The test has shown that the product comply with the standard for IEC/EN 60825-1/A1-A2 Class One LED products intended to be used for long time exposure, i.e., eight hours a day many days in a row.

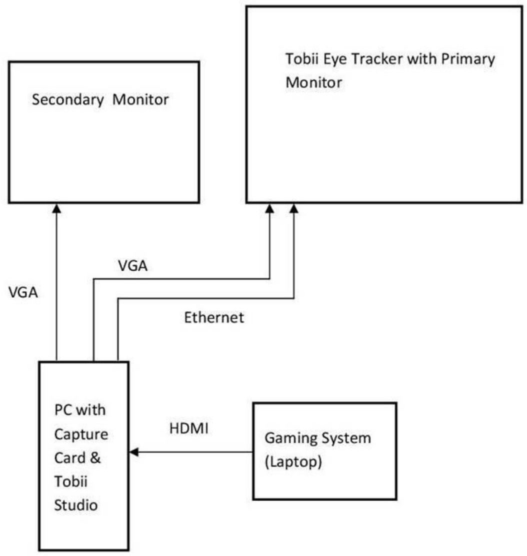


Figure 9 Gaming set-up with Tobii Eye Tracker.

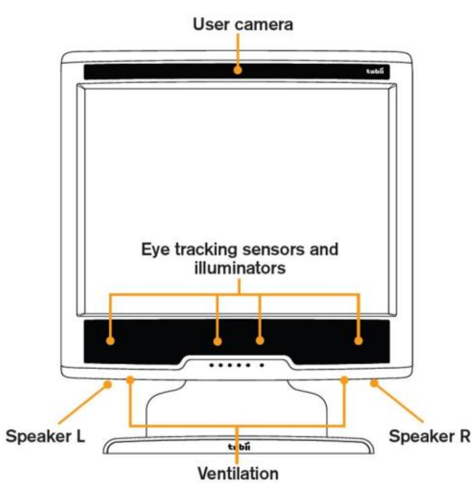


Figure 10 Front display of Tobii Eye Tracker.
Note. From *Tobii T60 & T120 Eye Tracker User Manual: Revision 4.0*, by Tobii, 2011, p. 16, Danderyd, Sweden: Tobii Technology AB. Copyright 2011 by Tobii Technology. Reprinted with permission.

The Eye Tracker has a stable data-rate of 120 Hz, i.e., 120 gaze data points per second are collected for each eye. Both horizontal and vertical screen position of the gaze point for both eyes was collected; the averages for both eyes were then computed for fixation. As recommended by Tobii user manual (Tobii, 2011), the distance from the person's eyes to the eye tracker should be approximately 65 cm. It is important to have the correct distance to the screen otherwise the eye tracker cannot track the entire area and a risk of losing some of the gaze data. The eye tracker should be placed with the gaze angle not exceed 42° to any point of the screen. A calibration procedure was performed for individual participants (Tobii, 2010). During the calibration process, the eye-tracker measures the characteristics of the participant's eyes and uses an internal, physiological 3-D eye model to calculate gaze data. This model includes information about the shapes, light refraction, and reflection properties of the different parts of the eyes (e.g., cornea and placement of the fovea). The participant is asked to look at specific points on the screen, known as calibration dots. During calibration, images of the eyes were collected and analyzed. The resulting information is then integrated with the eye model and the gaze point for each image sample is calculated.

Tobii Studio (3.2) Enterprise edition was used for eye tracking data analysis in this study. It is an eye tracking software that allows researchers (a) to record the integrated eye tracking data and in-game behaviors; (b) to replay eye tracking sessions and event logging that enable in-depth qualitative analysis; (c) to visualize the eye tracking data through heat maps and gaze plots that provide a powerful tool for qualitative analysis and presentation; and (d) to calculate eye tracking metrics for in-depth quantitative analysis. This latest 3.2 version features a new Dynamic AOI tool that allows researchers to define AOI on both static and dynamic stimuli and calculate eye tracking metrics.

Eye tracking measures. Tobii system employs Velocity-Threshold Identification (I-VT) for event detection and data is computed by a fixation velocity algorithm. The I-VT classifies eye movements based on the velocity of the directional shifts of the eye. Data points with angular velocity below the threshold are classified "fixation" and data points above are classified as "saccade," which the default threshold is set to 30 visual degrees per second (°/s). I-VT has a gap fill-in function to fill in data through linear interpolation where valid data is missing. Data between two data loss scenarios is filled in with a maximum gap length of 75 milliseconds (ms), as the minimum blink duration is 75 ms according to Komogortsev et al. (2010). The default value of the I-VT filter for the minimum fixation duration is set to 60 ms. If the duration is shorter than the parameter value, the fixation is reclassified as an unknown eye movement. This filter function is needed so as to remove data points, which are too short a time for the visual input to be registered by the brain, according to cognitive processes theory (Olsen et al., 2012).

The Dynamic Area of Interest (AOI) tool from Tobii Studio (3.2) enables researchers to define dynamic (moving and transforming) AOIs within different stimuli, for examples, movies, videos, screen recording, and games. Researchers predefined the AOIs and draw them around the researched object in the media. Activate the states throughout the timeline until the scenes were ended. During active state intervals, the

AOI collected eye gaze data. During inactive state intervals the AOI will not collect eye gaze data.

Eye and gaze tracking data were exported from Tobii Studio as tab-separated values files (.tsv) or Microsoft Excel file (.xls). In this study, AOI gaze events and raw gaze coordinates with validity coding were exported. The data exported were cleaned and transformed before imported into *SPSS* and/or *Mplus* for statistical analysis. Data transformation procedure is discussed later in the chapter.

Summary of measures. The constructs used in this study, their abbreviations, and their associated measures are listed in Table 10.

Table 10

Constructs Measured

Construct	Abbrv.	Source
Science Interest	SciI	19 items from SIS, Lamb, Annetta, Meldrum, & Vallett (2011)
Absorption Trait	TAS	34 items from Tellegen Absorption Scale (TAS) of the Multidimensional Personality Questionnaire (MPQ)[1]
Experience with Games	-	7 closed-ended items from Cheng (the current study)
Perceived Game Experience	GEx	1 self-rating item from Cheng (the current study)
Self-Efficacy for Technology & Science	SETS	16 items from SETS-SF, Ketelhut (2004)
Flow Experience (generic)	FSS	36 items from FSS-2, Jackson (2009) [2]
Flow Experience (game context)	eGF	30 items from eGF, Fu, Su, & Yu (2009)
Visual Attention	-	Eye Tracking Data (Tobii T120 & Tobii Studio)
Perceived Science Learning	SL	5 items from eGF, Fu, Su, & Yu (2009)
Perceived Enjoyment	PE	3 items adapted from Venkatesh (2000)

Note. [1] The University of Minnesota Press does not allow for the reproduction of test items in dissertations.
[2] Mind Garden Inc. does not allow for the reproduction of test items in dissertations.

Data Transformation

Eye tracking data transformation. In this study, three steps of eye tracking data transformation, i.e., from raw data to meaningful measurement data, was performed for each participant before any statistical analysis. Holmqvist et al. (2011) proposed a model of eye tracking measures and Figure 11 illustrated the multiple stages of a typical transformation procedure from raw eye-movement data to measurement values for data analysis. First, raw eye-movement data are recorded by the eye tracking system and transformed into lists of events such as fixation and saccades according to the factory-settings and their respective algorithms. This stage is called oculomotor event detection. The quality of the data is dependent on the proficiency of the algorithms during the transformation. Measures such as fixation duration are identified in the events and representations stage. The measure concept is expressed in words such as "fixation duration" is now with a value attached to it. Quantification of these measures requires calculations, which is called as operational definitions of the measure. Measurement values are produced according the calculation based on the operational definitions and research designs. In the last stage, the value produced is called the measurement stage, and it is a product of operational definitions of the measure.

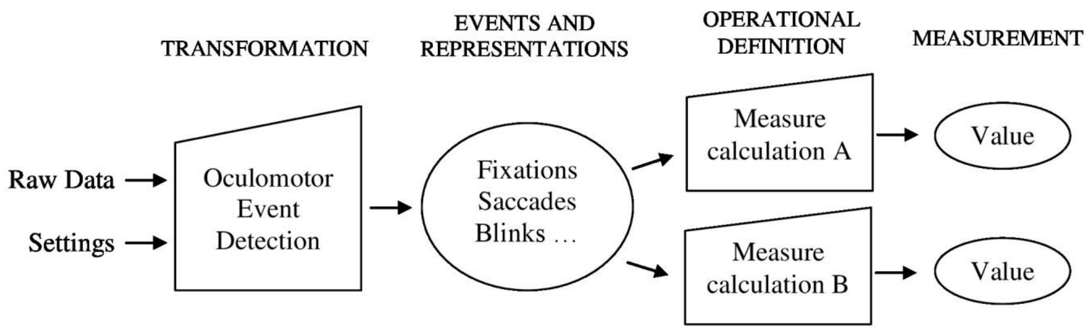


Figure 11 Multi-stages to transform eye-movement data to measurement data.
Note. Redrawn from *Eye Tracking: A Comprehensive Guide to Methods and Measures*, by Holmqvist et al., 2011, p. 458. Copyright 2011 by Oxford University Press. Reprinted with permission.

In this study, the three-step eye tracking data transformation is described as followed.

1. The 15-minute game was divided into scenes using Tobii Studio. The researcher predefined the AOIs for each scene that are relevant to the study. Using Tobii Studio (3.2), individual AOI was draw for each participant and added into each scene. While replaying the recorded scenes, the predefined AOIs were either active or inactive, controlled by the researcher. During active interval, the AOI collected the gaze data for further computation and stop collecting during inactive intervals.

2. Tobii Studio Statistics tool was used to calculate and display eye tracking metrics based on researcher's defined AOIs and data selection time intervals. Data was exported for further computation.
3. The data generated from the Tobii Studio Statistical tool were displayed according to individual AOIs using a unique identifier. Therefore, related AOIs data from each scene were grouped together and computed into one meaningful measurement value before statistical analysis. Tobii Studio can also generate non-AOIs data; so total value can be calculated by summing up all AOIs and non-AOIs values manually. Eight eye tracking variables were selected for this study because they are relevant to the operational definition of visual attention in game study. The eight visual attention variables are: Fixation duration on AOIs, total fixation duration, fixation count on AOIs, total fixation count, visit duration on AOIs, total visit duration, visit count on AOIs, and total visit count.

Categorical data transformation. In this study, both Flow scale scores and eye tracking data are employed in two ways. The first way is using the original continuous variables (i.e., the unstandardized scores) for regression statistics. The second way is to transform the continuous scores into categorical variables (High, Medium, or Low) for ANOVA statistics. The process of transformation to categorical data is as follows: the unstandardized scores are first calculated and converted into standardized scores (*z*-scores). Based on their z-scores, high, medium, or low Flow individuals can be categorized. For example, high Flow individuals are those whose z-scores fall into standard deviations of 0.5 or greater. Low Flow individuals are those whose z-scores fall into standard deviations of -0.5 or less. Medium Flow individuals are those whose z-scores fall between -0.5 and 0.5 standard deviations. The same approach was used in treating the eye tracking data.

Validity and Reliability of Self-Report Surveys and Eye tracking Data

Validity of self-report surveys. Exploratory factor analysis (EFA) for categorical data was used in selected measures to collect evidence about construct validity and the number of factors underlying the set of observable variables (Dimitrov, 2012; Conway & Huffcutt, 2003). A weighted least squares approach was implemented. Model was run in Mplus using WLSMV estimators where fit indices of Chi-square value (χ^2) and root mean square error of approximation (RMSEA) are reported. Hu and Bentler (1999) recommended that assessment of model of fit should be based on a joint evaluation of several fit indices as Chi-square value is sensitive to sample size whereas RMSEA and Comparative fit index (CFI) are less sensitive to sample size (e.g., Dimitrov, 2012; Fan, Thompson, & Wang, 1999).

The number-of-factor decision of Chi-square test showed that nine-factor solution is selected under the EFA WLSMV estimator in Mplus for FSS-2: χ^2 = 327.451, p = .705, RMSEA = .00, which indicated a good fit of the data is supported as the criteria of RMSEA < .06 is met (Hu & Bentler, 1999). The nine-factor model in this data set matched the proposed nine-factor in FSS-2 (Jackson, 2010). Six-factor solution is selected for eGF: χ^2 = 293.258, p = .158, RMSEA = .055, good fit of data for six-factor model matched the proposed factor model in eGF minus the social interaction subscale that did not include in this study (Fu, Su, & Yu, 2008). Six-factor solution is selected for SIS: $\chi^2 = 101.28$, $p = .418$, RMSEA = .027, good fit of data matched the proposed six subscales model in SIS (Lamb et al., 2011).

Validity of eye tracking data. Tobii eye-tracker captures the characteristics about the participants' eyes and provides the unprocessed data with validity code. The validity code is "an estimate of how certain the eye tracker is that the data given for an eye really originates from that eye" (Tobii, 2012, p. 133). The validity code scale starts at 0, which signifies eye certainly found, and ends at 4, which signifies eye not found. The combinations and their interpretations are summarized in Table 11.

Table 11

Validity Codes of Tobii Eye-Tracker

Validity codes	Left	Right
Both eyes found	0	0
One eye found, certain left	0	4
One eye found, probably left	1	3
One eye found, uncertain which one	2	2
One eye found, probably right	3	1
One eye found, certain right	0	4
No eyes found	4	4

Note. Validity codes are codes that estimate of how certain the eye tracker is the data given for an eye really originates from that eye.

The eye validity was summarized in Table 12 according to students who completed the particular scenes in the game. Four scenes were shown and only students who completed the scene were reported. Since not all students were able to proceed to the next stage, the number of participants (*n*) decreases for each subsequent scene. High percentage of the data had both eyes found, ranged from 92.52% and 99.47%. Therefore, it is confident that the raw data generated from the eye-tracker are valid.

Table 12

Percentage of Eye Validity for each Game Scene (N = 31)

Scene	Validity	Mean (%)	SD	Min (%)	Max (%)
Scene 1 – Docking	Eyes found	94.49	0.062	79.23	99.90
n=26	Both eyes found	92.52	0.083	72.10	99.84
	One eye found	1.98	0.038	0.02	14.59
	No eyes found	5.51	0.062	0.10	20.77
Scene 2 – Investigation	Eyes found	96.95	0.046	83.47	100.00
n=21	Both eyes found	94.91	0.108	49.55	99.92
	One eye found	2.05	0.072	0.04	33.92
	No eyes found	3.19	0.047	0.04	16.53
Scene 3 – Diagnosis	Eyes found	97.40	0.045	82.66	99.93
n=19	Both eyes found	96.21	0.061	78.67	99.88
	One eye found	1.20	0.022	0.02	9.81
	No eyes found	2.60	0.045	0.07	17.34
Mini Games	Eyes found	99.77	0.002	99.46	100
n=11	Both eyes found	99.47	0.004	98.45	100
	One eye found	0.33	0.003	0.01	1.01
	No eyes found	0.25	0.001	0.06	0.54

Note. Percentage (%) = # of validity code count / total counts of fixation & saccade of individuals)
n = only students who completed the scene

Reliability of self-report surveys. Estimation of reliability for congeneric measures approach has been used to estimate the internal consistency reliability of the scale scores of each measure. According to Dimitrov (2012, p. 186), the commonly used Cronbach's coefficient alpha can be a biased estimate of the scale reliability if the item measures are not essentially tau-equivalent and/or there are correlated errors. Therefore, the latent variable modeling (LVM) approach to estimating internal consistency reliability is preferable (e.g., Raykov & Shrout, 2002). In this study, Mplus was used to compute the estimation of scale reliability (REL), a latent variable modeling (LVM) approach to estimate internal consistency reliability. The widely accepted benchmark of .80 as desirable for scale reliability was adopted (Raykov & Pohl, 2013).

High reliability of the composite scores of both Flow scales is shown: REL = 0.914 (FSS-Sum) REL = 0.812 (eGF-Sum). High reliability of the two latent subscales from the eGF was shown: REL = 0.805 (eGF-GQ) and REL = 0.836 (eGF-FS). Moderate to high reliability for the two latent subscales from FSS-2 was shown: REL = 0.725 (FSS-GQ) and REL = 0.907 (FSS-FS). For the individual differences variables, moderate to high reliability were shown: The scale reliability of the five subscales of SIS are ranged between 0.529 (Peer attitudes toward science) and 0.746 (Family Encouragement). The scale reliability of the three subscales of SETS-SF are REL = 0.843 (Science process), REL = 0.801 (Computer usage), and REL = 0.561 (Video games). The scale reliability of TAS is REL = 0.773. High reliability of the two outcome variables: REL = 0.983 (PE) and REL = 0.838 (SL).

Not all students completed the Flow scales. Two of them did not return the eGF nor FSS-2 surveys, two students did not fill in the last page of the eGF survey (items 19 to 39), and one student did not submit the SETS-SF online survey. Table 13 summarizes the estimate of scale reliability of each survey with the numbers of returned survey. Table 14 illustrates the means and standard deviations of all the surveys used in this study.

Table 13

The Estimate of Scale Reliability (N = 31)

n	Survey	Scale / Subscales	# items	REL
27	eGF	Sum	30	0.812
		Perceived Game Quality	13	0.805
		Flow State	17	0.836
29	FSS-2	Sum	36	0.914
		Perceived Game Quality	12	0.725
		Flow State	24	0.907
31	SIS	Family Encouragement	4	0.746
		Teacher Influence	4	0.744
		Informal Learning Experiences	4	0.599
		Science Classroom Experiences	4	0.531
		Peer Attitudes toward Science	4	0.529
30	SETS-SF	Science Processes	5	0.843
		Computer Usage	5	0.801
		Video Games	3	0.561
31	TAS	Absorption Scale	34	0.773
27	PE	Perceived Enjoyment	3	0.833
27	eGF	Perceived Science Learning	5	0.838

Table 14

Survey Scores (N = 31)

Survey / Scale	*n*	# items	Mean	SD	Min	Max
FSS-Sum	29	36	140.90	15.621	104	173
FSS-GQ		12	47.83	4.751	36	58
FSS-FS		24	93.07	12.030	65	116
eGF-Sum	27	30	163.78	16.493	131	199
eGF-GQ		13	74.11	7.673	54	86
eGF-FS		17	89.67	11.978	60	113
SIS	31	20	70.65	7.135	58	88
Informal Learning Experiences		4	13.77	2.872	9	20
Family Encouragement		4	12.90	2.413	8	17
Teacher Influence		4	16.58	2.997	6	20
Science Classroom Experiences		4	15.94	2.581	11	21
Peer Attitudes toward Science		4	11.45	2.474	6	20
SETS-SF	30	13	57.67	6.578	37	66
Science Processes		5	18.60	2.078	48	78
Computer Usage		5	27.07	3.741	15	30
Video Games		3	12.00	2.289	5	15
GEx	31	1	85.39	15.419	30	100
TAS	31	34	61.35	7.787	48	78
SL	27	3	27.04	4.345	18	35
PE	27	5	16.33	3.162	8	21

Reliability of eye tracking data. The calibration process before the game starts ensures the reliability of the eye tracking data. Tobii Eye Trackers provides a simple process to ensure it generates reliable raw gaze date. The calibration process includes two stages. They are:

1. A tracker status box (Figure 12) that allows participants to visualize their position and adjust their sitting distance and position, such as chair position and table, or eye tracker stand, in order to obtain the desirable eye tracking data. The eyes of the participants, displayed as two white dots, should be in the center of the box and the distance indicator should display a value approximately 65 cm. The color of the bar at the bottom of the track status box should be green (Tobii, 2012).

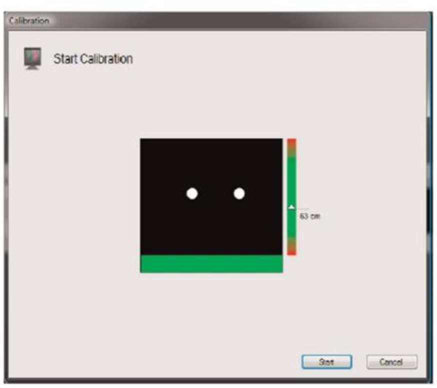
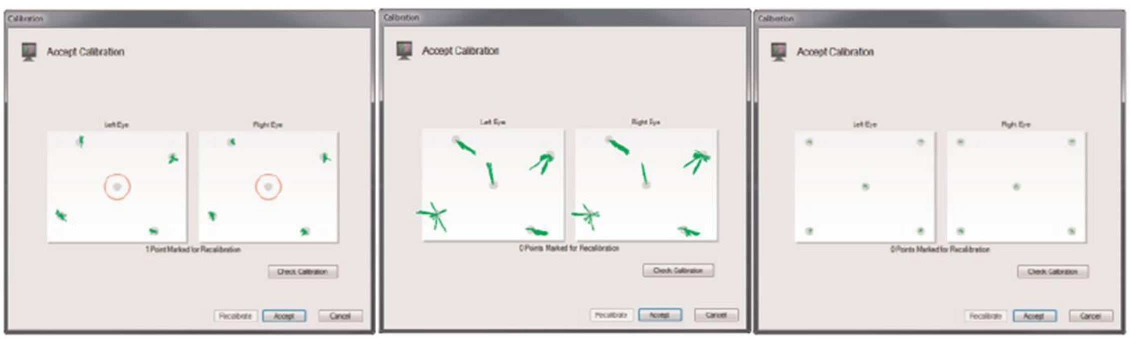


Figure 12 Screen shot of track status box.
It helps to adjust participant and the eye-tracker position.
Note. From *User Manual: Tobii Studio Version 3.2,* by Tobii, 2012, p. 32. Copyright 2012 by Tobii Technology. Reprinted with permission.

2. Participants are instructed to look at the points as they move over the screen. The calibration stop automatically when all calibration points have been shown and the results are displayed immediately. Figure 13 exemplifies the possible outcomes of this calibration process (Tobii, 2012). The calibration plot shows error vectors in green lines. The length of each green line indicates the difference between the gaze point calculated by the eye tracker and the actual dot position. If missing points (no lines) or large errors (long lines) occur during the calibration process, recalibration is required until reaching the perfect calibration.



a) b) c)

Figure 13 Screen shot of the calibration plots.
(a) Calibration point missing, (b) large errors in calibration, and (c) perfect calibration. *Note.* From *User Manual: Tobii Studio Version 3.2*, by Tobii, 2012, p. 32. Copyright 2012 by Tobii Technology. Reprinted with permission.

In the final study, a two stage calibration processes was conducted for each participant to obtain the desirable sitting distance and eye position to ensure the reliability of the eye tracking data. Perfect calibration obtained for each participant, i.e., the gaze point calculated by the eye tracker, and the actual dot position was matched, prior to the start of the game. If missing points or errors were observed, recalibration was done until reaching the perfect calibration.

Diagnostic Analysis of Neuromatrix

Cognitive task analysis. Three scenes in Neuromatrix were selected for analysis. Scene 1 is the mini-game in level 1. Scene 2 is the investigation in level 2, which player needs to communicate with the scientist and explore the laboratory to find hints. Scene 3 is the diagnostic process after the investigation to find out which part of the brain region was infected at the end of level 2. Color highlights were shown in Figure 2. Various cognitive processes that are required for gameplay of the selected scenes were documented according to the procedure suggested by Crandall, Klein, and Hoffman (2006). Cognitive task analysis enables researchers to deconstruct the game designs and compare different scenarios. Table 15 summarized the task description, game type, and game complexity of the three selected scenes. Four dimensions related to game complexity have been selected (Crandall, Klein, & Hoffman, 2006) for comparisons. They are: the complexity of task or mission, level of uncertainty, situational demands, and coordination.

The game quest types are based on the categories developed by Aarseth (1997). For Scene 1, it is considered as place-oriented (find a path to the destinations) and time-oriented (fixes the time limit for the completion of missions). For Scene 2, it is considered as object-oriented (set concrete targets for players to acquire). For Scene 3, it is a diagnostic procedure and do not have time/place limit, the no categorization of Aarseth (1997) was fitted. Therefore, Dickey's (2005) definition was adopted and categorized Scene 3 as messenger quest, which is designed to let players interact with the game-controlled objects, such as non-player characters (NPCs), and learn the necessary information in order to complete quest.

Table 15

Description and Game Complexity Dimensions of the Selected Scenes in Neuromatrix

Dimension of game complexity	Scene 1 (Docking Mini-game)	Scene 2 (Scientist investigation)	Scene 3 (Diagnosis)
Task description	• 2-Dimension End goal: • Docking the neurotransmitters Strategy: • Avoid enemy contact • Activate protection when encountering enemy • Charge when energy becomes low • Mini-map within game world	• 3-Dimension End goal: • Collect five items that help the diagnosis Strategy: • Visual search • Data gathering • Free exploration • Conversation with character	• 2-Dimension End goal: • Diagnosis of the infested brain region(s) Strategy • Retrieval of information • Evaluate information • Make conclusion • Reading ability is required
Quest Type	Time- & Place-oriented	Object-oriented	Messenger quest (Diagnostic process)
Complexity of task	Multiple simultaneous tasks	Multiple simultaneous and/or sequential, linked tasks	Single task, Decision making
Level of uncertainty	Low	High	Medium
Situational demands	Immediate action required, Time pressure	Action not immediately required, No time pressure	Immediate action required, No time pressure
Coordination	High	Medium to High	Low

Other than game structures, cognitive task analysis can be used to describe various mental processes for gameplay in selected scenes. Table 16 illustrates the mental processes related to gameplay. They are: the system or type related to dual-process theories of cognition, the knowledge types required to play the selected scenes, the sub-emotional variables elicited through gameplay, and the attention type required to play the selected scenes.

Table 16

Cognitive Processes Required for Playing the Selected Scenes in Neuromatrix

Mental Processes	Scene 1	Scene 2	Scene 3
Cognitive process (System or Type 1 or 2)	Type 1 predominates	Combination of Type 1 and Type 2	Type 2 predominates
Knowledge type	Procedural	Procedural Self-regulatory	Declarative Self-regulatory
Sub-emotional variables	Valence & Arousal	Valence & Arousal	Neutral or Valence
Attention	Alternating attention	Selective attention	Selective attention

The types of attention required for learning and memory can be categorized as selective, sustained, divided, and alternating (Semrud-Clikeman & Kutz, 2005). Selective and sustained attention types are important for orienting to and vigilance to the intended stimulus. Divided and alternating attention types are more complex and require executive functioning that coordinates the shifting of engagement or inhabitation of attention. Two types of attention were identified in the three selected scenes. Alternating attention is when ones need to shift their attention from one thing to another in a sequence, whereas selective attention enables a person to focus on the target stimuli from the environment and ignore the others. Researchers also suggested the role valence (negative vs. positive) and arousal (low vs. high), that interact in attentional control (Barrett, 1998; Jefferies, Smilek, Eich, & Enns, 2008). Scene 1 requires procedural knowledge to complete the stage so the Type 1 process predominates. It requires alternating attention in playing the game. For Scenes 2 and 3, the players require an additional knowledge type, self-regulatory knowledge, to complete the scenes, which they need to regulate their memory, thought, and learning the rules to be adaptive to the game. The differences are the nature of the scenes, where Scene 2 requires players to navigate in a 3-D virtual world and collect evidence whereas Scene 3 is in a 2-D environment that require players to read the evidence collected in Scene 2 and make decision. Therefore, Scene 2 needs procedural knowledge of navigation control while Scene 3 needs declarative knowledge from the evidence collected.

Affective concepts. In an emotional episode of gameplay, affective-related concepts related to this study have been identified and categorized according to Zhang's (2013) taxonomy of affective concepts, called affective response model (ARM). The categories were shown in Table 17. SciI can be classified as affectivity (category 2), FS as induced affective state (category 4), GQ and PE as process-based affective evaluation toward behaviors on a particular object (category 6.1), SL as outcome-based affective evaluation toward a particular object (category 5.2), and GEx as the learned affective evaluation/disposition toward behaviors on a type of objects (category 8). According to the definition of the affective responses dimension, the term "particular object" in this study is referred to Neuromatrix; whereas the term “type of objects” is referred to any SEGs or video games that students play in general.

Table 17

Taxonomy of Affective Concepts: Related to Game-based Learning

<table>
<tr><td colspan="2">Residing within a Person</td><td rowspan="2">Residing within a Stimulus</td><td colspan="5">Residing between a Person and a Stimulus (Affective Responses)</td></tr>
<tr><td>Temporally Constrained (State)</td><td>Temporally Unconstrained (Disposition)</td><td>Temporally Constrained (State)</td><td colspan="4">Temporally Unconstrained (Evaluation / Disposition)</td></tr>
<tr><td rowspan="4">(1) Free-floating Affective State</td><td rowspan="4">(2) Affectivity (e.g., Science Interest)</td><td rowspan="4">(3) Affective Characteristics</td><td rowspan="4">(4) Induced Affective State (e.g., Flow State)</td><td rowspan="2"></td><td colspan="2">Particular Stimulus</td><td rowspan="2">General Stimulus</td></tr>
<tr><td>Process-Based</td><td>Outcome-Based</td></tr>
<tr><td>Object Stimulus</td><td>(5.1) Process-Based Affective Evaluation Toward a Particular Object</td><td>(5.2) Outcome-Based Affective Evaluation Toward a Particular Object (e.g., Perceived Science Learning)</td><td>(7) Learned Affective Evaluation/ Disposition Toward a Type of Objects</td></tr>
<tr><td>Behavior-Stimulus</td><td>(6.1) Process-Based Affective Evaluation Toward a Behaviors on a Particular Object (e.g., Perceived game quality & Perceived Enjoyment)</td><td>(6.2) Outcome-Based Affective Evaluation Toward a Behaviors on a Particular Object</td><td>(8) Learned Affective Evaluation/ Disposition Toward Behaviors on a Type of Objects (e.g., Perceived Game Experience)</td></tr>
</table>

Note. From “The Affective Response Model: A Theoretical Framework of Affective Concepts and their Relationships in the ICT Context” by P. Zhang, 2013, *MIS Quarterly,* *37*(1), p. 259. Copyright 2013 by Regents of the University of Minnesota. Used with permission.

Furthermore, the ARM (Zhang, 2013) theorizing the possible relationships of psychological processes that underline the formation and influence of various affective concepts during HCI. It is important to understand the affective concepts and the individual differences factors related to gameplay and game-based learning. Hence, the relationships between these affective concepts are illustrated in the ARM nomological net (Figure 14) and can be used to systematically explain the results. It is hypothesized that affective antecedent (e.g., affectivity or science interest in this case) may influence the affective responses (i.e., the induced affective states, particular affective evaluations, and learned affective evaluations/dispositions).

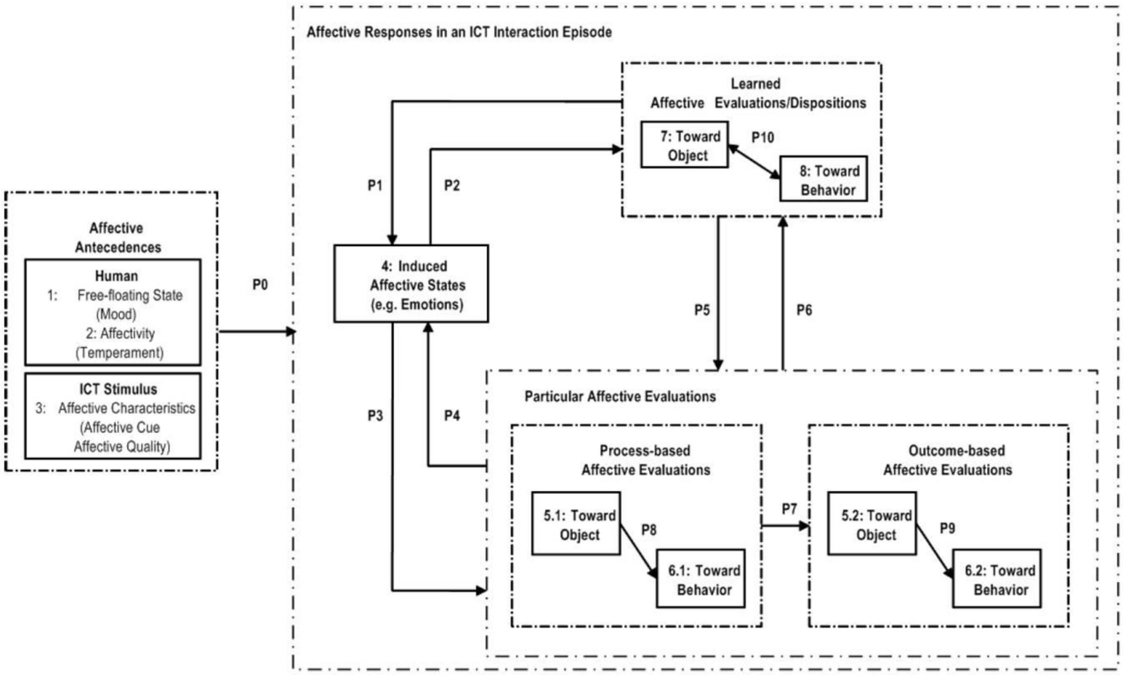


Figure 14 Nomological net for causal relationships.
Note. From "The Affective Response Model: A Theoretical Framework of Affective Concepts and their Relationships in the ICT Context" by P. Zhang, 2013, *MIS Quarterly, 37*(1), p. 263. Copyright 2013 by Regents of the University of Minnesota. Reprinted with permission.
P0 to P10 are the proposition of connecting different affective concepts.

Qualitative Scanpath Study

Scene selection. For the qualitative scanpath analysis, a subset of dynamic scenes (Scene 2) was selected. Three major reasons were identified for Scene 2 to be selected for the scanpath qualitative study. It is because (a) players who reached Scene 2 (i.e., completed level 1 in less than 10 minutes as the total play time was 15 minutes) demonstrated their gameplay skill and competency, such as smooth navigation in a 3-D environment, adjusting/adapting to the different game rules in each level promptly, and other gameplay techniques; (b) Scene 2 requires players to demonstrate good attentional control for effective selective attention, i.e., select target objects (AOIs) and ignore distracting objects in the game environment; and (c) the characteristic of Scene 2 is goal-directed free-exploration, where players have to explore the environment and figure out the game's rules through trial-and-error, then learn the implicit goal in order to complete the mission. So both bottom-up and top-down attentional processes are necessary to complete the scene. Students could visit either scientist's office to conduct investigation or visit both, or take the elevator back to first floor; and there was no time limit in this scene. It provides a rich background for this exploratory scanpath analysis.

Data visualization. Scene 2 segment for each participant was extracted using Tobii Studio. Individuals' gaze-overlaid video were exported and replayed from a video player. It allows researcher to play the gaze-overlaid video one frame at a time. The researcher then mapped a sequence diagram based on the individuals' gaze duration (dwell time or visit time) to visualize their visual attention order and possible cognitive strategies during gameplay. Scanpath visualization technique, *gaze duration sequence diagram* proposed by Raschke, Chen, and Ertl (2012) was used to map the gaze duration of AOIs and non-AOIs. Gaze duration was measured in the unit of second and coded manually into respective AOIs, non-AOIs, or just walking in the 3-D game environment. There were some cases that no gaze information was observed. It was then classified as "no record." A sample of gaze duration sequence diagram was shown in Figure 9. By referring to the Figure 15, the duration that lasted on the particular area was numbered inside color box. The number of shifting between non-AOI and AOI was calculated and recorded accordingly.

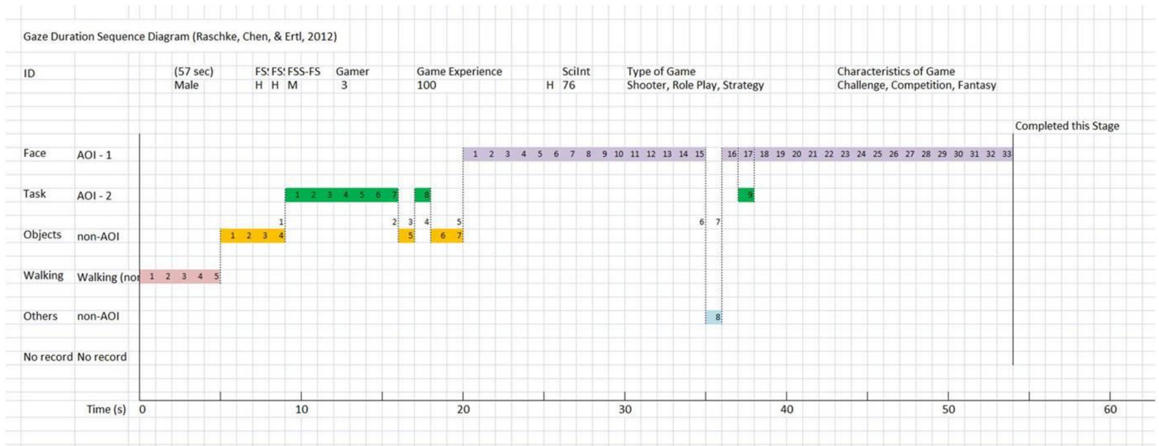


Figure 15 A sample of gaze duration sequence diagram for scanpath qualitative analysis.

Subsample. A total of 27 gaze duration sequence diagrams were mapped. Twenty-two individuals completed the mission in Scene 2, whereas five individuals had forced to stop playing the game when the 15-minutes play time was over.

Coding. After all individual's sequence diagram was mapped, the attentional control of selective attention patterns from each individual's sequence diagram was examined in detail. A descriptive coding method was used to form a categorized inventory, tabular account, and summary of the data's contents; then a process coding approach was employed to search for cognitive process, interaction, or emotion that embedded in the situations (Saldaña, 2013).

Three scanpath patterns were identified before the comparison analysis. They are: (a) mostly on tasks and/or interact with NPC (the AOIs of this game); (b) more on distractors (non-AOIs) and/or frequently shifting between tasks and distractors; and (c) spent significant amount of time walking in the game environment. By using a process coding approach, cognitive processes, attentional control, affective state, and possible emotional outcomes for the respective scanpath patterns were identified. A coding table was developed for qualitative scanpath analysis and summarized in Table 18.

Table 18

Coding for Three Scanpath Patterns

Descriptive Codes	Scanpath Patterns Identified		
	Mostly on tasks; and/or interact with NPC	More on distractors; and/or shifting between tasks and distractors	Spent significant amount of time walking in the game environment
Cognitive processes	• High perceptual load • Learn game rules fast • Clear goal • High perceptual fluency	• High perceptual load • High executive cognitive control • Vigilance • Perpetual scanning	• Low perceptual load • Goal is not clear
Attentional control	• Goal-directed • Top-down processes dominate • Maintain focus • Target processing	• Stimulus-driven • Bottom-up processes dominate • Cannot maintain focus • Distrator processing	• Involuntary "spill over" to perceiving distractor • Distractor processing
Affective state	• Medium arousal • Calm • Content • Happy • Excited	• High arousal • Alert • Nervous • Stressed • Tense	• Low arousal • Bored • Tired out • Upset
Possible outcomes	• Positive emotions • Complete scene fast	• Neutral or Negative emotions	• Negative emotions • Cannot complete scene

The circumplex model of affect (Russell, 1980) was used to describe the proposed affective states and outcomes that may be generated by the respective scanpath patterns. The circumplex model of affect suggests that all affective states arise from two fundamental neurophysiological systems, valence and arousal, and each emotion can be conceptualized as a linear combination of these two dimensions (Russell, 1980). Figure 16 showed the graphical representation of the circumplex model of affect with the respective emotional states.

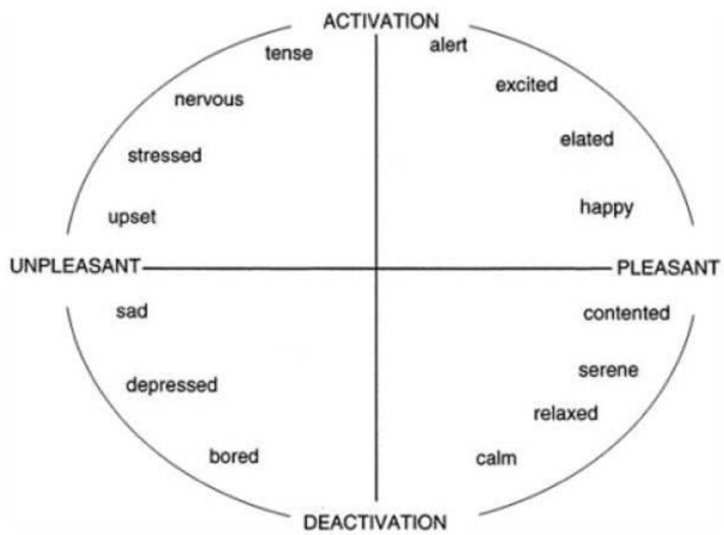


Figure 16 The circumplex model of affect**.**
The horizontal axis representing the valence dimension and the vertical axis representing the arousal dimension.
Note. From "The Circumplex Model of Affect: An Integrative Approach to Affective Neuroscience, Cognitive Development, and Psychopathology" by J. Posner, J. A. Russell, and B. S. Peterson (2005), *Development and Psychopathology*, *17*(5), p. 716. Copyright 2005 by Cambridge University Press. Reprint with permission.

Data Analysis

Descriptive statistics about the participant demographics and the mean scores of all the measures are reported. Homogeneity of sample was checked for robustness. Validity and reliability analysis were conducted for each instrument and reported earlier in the chapter. Statistical software packages, SPSS and Mplus, were employed in this study.

Effect of demographic characteristics on Flow and visual attention. Three-factor Analysis of Variance (3 x 2 x 2 ANOVA) was run testing the main effects and interaction of science grade, gender, and gamer status on Flow experience. This is an overview to understand the possible effects of participant characteristics on Flow, only composite scores of each Flow scale were reported, i.e., the FSS-sum and eGF-sum scores. Another three-factor (3 x 2 x 2) ANOVA was run testing the main effects and interaction of science grade, gender, and gamer status on eye tracking data (Total visit duration and Visit duration on AOIs). The eye tracking data is comprised with students who are successfully completed only Scene 1 or both Scenes 1 and 2, so repeated measurements for some of the participants were resulted (n = 45).

Research Question One. ***What are the associations between visual attention and Flow experience during gameplay?***

To answer the research question one, both quantitative and qualitative methods were used. Simple linear regression was run testing the relationships between variables of visual attention and Flow. Scenes 1 and 2 were selected for analysis. Independent variables in this analysis are the two Flow scales (FSS-2 and eGF; and their subsequent Sum scores, GQ scores, and FS scores). The dependent variables are the visual attention variables. The dependent variables include: Fixation duration on AOIs, total fixation duration, fixation count on AOIs, total fixation count, visit duration on AOIs, total visit duration, visit count on AOIs, and total visit count. The data were analyzed separately using SPSS. Pearson correlation coefficient, *F*-test results and their p-value, as well as the coefficient of determination (R^2) had been reported in the results chapter.

Multiple regression was employed to analyze the relationships of the two predictors (GQ and FS) of the two Flow scales on a set of dependent variables representing visual attention. F-test results, R^2, and part correlations are reported in the results chapter.

For the qualitative scanpath analysis, the aim is to apply the coding table (see Table 18) for each scanpath patterns to compare and contrast the gaze duration sequence diagrams and find possible connections with individuals' Flow experience (FSS-Sum; High, Medium or Low).

The qualitative data analysis consists of five steps. First step, the raw data of Scene 2 from the gaze duration sequence diagram was organized into a data table (excel spreadsheet). Two sets of data were entered into the table: (a) the descriptive data, such as gender, FSS-2 scores (High, Medium, or Low), GEx, SciI, time used to finished Scene 2, and their top three preferences of game genres; and (b) the visual attention data during gameplay, such as fixation duration on tasks/interact with NPC (AOIs), encountering non-AOIs, or just walking around the 3-D game environment. Second step, the raw data are transformed into meaningful measurement values. New variables were created, for example, More1 = (Non-AOI – AOI-Task) was computed, in which positive means longer duration on non-AOIs during gameplay. Means and standard deviations were calculated. Values that are one standard deviation either side of the mean (± 1 SD) were computed for each variable, which were used to inform decisions to categorize the observed values as High, Medium, and Low.

Third, after all observed values were transformed into categories, a particular variable was selected one at a time for pattern recognition. For instance, “Walking” was selected as a pattern recognition variable. High, low, and medium were sorted accordingly. When patterns were observed within and/or between other variables, they were recorded accordingly. A strong or significant pattern observed was highlighted. Forth, a cross-tabulated pattern table was created to show all patterns according to predictors (or variables that were manipulated for pattern recognition) and observed variables. Any predictors or observed variables with more than three significant patterns observed were highlighted for analysis.

Finally, all the significant scanpath patterns and other subsidiary patterns were used to compare with the preassigned coding system that was developed for the qualitative study (Table 18). Interpretation was made based on the analytical understandings of the respective pattern observed.

Research Question Two. ***What are the associations between visual attention, Flow experience, and their outcomes (perceived science learning and perceived enjoyment) through playing an SEG?***

Two-factor Analysis of Variance (3 x 3 ANOVA) was employed to examine the factors of Flow (high/medium/low) and a visual attention (high/medium/low) on the two outcome variables: SL and PE. Two Flow scales (FSS-2 and eGF) and their subsequent scores (Sum, GQ, and FS) were analyzed separately. The four visual attention variables are: fixation duration on AOI, total fixation duration, visit duration on AOI, and total visit duration. Possible main effects and interactions may be detected. The data were comprised with students who successfully completed only Scene 1 or both Scenes 1 and 2, so repeated measurements for some of the participants were obtained (n = 47).

To test on the individual relationships of Flow scales on the outcome variables, simple liner regression was run. Multiple regression was computed to test the relationship of the two predictors (GQ and FS from the two Flow scales) on outcome variables. Pearson correlation coefficient, F-test statistics, coefficient of determination (R^2), and part correlation are reported in the results chapter.

A list of predictors from visual attention variables from the combined data of Scene 1 and Scene 2 was computed for testing the relationships with the criterion variable of perceived science learning separately using simple linear regression analysis (n = 47). They are: Fixation duration on AOIs, total fixation duration, fixation count on AOIs, total fixation count, visit duration on AOIs, total visit duration, visit count on AOIs, and total visit count. Simple liner regression was run to test the relationships of the eye tracking data on the outcome variables. Pearson correlation coefficient, F-test statistics, and coefficient of determination (R^2) are reported in the results chapter.

Research Question Three. ***What individual differences factors related to students' Flow experience and visual attention in an SEG environment?***

Individual differences factors that revealed significant and meaningful correlations with Flow (criterion variables) were entered into stepwise multiple regression models. A set of possible predictor variables of individual traits (science interest, game experience, self-efficacy of science and technology, and absorption trait) was entered in a stepwise fashion to detect the strongest predictor of Flow model.

Stepwise multiple regression analysis was employed in this study because it has the advantage of allowing for the examination of how strongly each predictor variable contributed to the regression model. This approach allows researchers to include potentially useful predictors and then delete those that are not making significant partial contributions at a predetermined α-level. A finalized model will be useful for theoretical purposes as well as obtaining good predictive power (Agresti & Finley, 2009).

To further investigate a specific individual differences factor on visual attention and Flow experience, simple linear regression analysis had been employed. A list of variables of visual attention from the combined data of Scenes 1 and 2 was entered for testing the relationships with the predictor of SciI using simple linear regression analysis (n = 45). They are: Fixation duration on AOIs, total fixation duration, fixation count on AOIs, total fixation count, visit duration on AOIs, total visit duration, visit count on AOIs, and total visit count. Whereas two Flow scales (FSS-2 and eGF) and their subsequent scores (Sum, GQ and FS) were entered separately for testing the relationships with the predictor of SciI (n = 25).

CHAPTER FOUR: RESULTS

The primary goal of this study is to offer a cognitive-affective integrated model that (a) offers insight about the interplay between learners' positive subjective experience and cognitive processes in gameplay through a science SEG using an eye tracking analysis, and (b) provides an empirical examination of these proposed relationships. Specifically, to investigate the relationship between visual attention (gaze duration and scanpaths) and Flow experience while playing an SEG by, their outcomes of perceived science learning and perceived enjoyment, as well as to examine the influence of individual difference factors (science interest and perceived game experience) on visual attention and Flow.

This chapter was organized into two parts. The first part presents the impact of participants' demographic characteristics on Flow and visual attention. The second part focuses on the quantitative and qualitative results by each research question. Furthermore, two Flow surveys (eGF and FSS-2) were used in the study; the results of each Flow survey will be reported separately. Due to the small sample size, instead of treating Flow as nine dimensions, two conceptualizations of Flow were proposed: a unidimensional model of Flow as a global construct (composite or sum score) and a multidimensional model of Flow as two-latent constructs (item parceled into GQ and FS). Therefore, the results of the composite score of Flow survey (i.e., *FSS-Sum* and *eGF-*

*Su*m) and the results of Flow as two-latent constructs (i.e., *FSS-Q*, *FSS-FS*, *eGF-GQ*, and *eGF-FS*) will be reported separately.

Effects of Participant Characteristics on Flow

A three-factor (3 x 2 x 2) ANOVA was run testing the main effects and interaction of science grade, gender, and gamer status on Flow experience. The frequency count of the three factors on each Flow score was shown in Table 19. The means and standard deviations for Flow score by science grade, gender, and gamer status were summarized in Tables 20 and 21.

Table 19

Frequency Count for Flow Scores by Science Grade, Gender, and Gamer Status

		FSS-Sum (n = 29)	eGF-Sum (n = 27)
Science Grade	A	9	9
	B	16	14
	C or below	4	4
Gender	Male	22	21
	Female	7	6
Gamer	Frequent	19	18
	Moderate	10	9

Table 20

Means and Standard Deviations for FSS-Sum Score by Science Grade, Gender, and Gamer Status (n = 29)

SciGrade	Gender	Gamer	*M*	*SD*	*N*
C or below	Female	Frequent	116.00	.	1
	Male	Frequent	140.67	5.132	3
B	Female	Moderate	142.50	2.121	2
		Frequent	155.00	17.521	3
	Male	Moderate	152.75	20.759	4
		Frequent	138.00	7.257	7
A	Female	Moderate	145.00	-	1
	Male	Moderate	114.33	10.504	3
		Frequent	146.60	6.950	5
Total	Female	Moderate	143.33	2.082	3
		Frequent	145.25	24.185	4
	Male	Moderate	136.29	25.960	7
		Frequent	141.40	7.462	15

Table 21

Means and Standard Deviations for eGF-Sum Score by Science Grade, Gender, and Gamer Status (n = 27)

SciGrade	Gender	Gamer	*M*	*SD*	*N*
C or below	Female	Frequent	134.00	.	1
	Male	Frequent	164.67	18.230	3
B	Female	Moderate	165.00	.	1
		Frequent	169.00	8.000	3
	Male	Moderate	178.25	22.262	4
		Frequent	169.17	5.492	6
A	Female	Moderate	173.00	-	1
	Male	Moderate	138.33	11.015	3
		Frequent	161.20	9.418	5
Total	Female	Moderate	169.00	5.657	2
		Frequent	160.25	18.679	4
	Male	Moderate	161.14	27.267	7
		Frequent	165.36	10.172	14

FSS-2. The results from the test of between-subjects effects indicate that there is a statistically significant main effect of Science Grade, $F(2, 20) = 4.998$, $p < .05$, $p\eta^2 = .333$. There is also a statistically significant main effect of Gamer Status, $F(1, 20) = 7.086$, $p < .05$, $p\eta^2 = .262$. There was statistically significant of interactions between two factors but not for the three-factor interaction. The results of the three-factor ANOVA on

FSS-Sum scores, reported in Table 22, showed that there is a statistically significant interaction between Science Grade and Gender, $F(2, 20) = 6.545$, $p < .01$, $p\eta^2 = .184$; a statistically significant interaction between Science Grade and Gamer Status, $F(1, 20) = 17.720$, $p < .00$, $p\eta^2 = .471$; as well as a statistically significant interaction between Gender and Gamer status, $F(1, 20) = 4.496$, $p < .05$, $p\eta^2 = .396$. Figures 17, 18 and 19 showed the interactions between science grade and gender, between science grade and gamer status on FSS-Sum score, and interaction between gender and gamer status respectively.

By referring to the Cohen's guidelines for interpreting the magnitude of effect size: .01 = small, .06 = medium, and .14 = large (Cohen, 1988; Dimitrov, 2010), there are large effect sizes for science grade (η^2 =.14), the interaction between science grade and gender (η^2 =.18), and interaction between science grade and gamer status (η^2 =.24). There are medium effect sizes for gamer status (η^2 =.10), and interaction between gender and gamer status (η^2 =.06). However, there are no statistically significant results from the Tukey post-hoc test for Science Grade groups.

Table 22

Analysis of Variance for FSS-Sum

	df	*F*	$p\eta^2$	*p*
SciGrade	2	4.998	.333	.017
Gamer	1	7.086	.262	.015
SciGrade * Gender	2	6.545	.184	.007
SciGrade * Gamer	1	17.720	.470	.000
Gender * Gamer	1	4.496	.396	.047
S within group error	20	(134.69)		

Note. The value enclosed in parentheses is the mean square error (MS_W). S = subjects.

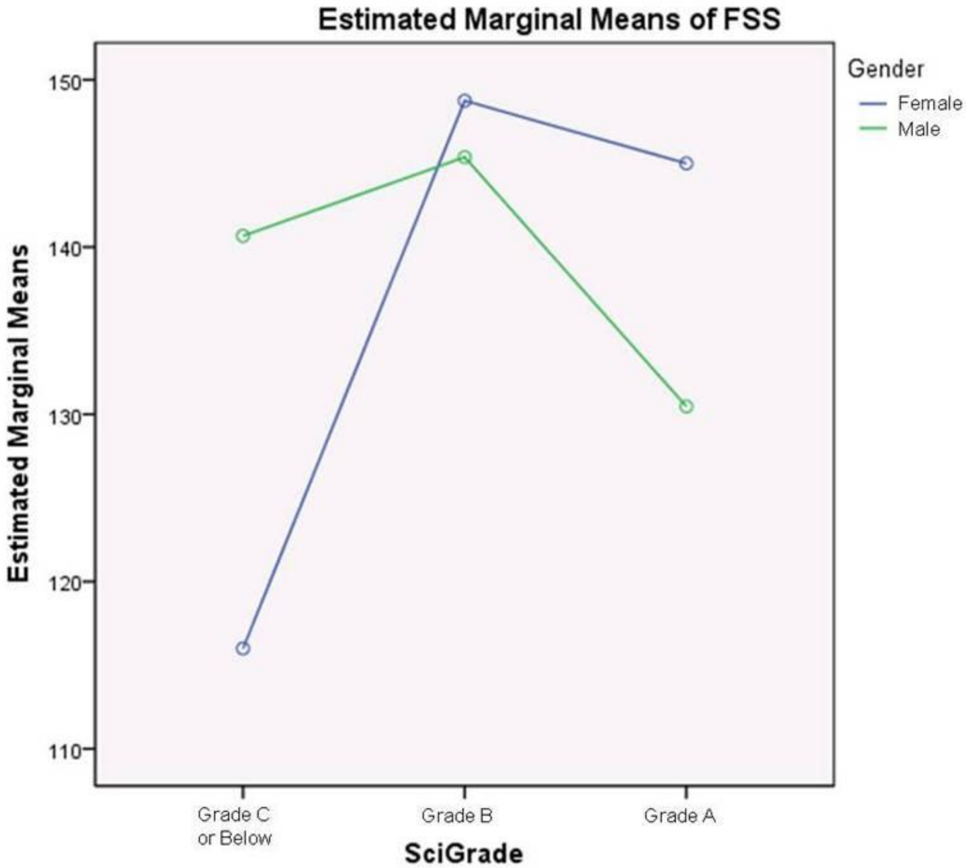


Figure 17 Interaction between science grade and gender on FSS-Sum score.

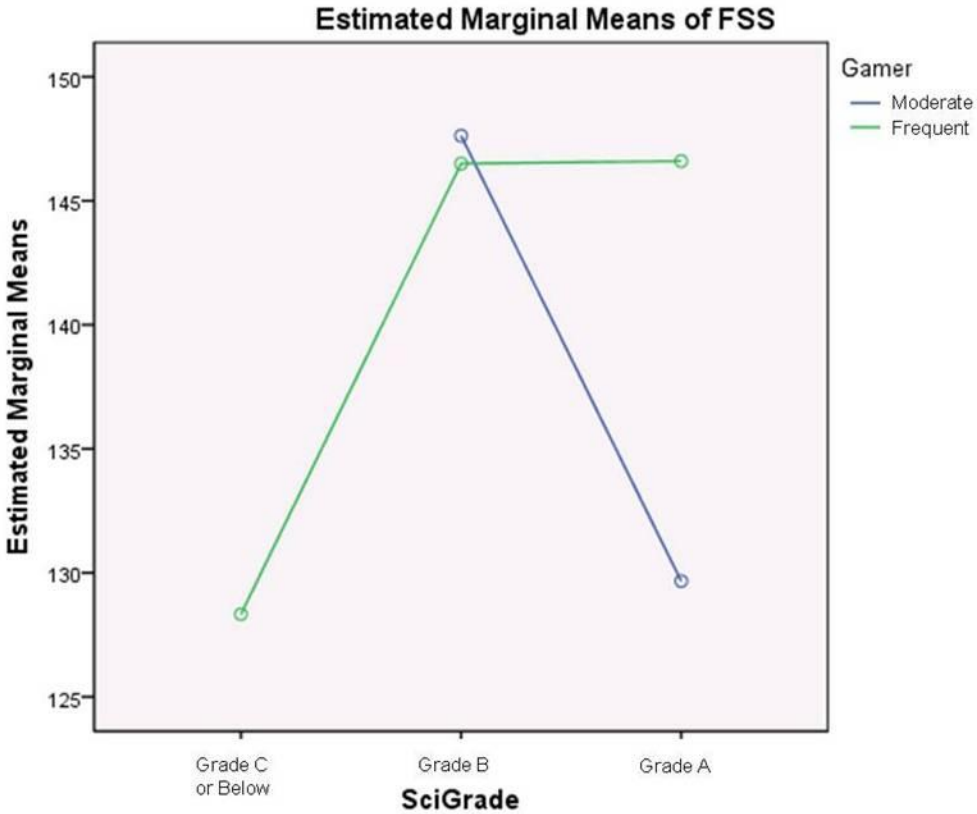


Figure 18 Interaction between science grade and gamer status on FSS-Sum score.

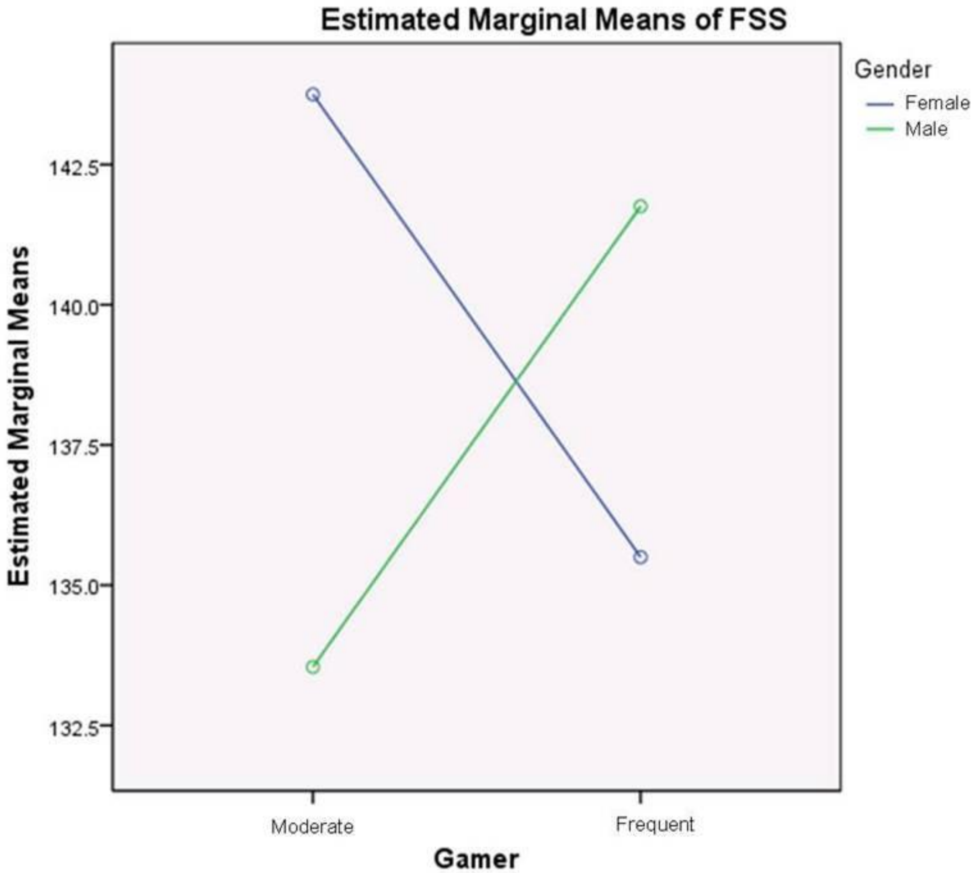


Figure 19 Interaction between gamer status and gender on FSS-Sum score.

eGF. The results of the three-factor ANOVA on eGF-Sum scores are shown as Table 23. The results from the test of between-subjects effects indicate that there is a statistically significant interaction between Science Grade and Gender, $F(2, 18) = 4.150$, $p < .05$, $p\eta^2 = .316$; a statistically significant interaction between Science Grade and Gamer, $F(1, 18) = 6.388$, $p < .05$, $p\eta^2 = .262$; as well as a statistically significant main effect of Science Grade, $F(2, 18) = 3.723$, $p < .05$, $p\eta^2 = .293$. Figures 20, 21, and 22 showed the interactions between science grade and gender, between science grade and gamer status on eGF-Sum score, and interaction between gender and gamer status respectively.

By referring to the Cohen's guidelines for interpreting the magnitude of effect size: .01 = small, .06 = medium, and .14 = large (Cohen, 1988; Dimitrov, 2010), there are large effect sizes for science grade (η^2 =.18), the interaction between science grade and gender (η^2 =.20), and interaction between science grade and gamer status (η^2 =.15). The large effect size is associated with the effect of science grade (.18), which indicates 18 percent of the differences in eGF-Sum scores are accounted for by Flow score differences among the three science grade groups. The results from the Tukey post-hoc test for Science Grade, reported in Table 24, show that students with B Science Grade have experienced more Flow than students with A Science Grade ($p < .05$) by a difference that varies between 2.40 and 30.68 units on the eGF-Sum scores, but there were no other differences among the other science grade groups.

Table 23

Analysis of Variance for eGF-Sum

	df	*F*	$p\eta^2$	*p*
SciGrade	2	3.723	.293	.044
SciGrade * Gender	2	4.150	.316	.033
SciGrade * Gamer	1	6.388	.262	.021
S within group error	18	(168.21)		

Note. The value enclosed in parentheses is the mean square error (MS_W). S = subjects.

Table 24

Multiple Comparisons for eGF-Sum Score among Science Grade Groups

SciGrade Groups	ΔM	SEΔM	95% CI for ΔM	
C or below - B	-14.43	7.353	-33.19	4.34
C or below - A	2.11	7.794	-17.78	22.00
B – A	16.54 *	5.541	2.40	30.68

Note. ΔM = Mean difference. SEΔM = Standard error of ΔM.
* $p < .05$.

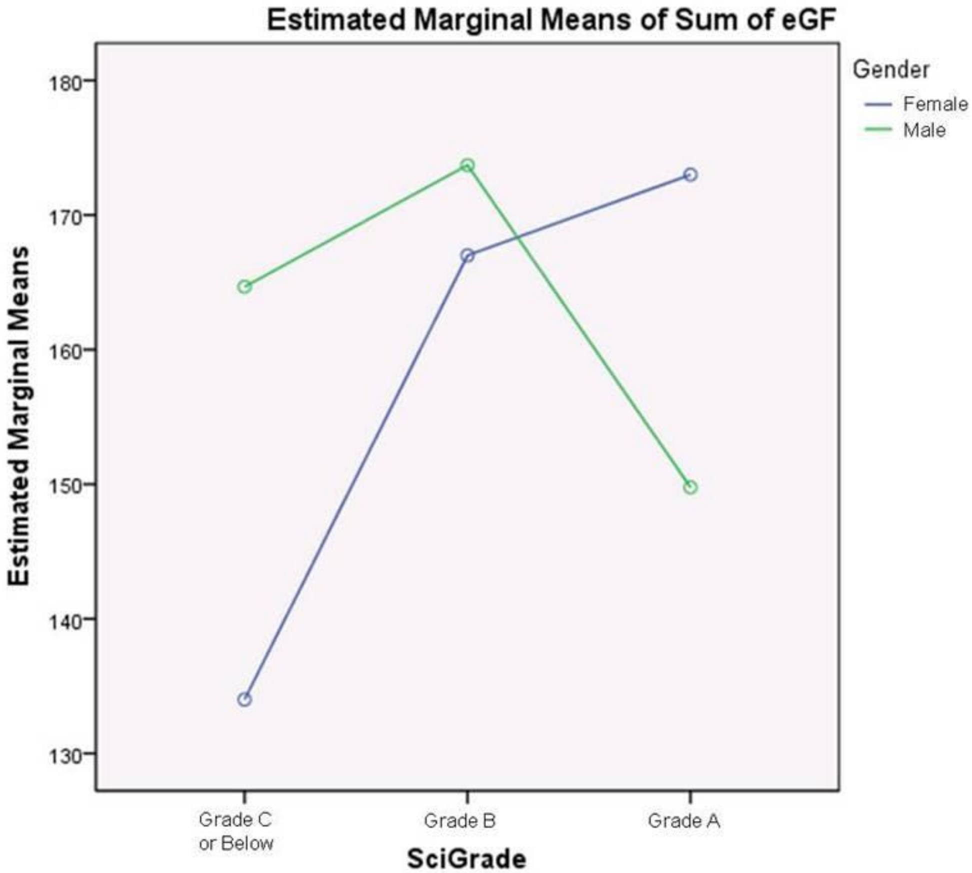


Figure 20 Interaction between science grade and gender on eGF-Sum score.

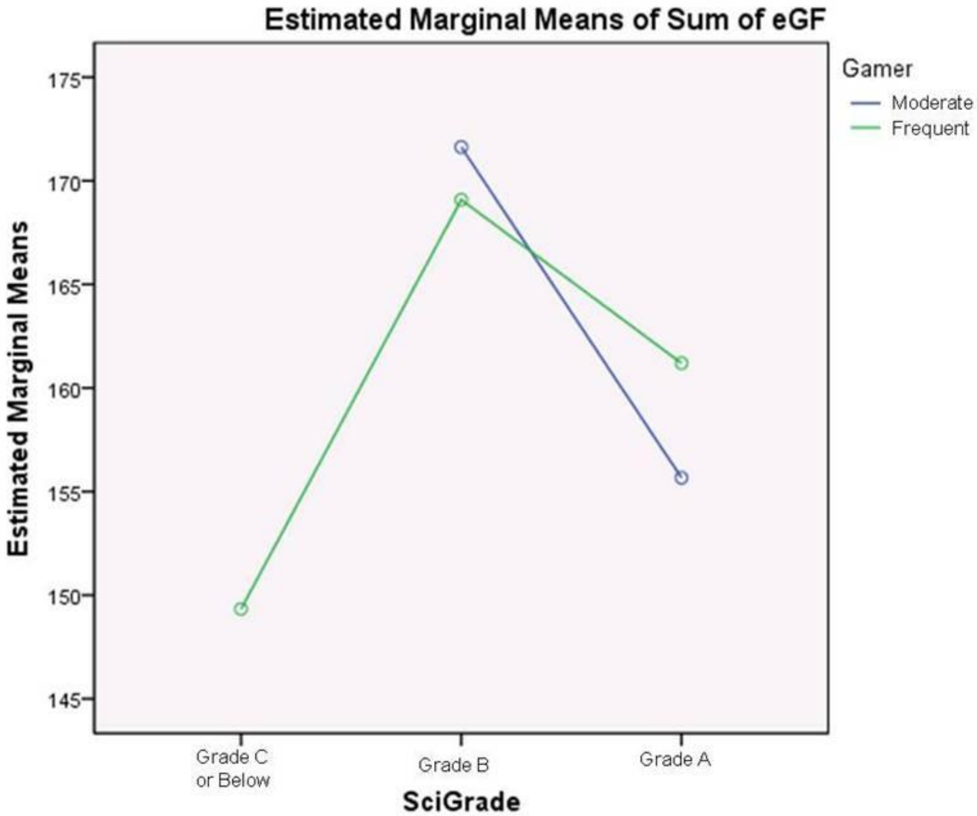


Figure 21 Interaction between science grade and gamer status on eGF-Sum score.

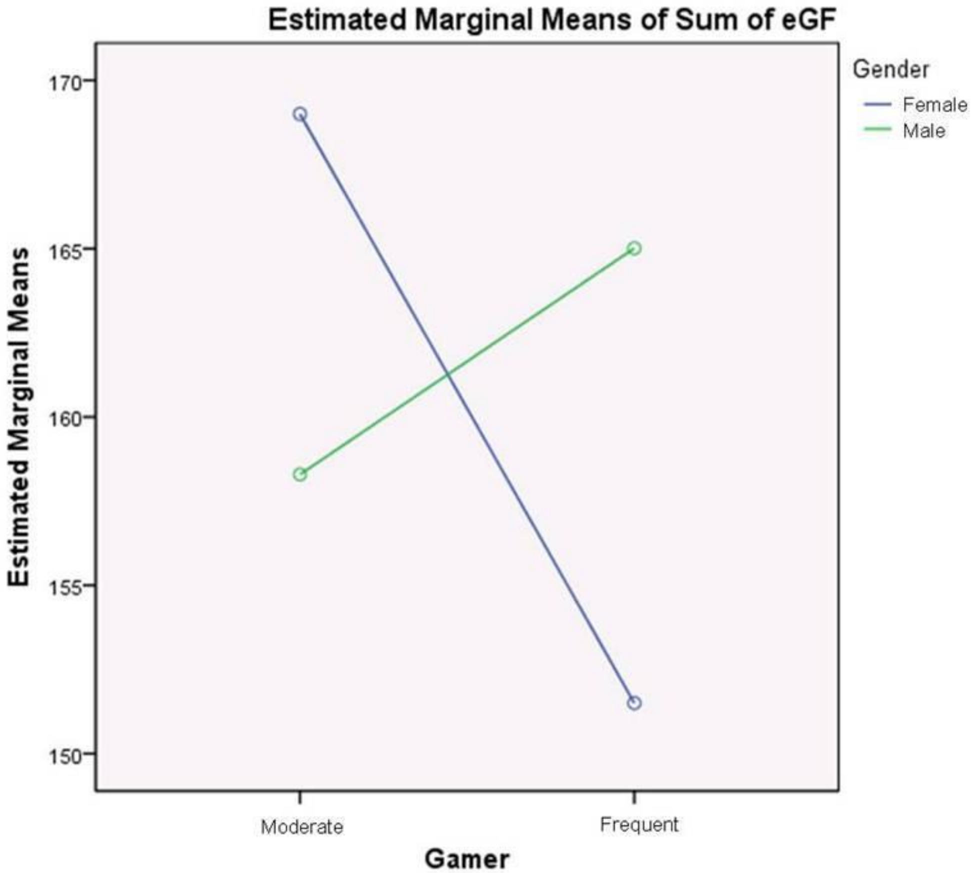


Figure 22 Interaction between gamer status and gender on eGF-Sum score.

Effects of Participant Characteristics on Visit Duration

A three-factor (3 x 2 x 2) ANOVA was run testing the main effects and interaction of science grade, gender, and gamer status on total visit duration and visit duration on AOIs (n = 45). However, there are no statistical significant effects on visit duration on AOIs. Only results from total visit duration are reported. The frequency count of the three factors on visit duration was shown in Table 25. The means and standard deviations for total visit duration by science grade, gender, and gamer status were summarized in Tables 26.

Table 25

Frequency Count for Total Visit Duration by Science Grade, Gender, and Gamer Status

		N
SciGrade	A	15
	B	22
	C	6
	D	2
Gender	Male	38
	Female	7
Gamer	Frequent	34
	Moderate	11

Table 26

Means and Standard Deviations for Total Visit Duration by Science Grade, Gender, and Gamer Status

SciGrade	Gender	Gamer	*M*	*SD*	*N*
D	Male	Frequent	651.54	13.173	2
C	Female	Frequent	940.76	0.940	2
	Male	Frequent	948.45	51.019	4
B	Female	Frequent	804.22	160.093	5
	Male	Moderate	658.81	90.169	6
		Frequent	765.96	170.656	11
A	Male	Moderate	934.83	90.502	5
		Frequent	810.33	115.673	10
Total	Female	Frequent	843.23	146.715	7
	Male	Moderate	784.27	167.688	11
		Frequent	800.95	147.501	27

The results of the three-factor ANOVA on total visit (or gaze) duration scores are shown as Table 27. The results from the test of between-subjects effects indicate that there is a statistically significant interaction between Science Grade and Gamer Status, $F(1, 37) = 5.979$, $p < .05$, $p\eta^2 = .139$, and a statistically significant main effect of Science Grade, $F(3, 37) = 5.819$, $p < .01$, $p\eta^2 = .321$. Figure 23 showed the interaction between science grade and gamer status. There are large effect sizes for science grade ($\eta^2 = .29$)

and interaction between science grade and gamer status (η^2 =.10). The large effect size is associated with the effect of science grade (.29), which indicates 29 percent of the differences in total visit duration are accounted for by duration differences among the three science grade groups. The results from the Tukey post-hoc test for Science Grade, reported in Table 28, showed that students with science grade C spent longer total visit time than students with grade D (p < .05) and students with grade B (p < .01), by a difference that varies between 15.72 and 572.99 units and between 43.28 and 357.63 units respectively. There were no other differences among the other science grade groups.

Table 27

Analysis of Variance for Total Visit Duration

	df	*F*	$p\eta^2$	*p*-
SciGrade	3	5.819	.321	.002
SciGrade * Gamer	1	5.979	.139	.019
S within group error	37	(16096.641)		

Note. The value enclosed in parentheses is the mean square error (MS_W). S = subjects.

Table 28

Multiple Comparisons for Total Visit Duration among Science Grade Groups

SciGrade Groups	ΔM	SEΔM	95% CI for ΔM	
D – B	-93.90	93.702	-345.93	158.14
D – A	-200.29	95.506	-457.18	56.60
C – D	294.35 *	103.591	15.72	572.99
C – B	200.45 **	58.433	43.28	357.63
C – A	94.06	61.285	-70.78	258.90

Note. Δ*M* = Mean difference. SEΔ*M* = Standard error of Δ*M*.
* $p < .05$. ** $p < .01$.

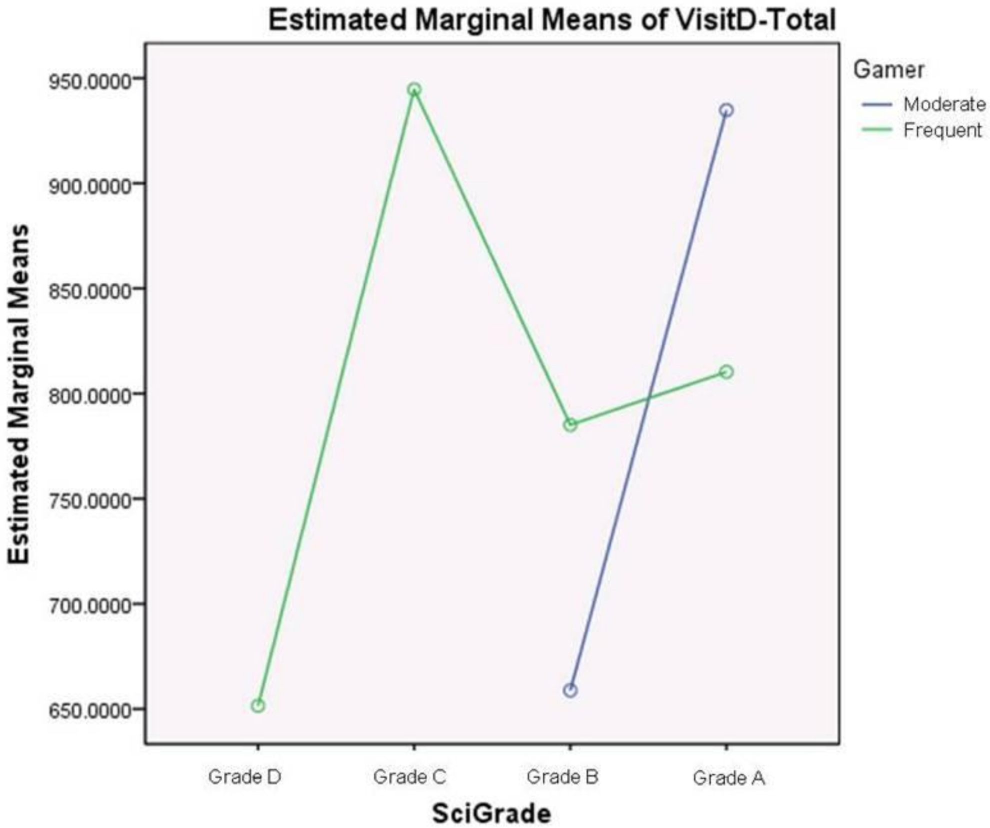


Figure 23 Interaction between science grade and gamer status on total visit duration.

Research Question (RQ) 1. What are the Associations Between Visual Attention and Flow Experience During Gameplay?

RQ 1a. Are there any relationships between the number/duration of fixations and gaze on the Areas of Interest (AOIs) and Flow experience while playing a Serious Educational Game (SEG)?

Simple linear regression was run testing the relationships between variables of visual attention and Flow. Two scenes, Scene 1 – docking and Scene 2 – scientist investigation, were selected for analysis. Results from the combined data from the two scenes are reported.

The means and standard deviations for the independent variables of two Flow scales (FSS-2 and eGF Scale) and the list of visual attention dependent variables (fixation duration on AOIs, total fixation duration, fixation count on AOIs, total fixation count, visit duration on AOIs, total visit duration, visit count on AOIs, and total visit count) are reported in Table 29.

Table 29

Means and Standard Deviations for FSS-2, eGF, and Visual Attention Variables (n = 47)

Variables	Mean	STD
Predictor variables		
FSS-Sum	140.13	15.245
FSS-GQ	47.51	4.736
FSS-FS	92.62	11.818
eGF-Sum	161.81	16.240
eGF-GQ	73.28	7.362
eGF-FS	88.53	12.188
Criterion variables		
Fixation Duration-AOI (second)	50.736	32.224
Fixation Duration-Total (second)	573.083	216.226
Fixation Count-AOI	149.98	98.828
Fixation Count-Total	1795.06	614.106
Visit Duration-AOI (second)	59.764	34.701
Visit Duration-Total (second)	806.401	147.503
Visit Count-AOI	54.49	35.524
Visit Count-Total	115.91	64.015

FSS-2 and fixation duration on AOIs. Predictors of FSS-2 was computed separately for testing the relationships with the criterion variable of fixation duration-AOI using simple linear regression analysis (FSS-Sum, FSS-GQ, and FSS-FS) and multiple regression for FSS-GQ and FSS-FS (n = 47).

The Pearson correlation coefficient between the predictor variable (X, FSS-Sum) and criterion variable (Y, Fixation Duration-AOI) is r = -.350, and is statistically significant at the .01 level, F (1, 45) = 6.276, p = .016. There is a negative linear relationship between FSS-Sum scores and fixation duration on AOIs, which means students with higher overall Flow experience have shorter fixation duration on AOIs during gameplay. The coefficient of determination, R^2 = .122, thus indicating that 12.2 percent of the variance in the fixation duration on AOIs is accounted for by the variance in the FSS-Sum. The simple linear regression equation for the prediction of fixation duration on AOIs (Y) from FSS-Sum (X) is: $\hat{Y}$ = (-0.739) X + 154.359. Table 30 summarizes the findings.

The Pearson correlation coefficient between the predictor variable (X, FSS-GQ) and criterion variable (Y, Fixation Duration-AOI) is r = -.353, and is statistically significant at the .01 level, F (1, 45) = 6.411, p = .015. There is a negative linear relationship, which means students with higher perceived game quality have shorter fixation duration on AOIs during gameplay. The coefficient of determination, R^2 = .125, thus indicating that 12.5 percent of the variance in the fixation duration on AOIs is accounted for by the variance in the FSS-GQ. The simple linear regression equation for the prediction of fixation duration on AOIs (Y) from FSS-GQ (X) is: $\hat{Y}$ = (-2.403) X + 164.888.

The Pearson correlation coefficient between the predictor variable (X, FSS-FS) and criterion variable (Y, Fixation Duration-AOI) is r = -.310, and is statistically significant at the .05 level, F (1, 45) = 4.777, p = .034. There is a negative linear relationship, which means students with higher Flow state have shorter fixation duration on AOIs during gameplay. The coefficient of determination, R^2 = .096, thus indicating that 9.6 percent of the variance in the fixation duration on AOIs is accounted for by the variance in the FSS-FS. The simple linear regression equation for the prediction of fixation duration on AOIs (Y) from FSS-FS (X) is: $\hat{Y}$ = (-0.845) X + 128.967.

Multiple regression was computed to test the relationship of the two predictors (FSS-GQ and FSS-FS) on fixation duration on AOIs. The two predictors account for a statistically significant proportion of the variance in the dependent variable, F(2, 44) = 3.507, p = .039. Specifically, R^2 = .137 indicates that 13.7 percent of the fixation duration on AOIs differences are accounted for by differences in FSS-GQ (X_1) and FSS-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)}$ = -.204. Thus, $(-.204)^2$ = .0416, shows that 4.16 percent of the variance of the variance of fixation duration on AOIs is uniquely accounted for by the variance of FSS-GQ. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{Y(2.1)}$ = -.133. Thus, $(-.133)^2$ = .0177 shows that 1.77 percent of the variance in fixation duration on AOIs is uniquely accounted for by the variance in FSS-FS.

Further, the regression coefficients are not statistically significant for neither FSS-GQ (p = .153) nor FSS-FS (p = .424). The multiple regression equation for predicting the dependent variable, Y (fixation duration-AOIs) from X_1 (FSS-GQ) and X_2 (FSS-FS) is: $\hat{Y}$ = (-1.782) X_1 + (-0.396) X_2 + 172.079. Table 32 summarizes the findings.

eGF and fixation duration on AOIs. Predictors of eGF was computed separately for testing the relationships with the criterion variable of fixation duration-AOI using simple linear regression analysis (eGF-Sum, eGF-GQ, and eGF-FS) and multiple regression for eGF-GQ and eGF-FS (n = 47). Tables 31 and 33 summarize the results.

Only eGF-GQ has the statistically significant relationship with Fixation duration on AOIs. There are no statistically significant relationships of eGF-Sum, eGF-FS, or the joint predictors of eGF-GQ and eGF-FS with fixation duration on AOIs.

The Pearson correlation coefficient between the predictor variable (X, eGF-GQ) and criterion variable (Y, Fixation Duration-AOI) is r = -.313, and is statistically significant at the .05 level, F (1, 45) = 4.900, p = .032. There is a negative linear relationship indicates that students with higher perceived game quality have shorter fixation duration on AOIs during gameplay. The coefficient of determination, R^2 = .098, thus indicating that 9.8 percent of the variance in the fixation duration on AOIs is accounted for by the variance in the eGF-GQ. The simple linear regression equation for the prediction of fixation duration on AOIs (Y) from eGF-GQ (X) is: $\hat{Y}$ = (-1.372) X + 151.237.

Table 30

Summary of Regression Analysis for FSS-2 Predicting Visual Attention Variables (n = 47)

Criterion Variables	FSS-Sum				FSS-Game Quality				FSS-Flow State			
	B	SE B	β	R^2	*B*	SE B	β	R^2	*B*	SE B	β	R^2
Fixation Duration-AOI	-0.739	0.295	-.350 *	.122 *	-2.403	0.949	-.353 *	.125 *	-0.845	0.386	-.310 *	.096 *
Fixation Duration-Total	-6.267	1.897	-.442 **	.195 **	-21.271	6.022	-.466 ***	.217 ***	-7.012	2.519	-.383 **	.147 **
Fixation Count-AOI	-2.168	0.911	-.335 *	.112 *	-6.783	2.942	-.325 *	.106 *	-2.519	1.189	-.301 *	.091 *
Fixation Count-Total	-19.750	5.234	-.490 ***	.240 ***	-73.955	15.878	-.570 ***	.325 ***	-20.988	7.086	-.404 **	.163 **
Visit Duration-AOI	-0.814	0.317	-.358 *	.128 *	-2.480	1.028	-.338 *	.115 *	-0.956	0.414	-.326 *	.106 *
Visit Duration-Total	-5.335	1.203	-.551 ***	.304 ***	-16.650	3.924	-.535 ***	.286 ***	-6.203	1.614	-.497 ***	.247 ***
Visit Count-AOI	-0.697	0.331	-.299 *	.090 *	-2.265	1.066	-.302 *	.091 *	-0.797	0.432	-.265	.070
Visit Count-Total	-1.462	0.587	-.348 *	.121 *	-5.495	1.841	-.406 **	.165 **	-1.550	0.774	.286	.082

*p < .05. **p < .01. ***p < .001.

Table 31

Summary of Regression Analysis for eGF Predicting Visual Attention Variables (n = 47)

Criterion Variables	eGF-Sum				eGF-Game Quality				eGF-Flow State			
	B	SE B	β	R^2	*B*	SE B	β	R^2	*B*	SE B	β	R^2
Fixation Duration-AOI	-0.426	0.289	-.215	.046	-1.372	0.620	-.313 *	.098 *	-0.256	0.392	-.097	.009
Fixation Duration-Total	-5.746	1.790	-.432 **	.186 **	-15.089	3.756	-.514 ***	.264 ***	-4.695	2.550	-.265	.070
Fixation Count-AOI	-1.589	0.876	-.261	.068	-3.555	1.930	-.265	.070	-1.523	1.187	-.188	.035
Fixation Count-Total	-18.594	4.909	-.492 ***	.242 ***	-49.955	9.958	-.599 ***	.359 ***	-14.781	7.180	-.293 *	.086 *
Visit Duration-AOI	-0.503	0.310	-.235	.055	-1.367	0.672	-.290 *	.084 *	-0.395	0.420	-.139	.019
Visit Duration-Total	-5.741	1.049	-.632 ***	.400 ***	-11.162	2.480	-.557 ***	.310 ***	-6.119	1.556	-.506 ***	.256 ***
Visit Count-AOI	-0.492	0.318	-.225	.051	-1.329	0.691	-.275	.076	-0.389	0.431	-.133	.018
Visit Count-Total	-0.921	0.571	-.234	.055	-2.804	1.227	-.323 *	.104 *	-0.611	0.778	-.116	.014

$*p < .05$. $**p < .01$. $***p < .001$.

Table 32

Summary of Multiple Regression Analysis for FSS-2 Predicting Visual Attention Variables (n = 47)

Variables	Variables	*B*	SE B	β	Part	R^2
Fixation Duration-AOI	FSS-Game Quality	-1.782	1.224	-.262	-.204	.137 *
	FSS-Flow State	-0.396	0.491	-.145	-.113	
Fixation Duration-Total	FSS-Game Quality	-16.979	7.759	-.372	-.289	.231 **
	FSS-Flow State	-2.739	3.109	-.150	-.116	
Fixation Count-AOI	FSS-Game Quality	-4.682	3.790	-.224	-.175	.121
	FSS-Flow State	-1.340	1.519	-.160	-.125	
Fixation Count-Total	FSS-Game Quality	-67.810	20.583	-.523 **	-.407	.329 ***
	FSS-Flow State	-3.920	8.248	-.075	-.059	
Visit Duration-AOI	FSS-Game Quality	-1.620	1.320	-.221	-.172	.136 *
	FSS-Flow State	-0.548	0.529	-.187	-.145	
Visit Duration-Total	FSS-Game Quality	-11.440	4.944	-.367 *	-.286	.329 ***
	FSS-Flow State	-3.324	1.981	-.266	-.207	
Visit Count-AOI	FSS-Game Quality	-1.678	1.378	-.224	-.174	.101
	FSS-Flow State	-0.374	0.552	-.124	-.097	
Visit Count-Total	FSS-Game Quality	-5.061	2.390	-.374 *	-.291	.167 *
	FSS-Flow State	-0.276	0.958	-.051	-.040	

*$p < .05$. **$p < .01$. ***$p < .001$.

Table 33

Summary of Multiple Regression Analysis for eGF Predicting Visual Attention Variables (n = 47)

Variables	Variables	*B*	SE B	β	Part	R^2
Fixation Duration-AOI	eGF-Game Quality	-1.388	0.666	-.317 *	-.298	.098
	eGF-Flow State	0.029	0.402	.011	.010	
Fixation Duration-Total	eGF-Game Quality	-14.072	4.013	-.479 ***	-.451	.273 ***
	eGF-Flow State	-1.808	2.424	-.102	-.096	
Fixation Count-AOI	eGF-Game Quality	-3.050	2.063	-.227	-.214	.081
	eGF-Flow State	-0.897	1.246	-.111	-.104	
Fixation Count-Total	eGF-Game Quality	-47.074	10.630	-.564 ***	-.531	.368 ***
	eGF-Flow State	-5.123	6.421	-.102	-.096	
Visit Duration-AOI	eGF-Game Quality	-1.294	0.722	-.275	-.258	.086
	eGF-Flow State	-0.129	0.436	-.045	-.043	
Visit Duration-Total	eGF-Game Quality	-8.728	2.438	-.436 ***	-.410	.424 ***
	eGF-Flow State	-4.328	1.473	-.358 **	-.336	
Visit Count-AOI	eGF-Game Quality	-1.255	0.743	-.260	-.245	.078
	eGF-Flow State	-0.131	0.449	-.045	-.042	
Visit Count-Total	eGF-Game Quality	-2.781	1.319	-.320 *	-.301	.104
	eGF-Flow State	-0.041	0.797	-.008	-.007	

*$p < .05$. **$p < .01$. ***$p < .001$.

FSS-2 and total fixation duration. The Pearson correlation coefficient between the predictor variable (*X*, FSS-Sum) and criterion variable (*Y*, Total Fixation Duration) is $r = -.442$, and is statistically significant at the .01 level, $F(1, 45) = 10.917$, $p = .002$. There is a negative linear relationship between FSS-Sum scores and total fixation duration, which means students with higher overall Flow experience have shorter total fixation duration during gameplay. The coefficient of determination, $R^2 = .195$, thus indicating that 19.5 percent of the variance in the total fixation duration is accounted for by the variance in the FSS-Sum. The simple linear regression equation for the prediction of total fixation duration (*Y*) from FSS-Sum (*X*) is: $\hat{Y} = (-6.267)\,X + 1451.241$. Table 30 summarizes the findings.

The Pearson correlation coefficient between the predictor variable (*X*, FSS-GQ) and criterion variable (*Y*, Total Fixation Duration) is $r = -.466$, and is statistically significant at the .001 level, $F(1, 45) = 12.476$, $p = .001$. There is a negative linear relationship means students with higher perceived game quality have shorter total fixation duration during gameplay. The coefficient of determination, $R^2 = .217$, thus indicating that 21.7 percent of the variance in the total fixation duration is accounted for by the variance in the FSS-GQ. The simple linear regression equation for the prediction of total fixation duration (*Y*) from FSS-GQ (*X*) is: $\hat{Y} = (-21.271)\,X + 1583.702$.

The Pearson correlation coefficient between the predictor variable (*X*, FSS-FS) and criterion variable (*Y*, Total Fixation Duration) is $r = -.383$, and is statistically significant at the .01 level, $F(1, 45) = 7.748$, $p = .008$. The negative linear relationship means that students with higher Flow state have shorter total fixation duration during gameplay. The coefficient of determination, $R^2 = .147$, thus indicating that 14.7 percent of the variance in the total fixation duration is accounted for by the variance in the FSS-FS. The simple linear regression equation for the prediction of total fixation duration (Y) from FSS-FS (X) is: $\hat{Y} = (-7.012)\ X + 1222.525$.

Multiple regression was computed to test the relationship of the two predictors (FSS-GQ and FSS-FS) on total fixation duration. The two predictors account for a statistically significant proportion of the variance in the dependent variable, $F(2, 44) = 6.595$, $p = .003$. Specifically, $R^2 = .231$ indicates that 23.1 percent of the total fixation duration differences are accounted for by differences in FSS-GQ (X_1) and FSS-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{\mathrm{Y}(1.2)} = -.289$. Thus, $(-.289)^2 = .0835$, shows that 8.35 percent of the variance in total fixation duration is uniquely accounted for by the variance of FSS-GQ. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{\mathrm{Y}(2.1)} = -.116$. Thus, $(-.116)^2 = .0135$ shows that 1.35 percent of the variance in total fixation duration is uniquely accounted for by the variance in FSS-FS.

Further, the regression coefficients of FSS-GQ is statistically significant for ($p = .034$) but not for FSS-FS ($p = .383$). The multiple regression equation for predicting the dependent variable, Y (total fixation duration) from X_1 (FSS-GQ) and X_2 (FSS-FS) is: $\hat{Y} = (-16.979)\ X_1 + (-2.739)\ X_2 + 1633.399$. Table 32 summarizes the findings.

eGF and total fixation duration. The Pearson correlation coefficient between the predictor variable (X, eGF-Sum) and criterion variable (Y, Total Fixation Duration) is $r = -.432$, and is statistically significant at the .01 level, $F\ (1, 45) = 10.300$, $p = .002$.

There is a negative linear relationship, which means students with higher overall Flow experience have shorter total fixation duration during gameplay. The coefficient of determination, $R^2 = .186$, thus indicating that 18.6 percent of the variance in the total fixation duration is accounted for by the variance in the eGF-Sum. The simple linear regression equation for the prediction of total fixation duration (Y) from eGF-Sum (X) is: $\hat{Y} = (-5.736)\ X + 1502.88$.

The Pearson correlation coefficient between the predictor variable (X, eGF-GQ) and criterion variable (Y, Total Fixation Duration) is $r = -.515$, and is statistically significant at the .001 level, $F\ (1, 45) = 16.138$, $p = .000$. The negative linear relationship means that students with higher perceived game quality have shorter total fixation duration during gameplay. The coefficient of determination, $R^2 = .264$, thus indicating that 26.4 percent of the variance in the total fixation duration is accounted for by the variance in the eGF-GQ. The simple linear regression equation for the prediction of total fixation duration (Y) from eGF-GQ (X) is: $\hat{Y} = (-15.089)\ X + 1678.746$. Table 31 summarizes the results.

The Pearson correlation coefficient between the predictor variable (X, eGF-FS) and criterion variable (Y, Total Fixation Duration) is R = -.265, and is statistically significant at the .05 level. However, there is no statistically significant relationship in F-test between eGF-FS and total fixation duration.

Multiple regression was computed to test the relationship of the two predictors (eGF-GQ and eGF-FS) on total fixation duration. The two predictors account for a statistically significant proportion of the variance in the dependent variable, $F(2, 44) =$

8.268, p = .001. Specifically, R^2 = .273 indicates that 27.3 percent of the total fixation duration differences are accounted for by differences in eGF-GQ (X_1) and eGF-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)} = -.451$. Thus, $(-.451)^2 = .2034$, shows that 20.34 percent of the variance of the variance of total fixation duration is uniquely accounted for by the variance of eGF-GQ. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{Y(2.1)} = -.096$. Thus, $(-.096)^2 = .0092$ shows that only 0.92 percent of the variance in total fixation duration is uniquely accounted for by the variance in eGF-FS. Further, the regression coefficients of eGF-GQ is statistically significant for (p = .001) but not for eGF-FS (p = .460). The multiple regression equation for predicting the dependent variable, Y (total fixation duration) from X_1 (eGF-GQ) and X_2 (eGF-FS) is: $\hat{Y} = (-14.072)\ X_1 + (-1.808)\ X_2 + 1764.323$. Table 33 summarizes the findings.

FSS-2 and fixation count on AOIs. Predictors of FSS-2 was computed separately for testing the relationships with the criterion variable of fixation count-AOI using simple linear regression analysis (FSS-Sum, FSS-GQ, and FSS-FS) and multiple regression for FSS-GQ and FSS-FS (n = 47).

The Pearson correlation coefficient between the predictor variable (X, FSS-Sum) and criterion variable (Y, Fixation Count-AOI) is r = -.335, and is statistically significant at the .05 level, F (1, 45) = 5.669, p = .022. The negative linear relationship between FSS-Sum scores and fixation count on AOIs means that students with higher overall Flow experience have lower fixation counts on AOIs during gameplay. The coefficient of determination, R^2 = .112, thus indicating that 11.2 percent of the variance in the fixation count on AOIs is accounted for by the variance in the FSS-Sum. The simple linear regression equation for the prediction of fixation count on AOIs (*Y*) from FSS-Sum (*X*) is: $\hat{Y}$ = (-2.168) *X* + 453.832. Table 30 summarizes the findings.

The Pearson correlation coefficient between the predictor variable (*X*, FSS-GQ) and criterion variable (*Y*, Fixation Count-AOI) is $r = -.325$, and is statistically significant at the .05 level, $F(1, 45) = 5.317$, $p = .026$. There is a negative linear relationship, which means students with higher perceived game quality have lower fixation counts on AOIs during gameplay. The coefficient of determination, $R^2 = .106$, thus indicating that 10.6 percent of the variance in the fixation count on AOIs is accounted for by the variance in the FSS-GQ. The simple linear regression equation for the prediction of fixation count on AOIs (*Y*) from FSS-GQ (*X*) is: $\hat{Y}$ = (-6.783) *X* + 472.251.

The Pearson correlation coefficient between the predictor variable (*X*, FSS-FS) and criterion variable (*Y*, Fixation Count-AOI) is $r = -.301$, and is statistically significant at the .05 level, $F(1, 45) = 4.491$, $p = .040$. There is a negative linear relationship, which means students with higher Flow state have lower fixation counts on AOIs during gameplay. The coefficient of determination, $R^2 = .091$, thus indicating that 9.1 percent of the variance in the fixation counts on AOIs is accounted for by the variance in the FSS-FS. The simple linear regression equation for the prediction of fixation count on AOIs (*Y*) from FSS-FS (*X*) is: $\hat{Y}$ = (-2.519) *X* + 383.274.

There is no statistically significant relationship between the joint predictors (FSS-GQ and FSS-FS) and fixation count on AOIs at the .05 level (Table 32).

eGF and fixation count on AOIs. Predictors of eGF was computed separately for testing the relationships with the criterion variable of fixation count-AOI using simple linear regression analysis (eGF-Sum, eGF-GQ, and eGF-FS) and multiple regression for eGF-GQ and eGF-FS (n = 47). However, there are no statistically significant relationships of eGF-Sum, eGF-GQ, eGF-FS, nor the joint predictors of eGF-GQ and eGF-FS with fixation count on AOIs (Tables 31 and 33).

FSS-2 and total fixation count. The Pearson correlation coefficient between the predictor variable (X, FSS-Sum) and criterion variable (Y, Total Fixation Count) is r = -.490, and is statistically significant at the .001 level, F (1, 45) = 14.241, p = .000. There is a negative linear relationship between FSS-Sum scores and total fixation count, which means students with higher overall Flow experience have fewer total fixation counts during gameplay. The coefficient of determination, R^2 = .240, thus indicating that 24.0 percent of the variance in the total fixation count is accounted for by the variance in the FSS-Sum. The simple linear regression equation for the prediction of total fixation count (Y) from FSS-Sum (X) is: $\hat{Y}$ = (-19.750) X + 4562.592. Table 30 summarizes the findings.

The Pearson correlation coefficient between the predictor variable (X, FSS-GQ) and criterion variable (Y, Total Fixation Count) is r = -.570, and is statistically significant at the .001 level, F (1, 45) = 21.695, p = .000. The negative linear relationship means that students with higher perceived game quality have fewer total fixation counts during gameplay. The coefficient of determination, R^2 = .325, thus indicating that 32.5 percent of the variance in the total fixation count is accounted for by the variance in the FSS-GQ.

The simple linear regression equation for the prediction of total fixation count (Y) from FSS-GQ (X) is: $\hat{Y}$ = (-73.955) X + 5308.706.

The Pearson correlation coefficient between the predictor variable (X, FSS-FS) and criterion variable (Y, Total Fixation Count) is r = -.404, and is statistically significant at the .01 level, F (1, 45) = 8.773, p = .005. The negative linear relationship means that students with higher Flow state have fewer total fixation counts during gameplay. The coefficient of determination, R^2 = .163, thus indicating that 16.3 percent of the variance in the total fixation count is accounted for by the variance in the FSS-FS. The simple linear regression equation for the prediction of total fixation count (Y) from FSS-FS (X) is: $\hat{Y}$ = (-20.988) X + 3738.906.

Multiple regression was computed to test the relationship of the two predictors (FSS-GQ and FSS-FS) on total fixation count. The two predictors account for a statistically significant proportion of the variance in the dependent variable, F(2, 44) = 10.774, p = .000. Specifically, R^2 = .329 indicates that 32.9 percent of the total fixation count differences are accounted for by differences in FSS-GQ (X_1) and FSS-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)}$ = -.407. Thus, $(-.407)^2$ = .1656, shows that 16.56 percent of the variance of the variance of total fixation count is uniquely accounted for by the variance of FSS-GQ. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{Y(2.1)}$ = -.059. Thus, $(-.059)^2$ = .0035 shows that only 0.35 percent of the variance in total fixation count is uniquely accounted for by the variance in FSS-FS.

Further, the regression coefficients of FSS-GQ is statistically significant for (p = .002) but not for FSS-FS (p = .637). The multiple regression equation for predicting the dependent variable, Y (total fixation count) from X_1 (FSS-GQ) and X_2 (FSS-FS) is: $\hat{Y}$ = (-67.810) X_1 + (-3.920) X_2 + 5379.847. Table 32 summarizes the findings.

eGF and total fixation count. The Pearson correlation coefficient between the predictor variable (X, eGF-Sum) and criterion variable (Y, Total Fixation Count) is r = -.492, and is statistically significant at the .001 level, F (1, 45) = 14.349, p = .000. There is a negative linear relationship, which means students with higher overall Flow experience have fewer total fixation counts during gameplay. The coefficient of determination, R^2 = .242 thus indicating that 24.2 percent of the variance in the total fixation count is accounted for by the variance in the eGF-Sum. The simple linear regression equation for the prediction of total fixation count (Y) from eGF-Sum (X) is: $\hat{Y}$ = (-18.594) X + 4803.724. Table 31 summarizes the results.

The Pearson correlation coefficient between the predictor variable (X, eGF-GQ) and criterion variable (Y, Total Fixation Count) is r = -.599, and is statistically significant at the .001 level, F (1, 45) = 25.167, p = .000. The negative linear relationship means that students with higher perceived game quality have fewer total fixation counts during gameplay. The coefficient of determination, R^2 = .359, thus indicating that 35.9 percent of the variance in the total fixation count is accounted for by the variance in the eGF-GQ. The simple linear regression equation for the prediction of total fixation count (Y) from eGF-GQ (X) is: $\hat{Y}$ = (-49.955) X + 5455.561.

The Pearson correlation coefficient between the predictor variable (*X*, eGF-FS) and criterion variable (*Y*, Total Fixation Count) is r = -.293, and is statistically significant at the .05 level, F (1, 45) = 4.238, p = .045. The negative linear relationship means that students with higher perceived Flow state have fewer total fixation counts during gameplay. The coefficient of determination, R^2 = .066, thus indicating that 6.6 percent of the variance in the total fixation count is accounted for by the variance in the eGF-FS. The simple linear regression equation for the prediction of total fixation count (*Y*) from eGF-FS (*X*) is: $\hat{Y}$ = (-14.781) X + 3103.688.

Multiple regression was computed to test the relationship of the two predictors (eGF-GQ and eGF-FS) on total fixation count. The two predictors account for a statistically significant proportion of the variance in the dependent variable, $F(2, 44)$ = 12.800, p = .000. Specifically, R^2 = .368 indicates that 36.8 percent of the total fixation count differences are accounted for by differences in eGF-GQ (X_1) and eGF-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)}$ = -.531. Thus, (-.531)^2 = .2820, shows that 28.20 percent of the variance of the variance of total fixation count is uniquely accounted for by the variance of eGF-GQ. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{Y(2.1)}$ = -.096. Thus, $(-.096)^2$ = .0092 shows that only 0.92 percent of the variance in total fixation count is uniquely accounted for by the variance in eGF-FS. Further, the regression coefficients of eGF-GQ is statistically significant for (p = .000) but not for eGF-FS (p = .429). The multiple regression equation for predicting the dependent variable, Y (total fixation count) from X_1 (eGF-GQ) and X_2

(eGF-FS) is: $\hat{Y}$ = (-47.074) X_1 + (-5.123) X_2 + 5698.027. Table 33 summarizes the findings.

FSS-2 and visit duration on AOIs. Predictors of FSS-2 was computed separately for testing the relationships with the criterion variable of visit duration-AOI using simple linear regression analysis (FSS-Sum, FSS-GQ, and FSS-FS) and multiple regression for FSS-GQ and FSS-FS (n = 47).

The Pearson correlation coefficient between the predictor variable (X, FSS-Sum) and criterion variable (Y, Visit Duration-AOI) is r = -.358, and is statistically significant at the .05 level, F (1, 45) = 6.597, p = .014. There is a negative linear relationship between FSS-Sum scores and visit duration on AOIs, which means students with higher overall Flow experience have shorter visit duration on AOIs during gameplay. The coefficient of determination, R^2 = .128, thus indicating that 12.8 percent of the variance in the visit duration on AOIs is accounted for by the variance in the FSS-Sum. The simple linear regression equation for the prediction of visit duration on AOIs (Y) from FSS-Sum (X) is: $\hat{Y}$ = (-0.814) X + 173.817. Table 30 summarizes the findings.

The Pearson correlation coefficient between the predictor variable (X, FSS-GQ) and criterion variable (Y, Visit Duration-AOI) is r = -.338, and is statistically significant at the .05 level, F (1, 45) = 5.820, p = .020. There is a negative linear relationship, which means students with higher perceived game quality have shorter visit duration on AOIs during gameplay. The coefficient of determination, R^2 = .115, thus indicating that 11.5 percent of the variance in the visit duration on AOIs is accounted for by the variance in the FSS-GQ. The simple linear regression equation for the prediction of visit duration on AOIs (Y) from FSS-GQ (X) is: $\hat{Y}$ = (-2.480) X + 177.574

The Pearson correlation coefficient between the predictor variable (X, FSS-FS) and criterion variable (Y, Visit Duration-AOI) is r = -.326, and is statistically significant at the .05 level, F (1, 45) = 5.338, p = .026. The negative linear relationship means students with higher Flow state have shorter visit duration on AOIs during gameplay. The coefficient of determination, R^2 = .106, thus indicating that 10.6 percent of the variance in the visit duration on AOIs is accounted for by the variance in the FSS-FS. The simple linear regression equation for the prediction of visit duration on AOIs (Y) from FSS-FS (X) is: $\hat{Y}$ = (-0.956) X + 148.321.

Multiple regression was computed to test the relationship of the two predictors (FSS-GQ and FSS-FS) on visit duration on AOIs. The two predictors account for a statistically significant proportion of the variance in the dependent variable, F(2, 44) = 3.453, p = .040. Specifically, R^2 = .136 indicates that 13.6 percent of the visit duration on AOIs differences are accounted for by differences in FSS-GQ (X_1) and FSS-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)}$ = -.172. Thus, (-.172)^2 = .0296, shows that 2.96 percent of the variance of visit duration on AOIs is uniquely accounted for by the variance of FSS-GQ. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{Y(2.1)}$ = -.145. Thus, (-.145)^2 = .0210 shows that only 2.10 percent of the variance in visit duration on AOIs is uniquely accounted for by the variance in FSS-GQ.

Further, the regression coefficients are not statistically significant for neither FSS-GQ (p = .226) nor FSS-FS (p = .305). The multiple regression equation for predicting the dependent variable, Y (visit duration-AOI) from X_1 (FSS-GQ) and X_2 (FSS-FS) is: $\hat{Y}$ = (-1.620) X_1 + (-0.548) X_2 + 187.526. Table 32 summarizes the findings.

eGF and visit duration on AOIs. Only eGF-GQ has the statistically significant relationship with visit duration on AOIs. There are no statistically significant relationships of eGF-Sum, eGF-FS, or the joint predictors of eGF-GQ and eGF-FS with visit duration on AOIs. Tables 31 and 33 summarize the results.

The Pearson correlation coefficient between the predictor variable (X, eGF-GQ) and criterion variable (Y, Visit Duration-AOI) is r = -.290, and is statistically significant at the .05 level, F (1, 45) = 4.130, p = .048. There is a negative linear relationship, which means students with higher perceived game quality have shorter visit duration on AOIs during gameplay. The coefficient of determination, R^2 = .084, thus indicating that 8.4 percent of the variance in the visit duration on AOIs is accounted for by the variance in the eGF-GQ. The simple linear regression equation for the prediction of visit duration on AOIs (Y) from eGF-GQ (X) is: $\hat{Y}$ = (-1.367) X + 159.903.

FSS-2 and total visit duration. The Pearson correlation coefficient between the predictor variable (X, FSS-Sum) and criterion variable (Y, Total Visit Duration) is r = -.551, and is statistically significant at the .001 level, F (1, 45) = 19.657, p = .000. There is a negative linear relationship between FSS-Sum scores and total visit duration, which means students with higher overall Flow experience have shorter total visit duration during gameplay. The coefficient of determination, $R^2 = .304$, thus indicating that 30.4 percent of the variance in the total visit duration is accounted for by the variance in the FSS-Sum. The simple linear regression equation for the prediction of total visit duration (Y) from FSS-Sum (X) is: $\hat{Y} = (-5.335)\ X + 1553.946$. Table 30 summarizes the findings.

The Pearson correlation coefficient between the predictor variable (X, FSS-GQ) and criterion variable (Y, Total Visit Duration) is $r = -.535$, and is statistically significant at the .001 level, $F\ (1, 45) = 18.006$, $p = .000$. There is a negative linear relationship means students with higher perceived game quality have shorter total visit duration during gameplay. The coefficient of determination, $R^2 = .286$, thus indicating that 28.6 percent of the variance in the total visit duration is accounted for by the variance in the FSS-GQ. The simple linear regression equation for the prediction of total visit duration (Y) from FSS-GQ (X) is: $\hat{Y} = (-16.650)\ X + 1597.453$.

The Pearson correlation coefficient between the predictor variable (X, FSS-FS) and criterion variable (Y, Total Visit Duration) is $r = -.497$, and is statistically significant at the .001 level, $F\ (1, 45) = 14.764$, $p = .000$. The negative linear relationship means that students with higher Flow state have shorter total visit duration during gameplay. The coefficient of determination, $R^2 = .247$, thus indicating that 24.7 percent of the variance in the total visit duration is accounted for by the variance in the FSS-FS. The simple linear regression equation for the prediction of total visit duration (Y) from FSS-FS (X) is: $\hat{Y} = (-6.203)\ X + 1380.926$.

Multiple regression was computed to test the relationship of the two predictors (FSS-GQ and FSS-FS) on total visit duration. The two predictors account for a statistically significant proportion of the variance in the dependent variable, $F(2, 44) = 10.774$, $p = .000$. Specifically, $R^2 = .329$ indicates that 32.9 percent of the total visit duration differences are accounted for by differences in FSS-GQ (X_1) and FSS-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)} = -.286$. Thus, $(-.286)^2 = .0818$, shows that 8.18 percent of the variance of the variance of total visit duration is uniquely accounted for by the variance of FSS-GQ. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{Y(2.1)} = -.207$. Thus, $(-.207)^2 = .0428$ shows that 4.28 percent of the variance in total visit duration is uniquely accounted for by the variance in FSS-FS.

Further, the regression coefficients of FSS-GQ is statistically significant for ($p = .025$) but not for FSS-FS ($p = .100$). The multiple regression equation for predicting the dependent variable, Y (total visit duration) from X_1 (FSS-GQ) and X_2 (FSS-FS) is: $\hat{Y} = (-11.440)\ X_1 + (-3.324)\ X_2 + 1657.770$. Table 32 summarizes the findings.

eGF and total visit duration. The Pearson correlation coefficient between the predictor variable (X, eGF-Sum) and criterion variable (Y, Total Visit Duration) is $r = -.632$, and is statistically significant at the .001 level, $F\ (1, 45) = 29.940$, $p = .000$. There is a negative linear relationship, which means students with higher overall Flow experience have shorter total visit duration during gameplay. The coefficient of determination, $R^2 = .400$, thus indicating that 40.0 percent of the variance in the total visit duration is accounted for by the variance in the eGF-Sum. The simple linear regression equation for the prediction of total visit duration (Y) from eGF-Sum (X) is: $\hat{Y} = (-5.741)\ X + 1735.356$.

The Pearson correlation coefficient between the predictor variable (*X*, eGF-GQ) and criterion variable (*Y*, Total Visit Duration) is $r = -.557$, and is statistically significant at the .001 level, $F(1, 45) = 20.255$, $p = .000$. The negative linear relationship means that students with higher perceived game quality have shorter total visit duration during gameplay. The coefficient of determination, $R^2 = .310$, thus indicating that 31.0 percent of the variance in the total visit duration is accounted for by the variance in the eGF-GQ. The simple linear regression equation for the prediction of total visit duration (*Y*) from eGF-GQ (*X*) is: $\hat{Y} = (-11.162)\ X + 1624.317$. Table 31 summarizes the results.

The Pearson correlation coefficient between the predictor variable (*X*, eGF-FS) and criterion variable (*Y*, Total Visit Duration) is $r = -.506$, and is statistically significant at the .001 level, $F(1, 45) = 15.456$, $p = .000$. The negative linear relationship means that students with higher perceived Flow state have shorter total visit duration during gameplay. The coefficient of determination, $R^2 = .256$, thus indicating that 25.6 percent of the variance in the total visit duration is accounted for by the variance in the eGF-FS. The simple linear regression equation for the prediction of total visit duration (*Y*) from eGF-FS (*X*) is: $\hat{Y} = (-6.119)\ X + 1348.124$.

Multiple regression was computed to test the relationship of the two predictors (eGF-GQ and eGF-FS) on total visit duration. The two predictors account for a statistically significant proportion of the variance in the dependent variable, $F(2, 44) = 16.165$, $p = .000$. Specifically, $R^2 = .424$ indicates that 42.4 percent of the total visit duration differences are accounted for by differences in eGF-GQ (X_1) and eGF-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)} = -.410$. Thus,

$(-.410)^2 = .1681$, shows that 16.81 percent of the variance of the variance of total visit duration is uniquely accounted for by the variance of eGF-GQ. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{\mathrm{Y}(2.1)} = -.336$. Thus, $(-.336)^2 = .1129$ shows that only 11.29 percent of the variance in total visit duration is uniquely accounted for by the variance in eGF-FS. Further, the regression coefficient of eGF-GQ is statistically significant for ($p = .001$) as well as for eGF-FS ($p = .005$). The multiple regression equation for predicting the dependent variable, Y (total visit duration) from X_1 (eGF-GQ) and X_2 (eGF-FS) is: $\hat{Y} = (-8.728)\ X_1 + (-4.328)\ X_2 + 1829.157$. Table 33 summarizes the findings.

FSS-2 and visit count on AOIs. Predictors of FSS-2 Scales was computed separately for testing the relationships with the criterion variable of visit count-AOI using simple linear regression analysis (FSS-Sum, FSS-GQ, and FSS-FS) and multiple regression for FSS-GQ and FSS-FS ($n = 47$).

The Pearson correlation coefficient between the predictor variable (X, FSS-Sum) and criterion variable (Y, Visit Count-AOI) is $r = -.299$, and is statistically significant at the .05 level, $F\ (1, 45) = 4.426$, $p = .041$. The negative linear relationship between FSS-Sum scores and visit count on AOIs means that students with higher overall Flow experience have fewer visit counts on AOIs during gameplay. The coefficient of determination, $R^2 = .090$, thus indicating that 9.0 percent of the variance in the visit count on AOIs is accounted for by the variance in the FSS-Sum. The simple linear regression equation for the prediction of visit count on AOIs (Y) from FSS-Sum (X) is: $\hat{Y} = (-0.697)\ X + 152.200$. Table 30 summarizes the findings.

The Pearson correlation coefficient between the predictor variable (*X*, FSS-GQ) and criterion variable (*Y*, Visit Count-AOI) is r = -.302, and is statistically significant at the .05 level, F (1, 45) = 4.514, p = .039. There is a negative linear relationship, which means students with higher perceived game quality have fewer visit counts on AOIs during gameplay. The coefficient of determination, R^2 = .091, thus indicating that 9.1 percent of the variance in the visit count on AOIs is accounted for by the variance in the FSS-GQ. The simple linear regression equation for the prediction of visit count on AOIs (*Y*) from FSS-GQ (*X*) is: $\hat{Y}$ = (-2.265) X + 162.094.

There are no statistically significant relationships between FSS-FS, the joint predictors of FSS-GQ and FSS-FS with visit count on AOIs at .05 level (Table 32).

eGF and visit count on AOIs. There are no statistically significant relationships of eGF-Sum, eGF-GQ, eGF-FS, nor the joint predictors of eGF-GQ and eGF-FS with visit count on AOIs (Tables 31 and 33).

FSS-2 and total visit count. The Pearson correlation coefficient between the predictor variable (*X*, FSS-Sum) and criterion variable (*Y*, Total Visit Count) is r = -.348, and is statistically significant at the .01 level, F (1, 45) = 6.207, p = .016. There is a negative linear relationship between FSS-Sum scores and total visit count, which means students with higher overall Flow experience have fewer total visit counts during gameplay. The coefficient of determination, R^2 = .121, thus indicating that 12.1 percent of the variance in the total visit count is accounted for by the variance in the FSS-Sum.

The simple linear regression equation for the prediction of total visit duration (*Y*) from FSS-Sum (*X*) is: $\hat{Y}$ = (-1.462) *X* + 320.767. Table 30 summarizes the findings.

The Pearson correlation coefficient between the predictor variable (*X*, FSS-GQ) and criterion variable (*Y*, Total Visit Count) is $r = -.406$, and is statistically significant at the .01 level, $F\ (1, 45) = 8.908$, $p = .005$. The negative linear relationship means that students with higher perceived game quality have fewer total visit counts during gameplay. The coefficient of determination, $R^2 = .165$, thus indicating that 16.5 percent of the variance in the total visit count is accounted for by the variance in the FSS-GQ. The simple linear regression equation for the prediction of total visit count (*Y*) from FSS-GQ (*X*) is: $\hat{Y}$ = (-5.495) *X* + 376.964.

Only marginal statistically significant relationship was shown between FSS-FS and Total Visit Count. The Pearson correlation coefficient between the predictor variable (*X*, FSS-FS) and criterion variable (*Y*, Total Visit Count) is $r = -.286$, and is marginally statistically significant at the .05 level, $F\ (1, 45) = 4.015$, $p = .051$. The negative linear relationship means that students with higher Flow state have fewer total visit counts during gameplay. The coefficient of determination, $R^2 = .082$, thus indicating that only 8.2 percent of the variance in the total visit count is accounted for by the variance in the FSS-FS. The simple linear regression equation for the prediction of total visit duration (*Y*) from FSS-FS (*X*) is: $\hat{Y}$ = (-1.550) *X* + 259.495.

Multiple regression was computed to test the relationship of the two predictors (FSS-GQ and FSS-FS) on total visit count. The two predictors account for a statistically significant proportion of the variance in the dependent variable, $F(2, 44) = 4.405$, p =

.018. Specifically, R^2 = .167 indicates that 16.7 percent of the total visit count differences are accounted for by differences in FSS-GQ (X_1) and FSS-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)} = -.291$. Thus, $(-.291)^2 = .0847$, shows that 8.47 percent of the variance of the total visit count is uniquely accounted for by the variance of FSS-GQ. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{Y(2.1)} = -.040$. Thus, $(-.040)^2 = .0016$ shows that only 0.16 percent of the variance in total visit count is uniquely accounted for by the variance in FSS-FS.

Further, the regression coefficients of FSS-GQ is statistically significant for (p = .040) but not for FSS-FS (p = .774). The multiple regression equation for predicting the dependent variable, Y (total fixation count) from X_1 (FSS-GQ) and X_2 (FSS-FS) is: $\hat{Y} = (-5.061)\ X_1 + (-0.276)\ X_2 + 381.978$. Table 32 summarizes the findings.

eGF and total visit count. Only eGF-GQ showed statistically significant relationship with total visit count at the .05 level. There are no statistically significant relationships of eGF-Sum, eGF-FS, or the joint predictors of eGF-GQ and eGF-FS with total visit count. Tables 31 and 33 summarize the results.

The Pearson correlation coefficient between the predictor variable (X, eGF-GQ) and criterion variable (Y, Total Visit Count) is $r = -.323$, and is statistically significant at the .05 level, F (1, 45) = 5.224, p = .027. The negative linear relationship means that students with higher perceived game quality have fewer total visit counts during gameplay. The coefficient of determination, R^2 = .104, thus indicating that 10.4 percent of the variance in the total visit count is accounted for by the variance in the eGF-GQ.

The simple linear regression equation for the prediction of total visit count (*Y*) from eGF-GQ (*X*) is: $\hat{Y} = (-2.804)\,X + 321.394$.

Summary. The results showed that there is a statistically significant negative linear relationship between visual attention and Flow experience during gameplay (Figure 24). From moderately negative to strongly negative linear relationships ($r = -.290$ between visit duration on AOIs and FSS-Sum; $r = -.632$ between total visit duration and eGF-Sum). The negative linear relationship means that students with higher Flow experience have fewer counts or shorter durations during gameplay.

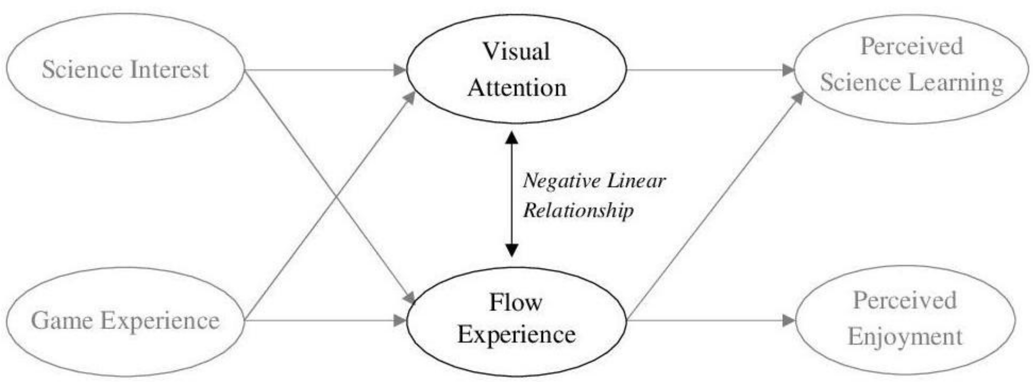


Figure 24 Negative linear relationship between visual attention and Flow experience during gameplay.

The results showed that among the eight visual attention variables, only total fixation count and total visit duration had statistically significant with all FSS and eGF variables (FSS-Sum, GQ, FS; eGF-Sum, GQ, FS). In particular, FSS-Sum and FSS-GQ had statistically significant relationships with all eight visual attention variables (total/AOIs – fixation duration, fixation count, visit duration, and visit count); whereas FSS-FS only showed statistically significant relationships with six visual attention variables (total/AOIs – fixation duration, fixation count, and visit duration). For the context-specific eGameFlow scale, eGF-GQ had statistically significant relationships with six visual attention variables (Total/AOIs fixation duration and visit duration, total fixation count, and total visit count); whereas only three visual attention variables with eGF-Sum (total fixation duration, total fixation count, and total visit duration) and two with eGF-FS (total fixation count and total visit duration).

The coefficient of determination (R^2) showed that, in general, eGF explained more variances in those significant correlated visual attention variables than that of FSS-2. For instance, 40 percent of the variability observed in the total visit duration can be explained by eGF-Sum but only 30.4 percent of the variance in the total visit duration is explained by FSS-Sum.

When comparing the coefficient of determination (R^2) from the two conceptualization of Flow, the multidimensional reflective measure (two-latent model, FSS/eGF – GQ and FS) generally explained more variances in visual attention variables than that of the unidimensional sum scores (FSS/eGF-Sum). For instance, 32.9 percent of the total fixation count differences are accounted for by the differences in FSS-GQ and FS; whereas only 24 percent of the variability observed in the total fixation count can be explained by FSS-Sum.

RQ 1b. Are there any differences in scanpaths (duration and pattern) while playing an SEG between high Flow and low Flow individuals?

Qualitative scanpath analysis was conducted by comparing the gaze duration sequence diagrams of individual students while playing Scene 2 of Neuromatrix. Several patterns were observed between high Flow and low Flow individuals. When observing the scanpath patterns between AOIs (target), non-AOIs (distractor), and Flow experience, students who classified as low Flow (FSS-Sum) spent more time interacting with the NPC but not on tasks, whereas the high Flow students neither spent much time interacting with NPC nor on tasks. High Flow students also located the first task mission relatively fast, as compared with the other two Flow groups (medium and low). Since high Flow students did not spent a lot of time on distractor either, the overall time to finish the scene was relatively short. High Flow students had few shifting between AOIs (tasks and NPC) and non-AOIs, whereas low Flow students had more shifting during gameplay. Students who classified as medium Flow spent longer time to finish the scene while low Flow students finished the scene in medium time range. In general, high Flow students tend to have high science interest. The high Flow was more related to GQ than FS, whereas low Flow was more associated with low FS instead of GQ.

To further explore the scanpath patterns, a deeper level of analysis was conducted. The pattern recognition suggests that students spent medium duration in tasks exhibited more shifting between AOIs and non-AOIs, tended to spent longer time to first locate the tasks, as well as spent more time walking around the 3-D game environment. Therefore, they tended to spent longer time to complete the scene. This group composed of more female students and relatively low science interest students. On the other hand, students spent more time on tasks did not report their Flow experience as low; whereas students spent less time on tasks reported high science interest. Students who spent a lot of time on non-AOIs displayed more shifting between non-AOIs, tasks, and NPC, and spent longer time to complete the scene. Students in this category neither reported their Flow experience nor their science interest as high.

There were students spent a lot of time walking around the 3-D game environment (81 to 178 seconds, as compared to the mean of 44 seconds) exhibited medium durations on AOIs and non-AOIs, medium shifting between AOIs and non-AOIs, as well as spent longer time to complete the scene. Moreover, many of them were categorized as low perceived game experience. For students who spent less time walking (7 to 18 seconds) showed less time on AOIs, less shifting, less time on non-AOIs, and faster to complete the scene. No students report their Flow experience (especially GQ) as low, but reported more on their science interest as high.

RQ 2. What are the Associations Between Visual Attention, Flow Experience, and their Outcomes (Perceived Science Learning and Perceived Enjoyment) through Playing an SEG?

RQ 2a. Are there any interactive effects of visual attention and Flow experience (high, medium, and low) on perceived science learning and perceived enjoyment?

The results showed that the only statistically significant interactive effects were found between total fixation duration and FSS-2 on perceived science learning. There is no statistical significant interactive effect of visual attention and Flow on perceived enjoyment. Therefore, the following will only report the results of the interactive effects of FSS and total fixation duration on perceived science learning.

A two-factor (3 x 3) ANOVA was run testing the main effects and interaction of High, Medium, and Low of FSS and eGF (Sum, GQ, FS) scores and gaze data (fixation duration on AOI, total fixation duration, visit duration on AOI, and total visit duration) on perceived science learning. The data were comprised with students who successfully completed Scene 1 only or both Scenes 1 and 2, so repeated measurements for some of the participants were resulted (*n* = 47). However, there are no statistical significant interactive effects on visit duration (AOIs & total) or fixation duration on AOIs. Only results from total fixation duration are reported. There are no statistically significant interactive effects found between the gaze data and eGF scores, thus only results from FSS-2 are reported.

FSS-Sum. The means and standard deviations for perceived science learning by total fixation duration and FSS-Sum scores was summarized in Tables 34.

Table 34

Means and Standard Description for Perceived Science Learning Score by FSS-Sum and Total Fixation Duration

	FixD-Total											
FSS-Sum	High			Medium			Low			Total		
	n	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
High	4	30.50	2.887	1	20.00	-	6	32.18	2.483	11	30.45	4.275
Medium	12	26.92	1.929	7	24.00	4.796	7	27.29	4.348	26	26.23	3.691
Low	7	22.86	2.545	3	28.33	1.155	-	-	-	10	24.50	3.408

The results of the two-factor ANOVA on perceived science learning scores are shown as Table 35. The results from the test of between-subjects effects indicate that there is a statistically significant interaction between total fixation duration and FSS-Sum scores, $F(3, 39) = 6.243$, $p = .001$, $p\eta^2 = .324$, and a statistically significant main effect of total fixation duration, $F(2, 39) = 5.855$, $p < .01$, $p\eta^2 = .231$. The interaction between total fixation duration and FSS-Sum on perceived science learning is showed in Figure 25. By referring to the Cohen's guidelines for interpreting the magnitude of effect size: .01 = small, .06 = medium, and .14 = large (Cohen, 1988; Dimitrov, 2010), there are large effect sizes for total fixation duration ($\eta^2 = .16$), and the interaction between total fixation duration and FSS-Sum scores ($\eta^2 = .26$). The large effect size is associated with the effect of total fixation duration (.16), which indicates 16 percent of the differences in perceived science learning scores are accounted for by score differences among the three total fixation duration groups.

Table 35

Analysis of Variance for Perceived Science Learning

	df	*F*	$p\eta^2$	*p-*
FixD-Total	2	5.855	0.231	.006
FixD-Total x FSS-Sum	3	6.243	0.324	.001
S within group error	39	(9.992)		

Note. The value enclosed in parentheses is the mean square error (MS_W). S = subjects.

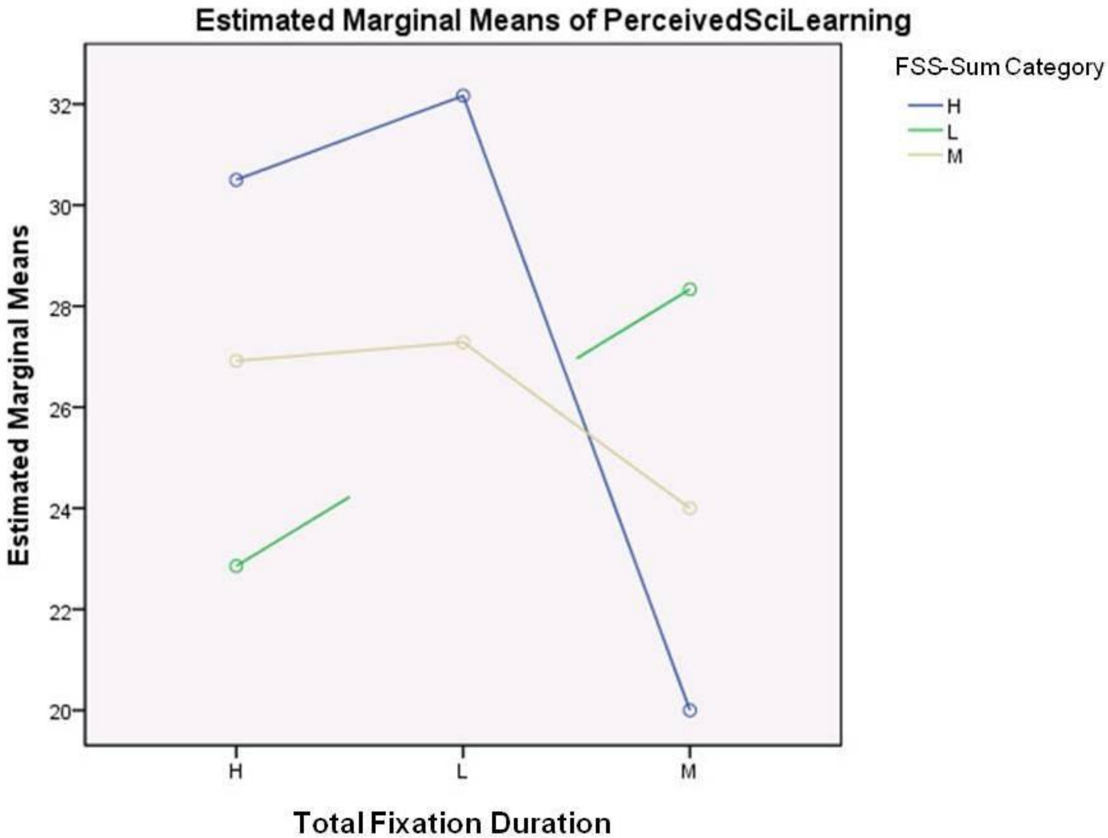


Figure 25 Interaction between FSS-Sum and total fixation duration on perceived science learning.
Note. H = high; L = low; and M = medium

The results from the Tukey post-hoc tests for FSS-Sum groups and total fixation duration groups were reported in Table 36 and 37 respectively. It shows that students classified as high FSS-Sum scores have higher perceived science learning scores than students classified as low FSS-Sum Scores ($p < .001$) and students classified as medium Flow ($p < .01$), by a difference that varies between 2.59 and 9.32 units on the perceived science learning scores and a difference that varies between 1.45 and 6.99 units respectively, but there were no statistically significant differences between medium and low Flow groups.

Table 36

Multiple Comparisons for Perceived Science Learning Score among FSS-Sum Groups

FSS-Sum Groups	ΔM	SEΔM	95% CI for ΔM	
High – Low	5.95 ***	1.381	2.59	9.32
High – Medium	4.22 **	1.137	1.45	6.99
Medium – Low	1.73	1.176	-1.13	4.60

Note. ΔM = Mean difference. SEΔM = Standard error of ΔM.
*p < .05. **p < .01. ***p < .001.

Moreover, students with the longest (or high) total fixation duration have lower perceived science learning scores than students with shortest (or low) total fixation duration ($p < .05$) by a difference that varies between 0.56 and 5.91 units less on perceived science learning. Students with the medium total fixation duration have lower perceived science learning scores than students with lowest total fixation duration ($p < .01$) by a difference that varies between 1.57 and 7.88 units less on perceived science learning. There were no statistically significant differences between high and medium total fixation duration groups.

Table 37

Multiple Comparisons for Perceived Science Learning Score among Total Fixation Duration Groups

FixD-Total Groups	Δ*M*	SEΔ*M*	95% CI for Δ*M*	
High – Low	-3.23 *	1.097	-5.91	-0.56
High – Medium	1.49	1.159	-1.34	4.31
Medium – Low	-4.72 **	1.295	-7.88	-1.57

Note. Δ*M* = Mean difference. SEΔ*M* = Standard error of Δ*M.*
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

FSS-GQ. The means and standard deviations for perceived science learning by total fixation duration and FSS-GQ scores were summarized in Tables 38.

Table 38

Means and Standard Description for Perceived Science Learning Score by FSS-GQ and Total Fixation Duration

FSS-Game Quality	FixD-Total											
	High			Medium			Low			Total		
	n	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
High	4	30.50	2.887	1	20.00	-	6	32.17	2.483	11	30.45	4.275
Medium	6	25.50	1.517	8	27.13	2.588	7	27.29	4.348	21	26.71	3.036
Low	13	25.38	3.429	2	18.00	.000	-	-	-	15	24.40	4.102

The results of the two-factor ANOVA on perceived science learning scores are shown as Table 39. The results from the test of between-subjects effects indicate that there is a statistically significant interaction between total fixation duration and FSS-GQ scores, $F(3, 39) = 6.197$, $p = .002$, $p\eta^2 = .323$; a statistically significant main effect of total fixation duration, $F(2, 39) = 8.825$, $p = .001$, $p\eta^2 = .312$; as well as the main effect of FSS-GQ, $F(2, 39) = 3.732$, $p = .033$, $p\eta^2 = .161$. The interaction between total fixation duration and FSS-GQ on perceived science learning is showed in Figure 26. By referring to the Cohen's (Cohen, 1988; Dimitrov, 2010), there are large effect sizes for total fixation duration ($\eta^2 = .21$), the interaction between total fixation duration and FSS-GQ scores ($\eta^2 = .22$), and a medium effect size for FSS-GQ scores ($\eta^2 = .09$). The large effect size is associated with the effect of total fixation duration (.21), which indicates 21 percent of the differences in perceived science learning scores are accounted for by score differences among the three total fixation duration groups.

Table 39

Analysis of Variance for Perceived Science Learning

	df	*F*	$p\eta^2$	*p*-
FixD-Total	2	8.825	0.312	.001
FSS-GQ	2	3.732	0.161	.033
FixD-Total x FSS-GQ	3	6.197	0.323	.002
S within group error	39	(9.454)		

Note. The value enclosed in parentheses is the mean square error (MS_W). S = subjects.

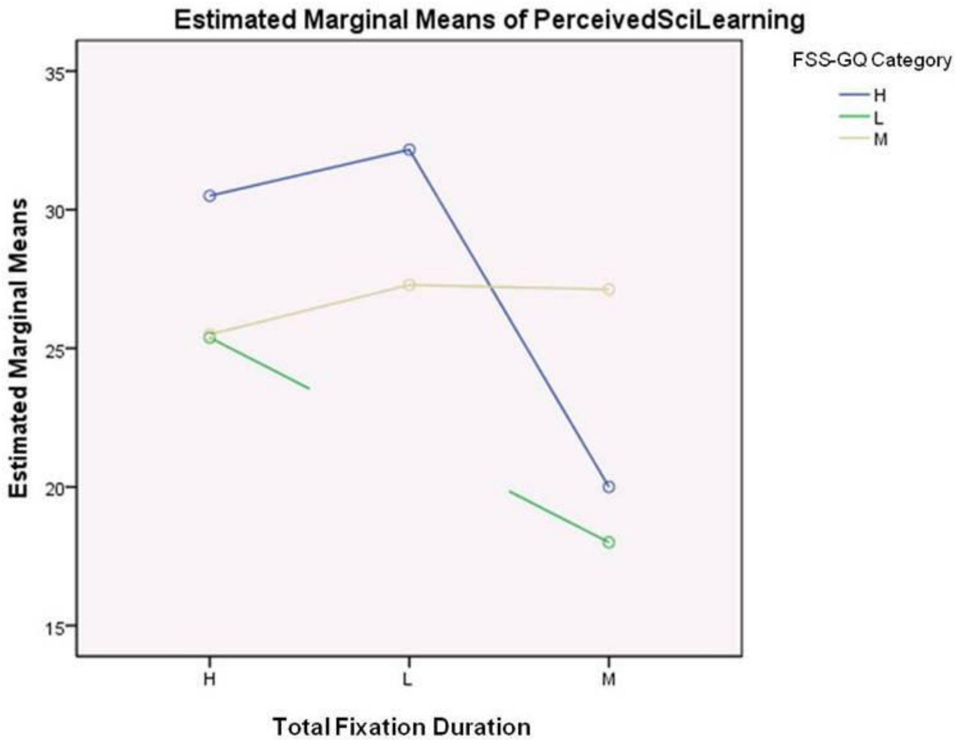


Figure 26 Interaction between FSS-GQ and total fixation duration on perceived science learning.
Note. H = high; L = low; and M = medium

The results from the Tukey post-hoc tests for FSS-GQ groups and total fixation duration groups were reported in Table 40 and 41 respectively. It shows that students classified as high FSS-GQ scores have higher perceived science learning scores than students classified as low FSS-GQ Scores ($p < .001$) and students classified as medium Flow ($p < .01$), by a difference that varies between 3.08 and 9.03 units on the perceived science learning scores and a difference that varies between 0.95 and 6.53 units respectively, but there were no statistically significant differences between medium and low Flow groups.

Table 40

Multiple Comparisons for Perceived Science Learning Score among FSS-GQ Groups

FSS-Game Quality Groups	ΔM	SEΔM	95% CI for ΔM	
High – Low	6.05 ***	1.221	3.08	9.03
High – Medium	3.74 *	1.144	0.95	6.53
Medium – Low	2.31	1.039	-0.22	4.85

Note. ΔM = Mean difference. SEΔM = Standard error of ΔM.
*$p < .05$. **$p < .01$. ***$p < .001$.

Moreover, students with the longest (or high) total fixation duration have lower perceived science learning scores than students with shortest (or low) total fixation duration ($p < .05$) by a difference that varies between 0.63 and 5.83 units less on perceived science learning. Students with the medium total fixation duration also have lower perceived science learning scores than students with low total fixation duration ($p < .01$) by a difference that varies between 1.65 and 7.79 units less on perceived science learning. There were no statistically significant differences between high and medium total fixation duration groups.

Table 41

Multiple Comparisons for Perceived Science Learning Score among Total Fixation Duration Groups

FixD-Total Groups	Δ*M*	SEΔ*M*	95% CI for Δ*M*	
High – Low	-3.23 *	1.067	-5.83	-0.63
High – Medium	1.49	1.127	-1.26	4.23
Medium – Low	-4.72 **	1.260	-7.79	-1.65

Note. Δ*M* = Mean difference. SEΔ*M* = Standard error of Δ*M*.
*p < .05. **p < .01. ***p < .001.

FSS-FS. The means and standard deviations for perceived science learning by total fixation duration and FSS-FS scores was summarized in Tables 42.

Table 42

Means and Standard Description for Perceived Science Learning Score by FSS-FS and Total Fixation Duration

FSS-Flow State	FixD-Total High			FixD-Total Medium			FixD-Total Low			Total		
	n	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
High	4	31.00	2.309	-	-	-	6	32.17	2.483	10	31.70	2.359
Medium	12	27.08	1.311	8	23.50	4.660	5	26.60	5.128	25	25.84	3.771
Low	7	27.08	1.311	3	28.33	1.155	2	29.00	.000	12	24.92	3.554

The results of the two-factor ANOVA on perceived science learning scores are shown as Table 43. The results from the test of between-subjects effects indicate that there is a statistically significant interaction between total fixation duration and FSS-FS scores, $F(3, 39) = 5.851$, $p = .002$, $p\eta^2 = .310$, and a statistically significant main effect of FSS-FS, $F(2, 39) = 11.182$, $p = .000$, $p\eta^2 = .364$. The interaction between total fixation duration and FSS-FS on perceived science learning is showed in Figure 27. There are large effect sizes for FSS-FS ($\eta^2 = .27$) and the interaction between total fixation duration and FSS-FS scores ($\eta^2 = .21$). The large effect size is associated with the effect of FSS-FS (.27), which indicates 27 percent of the differences in perceived science learning scores are accounted for by perceived science learning score differences among the three FSS-FS groups.

Table 43

Analysis of Variance for Perceived Science Learning

	df	*F*	$p\eta^2$	*p*-
FSS-FS	2	11.182	0.364	.000
FixD-Total x FSS-FS	3	5.851	0.310	.002
S within group error	39	(8.847)		

Note. The value enclosed in parentheses is the mean square error (MS_W). S = subjects.

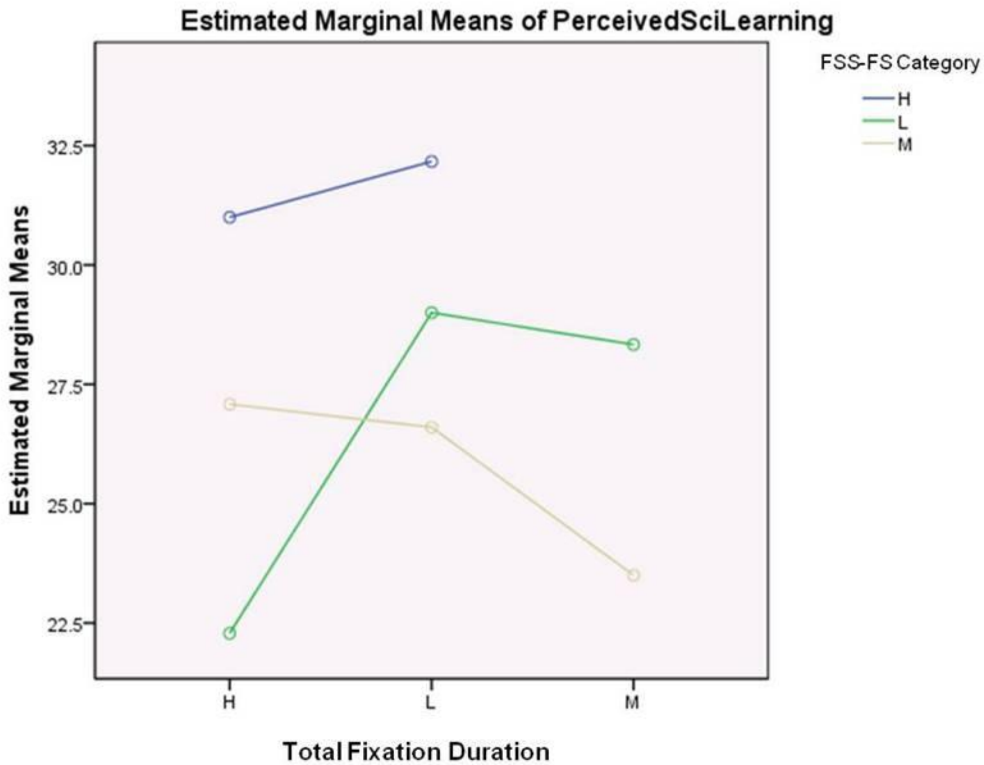


Figure 27 Interaction between FSS-FS and total fixation duration on perceived science learning.
Note. H = high; L = low; and M = medium

The results from the Tukey post-hoc tests for FSS-FS groups and total fixation duration groups were reported in Table 44 and 45 respectively. It shows that students classified as high FSS-FS scores have higher perceived science learning scores than students classified as low FSS-FS Scores ($p < .001$) and students classified as medium Flow ($p < .001$), by a difference that varies between 3.69 and 9.89 units on the perceived science learning scores and a difference that varies between 3.15 and 8.57 units respectively, but there were no statistically significant differences between medium and low Flow groups.

Table 44

Multiple Comparisons for Perceived Science Learning Score among FSS-FS Groups

FSS-Flow State Groups	ΔM	SEΔM	95% CI for ΔM	
High – Low	6.78 ***	1.274	3.69	9.89
High – Medium	5.86 ***	1.113	3.15	8.57
Medium – Low	0.92	1.045	-1.62	3.47

Note. ΔM = Mean difference. SEΔM = Standard error of ΔM.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Moreover, students with the longest (or high) total fixation duration have lower perceived science learning scores than students with shortest (or low) total fixation duration ($p < .01$) by a difference that varies between 0.72 and 5.75 units less on perceived science learning. Students with the medium total fixation duration also have lower perceived science learning scores than students with low total fixation duration ($p < .001$) by a difference that varies between 1.75 and 7.69 units less on perceived science learning. There were no statistically significant differences between high and medium total fixation duration groups.

Table 45

Multiple Comparisons for Perceived Science Learning Score among Total Fixation Duration Groups

FixD-Total Groups	Δ*M*	SEΔ*M*	95% CI for Δ*M*	
High – Low	-3.23 **	1.032	-5.75	-0.72
High – Medium	1.49	1.090	-1.17	4.14
Medium – Low	-4.72 ***	1.219	-7.69	-1.75

Note. Δ*M* = Mean difference. SEΔ*M* = Standard error of Δ*M*.
*p < .05. **p < .01. ***p < .001.

RQ 2b. Whether students' Flow experience has positive relationship with perceived science learning?

The means and standard deviations for perceived science learning by Flow scores were summarized in Tables 46 and 47.

Table 46

Means and Standard Deviations for Perceived Science Learning and FSS-2 Scores (n = 28)

Variables	Mean	STD
Criterion variable		
Perceived Science Learning	27.11	4.280
Predictor variables		
FSS-Sum	141.00	15.856
FSS-GQ	47.82	4.839
FSS-FS	93.18	12.199

Table 47

Means and Standard Deviations for Perceived Science Learning and eGF Scores (n = 26)

Variables	Mean	STD
Criterion variable		
Perceived Science Learning	26.85	4.333
Predictor variables		
eGF-Sum	162.42	17.140
eGF-GQ	73.31	7.863
eGF-FS	89.12	12.375

FSS-2. Predictors of FSS-2 Scales was computed for testing the relationships with the criterion variable of perceived science learning separately using simple linear regression analysis (FSS-Sum, FSS-GQ, and FSS-FS) and multiple regression for FSS-GQ and FSS-FS (n = 28). Table 48 summarizes the result.

The Pearson correlation coefficient between the predictor variable (X, FSS-Sum) and criterion variable (Y, perceived science learning) is r = .618, and is statistically significant at the .001 level, F (1, 26) = 16.045, p < .001. There is a positive linear relationship between FSS-Sum scores and perceived science learning scores, which means students with higher overall Flow experience have more perceived science learning after gameplay. The coefficient of determination, $R^2 = .382$, thus indicating that 38.2 percent of the variance in the perceived science learning scores is accounted for by the variance in the FSS-Sum. The simple linear regression equation for the prediction of perceived science learning scores (Y) from FSS-Sum (X) is: $\hat{Y} = (0.167)\ X + 3.593$.

Table 48

Summary of Simple Linear Regression Analysis for Variables Predicting Perceived Science Learning (n = 28)

Variable	*B*	SE B	β	R^2
FSS-Sum	0.167	0.042	.618 ***	.382 ***
FSS-GQ	0.447	0.150	.505 **	.255 **
FSS-FS	0.211	0.055	.603 ***	.363 ***

$*p < .05$. $**p < .01$. $***p < .001$.

The Pearson correlation coefficient between the predictor variable (X, FSS-GQ) and criterion variable (Y, perceived science learning) is $r = .505$, and is statistically significant at the .01 level, $F\ (1, 26) = 8.913$, $p = .006$. There is a positive linear relationship between FSS-GQ scores and perceived science learning scores, which indicates that students with higher perceived game quality have more perceived science learning after gameplay. The coefficient of determination, $R^2 = .255$, thus indicating that 25.5 percent of the variance in the perceived science learning scores is accounted for by the variance in the FSS-GQ. The simple linear regression equation for the prediction of perceived science learning scores (Y) from FSS-GQ (X) is: $\hat{Y}$ = (0.505) X + 5.732.

The Pearson correlation coefficient between the predictor variable (X, FSS-FS) and criterion variable (Y, perceived science learning) is r = .603, and is statistically significant at the .001 level, F (1, 26) = 14.818, p = .001. There is a positive linear relationship between FSS-FS scores and perceived science learning scores, which means students with higher Flow state experience have more perceived science learning after gameplay. The coefficient of determination, R^2 = .363, thus indicating that 36.3 percent of the variance in the perceived science learning scores is accounted for by the variance in the FSS-FS. The simple linear regression equation for the prediction of perceived science learning scores (Y) from FSS-FS (X) is: $\hat{Y}$ = (0.211) X + 7.408. Hence, for every one unit of FSS-Sum, FSS-GQ, and FSS-FS, the perceived science learning score increases by 0.167 units, 0.505 units, and 0.211 units, respectively.

Multiple regression was computed to test the relationship of the two predictors (FSS-GQ and FSS-FS) on perceived science learning. The two predictors account for a statistically significant proportion of the variance in the dependent variable, perceived science learning score, F(2, 25) = 7.714, p = .002. Specifically, R^2 = .382 indicates that 38.2 percent of the perceived science learning score differences are accounted for by differences in FSS-GQ (X_1) and FSS-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)}$ = .136. Thus, $(.136)^2$ = .0490 shows that 4.90 percent of the variance in perceived science learning is uniquely accounted for by the variance in FSS-GQ. Likewise, the part correlation between Y and X_2, partialling out X_1 from X_2, is:

$r_{Y(2.1)} = .355$. Thus, $(.355)^2 = .1260$ shows that 12.60 percent of the variance in perceived science learning is uniquely accounted for by the variance in FSS-FS.

Further, the regression coefficients are statistically significant, at the .05 level, for FSS-FS ($p = .033$), but not for FSS-GQ ($p = .394$). The positive regression coefficient (0.168) of FSS-FS indicates that, the predicted score, perceived science learning scores ($\hat{Y}$), increases by 0.168 when X_2 increases by one unit assuming that the value of X_1 does not change. The multiple regression equation for predicting the dependent variable, Y (perceived science learning) from X_1 (FSS-GQ) and X_2 (FSS-FS) is: $\hat{Y} = (0.163)\ X_1 + (0.168)\ X_2 + 3.662$. Table 49 summarizes the result.

Table 49

Summary of Multiple Regression Analysis for Variables Predicting Perceived Science Learning (n = 28)

Variable	*B*	SE B	β	R^2
FSS-GQ	0.163	0.188	.184	.382 ***
FSS-FS	0.168	0.074	.479 *	

*$p < .05$. **$p < .01$. ***$p < .001$.

eGF. Predictors of eGF Scales was computed for testing the relationships with the criterion variable of perceived science learning separately using simple linear regression analysis (eGF-Sum, eGF-GQ, and eGF-FS) and multiple regression for eGF-GQ and eGF-FS (n = 26). There is no statistically significant result from eGF-GQ on perceived science learning.

The Pearson correlation coefficient between the predictor variable (X, eGF-Sum) and criterion variable (Y, perceived science learning) is $r = .607$, and is statistically significant at the .001 level, F (1, 24) = 14.028, $p = .001$. There is a positive linear relationship between eGF-Sum scores and perceived science learning scores, which means students with higher overall Flow experience have more perceived science learning after gameplay. The coefficient of determination, $R^2 = .369$, thus indicating that 36.9 percent of the variance in the perceived science learning scores is accounted for by the variance in the eGF-Sum. The simple linear regression equation for the prediction of perceived science learning scores (Y) from eGF-Sum (X) is: $\hat{Y} = (0.154)\ X + 1.907$. Table 50 summarizes the result.

The Pearson correlation coefficient between the predictor variable (X, eGF-FS) and criterion variable (Y, perceived science learning) is $r = .710$, and is statistically significant at the .001 level, F (1, 24) = 24.465, $p < .001$. There is a positive linear relationship between eGF-FS scores and perceived science learning scores, which means students with higher Flow state experience have more perceived science learning after gameplay. The coefficient of determination, $R^2 = .505$, thus indicating that 50.5 percent of the variance in the perceived science learning scores is accounted for by the variance in the eGF-FS. The simple linear regression equation for the prediction of perceived science learning scores (Y) from eGF-FS (X) is: $\hat{Y} = (0.248)\ X + 4.677$.

Table 50

Summary of Simple Linear Regression Analysis for Variables Predicting Perceived Science Learning (n = 26)

Variable	*B*	SE B	β	R^2
eGF-Sum	0.154	0.041	.607 ***	.369 ***
eGF-Game Quality	0.113	0.110	.206	.042
eGF-Flow State	0.249	0.050	.710 ***	.505 ***

*$p < .05$. **$p < .01$. ***$p < .001$.

Thus, for every one unit of eGF-Sum and eGF-FS, the perceived science learning score increases by 0.154 units and 0.248 units, respectively.

Multiple regression was computed to test the relationship of the two predictors (eGF-GQ and eGF-FS) on perceived science learning. The two predictors account for a statistically significant proportion of the variance in the dependent variable, perceived science learning score, $F(2, 23) = 12.106$, $p < .001$. Specifically, $R^2 = .513$ indicates that 51.3 percent of the perceived science learning score differences are accounted for by differences in eGF-GQ (X_1) and eGF-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{Y(1.2)} = -.090$. Thus, $(-.090)^2 = .0081$ shows that 0.81 percent of the variance in perceived science learning is uniquely accounted for by the variance in eGF-GQ. Likewise, the part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{Y(2.1)} = .686$. Thus, $(.686)^2 = .4706$ shows that 47.06 percent of the variance in perceived science learning is uniquely accounted for by the variance in eGF-FS.

Further, the regression coefficients are statistically significant, at the .01 level, for eGF-FS (p = .000), but not for eGF-GQ (p = .554). The positive regression coefficient (0.263) of eGF-FS indicates that, the predicted score, perceived science learning scores ($\hat{Y}$), increases by 0.263 when X_2 increases by one unit assuming that the value of X_1 does not change. The multiple regression equation for predicting the dependent variable, Y (perceived science learning) from X_1 (eGF-GQ) and X_2 (eGF-FS) is: $\hat{Y} = (-0.054)\ X_1 + (0.263)\ X_2 + 7.399$. Table 51 summarizes the result.

Table 51

Summary of Multiple Regression Analysis for Variables Predicting Perceived Science Learning (n = 26)

Variable	B	SE B	β	R^2
eGF-GQ	-0.054	0.088	-.098	.513 ***
eGF-FS	0.263	0.056	.750 ***	

*p < .05. **p < .01. ***p < .001.

RQ 2c. Is there a strong positive relationship between Flow and perceived enjoyment?

The means and standard deviations for perceived enjoyment by Flow scores were summarized in Tables 52 and 53.

Table 52

Means and Standard Deviations for Perceived Enjoyment and FSS-2 Scores (n = 28)

Variables	Mean	STD
Criterion variable		
Perceived Enjoyment	16.21	3.166
Predictor variables		
FSS-Sum	141.00	15.856
FSS-Game Quality	47.82	4.839
FSS-Flow State	93.18	12.199

Table 53

Means and Standard Deviations for Perceived Enjoyment and eGF Scores (n = 26)

Variables	Mean	STD
Criterion variable		
Perceived Enjoyment	16.00	3.175
Predictor variables		
eGF-Sum	162.42	17.140
eGF-Game Quality	73.31	7.863
eGF-Flow State	89.12	12.375

FSS-2. Predictors of FSS-2 Scales was computed for testing the relationships with the criterion variable of perceived enjoyment separately using simple linear regression analysis (FSS-Sum, FSS-GQ, and FSS-FS) and multiple regression for FSS-GQ and FSS-FS (n = 28). Table 54 summarizes the results.

The Pearson correlation coefficient between the predictor variable (X, FSS-Sum) and criterion variable (Y, perceived enjoyment) is r = .629, and is statistically significant at the .001 level, F (1, 26) = 16.997, p < .001. There is a positive linear relationship between FSS-Sum scores and perceived enjoyment scores, which means students with higher overall Flow experience have more perceived enjoyment after gameplay. The coefficient of determination, R^2 = .395, thus indicating that 39.5 percent of the variance in the perceived enjoyment scores is accounted for by the variance in the FSS-Sum. The simple linear regression equation for the prediction of perceived enjoyment scores (Y) from FSS-Sum (X) is: $\hat{Y}$ = (0.126) X – 1.483.

The Pearson correlation coefficient between the predictor variable (X, FSS-GQ) and criterion variable (Y, perceived enjoyment) is r = .479, and is statistically significant at the .05 level, F (1, 26) = 5.996, p = .021. There is a positive linear relationship between FSS-GQ scores and perceived enjoyment scores, which means students with higher perceived game quality have more perceived enjoyment after gameplay. The coefficient of determination, R^2 = .187, thus indicating that 18.7 percent of the variance in the perceived enjoyment scores is accounted for by the variance in the FSS-GQ. The simple linear regression equation for the prediction of perceived enjoyment scores (Y) from FSS-GQ (X) is: $\hat{Y}$ = (0.283) X + 2.667.

The Pearson correlation coefficient between the predictor variable (X, FSS-FS) and criterion variable (Y, perceived enjoyment) is r = .645, and is statistically significant at the .001 level, F (1, 26) = 18.543, p < .001. There is a positive linear relationship between FSS-FS scores and perceived enjoyment scores, which means students with higher Flow state experience have more perceived enjoyment after gameplay. The coefficient of determination, R^2 = .416, thus indicating that 41.6 percent of the variance in the perceived enjoyment scores is accounted for by the variance in the FSS-FS. The simple linear regression equation for the prediction of perceived enjoyment scores (Y) from FSS-FS (X) is: $\hat{Y}$ = (0.167) X + 0.609.

Hence, for every one unit of FSS-Sum, FSS-GQ, and FSS-FS, the perceived enjoyment score increases by 0.126 units, 0.283 units, and 0.167 units, respectively.

Multiple regression was computed to test the relationship of the two predictors (FSS-GQ and FSS-FS) on perceived enjoyment. The two predictors account for a statistically significant proportion of the variance in the dependent variable, perceived enjoyment score, F(2, 23) = 8.915, p = .001. Specifically, R^2 = .416 indicates that 41.6 percent of the perceived enjoyment score differences are accounted for by differences in FSS-GQ (X_1) and FSS-FS (X_2). The part correlation between Y and X_1, partialling out X_2 from X_1, is: $r_{\mathrm{Y}(1.2)} = 0$. The part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{\mathrm{Y}(2.1)}$ = .478. Thus, $(.478)^2$ = .2285 shows that 22.85 percent of the variance in perceived enjoyment is uniquely accounted for by the variance in FSS-FS.

Further, the regression coefficients are statistically significant, at the .01 level, for FSS-FS (p = .004), but not for FSS-GQ (p = .999). The positive regression coefficient (0.167) of FSS-FS indicates that, the predicted score, perceived enjoyment scores ($\hat{Y}$), increases by 0.167 when X_2 increases by one unit assuming that the value of X_1 does not change. The multiple regression equation for predicting the dependent variable, Y (perceived enjoyment) from X_1 (FSS-GQ) and X_2 (FSS-FS) is: $\hat{Y} = (0)\ X_1 + (0.167)\ X_2 + 0.605$; or $\hat{Y} = (0.167)\ X_2 + 0.605$.

Table 54

Summary of Regression Analysis for Variables Predicting Perceived Enjoyment (n = 28)

Variable	*B*	SE B	β	R^2
FSS-Sum	0.126	0.030	.629 ***	.395 ***
FSS-Game Quality	0.283	0.116	.433 *	.187 *
FSS-Flow State	0.167	0.039	.645 ***	.416 ***
Multiple Regression				
FSS-GQ	0.000	0.135	.000	.416 ***
FSS-FS	0.167	0.053	.645 **	

*$p < .05$. **$p < .01$. ***$p < .001$.

eGF. Predictors of eGame Flow Scales was computed for testing the relationships with the criterion variable of perceived enjoyment separately using simple linear regression analysis (eGF-Sum, eGF-GQ, and eGF-FS) and multiple regression for eGF-GQ and eGF-FS (n = 26). Table 55 summarizes the result.

Table 55

Summary of Regression Analysis for Variables Predicting Perceived Enjoyment (n = 26)

Variable	B	SE B	β	R^2
eGF-Sum	0.126	0.028	.681 ***	.464 ***
eGF-Game Quality	0.193	0.072	.479 *	.230 *
eGF-Flow State	0.164	0.040	.639 ***	.409 ***
Multiple Regression				
eGF-GQ	0.106	0.067	.263	.467 ***
eGF-FS	0.137	0.043	.533 **	

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

The Pearson correlation coefficient between the predictor variable (X, eGF-Sum) and criterion variable (Y, perceived enjoyment) is $r = .681$, and is statistically significant at the .001 level, F (1,24) = 20.802, $p < .001$. There is a positive linear relationship between eGF-Sum scores and perceived enjoyment scores, which means students with higher overall flow experience have more perceived enjoyment after gameplay. The coefficient of determination, $R^2 = .464$, thus indicating that 46.4 percent of the variance in the perceived enjoyment scores is accounted for by the variance in the eGF-Sum. The simple linear regression equation for the prediction of perceived enjoyment scores (Y) from eGF-Sum (X) is: $\hat{Y} = (0.126)\ X - 4.501$.

The Pearson correlation coefficient between the predictor variable (X, eGF-GQ) and criterion variable (Y, perceived enjoyment) is $r = .479$, and is statistically significant at the .05 level, F (1, 24) = 7.150, $p = .013$. There is a positive linear relationship between eGF-GQ scores and perceived enjoyment scores, which means students with higher perceived game quality have more perceived science learning after gameplay. The coefficient of determination, $R^2 = .230$, thus indicating that 23.0 percent of the variance in the perceived enjoyment scores is accounted for by the variance in the eGF-GQ. The simple linear regression equation for the prediction of perceived enjoyment scores (Y) from eGF-GQ (X) is: $\hat{Y} = (0.193)\ X + 1.818$.

The Pearson correlation coefficient between the predictor variable (X, eGF -FS) and criterion variable (Y, perceived enjoyment) is $r = .639$, and is statistically significant at the .001 level, $F\ (1, 24) = 16.593$, $p < .001$. There is a positive linear relationship between eGF-FS scores and perceived enjoyment scores, which means students with higher Flow state experience have more perceived enjoyment after gameplay. The coefficient of determination, $R^2 = .409$, thus indicating that 40.9 percent of the variance in the perceived enjoyment scores is accounted for by the variance in the eGF-FS. The simple linear regression equation for the prediction of perceived enjoyment scores (Y) from eGF-FS (X) is: $\hat{Y} = (0.164)\ X + 1.383$.

Thus, for every one unit of eGF-Sum, eGF-GQ and eGF-FS, the perceived enjoyment score increases by 0.126 units, 0.193 units, and 0.164 units, respectively.

Multiple regression was computed to test the relationship of the two predictors (eGF-GQ and eGF-FS) on perceived enjoyment. The two predictors account for a statistically significant proportion of the variance in the dependent variable, perceived enjoyment score, $F(2, 23) = 10.066$, $p = .001$. Specifically, $R^2 = .467$ indicates that 46.7 percent of the perceived enjoyment score differences are accounted for by differences in eGF-GQ (X_1) and eGF-FS (X_2). The part correlation between Y and X_1, partialling out X_2

from X_1, is: $r_{Y(1.2)} = .241$. Thus, $(.241)^2 = .0581$ shows that 5.81 percent of the variance in perceived enjoyment is uniquely accounted for by the variance in eGF-GQ. Likewise, the part correlation between Y and X_2, partialling out X_1 from X_2, is: $r_{Y(2.1)} = .487$. Thus, $(.487)^2 = .2372$ shows that 23.72 percent of the variance in perceived enjoyment is uniquely accounted for by the variance in eGF-FS.

Further, the regression coefficients are statistically significant, at the .01 level, for eGF-FS ($p = .004$), but not for eGF-GQ ($p = .127$). The positive regression coefficient (0.137) of eGF-FS indicates that, the predicted score, perceived enjoyment scores ($\hat{Y}$), increases by 0.137 when X_2 increases by one unit assuming that the value of X_1 does not change. The multiple regression equation for predicting the dependent variable, Y (perceived enjoyment) from X_1 (eGF-GQ) and X_2 (eGF-FS) is: $\hat{Y} = (-0.106)\ X_1 + (0.137)\ X_2 - 3{,}975$.

RQ 2d. Are there any relationships between gaze duration during gameplay and perceived science learning or perceived enjoyment?

The means and standard deviations of the variables are listed in Table 56. The results showed that among the eight visual attention variables only three of the predictor variables are statistically significant. The three predictors are: Total fixation duration, total fixation count, and total visit duration, which correlate with the perceived science learning scores.

Table 56

Means and Standard Deviations for Perceived Science Learning and Visual Attention Variables (n = 47)

Variables	Mean	STD
Criterion variable		
Perceived Science Learning	26.85	4.263
Predictor variables		
Fixation Duration-AOI (second)	50.736	32.224
Fixation Duration-Total (second)	573.083	216.226
Fixation Count-AOI	149.98	98.828
Fixation Count-Total	1795.06	614.106
Visit Duration-AOI (second)	59.764	34.701
Visit Duration-Total (second)	806.401	147.503
Visit Count-AOI	54.49	35.524
Visit Count-Total	115.91	64.015

The Pearson correlation coefficient between the predictor variable (X, total fixation duration) and criterion variable (Y, perceived science learning) is r = -.317, and is statistically significant at the .05 level, F (1, 45) = 5.018, p = .030. There is a negative linear relationship between total fixation duration and perceived science learning, which means students with longer total fixation duration have lower perceived science learning after gameplay. The coefficient of determination, R^2 = .100, thus indicating that 10.0 percent of the variance in the perceived science learning scores is accounted for by the variance in the total fixation duration. The simple linear regression equation for the prediction of perceived science learning scores (*Y*) from total fixation duration (*X*) is: $\hat{Y}$ = (-0.006) *X* + 30.430. Table 57 summarizes the result.

The correlation coefficient between total fixation count (*X*) and perceived science learning (*Y*) is $r = -.351$, and is statistically significant at the .05 level, $F(1, 45) = 6.306$, $p = .016$. There is a negative linear relationship between total fixation count and perceived science learning, which means students with more total fixation count have lower perceived science learning after gameplay. The coefficient of determination, $R^2 = .123$, thus indicating that 12.3 percent of the variance in the perceived science learning scores is accounted for by the variance in the total fixation count. The simple linear regression equation for the prediction of perceived science learning scores (*Y*) from total fixation count (*X*) is: $\hat{Y} = (-0.002) X + 31.220$.

The correlation coefficient between total visit duration (*X*) and perceived science learning (*Y*) is $r = -.424$, and is statistically significant at the .01 level, $F(1, 45) = 9.842$, $p = .003$. There is also a negative linear relationship between total visit duration and perceived science learning, which means students with longer total visit duration have lower perceived science learning after gameplay. The coefficient of determination, $R^2 = .179$, thus indicating that 17.9 percent of the variance in the perceived science learning scores is accounted for by the variance in the total visit duration. The simple linear regression equation for the prediction of perceived science learning scores (*Y*) from total visit duration (*X*) is: $\hat{Y} = (-0.012) X + 36.724$. Thus, for every one unit of total fixation duration, total fixation count, and total visit duration, the perceived science learning score decreases by 0.006 unit, 0.002 unit, and 0.012 unit, respectively.

Table 57

Summary of Regression Analysis for Variables Predicting Perceived Science Learning (n = 47)

Variable	*B*	SE B	β	R^2
Fixation Duration-AOI	-0.031	0.019	-.234	.055
Fixation Duration-Total	-0.006	0.003	-.317 *	.100 *
Fixation Count-AOI	-0.011	0.006	-.252	.063
Fixation Count-Total	-0.002	0.001	-.351 *	.123 *
Visit Duration-AOI	-0.030	0.018	-.243	.059
Visit Duration-Total	-0.012	0.004	-.424 **	.179 **
Visit Count-AOI	-0.029	0.017	-.241	.058
Visit Count-Total	-0.018	0.010	-.269	.072

*$p < .05$. **$p < .01$. ***$p < .001$.

Same list of visual attention predictors was entered for testing the relationships with the criterion variable of perceived enjoyment separately using simple linear regression analysis (n = 47). The results showed that three predictor variables, total fixation duration, total fixation count, and total visit duration, are statistically significant that correlate with perceived enjoyment. The means and standard deviations of the variables are listed in Table 58.

Table 58

Means and Standard Deviations for Perceived Enjoyment and Visual Attention Variables

Variables	Mean	STD
Criterion variable		
Perceived Enjoyment	15.87	3.097
Predictor variables		
Fixation Duration-AOI (second)	50.736	32.224
Fixation Duration-Total (second)	573.083	216.226
Fixation Count-AOI	149.98	98.828
Fixation Count-Total	1795.06	614.106
Visit Duration-AOI (second)	59.764	34.701
Visit Duration-Total (second)	806.401	147.503
Visit Count-AOI	54.49	35.524
Visit Count-Total	115.91	64.015

The Pearson correlation coefficient between the predictor variable (X, total fixation duration) and criterion variable (Y, perceived enjoyment) is r = -.355, and is statistically significant at the .05 level, F (1, 45) = 6.495, p = .014. There is a negative linear relationship between total fixation duration and perceived enjoyment, which means students with longer total fixation duration have lower perceived enjoyment after gameplay. The coefficient of determination, R^2 = .126, thus indicating that 12.6 percent of the variance in the perceived enjoyment scores is accounted for by the variance in the total fixation duration. The simple linear regression equation for the prediction of perceived enjoyment scores (Y) from total fixation duration (X) is: $\hat{Y}$ = (-0.005) X + 18.787. Table 59 summarizes the result.

The correlation coefficient between total fixation count (X) and perceived enjoyment (Y) is r = -.326, and is statistically significant at the .05 level, F (1, 45) = 5.345, p = .025. There is a negative linear relationship between total fixation count and perceived science learning, which means students with more total fixation count have lower perceived enjoyment after gameplay. The coefficient of determination, R^2 = .106, thus indicating that 10.6 percent of the variance in the perceived enjoyment scores is accounted for by the variance in the total fixation count. The simple linear regression equation for the prediction of perceived enjoyment scores (Y) from total fixation count (X) is: $\hat{Y}$ = (-0.002) X + 18.822.

The correlation coefficient between total visit duration (X) and perceived enjoyment (Y) is r = -.525, and is statistically significant at the .001 level, F (1, 45) = 17.140, p = .000. There is also a negative linear relationship between total visit duration and perceived enjoyment, which means students with longer total visit duration have lower perceived enjoyment after gameplay. The coefficient of determination, R^2 = .276, thus indicating that 27.6 percent of the variance in the perceived enjoyment scores is accounted for by the variance in the total visit duration. The simple linear regression equation for the prediction of perceived enjoyment scores (Y) from total visit duration (X) is: $\hat{Y}$ = (-0.011) X + 24.765. Thus, for every one unit of total fixation duration, total fixation count, and total visit duration, the perceived enjoyment score decreases by 0.005 unit, 0.002 unit, and 0.011 unit, respectively.

Table 59

Summary of Regression Analysis for Variables Predicting Perceived Enjoyment (n = 47)

Variable	*B*	SE B	β	R^2
Fixation Duration-AOI	-0.020	0.014	-.203	.041
Fixation Duration-Total	-0.005	0.002	-.355 *	.126 *
Fixation Count-AOI	-0.006	0.005	-.201	.040
Fixation Count-Total	-0.002	0.001	-.326 *	.106 *
Visit Duration-AOI	-0.020	0.013	-.219	.048
Visit Duration-Total	-0.011	0.003	-.525 ***	.276 ***
Visit Count-AOI	-0.016	0.013	-.179	.032
Visit Count-Total	-0.010	0.007	-.202	.041

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Summary. The results showed that there is a statistically significant interaction between total fixation duration and FSS-2 (FSS-Sum, GQ, FS) on perceived science learning (Figure 28). By referring to the Cohen's guidelines for interpreting the magnitude of effect size: .01 = small, .06 = medium, and .14 = large (Cohen, 1988; Dimitrov, 2010), there are large effect size for those interactions between total fixation duration and Flow ($\eta^2_{\text{FSS-Sum}} = .26$; $\eta^2_{\text{FSS-GQ}} = .22$; $\eta^2_{\text{FSS-FS}} = .21$).

There is a positively linear relationship between Flow and perceived science learning (e.g., $r_{\text{FSS-Sum}} = .618$; $r_{\text{eGF-Sum}} = .607$). The coefficient of determination (R^2) showed that the subscale Flow state (FSS/eGF-FS) explained more variance in perceived science learning than the other subscale perceived game quality (FSS/eGF-GQ). For instance, 50.5 percent of the variance in perceived science learning is accounted for by the variance in the eGF-FS whereas there is no statistically significant relationship for eGF-GQ and perceived science learning (R^2 = .042)

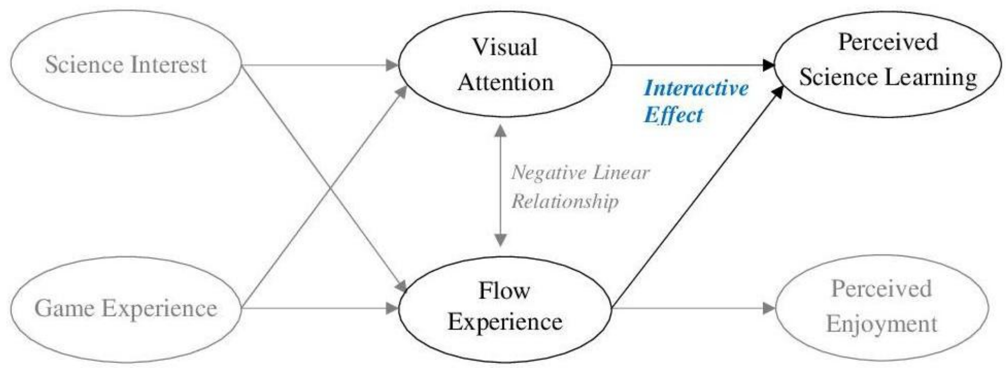


Figure 28 Interactive effect between visual attention and Flow experience on perceived science learning.

There is no interactive effect between Flow and visual attention on perceived enjoyment. However, there is a strong positive linear relationship between Flow and perceived enjoyment (Figure 29). Pearson correlation coefficient indicated between the FSS-FS and perceived enjoyment is r = .645 and that of eGF-FS is r = .639 (p < .001).

The results from the regression analysis showed that the subscale of Flow state (FSS/eGF-FS) explained more variance in perceived enjoyment than the other subscale of perceived game quality (FSS/eGF-GQ). For instance, 40.9 percent of the variance in perceived enjoyment is accounted for by the variance in the eGF-FS but only 23.0

percent of the variance of perceived enjoyment can be explained by the variance in the eGF-GQ.

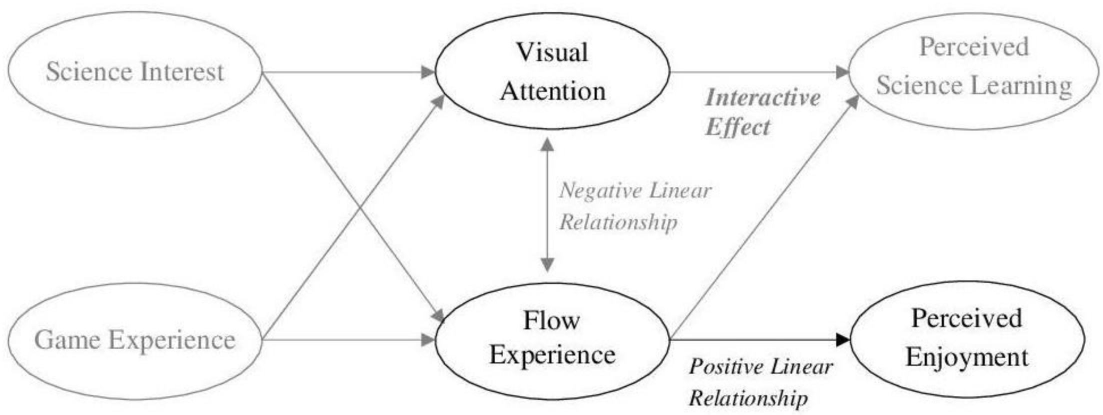


Figure 29 Positive linear relationship between Flow and perceived enjoyment.

RQ 3. What Individual Differences Factors Related to Students' Flow Experience and Visual Attention in an SEG Environment?

RQ 3a. What individual difference factors are the predictors of Flow experience?

Stepwise multiple regression models were calculated with both GQ and FS as criterion variables, as well as the composite score. A set of possible predictor variables of individual traits (science interest, perceived game experience, self-efficacy of science and technology, and absorption trait) was entered in a stepwise fashion to detect the strongest predictor of Flow model.

For the regression analysis for FSS-Sum, one predictor model was resulted. Science interest composite score accounting for 21.8 percent of the variance of FSS-Sum, *F*(1,26) = 7.251, *p*<.05. For every one unit of the science interest score, the predicted FSS-Sum score increases by 1.03 units. Table 60 summarizes the results of the stepwise regression.

The regression analysis for FSS-GQ demonstrated that the set of two predictor variables model (Science interest and SETS-SF subscale: Computer usage) were significant, *F*(2,25) = 6.313, *p*<.01. Since the two predictors has low correlation (*r* = .42), both of them are uniquely representing in the model, explaining 33.6 percent of the variance in perceived game quality. Science Interest scores was the strongest predictor as it alone explains 19.4 percent of the variance in perceived game quality. For predicting the FSS-FS, one predictor model was resulted. Science interest subscale: Teacher influence accounting for 23.8 percent of the variance in Flow state, *F*(1,26) = 8.134, *p*<.01. For every one unit of the science interest subscale: teacher influence, the predicted FSS-FS score increases by 1.90 units.

Table 60

Stepwise Regression for FSS-2 (n = 28)

Criterion Variable	Predictor Variables	B	SE B	BETA	Unique Variance (%)
FSS-Sum R^2 =.218 ; F(1,26)=7.251, p=.012	SIS – Sum	1.027	0.381	0.467*	21.8
FSS-GQ R^2 =.336 ; $F(2,25)$=6.313, p=.006	SETS - Computer Usage	0.608	0.215	0.471**	14.2
	SIS – Sum	0.304	0.112	0.451*	19.4
FSS-FS R^2 =.238 ; F(1,26)=8.134, p=.008	SIS – Teacher Influence	1.898	0.666	0.488**	23.8

Note. Only significant beta weights are shown (n = 28).
* p<.05. ** p<.01.

For the regression analysis for eGF-Sum, one predictor model was resulted. Science interest subscale: Teacher influence score accounting for 17.8 percent of the variance of eGF-Sum, F(1,22) = 4.753, p<.05. For every one unit of the science interest subscale: teacher influence score, the predicted eGF-Sum score increases by 2.29 units. Table 61 summarizes the results of the stepwise regression.

The regression analysis for eGF-GQ demonstrated that the set of two predictor variables model (SIS subscale: Teacher influence and SETS-SF subscale: Computer usage) were significant, F(2,21) = 8.322, p<.01. Since the two predictors has low correlation (r = -.43), both of them are uniquely representing in the model, explaining 44.2 percent of the variance in perceived game quality. Self-efficacy subscale: Computer usage was the strongest predictor as it alone explains 24 percent of the variance in perceived game quality. For every one unit of the science interest subscale: teacher influence and self-efficacy subscale: computer usage, the predicted eGF-GQ score increases by 1.69 units and 1.10 units, respectively. However, there is no predictor model was found for eGF-FS scale.

Table 61

Stepwise Regression for eGF (n = 24)

Criterion Variable	Predictor Variables	B	SE B	BETA	Unique Variance (%)
eGF-Sum					
R^2 =.178 ; F(1,22)=4.753, p=.040	SIS – Teacher Influence	2.285	1.048	0.421*	17.8
eGF-GQ					
R^2 =.442 ; F(2,21)=8.322, p=.002	SIS – Teacher Influence	1.688	0.447	0.681***	20.2
	SETS – Computer Usage	1.089	0.362	0.542**	24.0
eGF-FS					
No model fit					

Note. Only significant beta weights are shown (n = 24).
* p<.05. ** p<.01. *** p<.001.

With the same procedure, stepwise multiple regression models were calculated with gaze data (total fixation duration, total fixation count, total visit duration, and total visit count). A set of possible predictor variables of individual traits (science interest, perceived game experience, self-efficacy of science and technology, and absorption trait) was entered in a stepwise fashion to detect the strongest predictor of visual attention variables. However, no predictor model was found for any of the visual attention variables.

RQ 3b. Is there any correlation between science interest and visual attention?

A list of variables of visual attention from the combined data of Scene 1 and Scene 2 was entered for testing the relationships with the predictor of science interest using simple linear regression analysis (n = 45). They are: Fixation duration on AOIs, total fixation duration, fixation count on AOIs, total fixation count, visit duration on AOIs, total visit duration, visit count on AOIs, and total visit count. The means and standard deviations of the variables are listed in Table 62. The results showed that only total fixation duration, total fixation count, and total visit duration are statistically significant.

Table 62

Means and Standard Deviations for Science Interest Scale and Visual Attention Variables

Variables	Mean	STD
Predictor variable		
Science Interest	70.09	7.106
Criterion variables		
Fixation Duration-AOI (second)	50.746	32.604
Fixation Duration-Total (second)	579.58	218.730
Fixation Count-AOI	147.67	98.168
Fixation Count-Total	1796.91	627.512
Visit Duration-AOI (second)	59.362	35.123
Visit Duration-Total (second)	803.541	150.099
Visit Count-AOI	54.31	36.214
Visit Count-Total	114.96	65.234

The Pearson correlation coefficient between the predictor variable (*X*, science interest) and criterion variable (*Y*, total fixation duration) is $r = -.471$, and is statistically significant at the .001 level, F (1, 43) = 12.287, $p < .001$. There is a negative linear relationship between science interest and total fixation duration, which means students with higher science interest score have shorter total fixation duration during gameplay. The coefficient of determination, $R^2 = .222$, thus indicating that 22.2 percent of the variance in the total fixation duration is accounted for by the variance in the science interest scores. The simple linear regression equation for the prediction of total fixation duration (Y) from science interest scores (X) is: $\hat{Y}$ = (-14.511) X + 1596.667. Table 63 summarizes the result.

There is also a negative linear relationship between the total fixation count (Y) and science interest scores (X). The correlation coefficient (r = -.452) is statistically significant at the .01 level, F (1, 43) = 11.052, p = .002, i.e., students with higher science interest scores have lower total number of fixation count. The R^2 = .204, thus indicating that 20.4 percent of the variance in the total fixation count is accounted for by the variance in the science interest scores. The simple linear regression equation for the prediction of total fixation count (Y) from science interest scores (X) is: $\hat{Y}$ = (-39.932) X + 4595.730.

For the total visit duration, there is a negative linear relationship with science interest score (X). The correlation coefficient (r = - .375) is statistically significant at the .05 level, F (1, 43) = 7.042, p = .011. The coefficient of determination, R^2 = .141, thus indicating that 14.1 percent of the variance in the total visit duration is accounted for by the variance in the science interest scores. The simple linear regression equation for the prediction of total visit duration (Y) from science interest scores (X) is: $\hat{Y}$ = (-7.924) X + 1358.833.

Thus, for every one unit of science interest score, the total fixation duration, total fixation count, and total visit duration decreases by 14.51 units, 39.93 units, and 7.92 units, respectively.

Table 63

Summary of Regression Analysis for Science Interest Predicting the Following Visual Attention Variables (n = 45)

Variable	*B*	SE B	β	R^2
Fixation Duration-AOI	-1.238	0.674	-.270	.073
Fixation Duration-Total	-14.511	4.140	-.471	.222 ***
Fixation Count-AOI	-3.861	2.023	-.279	.078
Fixation Count-Total	-39.932	12.012	-.452	.204 **
Visit Duration-AOI	-1.324	0.726	-.268	.072
Visit Duration-Total	-7.924	2.986	-.375	.141 *
Visit Count-AOI	-1.053	0.760	-.207	.043
Visit Count-Total	-2.359	1.353	-.257	.066

*$p < .05$. **$p < .01$. ***$p < .001$.

RQ 3c. Is there any correlation between science interest and Flow experience?

While two sets of Flow survey scores were entered for testing the relationships with the predictor of science interest using simple linear regression analysis ($n = 25$), only FSS-2 scores showed statistically significant. The means and standard deviations of the variables are listed in Table 64.

Table 64

Means and Standard Deviations for Science Interest Scale and FSS-2 Scales (n = 25)

Variables	Mean	STD
Predictor variable		
Science Interest	70.48	7.054
Criterion variables		
FSS-Sum	141.08	16.753
FSS-Perceived Game Quality	47.84	5.113
FSS-Flow State	93.24	12.801

The Pearson correlation coefficient between the predictor variable (*X*, science interest) and criterion variable (*Y*, FSS-Sum) is $r = .483$, and is statistically significant at the .05 level, $F(1, 23) = 7.000$, $p = .014$. There is a positive linear relationship between science interest and the FSS-sum scores, which mean students with higher science interest score experienced higher flow score. The coefficient of determination, $R^2 = .233$, thus indicating that 23.3 percent of the variance in the FSS-sum scores is accounted for by the variance in the science interest scores. The simple linear regression equation for the prediction of FSS-Sum scores (*Y*) from science interest scores (*X*) is: $\hat{Y} = (1.147)\, X + 60.225$. Table 65 summarizes the results.

Positive linear relationship between the FSS-GQ (*Y*) and science interest scores (*X*) was observed, i.e., students with higher science interest score experienced higher perceived game quality scores. The correlation coefficient ($r = .414$) is statistically significant at the .05 level, $F(1, 23) = 4.744$, $p = .040$. The $R^2 = .171$, thus indicating that

17.1 percent of the variance in the FSS-GQ is accounted for by the variance in the science interest scores. The simple linear regression equation for the prediction of FSS-GQ (*Y*) from science interest scores (*X*) is: $\hat{Y} = (0.30)\ X + 26.72$.

The Pearson correlation coefficient between the science interest (*X*) and FSS-FS (*Y*) is $r = .467$, and is statistically significant at the .05 level, $F\ (1, 23) = 6.416$, $p = .019$. There is a positive linear relationship between science interest and the FSS-FS scores, i.e., students with higher science interest score experienced higher Flow state score. The coefficient of determination, $R^2 = .218$, thus indicating that 21.8 percent of the variance in the FSS-FS scores is accounted for by the variance in the science interest scores. The simple linear regression equation for the prediction of FSS-FS scores (*Y*) from science interest scores (*X*) is: $\hat{Y} = (0.848)\ X + 33.508$. In sum, for every one unit of science interest score, the FSS-Sum, FSS-GQ, and FSS-FS scores increases by 1.15 units, 0.30 unit, and 0.85 unit, respectively.

Table 65

Summary of Regression Analysis for Science Interest Scale Predicting the Following Flow Scales (n = 25)

Variable	*B*	SE B	β	R^2
FSS-Sum	1.147	0.434	.483 *	.233 *
FSS-Game Quality	0.300	0.138	.414 *	.171 *
FSS-Flow State	0.848	0.848	.467 *	.218 *

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Summary. The results from the stepwise regression showed that one predictor model was found in FSS-Sum, FSS-FS, and eGF-Sum, where science interest subscale (SIS-Teacher Influence) was the strong predictor of FSS-FS ($p < .01$) and eGF-Sum ($p < .05$). Two-predictor model was found in both GQ subscale (FSS-GQ and eGF-GQ), where Self-efficacy for computer use (SETS-Computer Usage) and science interest (sum or teacher influence) were the predictor of perceived game quality (Figure 30).

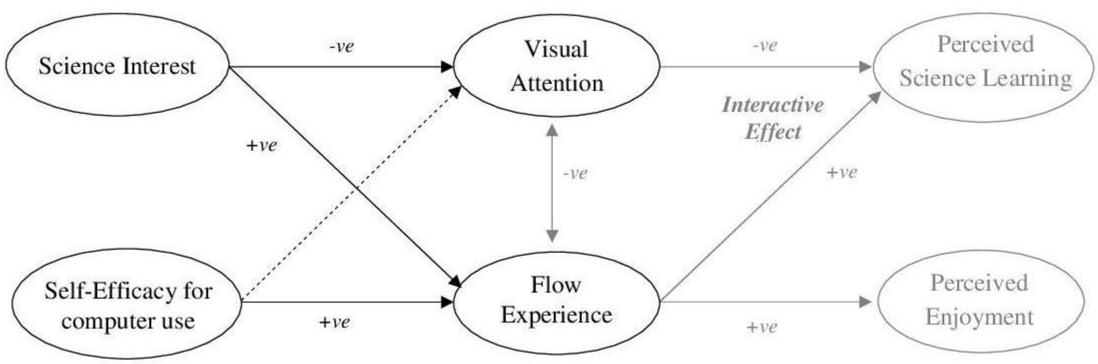


Figure 30 Science interest and self-efficacy for computer use are the predictors of Flow in a science SEG.

The Pearson correlation coefficient showed that there is a moderate negative linear relationship between science interest and visual attention variables ($r_{\text{total fixation duration}} = -.471$; $r_{\text{total fixation count}} = -.452$). On the other hand, there is a moderate positive linear relationship between science interest and Flow ($r_{\text{FSS-Sum}} = .483$; $r_{\text{FSS-GQ}} = .414$; $r_{\text{FSS-GQ}} = -.467$). Figure 30 indicated the linear relationship between science interest and visual attention or Flow experience. The coefficient of determination (R^2) showed that science interest explained more variance in the subscale Flow state than that in the subscale perceived game quality, where 21.8 percent of the variance in the FSS-FS scores is accounted for by the variance in the science interest scores, but only 17.1 percent of the variance in the FSS-GQ is accounted for by the variance in the science interest scores.

CHAPTER FIVE: DISCUSSION

Based on an interdisciplinary review of the literature from cognitive psychology, affective science, Flow theory, and game-based learning, I proposed a theoretical model that examined the following three relationships in a science SEG environment: (a) the relationship between the visual attention and Flow experience, (b) the outcomes of visual attention and Flow, and (c) individual differences factors with regards to visual attention and Flow (see Figure 1). The present investigation was designed to test these relationships that are theoretically related to the cognitive processes in gameplay. In this section, I will summarize the results from Chapter 4 and explain the findings based on the cognitive-affective integrated framework of cognitive psychology. I will also examine the measurement perspective of Flow by comparing the generic and context-specific Flow scales, as well as by comparing the two conceptualizations of Flow – that is, treating Flow as a unidimensional measure (sum scores) or a multidimensional reflective measure (two-latent-constructs model: perceived game quality and Flow state).

Demographic Effect on Flow and Visual Attention

Three demographic items – students' science grade, gamer status (moderate or frequent), and gender – were selected to test the possible interactive effects of these variables on Flow experience and on visual attention in a science SEG environment. The results revealed that science grade plays an important role in both Flow experience and visual attention.

Impact of science grade, gender, and gamer status on Flow. The results showed that Grade B students obtained the highest Flow experience regardless of their gender and gamer status. Post-hoc study showed a statistically significant difference in Flow between Grade A and Grade B students, where Grade B students scored higher in Flow; but no differences among the other science grade groups. The cause of this difference was not clear, but it is speculated that Grade A students may spend more time studying and less time in other activities, such as playing digital games. Grade A students may also be less confident about their perceived skill mastery in digital games than students in the Grade B group. One important characteristic of Flow is the challenge-skill balance. Students' skill mastery depends on their previous exposures to gameplay, and lower perceived game skill may affect players' elicitation of Flow experience.

As for the interaction between science grade and gamer status, both moderate and frequent gamers obtained similar levels of Flow in the Grade B group; likewise, the frequent gamers in the Grade A group had a similarly high Flow experience as well. It is believed that, since frequent gamers have high levels of exposure to digital games and are more confident in their perceived game skill, they can therefore achieve the desired challenge-skill balance while playing Neuromatrix, the SEG used in this study. However, the Flow experience dropped dramatically among the moderate gamers in the Grade A group. Presumably the Grade A moderate gamers do not spend as much time playing games as the moderate gamers in the Grade B group, perhaps because spend more time studying, or they do not have the same confidence in their perceived game skill as their counterparts. These factors, in turn affect their challenge-skill balance and ultimately their Flow experience.

All students from the Grade C or below group reported that they are frequent gamers. Unlike the other frequent gamers in the Grade A and B groups, however, they experienced the lowest level of Flow. The issue of perceived balance between challenges and skills may also apply to this group of students. Students with lower science achievement (Grade C or below) may spend less time studying but more time on other activities, such as playing digital games. Even among the frequent gamers, they may actually spend more time on gameplay than those with higher science grades. Their perceived game skill level may thus be the highest, making Neuromatrix not challenging enough to match their skill level and hence hindering their Flow experience.

As for the interactive effect between gender and gamer status, female gamers experienced lower levels of Flow than their male counterparts among all frequent gamers, but the trend was opposite for the moderate gamers group, as female experienced much higher Flow than their male counterparts. The reason for this interaction between gender and gamer status is not clear. There is a need to further explore whether other game- or gender-specific variables, such as self-efficacy of gameplay or preferred game types, may have an effect on students' Flow experience.

Impact of science grade and gamer status on visual attention. There is also a significant interactive effect between science grade and gamer status on visual attention. Among the frequent gamers, there was not much difference in total visit duration (cumulative duration of a series of consecutive fixations within an area) between the Grade A and B groups, and both groups had moderate total visit duration during gameplay. However, there was a significant difference between the Grade A and B groups for moderate gamers, as Grade A students had a much higher total visit duration in gameplay than those in the Grade B group. As discussed earlier, the moderate gamers in the Grade A group may not have the same skill mastery in digital games when compared to their counterparts in the Grade B group, and so higher total visit duration resulted. Evidence from research studies on airplane pilots has indicated that novice pilots have a higher dwell time (another name for visit duration) than experienced pilots during a navigational task; in addition, usability studies have shown that long dwell time may be related to users' slower cognitive processes in extracting information from the environment (Holmqvist et al., 2011). Therefore, the high visit duration observed in the moderate gamers of the Grade A group may indicate their uncertainty during gameplay, poorer situation awareness, or difficulty in extracting general information from the SEG environment.

RQ 1. What are the Associations Between Visual Attention and Flow Experience During Gameplay?

Psychological perspective. Evidence from cognitive psychology and neuroscience suggests that our cognitive processes are significantly affected by and subsumed within our emotional processes. It is time to expand our current framework in the study of game-based learning through an interdisciplinary approach in order to inform our theoretical understanding of the interplay between cognition and affect. SEG researchers should look into the details of and empirically investigate the relationships between positive affect and cognitive processes in gameplay. The results from this study showed that a statistically significant negative correlation between Flow experience and visual attention (Figure 31). In other words, students with higher Flow levels had lower fixation counts and shorter visit duration during gameplay, with Flow experience explaining as much as 36% and 40% of the variances in the total fixation count and total visit duration respectively. Visual attention is closely associated with Flow experience; in particular, there is a correlation between total visit duration and the Flow subscale of perceived game quality (GQ).

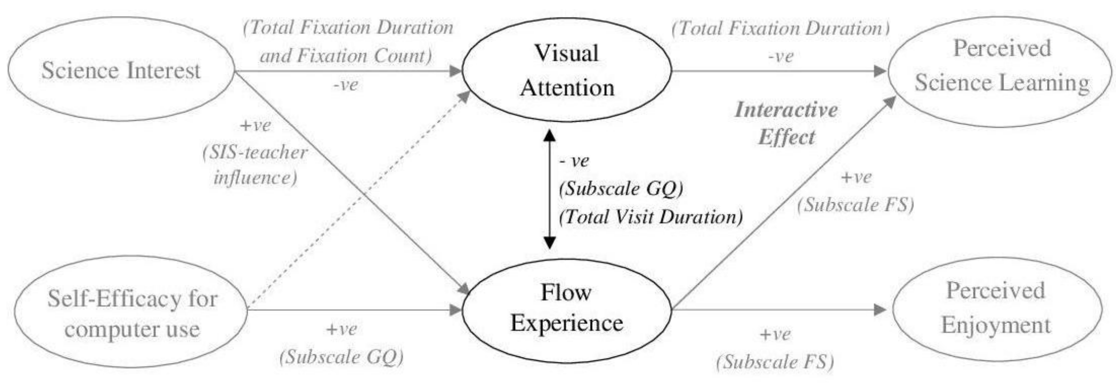


Figure 31 Negative linear relationship between visual attention and Flow experience during gameplay.

Evidence from an experimental study conducted by Jennett et al. (2008) suggest that individuals' eye movements decrease in the immersive game condition because their attention becomes more focused on visual components that are relevant to the game.

Thus, lower fixation counts may indicate that students' attention is more focused during gameplay and that they feel more immersed in the SEG. The findings can be explained by Flow theory, in which total concentration on task at hand and action-awareness merging are two of the nine conceptual elements of Flow experience; for that reason, lower fixation counts could be associated with immersion, or a feeling of being completely focused and absorbed in gameplay, which is the hallmark of Flow.

Visit duration is often defined as the sum of all fixation durations during a visit to an area. When students are playing in a dynamic 3-D game environment, long visit duration may correlate with difficulty in extracting information from the game scenes, feeling uncertainty regarding the game environment, or poor situational awareness, as indicated by the expert-novice research and usability studies mentioned earlier. The dual-process theories of cognition may also help to explain the cognitive operations that occur during long visit duration and how they relate to Flow experience. The theory suggests that, when tasks become more difficult, System 2 takes over and supports a more detailed and specific processing that attempts to solve the immediate problem. This experience may occur in long visit duration as well, with System 2 taking over when students encounter difficulty in gameplay. This shift requires self-control and cognitive efforts to overcome the impulses of System 1, the default mode of processing. Students may feel that they were making a greater effort during gameplay when System 2 was in operation.

On the other hand, short visit duration may indicate better navigational skill, more efficient selective visual attention, higher perceptual fluency (familiarity), and faster cognitive processing; i.e., System 1 may run automatically in a comfortable, low-effort mode. In this situation, students are experiencing a state of cognitive ease during gameplay. A person in a state of cognitive ease may feel a positive mood, and the work being one may seem familiar and effortless (Kahneman, 2011). Similarly, de Manzano et al. (2010) proposed that Flow can be viewed as a state of effortless attention that arises through an interaction between positive affect and high attention, whereas Kahneman (2011) stated that cognitive ease is both a cause and a consequence of pleasant feelings. Therefore, short visit duration is closely related to high level of Flow experience and may serve as an indicator of efficient visual attention and a state of cognitive ease in an SEG environment.

Moreover, patterns emerging from the qualitative scanpath analysis showed that a combination of top-down and bottom-up processes in attentional control was observed in the high Flow group. High Flow students did not spent much time on tasks (AOIs) or on distractors (non-AOIs). This result may indicate that players constantly distinguished tasks from distractors in a proficient way, an activity that involves a certain degree of bottom-up processes (stimulus-driven attention), and that they demonstrated efficiency of selective attention as well as cognitive processing in gameplay. In addition, high Flow students learned the game rules quickly. Scanpath patterns showed that they located the first task mission faster than the lower Flow students. This fact may indicate that they performed better in becoming attuned to the predictive relationships present in a task and oriented their attention rapidly in response to the next task. It may also imply that they had a clear goal in mind and established attentional behavior that was sensitive to the predictive relations between the tasks and the mission goal, which in turn enable them to play the game successfully using a top-down (goal-directed attention) strategy. Therefore, gaining effective control of the two attentional processes (bottom-up and top-down) enabled the players to begin to have a sense of control over the environment (reflected by the higher GQ scores) and caused their participation to seem effortless (efficient selective attention and cognitive processing when System 1 is running). They became so focused on the SEG and felt so immersed in the gameplay that they totally dissolved into the surroundings and lost their self-consciousness. This experience was reflected by lower fixation counts, shorter visit duration, and fewer shifting between AOIs and non-AOIs. Such measures indicate the characteristics of Flow, the optimal state of experience.

On the contrary, the qualitative scanpath analysis showed that medium or low Flow students exhibited higher shifting between AOIs and non-AOIs, spent longer time in locating the first task, wandered around the 3-D game environment longer, and spent more time completing the mission. It is probable that they experienced loss of control, got bored by wandering around without a clear goal in mind, or felt frustrated when they could not figure out the game rules. Because of their disorientation during gameplay, these students required more cognitive efforts to perceive the environment and make sense of it. More shifting between AOIs and non-AOIs may imply that students were in a state of vigilance. Both perceptual load and cognitive load were high as they could not efficiently filter out the distractors from target objects (poorer selective attention efficiency). This experience may lead to higher arousal, alertness, and sense of effort. Moreover, students spent more time walking in the game environment may represent low cognitive demand, which may lead to low arousal and a state of mind wandering. This cognitive-affective overload or underload may lead to difficulty in reaching the higher level of Flow, for which feelings of effortlessness and immersion are essential.

Measurement perspective. With regard to the two Flow scales (FSS-2 and eGF), FSS-2 predicted more relationships with visual attention variables than did eGF. The scores of FSS-Sum and FSS-GQ had statistically significant relationships with all eight visual attention variables, whereas only three visual attention variables had statistically significant relationships with eGF-Sum. However, eGF (Sum, GQ, and FS) explained more of the variance in those significantly correlated visual attention variables than did FSS-2. For instance, 40.0% of the variability observed in total visit duration can be explained by eGF-Sum, but only 30.4% of the variance in total visit duration was explained by FSS-Sum. This result suggests that the generic Flow scale, FSS-2, demonstrates more robust psychometric properties and has a higher positive predictive value than eGF because it increases the probability that a relationship will be identified. On the other hand, the context-specific eGF scale is more sensitive as it detects more precise relationships and captures a higher level of variability invisual attention variables than FSS-2. In order to better differentiate the measurement validity of these two Flow scales with regard to game-based learning, it is necessary to further evaluate their respective psychometric properties, especially the measures of sensitivity, specificity, and predictive value, with larger samples. Moreover, research effort should be invested in further testing the sensitivity of both Flow scales to fixation counts and total visit duration, as these are the two critical visual attention variables in determining the cognitive-affective aspect of gameplay processes. The eGF scale seems able to capture the essence of gameplay-related visual attention variables better than the generic FSS-2; this Flow scale may become a useful diagnostic measurement tool in predicting Flow in game-based learning and may thus serve as a useful tool in assessing the effectiveness of SEGs.

When compared the two conceptualizations of Flow in this study, the findings showed that the unidimensional measure (sum scores) identified more significant relationships with regard to visual attention than did the multidimensional reflective measure (GQ and FS) for both Flow scales. However, the results from both FSS-2 and eGF showed that the multidimensional measure explains more variances in gameplay-related visual attention variables than the sum score. For example, in the case of FSS-2, the R^2 difference is as high as 8.9% when explaining the variability observed in total fixation counts ($R^2_{\text{FSS-GQ \& FS}}$ = 32.9% as compared to $R^2_{\text{FSS- Sum}}$ = 24.0%).

Flow researchers have generally agreed that multidimensional measures of Flow offer a more realistic approach and have been supported by substantive empirical evidence (Hoffman & Novak, 2009; Jackson, 2012). Therefore, SEG and Flow researchers should continue to investigate the use of higher-order factors to provide a more holistic definition of Flow in game-based learning, that can be tested for statistical fit in a structural model, as well as allowing the higher-order factors to be broken down into two or more constituent constructs depending on the theoretical framework and empirically measuring performance of the respective models (Hoffman & Novak, 2009).

RQ 2. What are the Associations Between Visual Attention, Flow Experience, and their Outcomes (Perceived Science Learning and Perceived Enjoyment) through Playing an SEG?

Perceived science learning. There is a statistically significant interactive effect of visual attention and Flow on perceived science learning, but a relationship was found only between the total fixation duration and FSS-2. As discussed earlier, short visit duration represents efficiency of selective visual attention and may serve as an indicator of Flow experience during gameplay, whereas, in this case, total fixation duration may be an indicator of perceived learning in a science SEG environment. Figure 32 summarizes the interactive effect of visual attention and Flow experience on perceived science learning.

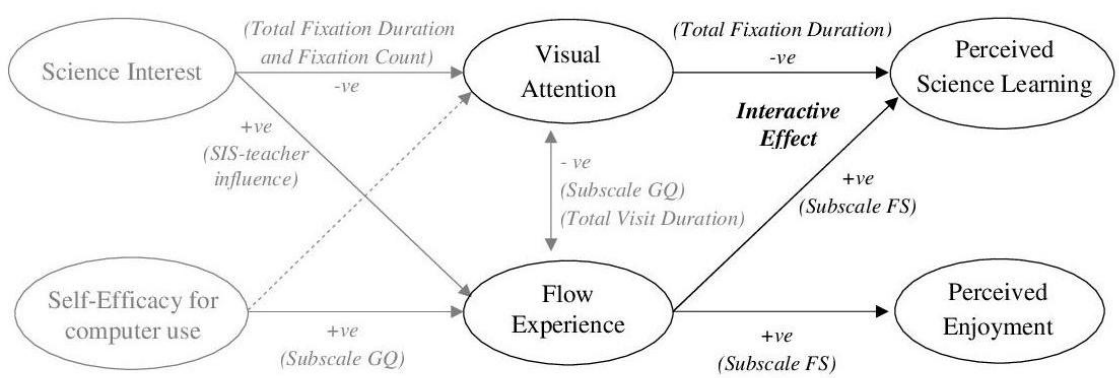


Figure 32 Relationships between visual attention, Flow experience, and their outcomes in a science SEG.

Psychological perspective. Learning is a complex process that involves not only aspects of cognitive processing such as working memory capacity and other executive functions, but also attentional processing that determines if the learning materials can enter into our conscious attention. Selective attention is important as we are forced to choose to orient ourselves toward some sensory objects rather than others due to our limited mental resources. Substantial research has examined the dynamics of visual orientation and the effects of learning, both implicit and explicit, on the processes involved in shifting attention from one visual object to another (Lambert, 2003). According to the eye-mind hypothesis (Just & Carpenter, 1980; Yarbus, 1967), fixation duration represents cognitive processing. When a participant looks at an object, he or she also simultaneously processes it attentionally and cognitively. However, the eye-mind hypothesis may become controversial when applied in real-world situations. Fixation does not necessarily entail processing and there is no guarantee that all objects that we look at are registered into our attentional system. Yet, at the same time, processing does not happen only at the moment when we fixate on an item but may continue for a long time after the eye has left the fixated point (Holmqvist et al., 2011). In spite of the presence of conflicting arguments of eye-mind hypothesis, we must not forget that seeing is an attentional process in which the eye has strong selectivity in the processing of foveal and non-foveal objects. After all, perceptual and attentional processes are intimately related based on the design of our visual system (Lambert, 2003). Therefore, total visit duration may tell us about the overall efficiency of our selective attention and cognitive processes that affect Flow experience, whereas total fixation duration tells us what specific visual stimuli (or learning materials) we have looked at in the environment that may possibly pass through the selective filter into our conscious attention, thereby leading to learning.

The results showed that perceived science learning is negatively correlated with visual attention, but positively correlated with Flow. This seems to violate our assumption that longer fixation duration may correspond to more learning as participants receive more visual input from the game environment. Yet the information-processing model argues that there is a processing bottleneck (Broadbent, 1958), in that not all visual stimuli can pass through the attentional filter into our conscious attention; rather, selective attention is necessary. Therefore, effective visual orientation and efficient selective attention are crucial in learning. Long fixation may indicate poor selective attention, difficulty in processing the information, or a feeling of sensory overload (too much visual input).

This study raises an important issue regarding the interactive effect of visual attention and Flow experience on perceived science learning under the cognitive-affective integrated framework. When we look at the ANOVA interaction results for the low fixation duration group, only the high Flow students showed high perceived science learning, and their scores are the highest of all. It seems that when students experienced high level of Flow, even if they spent less time fixated on the game environment, they subjectively felt that they had learned a lot. It may be that their low fixation duration indicates efficient selective attention and cognitive processes.

Interestingly, high Flow students, although they had long fixation duration, still maintained a significantly high perceived science learning score. This may be because their System 1 was running under the experience of Flow, as dual-process theories of cognition suggest that a positive affective state may loosen the control of System 2 over performance. They may feel that their attention was effortless even they had spent long fixation duration. In contrast, high fixation-duration students with low Flow attained relatively low perceived science learning scores. It may have been the case that their low Flow experience did not help to loosen the control of System 2, so System 2 was in operation during gameplay. They may thus have felt that they had to make greater effort to process a large amount of information in the game environment (long fixation duration) and became overwhelmed, which resulted in lower perceived science learning. It may also be possible that their selective attention was not as efficient as the other groups and so impeded learning.

The medium fixation duration group, on the other hand, revealed a very different pattern. In this group, high Flow students reported the lowest perceived science learning scores while the low Flow students indicated much higher perceived science learning scores than the other groups. Since game-based learning is a complex process, the outcomes of Flow and visual attention – perceived enjoyment and perceived learning in this case, can be treated as two separate entities even though both seem to be closely related to SEG. High Flow students with medium fixation duration may have felt neither efficient in selective attention (as reflected by short fixation duration) nor cognitively running in System 1 (as discussed in the previous paragraph with regard to the high Flow and long fixation duration group); as a result, they may have felt that they did not learn much from the SEG (low perceived science learning scores) even they enjoyed the gameplay (high Flow scores). On the contrary, the low Flow students could have perceived more science learning because they obtained more information in the game environment during their moderately long fixations, but did not feel overloaded like the high fixation group, even though they did not enjoy the SEG as much as other players.

In conclusion, in order for students to benefit from the cognitive-affective integration and achieve positive learning, efficiency of selective attention and cognitive processes are the keys. Otherwise, perceived enjoyment and learning will become separate entities, and students may not have deep engagement experience in a game-based learning environment as intended.

Measurement perspective. The results from the regression analysis showed that the construct of Flow state (FSS-FS; $R^2 = .363$) explained more of the variance in perceived science learning than that of perceived game quality (FSS-GQ; $R^2 = .255$). This is different from the comparison between Flow experience and visual attention, in which GQ explained more variance in visual attention variables than FS. So the real feeling of Flow, such as sense of control, loss of self-consciousness, and transformation of time, has a bigger impact on students' perceived learning in an SEG environment than factors of perceived game quality such as challenge-skill balance, unambiguous feedback, and clear goals.

Similar to early findings, the context-specific eGF was more sensitive in capturing the relationship between Flow state and perceived science learning than FSS-2; eGF-FS explained 50.5% of the variance in perceived science learning, whereas FSS-FS explained only 36.3%.

Regarding the conceptualization of Flow, the unidimensional sum score model of FSS-2 was as good as the multidimensional two-latent-construct model in predicting the students' perceived science learning in an SEG environment. However, the two-latent-construct model of eGF (eGF-GQ & FS; $R^2 = .513$) accounted for more variance in perceived science learning than that of sum score (eGF-Sum; $R^2 = .369$).

In conclusion, the subscale perceived game quality (GQ) may have more impact on players' navigation in the game environment and is highly associated with visual attention. Flow state (FS), on the other hand, may have more influence on how much the players subjectively feel that they have learned. The result can be explained by the Affective Response Model (Zhang, 2013), where FS is considered as an induced affective state that has an effect on the evaluative process in an HCI episode. In studies of game-based learning, consequences of Flow state may be linked to happiness and satisfaction, with the pleasant feelings enhancing students' perceived learning after gameplay.

Perceived enjoyment. Unlike perceived learning, which involves the efficiency of attentional and cognitive processes on which Flow has an impact, perceived enjoyment has a more direct link to Flow experience than to visual attention, as both enjoyment and Flow represent similar positive affective states. The results showed no interactive effect of visual attention and Flow in predicting perceived enjoyment. Since total visit duration is closely associated with Flow experience, it is not surprising that total visit duration has a statistically significant relationship with perceived enjoyment accordingly to the simple linear regression analysis (Figure 32).

From a measurement perspective, Flow state (FSS-FS; R^2 = .416) explained more variance in perceived enjoyment than did perceived game quality (FSS-GQ; R^2 = .187). This is because GQ is treated as representing the prerequisite elements for achieving Flow of an SEG design, whereas FS is a diagnosis of whether a player has actually reached Flow (Salen & Zimmerman, 2004). Therefore, FS can be considered as the real affective state and is more effective in predicting students' perceived enjoyment than GQ.

The results indicated that the unidimensional model of Flow was as efficient as the multidimensional model of Flow in predicting students' perceived enjoyment, where both sum-score and two-latent-construct models showed similar results and accounted for similar variances in perceived enjoyment. Moreover, both Flow scales (FSS-2 and eGF) had a similar predictive ability with regard to perceived enjoyment scores.

RQ 3. What Individual Differences Factors Related to Students' Flow Experience and Visual Attention in an SEG Environment?

Predictive modeling for Flow. Stepwise regression is a model selection (or variable selection) method that aims to choose a small subset from the large set of candidate predictor variables by an iterative, constructive progress. The resulting regression model is simple, yet has good predictive ability. In this study, a pool of candidate individual differences variables related to game-based learning and Flow experience were included in the regression model. The results suggested that science interest is an crucial predictor in explaining Flow experience, as it appeared in all the predictive models from both Flow scales (FSS-Sum, -GQ, and -FS; eGF-Sum and -GQ, but not eGF-FS where no predictive model was found). The SIS sum score predicted

FSS-Sum and FSS-GQ, whereas the SIS-Teacher Influence subscale predicted FSS-FS, eGF-Sum, and eGF-GQ.

The four items that reflected the construct of the SIS Teacher Influence subscale are “My teachers encourage me to do my best,” “My science teachers have encouraged me to learn about science,” “My science teachers make science interesting,” and “My science teachers are enthusiastic about science.” The words used in these statements, such as “interesting” and “enthusiastic,” depict positive affective states. They are characterized as positive valence and optimal arousal when referring to the Circumplex model of affect (Russell, 1980). These affective states are associated with pleasant feelings and perceived personal relevance. It is interesting to note that similar phrasings describing affective states were used in statements contained in another SIS subscale, *Family Encouragement*, but this construct did not show up in any of the predictive models of Flow. Teachers may play a more influential role in students’ positive experience in game-based learning than families do. It is possible that the teachers’ words carry more meaning to the students, as they represent unbiased opinions and honest assessments of students’ perceived science ability without any familial bias attached to it. This construct may thus carry more weight on the SIS and may better predict students’ overall Flow experience in game-based science learning.

Besides science interest, a subscale from the SETS-SF, Self-Efficacy for Computer Use, was also selected in the predictive models of both FSS-GQ and eGF-GQ in the stepwise regression analysis. This may be due to the fact that the SEG used in this study is a computer-based game in which students relied on the keyboard and mouse to control navigation. How confident a student is in using the keyboard and mouse controls may determine his or her navigational skill in gameplay, which is more directly related to the dimension of GQ in Flow. Hence, this construct was selected only in the predictive model of GQ, but not in the FS model. Self-efficacy for computer use serves as another important indicator in game-based learning, because in Flow theory how a person *perceives* a situation as a challenge and how it incorporates their perceived skill are critical to the occurrence of Flow, rather than the actual demands of a situation or one's objective ability level (Jackson, 2012; Jackson & Csikszentmihalyi, 1999). The challenge-skill balance sets a foundation for Flow to occur and may be considered as an antecedent of Flow (Hoffman & Novak, 1996). Students' perceived self-efficacy for computer use, in this case, may represent their high perceived game skill, and thus it becomes a predictor variable of perceived game quality in a stepwise regression. Figure 33 illustrates the relationships among individual differences factors, visual attention, and Flow experience.

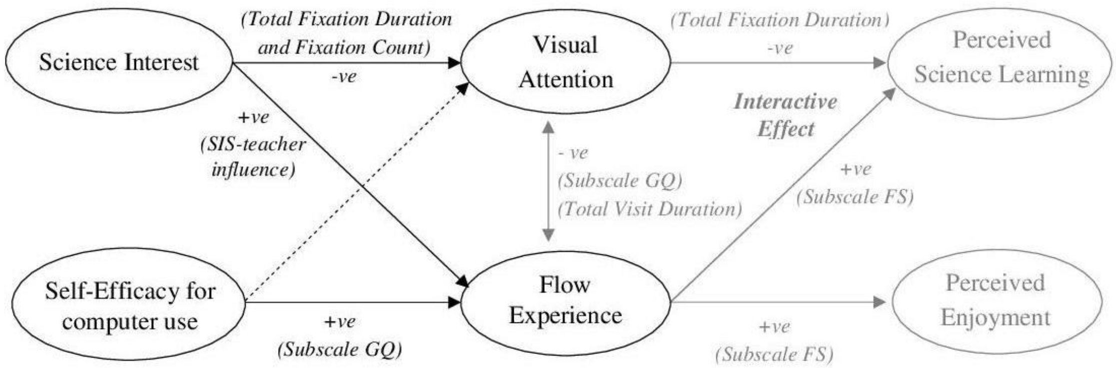


Figure 33 Relationship between individual differences factors, visual attention, and Flow experience.

From a measurement perspective, more predictive models were detected in FSS-2 than in eGF; one predictor model was found in FSS-FS (R^2 = .238) but none was found in the eGF-FS. However, the two-predictor model found in eGF explained more variance in eGF-GQ than that in FSS-GQ ($R^2_{\text{eGF-GQ}}$ = .442 as compared to $R^2_{\text{FSS-GQ}}$ = .336). Further examination of the psychometric properties of each Flow scale is needed in order to understand the differences in the explanations of variances in these two dimensions of Flow (GQ and FS) in an SEG environment.

Predictive modeling for visual attention. Stepwise regression with the same pool of candidate individual differences variables was used to test the predictive model of visual attention. There was no model fit for any of the visual attention variables. Nonetheless, the qualitative scanpath analysis showed some patterns about the relationships between students' perceived game experience, science interest, and visual attention that may affect the process of gameplay. Individual differences may have an impact on the attentional control and cognitive processes in gameplay, but the subtleties of their operations may be too difficult to detect in a regression model; as a result, no predictor model was found in stepwise regression.

From a psychological perspective, perceived game experience (found to be a predictor in the pilot study, and patterns found in scanpath analysis) and self-efficacy for computer use (found to be a predictor in the final study) may serve as key affective concepts in game-based learning, consciously or unconsciously affecting aspects of players' cognitive processing such as perceptual fluency and cognitive ease. In terms of the dual-process theories of cognition as applied to gameplay (Svahn, 2009), students who show confidence with their perceived skills in computer use or are experienced in digital games may start with a default heuristic or System 1 mode of processing during gameplay as they are more adapted to the 3-D navigation and game environments. Playing a game reasonably well provides a foundation for students to obtain Flow and becomes the antecedent of Flow in an SEG environment. The dotted line in Figure 33 illustrates how self-efficacy for computer use may have an indirect effect on visual attention.

Science interest, on the other hand, serves a different purpose in visual attention and Flow experience, as the following sections will discuss in detail.

Science interest and visual attention. There was a negative correlation between science interest and visual attention. The results showed that science interest has statistically significant relationships with three of the visual attention variables: the total fixation duration, total fixation counts, and total visit duration. These three visual attention variables consistently displayed statistically significant relationships in the study, and it appears that they play a critical role in explaining students' cognitive processes and Flow experience in a game-based learning environment.

Forgas (2001) suggested that task familiarity, complexity, and novelty, along with personal relevance, motivation, and cognitive capacity are variables that determine processing choices. It may be the case that science interest affects students' processing choice during gameplay. The story background of Neuromatrix is a science research laboratory with many science-related objects such as petri dishes, volumetric flasks, and science posters. Students with high science interest may unconsciously gravitate towards things with which they are familiar. The positive affective state generated from familiarity and the processes of selective attention operate together in prioritizing thoughts and actions that enhance players' perceptual fluency and increase their efficiency in selective attention, in turn enabling them to attain a state of cognitive ease. The players became more immersed in the game environment and felt more efficient in cognitive processing due to the operation of System 1. This cognitive-affective processing can be reflected by lower fixation counts and by shorter fixation and visit durations.

Science interest and Flow. The results showed that science interest has a positive correlation with Flow experience, and this variable explained the variance in Flow state (FSS-FS; R^2 = .218) better than the variance in perceived game quality (FSS-GQ; R^2 = .171). When compare these results to previous findings, we see that perceived game experience and self-efficacy of computer use are more related to GQ, whereas science interest is more associated with FS. The visual attention perspective may explain the possible effect of science interest on the attentional and cognitive processes, which at the same time are correlated with Flow experience within the cognitive-affective integrated framework. The familiarity with the laboratory setting and science equipment that appear in Neuromatrix may help students to become more immersed in the game environment and facilitate their elicitation of Flow experience throughout their gameplay.

From a measurement perspective, only FSS-2 showed statistically significant correlations with science interest; no significant relationship was found in eGF. This may be because FSS-2 shows more robust psychometric properties and is easier to apply in a broader context. Thus, it has a higher probability of identifying relationships even when the variables are not game-related, such as science interest in this case. In contrast, the sensitivity of eGF measure may indicate that this instrument can detect only relationships that are game-related, and thus that it would not be able to detect significant relationships with science interest in a regression analysis. However, this measurement validity issue requires further exploration with larger samples.

Conclusion

In summary, vision attention and Flow experience are highly associated. Together they have an interactive effect on perceived science learning. Three visual attention variables have been identified that may serve as indicators of Flow and perceived learning in a science SEG environment. They are total fixation count, total fixation duration, and total visit duration. The resulting, updated model of visual attention and

Flow in a science SEG (Figure 34) illustrates the relationships between individual differences, visual attention, and Flow experience, as well as the outcomes of perceived science learning and perceived enjoyment.

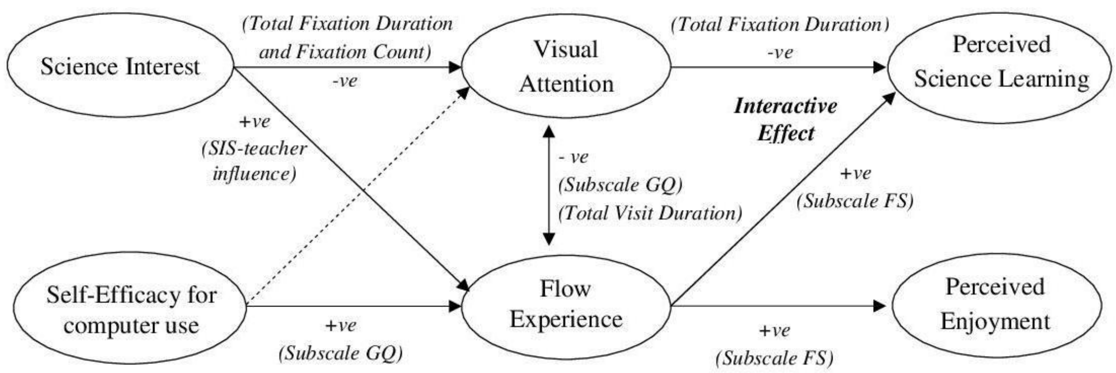


Figure 34 Finalized model of visual attention and Flow in a science SEGs.

Low fixation counts may indicate that students' attention is more focused during gameplay and that the students feel more immersed in an SEG. Short visit duration represents the efficiency of selective visual attention and may serve as an indicator of Flow experience during gameplay. Total fixation duration tells us what specific learning materials students looked at in the environment that may possibly pass through the selective filter into our conscious attention, which may ultimately lead to learning. However, it is still necessary for students to obtain a state of cognitive ease, through the efficiency of selective attention and System 1 processing, in order to benefit from the integration of cognitive-affective processes and create deeper learning experiences in an SEG.

Individual differences factors may have an influence on different dimensions of Flow by affecting our attentional and cognitive processes. Stepwise regression showed that self-efficacy for computer use predicts the dimension of perceived game quality in Flow. This finding suggests that students' confidence in using the keyboard and mouse controls will determine their navigational skill in gameplay and affect players' cognitive demands, as well as their perceived challenge-skill balance. Proficiency in game skills is a necessary condition for game-based learning, but not a sufficient condition for eliciting Flow experience. It only provides a foundation for students to obtain a state of cognitive ease and becomes the antecedent of Flow in an SEG. While the hypothesis that perceived game experience would be an individual-related factor predicting Flow and visual attention in the pilot study was not confirmed in this final study, an updated model of Flow and visual attention in SEGs was suggested (Figure 34). But perceived game experience and self-efficacy for computer use are concepts with similar meanings, as both constructs reflect students' proficiency in gameplay. So the construct of perceived game experience was replaced by self-efficacy for computer use, which seems to have a more direct effect on Flow through the perceived challenge-skill balance and the player's sense of control (solid line), as well as an indirect effect on visual attention through efficient selective attention with good and reliable 3-D navigation (dotted line).

Science interest, on the other hand, may have a more holistic influence over the cognitive processes of gameplay. Students with high science interest may unconsciously gravitate toward things with which they are familiar; familiarity and perceptual fluency determine our processing choices and also affect the processes of selective attention. So science interest affects students' attentional processes in a science SEG. The positive affective state generated from familiarity increases students' efficiency in selective attention, which in turn assists them in attaining a state of cognitive ease. The players became more immersed in the game environment and felt more efficient in cognitive processing due to the operation of System 1, ultimately facilitating the elicitation of Flow experience in game-based learning.

The interactive effect of visual attention and Flow on perceived science learning is the most important finding identified in this study. Based on this finding, game-based learning researchers should conduct well-designed experimental studies to tease out the relationships between visual attention and Flow in affecting perceived learning through SEGs. It appears that differences in cognitive and affective processing during gameplay affect our perceived learning and perceived enjoyment when playing an SEG. Systematic investigations may help to explain the integration of cognitive and affective processes, and the knowledge gained will contribute to the design of SEGs that more effective in producing positive science learning.

From a measurement perspective, there is a need to better differentiate the measurement validity of the two Flow scales with regard to game-based learning and to further evaluate their respective psychometric properties, particularly their measures of sensitivity, specificity, and predictive value, with larger samples. The generic FSS-2 scale seems to have a higher positive predictive value, whereas the context-specific eGF scale shows more sensitivity and captures more fully the impact of game-related visual attention variables. Further examination of the sensitivity measure of this eGF scale may help to transform it into a useful measurement tool for use in predicting Flow in game-based learning and in assessing the effectiveness of SEGs.

In light of this gameplay process study focusing on students' visual attention and Flow in a science SEG, the following implications are offered. de Freitas (2006) suggested that a well-designed Serious Game should "get the correct balance between delightful play and fulfilling specified learning outcomes" (p. 5). Therefore, an effective SEG should align gameplay and learning objectives, as doing so may magnify the learning impact. The findings of this study support the existence of a cognitive-affective integration that has an interactive effect on students' perceived science learning in an SEG environment. Instructional SEG designers should emphasize application of pedagogical principles to create a meaningful gameplay experience that deeply engages students, leading them into a state of Flow in which they are so absorbed in the task that they seem to forget time and place and feel the joy that comes from learning difficult and complex science concepts in an SEG environment.

Moreover, the findings showed that science interest is a strong predictor of Flow, which further impacts students' learning from an SEG. It is thus essential for teachers and parents to take an active role in instilling students' science interest in early years. They should support and encourage students' development of interest in science and other STEM fields through exposure to various formal and informal learning contexts.

In conclusion, the leverage of technology and informal learning contexts (both digital and physical) to increase students' engagement in science learning can ultimately promote student interest in STEM careers, thereby contributing to the development of a more diverse science and engineering workforce to meet the global challenges of the 21st century.

APPENDICES

APPENDIX A

Science Interest Survey (SIS)

Subscale	Item
Family Encouragement	My family has encouraged me to study science.
	People in my family are not interested in science. (R)
	My family is enthusiastic about a science career for me.
	My family is interested in the science courses I take.
Peer Attitudes toward Science	My friends do not like science. (R)
	My friends view science as nerdy. (R)
	My friends do not like to watch science programs on TV. (R)
Teacher Influence	My teachers encourage me to do my best.
	My science teachers have encouraged me to learn about science.
	My science teachers make science interesting.
	My science teachers are enthusiastic about science.
Informal Learning Experiences	I do not enjoy visiting science museums and science centers. (R)
	Visiting science museums and exhibits makes me consider a career in science.
	Visiting science museums and exhibits makes me want to learn more about a science topic.
Science Classroom Experiences	The topics taught in my science class are important in the real world.
	The topics taught in my science class are boring. (R)
	My science classroom has interesting equipment.
	We do not use most of the equipment in our science classroom. (R)

APPENDIX B

Demographic and Game Experience Survey

Thank you for participating in the Serious Educational Games study from George Mason University!

This survey is not a test there are no right or wrong answers. Your responses are voluntary and will be confidential. Responses will not be identified by individual. All responses will be compiled together and analyzed as a group.

The purpose of this survey is to better understand your game experience and what you think about science and games. It is extremely important that we have a good understanding of what you think.

Please take your time with each question. Thank you for your time and help in this important project.

After the surveys, let's play some games!

Part 1: Demographic Information

1. Student Number: ____________________

2. What type of school do you attend?
   - o Public School
   - o Private School
   - o Charter School
   - o Other (Please specify): ____________________

3. Your Current (or last semester) Grade Level: ____________________

4. What letter grade did you receive in your current (or last semester) science class?_______

5. Age: ____________________

6. Gender:
   - o Male
   - o Female

7. How would you describe yourself? (Choose one or more from the following racial groups)

- o Indigenous American
- o Asian
- o Black or African American
- o Hispanic or Latino
- o Native Hawaiian, or Other Pacific Islander
- o Middle Eastern
- o White or Caucasian
- o Other (please specify): ____________________

Part 2: Game Experience

Directions:
Read each statement carefully.
Check the box next to the item that describes how you feel about each statement.

8. Do you play video games or computer games frequently, moderately, or never?

- o Frequent Gamer
- o Moderate Gamer
- o Non-Gamer

If you have experience with video games:

Rating the level of experience with video games from 0 to 100 using the scale given below:

0	10	20	30	40	50	60	70	80	90	100
Very Poor					Moderate					Excellent

9. My level of experience with video games: (0 to 100) _______________

10. Do you play games online, on computer, or on other game platforms?

- o Online
- o Computer
- o Console
- o Arcade
- o Handheld/Mobile
- o All of the above
- o Other (please specify): ____________________

11. Do you play games most often by yourself or with others?
- By yourself
- With others
- Both

12. Which of the following THREE (3) types of video games do you play the most? (Maximum 3 choices only)

	My Top 3
Role-playing	1 - Play Most
Shooter	2 - Second Most
Strategy (e.g., Civilization)	3 - Third Most
Sports	
Action	
Adventure	
Simulation	
Fighting	
Music /Dance	
Casual /Trivia (e.g., angry birds, bubble ball)	
Puzzle /Board /Card games	

13. Which of following THREE (3) characteristics of games do you like the most? (Maximum 3 choices only)

	My Top 3
Competition (the goal is to achieve an outcome that is superior to others)	1 - Most Like
Challenge (tasks require effort and are non-trivial)	2 - Second Most
Exploration (there is a context-sensitive environment that can be investigated)	3 - Third Most
Fantasy (existence of a make-believe environment, characters or narrative)	
Goals (there are explicit aims and objectives)	
Interaction (an action will change the state of play and generate feedback)	
Outcomes (there are measurable results from game play, e.g., scores)	
People (other individuals take part)	
Rules (the activity is bounded by artificial constraints)	
Safety (the activity has no consequence in the real world)	

Thank you for your comment!

APPENDIX C

Self-Efficacy for Technology and Science – Short Form (SETSSF)

	Item	Subscale
1	No matter how hard I try, I cannot figure out the main idea in science class.	Science Process
2*	It is easy for me to look at the results of an experiment and tell what they mean.	Science Process
3	Once I have a question, it is hard for me to design an experiment to test it.	Science Process
4	I have trouble figuring out the main ideas of what my science teacher is teaching us.	Science Process
5	No matter how hard I try, videogames are too difficult for me to learn.	Video Games
6	Even when I try hard, I don't do well at playing videogames	Video Games
7	I can only succeed at the easiest videogame.	Video Games
8	No matter how hard I try, I do not do well when playing computer games.	Video Games
9*	Videogames are easy to figure out for me even when I do not try.	Video Games
10	Even when I try hard, learning how to play a new videogame is complicated for me.	Video Games
11	When playing in a simulation game, I only do well for short periods of time.	Video Games

Note. *Reverse scoring

APPENDIX D

eGameFlow Scale

Game: ________________________Student No.: ________________________

Directions: Read each statement. Circle the number that describes how you feel about each statement. From “1 – strongly disagree” to “7 – strongly agree.”

		Strongly disagree	Disagree	Somewhat disagree	Don’t know	Somewhat agree	Agree	Strongly agree
1	Most of the gaming activities are related to the learning task.	1	2	3	4	5	6	7
2	No distraction from the task is highlighted.	1	2	3	4	5	6	7
3	Generally speaking, I can remain concentrated in the game.	1	2	3	4	5	6	7
4	I am not distracted from tasks that the player should concentrate on.	1	2	3	4	5	6	7
5	I am not burdened with tasks that seem unrelated.	1	2	3	4	5	6	7
6	Workload in the game is adequate.	1	2	3	4	5	6	7
7	Overall game goals were presented in the beginning of the game.	1	2	3	4	5	6	7
8	Overall game goals were presented clearly.	1	2	3	4	5	6	7
9	Intermediate goals were presented in the beginning of each scene.	1	2	3	4	5	6	7
10	Intermediate goals were presented clearly.	1	2	3	4	5	6	7
11	I received feedback on my progress in the game.	1	2	3	4	5	6	7
12	I received immediate feedback on my actions.	1	2	3	4	5	6	7

13	I am notified of new tasks immediately.	1	2	3	4	5	6	7
14	I am notified of new events immediately.	1	2	3	4	5	6	7
15	I receive information on my success (or failure) of intermediate goals immediately	1	2	3	4	5	6	7
16	The game provides "hints" in text that help me overcome the challenges.	1	2	3	4	5	6	7
17	The game provides video or audio auxiliaries that help me overcome the challenges.	1	2	3	4	5	6	7
18	The difficulty of challenges increase as my skills improved.	1	2	3	4	5	6	7
19	The game provides new challenges with an appropriate pacing.	1	2	3	4	5	6	7
20	The game provides different levels of challenges that tailor to different players.	1	2	3	4	5	6	7
21	I feel a sense of control and impact over the game.	1	2	3	4	5	6	7
22	I know next step in the game.	1	2	3	4	5	6	7
23	I feel a sense of control over the game.	1	2	3	4	5	6	7
24	I forget about time passing while playing the game.	1	2	3	4	5	6	7
25	I become unaware of my surroundings while playing the game.	1	2	3	4	5	6	7
26	I temporarily forget worries about everyday life while playing the game.	1	2	3	4	5	6	7
27	I experience an altered sense of time.	1	2	3	4	5	6	7
28	I can become involved in the game.	1	2	3	4	5	6	7
29	I feel emotionally involved in the game.	1	2	3	4	5	6	7
30	I feel viscerally (deep inward feeling) involved in the game.	1	2	3	4	5	6	7
31	The game increases my knowledge.	1	2	3	4	5	6	7
32	I catch the basic ideas of the knowledge taught.	1	2	3	4	5	6	7
33	I try to apply the knowledge in the game.	1	2	3	4	5	6	7
34	The game motivates the player to integrate the knowledge taught.	1	2	3	4	5	6	7
35	I want to know more about the knowledge taught.	1	2	3	4	5	6	7

Rate the game from 0 to 100 using the scale given below:

0	10	20	30	40	50	60	70	80	90	100
Very Poor					Moderate					Excellent

Overall sense of enjoyment of this game is: (0 – 100) ________________

~ Thank you ~

APPENDIX E

Perceived Enjoyment Scale (PE; Venkatesh, 1999, 2000)

		Strongly disagree	Disagree	Somewhat disagree	Don't know	Somewhat agree	Agree	Strongly agree
36	I find playing this game to be enjoyable.	1	2	3	4	5	6	7
37	The actual process of playing this game is pleasant.	1	2	3	4	5	6	7
38	I have fun playing this game.	1	2	3	4	5	6	7

APPENDIX F

Knowledge Assessment (Neuromatrix)

Extracted from the subscale of *eGameFlow*.

		Strongly disagree	Disagree	Somewhat disagree	Don't know	Somewhat agree	Agree	Strongly agree
31	The game increases my knowledge.	1	2	3	4	5	6	7
32	I catch the basic ideas of the knowledge taught.	1	2	3	4	5	6	7
33	I try to apply the knowledge in the game.	1	2	3	4	5	6	7
34	The game motivates the player to integrate the knowledge taught.	1	2	3	4	5	6	7
35	I want to know more about the knowledge taught.	1	2	3	4	5	6	7

REFERENCES

Aarseth, E. J. (1997). *Cybertext: Perspectives on Ergodic literature*. Baltimore, MD: The John Hopkins University Press.

Abt, C. C. (1970). *Serious games*. New York, NY: Viking Press.

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly, 24*, 665-694.

Agresti, A., & Finlay, B. (2009). *Statistical methods for the social sciences* (4th ed.). Upper Saddle River, NJ: Pearson Prentice Hall.

Akilli, G. K. (2007). Games and simulations: A new approach in Education? In D. Gibson, C. Aldrich, & M. Prensky, (Eds.), *Games and simulations in online learning: Research and development frameworks* (pp. 1-20). Hershey, PA: Information Science Publishing.

Alkan, S., & Cagiltay, K. (2007). Studying computer game learning experience through eye tracking. *British Journal of Educational Technology, 38*, 538-542. doi:10.1111/j.1467-8535.2007.00721.x

Annetta, L. A. (2008a). Video games in education: Why they should be used and how they are being used. *Theory Into Practice, 47*, 229-239.

Annetta, L. A. (Ed.). (2008b). *Serious educational games: From theory to practice*. The Netherlands: Sense Publishers.

Awh, E., & Pashler, H. (2000). Evidence for split attentional foci. *Journal of Experimental Psychology: Human Perception and Performance*, *26*, 834-846. doi:10.1037//0096-1523-26-2-834

Baddeley, A. (2000). The episodic buffer: A new component of working memory. *Trends in Cognitive Sciences, 4*, 417-423. doi:10.1016/S1364-6613(00)01538-2

Baddeley, A. (2007). *Working memory, thought and action*. New York, NY: Oxford University Press.

Baddeley, A. (2012). How does emotion influence working memory? In S. Masmoudi, D. Y. Dai, & A. Naceur (Eds.), *Attention, representation, and human performance: Integration of cognition, emotion, and motivation* (pp. 3-18). New York, NY: Psychology Press.

Baddeley, A. D., & Hitch, G. (1974). *Working memory.* In G.H. Bower (Ed.), *The psychology of learning and motivation: Advances in research and theory* (Vol. 8, pp. 47–89). New York, NY: Academic Press.

Baddeley, A., & Weiskrantz, L. (Eds.). (1993). *Attention, selection, awareness, and control: A tribute to Donald Broadbent*. New York, NY: Oxford University Press.

Bardzell, J., Bardzell, S., Pace, T., & Karnell, J. (2008, April). *Making user engagement visible: A multimodal strategy for interactive media experience research*. Paper presented at the ACM CHI 2008 Conference, Florence, Italy.

Barrett, L. F. (1998). Discrete emotions or dimensions? The role of valence focus and arousal focus. *Cognition and Emotion*, *12*, 579-599. doi:10.1080/026999398379574

Barrett, L. F. (2006). Solving the emotion paradox: Categorization and the experience of emotion. *Personality and Social Psychology Review, 10*(1), 20-46.

Barrett, L. F., & Russell, J. A. (1999). Structure of current affect. *Current Directions in Psychological Science, 8*(1), 10-14. doi: 10.1111/1467-8721.00003

Bassi, M., & Delle Fave, A. (2004). Adolescence and the changing context of optimal experience in time: Italy 1986-2000. *Journal of Happiness Studies, 5*, 155-179. doi:10.1023/B:JOHS.0000035914.66037.b5

Blade, R. A., & Padgett, M. L. (2002). Virtual environments standards and terminology. In K. M. Stanney (Ed.), *Handbook of virtual environments: Design, implementation, and applications* (pp. 15-27). Mahwah, NJ: Lawrence Erlbaum.

Bowling, A. (2001). *Measuring disease: A review of disease-specific quality of life measurement scales* (2nd ed.). Philadelphia, PA: Open University Press.

Broadbent, D. E. (1958). *Perception and communication*. New York, NY: Oxford University Press.

Brown, E., & Cairns, P. (2004, April). *A grounded investigation of game immersion*. Paper presented at the CHI '04 extended abstracts on Human factors in computing systems (pp. 1297-1300), Vienna, Austria.

Bruya, B. (2010). *Effortless attention: A new perspective in the cognitive science of attention and action*. Cambridge, MA: The MIT Press.

Bryant, J., & Fondren, W. (2009). Psychological and communicological theories of learning and emotion underlying serious games. In U. Ritterfeld, M. Cody, & P. Vorderer (Eds.), *Serious games: Mechanisms and effects* (pp. 103-116). New York, NY: Routledge.

Burnham, W. H. (1908). Attention and interest. *The American Journal of Psychology, 19*(1), 14-18.

Cairns, P., Cox, A., Berthouze, N., Dhoparee, S., & Jennett, C. (2006, June). *Quantifying the experience of immersion in games*. Paper presented at the Workshop on the Cognitive Science of Games and Gameplay: Annual Meeting of the Cognitive Science Society, Vancouver, Canada.

Chandra, S., Srivastava, S. C., & Theng, Y. L. (2009, July). *Role of cognitive absorption and trust for collaboration in virtual world*. Paper presented at the Pacific Asia Conference on Information Systems (PACIS 2009), Hyderabad, India.

Chen, J. (2007). Flow in games (and everything else). *Communications of the ACM, 50*(4), 31-34. doi:10.1145/1232743.1232769

Cherry, E. C. (1953). Some experiments on the recognition of speech, with one and with two ears. *The Journal of the Acoustical Society of America, 25*, 975-979.

Chisholm, J. D., & Kingstone, A. (2012). Improved top-down control reduces oculomotor capture: The case of action video game players. *Attention, Perception, and Psychophysics, 74*, 257-262. doi:10.3758/s13414-011-0253-0

Chou, T.-J., & Ting, C.-C. (2003). The role of flow experience in cyber-game addiction. *Cyberpsychology & Behavior, 6*, 663-675.

Chun, M. M., & Wolfe, J. M. (2005). Visual attention. In E. B. Goldstein (Ed.), *Blackwell handbook of sensation & perception* (pp. 272-310). Malden, MA: Blackwell Publishing.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.

Cohn, M. A., & Fredrickson, B. L. (2009). Positive emotions. In C. R. Snyder, & S. J. Lopez (Eds.), *Oxford handbook of positive psychology* (2nd ed., pp. 13-24). New York, NY: Oxford University Press.

Compton, R. J. (2003). The interface between emotion and attention: A review of evidence from psychology and neuroscience. *Behavioral and Cognitive Neuroscience Review, 2*(2), 115-129. doi:10.1177/1534582303002002003

Conway, J. M., & Huffcutt, A. I. (2003). A review and evaluation of exploratory factor analysis practices in organizational research. *Organizational Research Methods, 6*(2), 147-168. doi:10.1177/1094428103251541

Coull, J. T. (1998). Neural correlates of attention and arousal: Insights from electrophysiology, functional neuroimaging and psychopharmacology. *Progress in Neurobiology*, *55*, 343-361.

Cowley, B., Charles, D., Black, M., & Hickey, R. (2006). User-system-experience model for user centered design in computer games. In V. Wade, H. Ashman, & B. Smyth (Eds.), *Lecture Notes in Computer Science: Vol. 4018. Adaptive Hypermedia and Adaptive Web-based Systems* (pp. 419-424). Dublin, Ireland: Springer. doi: 10.1007/11768012_62

Crandall, B., Klein, G., & Hoffman, R. R. (2006). *Working minds: A practitioner's guide to cognitive task analysis*. Cambridge, MA: The MIT Press.

Creswell, J. W. (2008). *Research design: Qualitative, quantitative, and mixed methods approach.* Thousand Oaks, CA: Sage.

Csikszentmihalyi, M. (1975). *Beyond boredom and anxiety: Experiencing flow in work and play*. San Francisco, CA: Jossey-Bass.

Csikszentmihalyi, M. (1982). Toward a psychology of optimal experience. In L. Wheeler (Ed.), *Review of personality and social psychology* (Vol. 3, pp. 13-36). Beverly Hills, CA: Sage.

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience.* New York, NY: Harper and Row.

Csikszentmihalyi, M. (1996). *Creativity: Flow and the psychology of discovery and intervention.* New York, NY: HarperCollins.

Csikszentmihalyi, M. (1997). *Finding flow: The psychology of engagement with everyday life*. New York, NY: Basic Books.

Csikszentmihalyi, M., and Larson, R. (1987). Validity and reliability of the Experience-Sampling Method. *Journal of Nervous and Mental Disease, 175*, 526-536.

Csikszentmihalyi, M., and LeFevre, J. (1989). Optimal experience in work and leisure. *Journal of Personality and Social Psychology, 56*, 815-822. doi:10.1037/0022-3514.56.5.815

Dalgarno, B., & Lee, M. J. W. (2010). What are the learning affordances of 3-D virtual environments? *British Journal of Educational Technology, 41*(1), 10-32. doi:10.1111/j.1467-8535.2009.01038

Davidson, R. J., Scherer, K. R., & Goldsmith, H. H. (Eds.). (2003). *Handbook of affective sciences*. New York, NY: Oxford University Press.

de Freitas, S. (2006). *Learning in immersive worlds: A review of game-based learning*. Bristol, UK: Joint Information Systems Committee (JISC) E-Learning

de Freitas, S., Rebolledo-Mendez, G., Liarokapis, F., Magoulas, G., & Poulovassilis, A. (2010). Learning as immersive experiences: Using the four-dimensional framework for designing and evaluating immersive learning experiences in a virtual world. *British Journal of Educational Technology, 41*(1), 69-85. doi:10.1111/j.1467-8535.2009.01024.x

De Houwer, J., & Hermans, D. (Eds.). (2010). *Cognition and emotion*. New York, NY: Psychology Press.

de Manzano, Ö., Theorell, T., Harmat, L., & Ullén, F. (2010). The psychophysiology of flow during piano playing. *Emotion, 10*(3), 301-311. *doi*:10.1037/a0018432

Delle Fave, A., Massimini, F., & Bassi, M. (2011). *Psychological selection and optimal experience across cultures: Social empowerment through personal growth*. New York, NY: Springer.

Derryberry, A. (2007). *Serious games: Online games for learning*. Retrieved from http://www.adobe.com/eeurope/resources/elearning/pdfs/serious_games_wp.pdf?PID=4172469

Deutsch, J. A., & Deutsch, D. (1963). Attention: Some theoretical considerations. *Psychological Review, 70*(1), 80-90.

Dickey, M. D. (2005). Three-dimensional virtual worlds and distance learning: Two case studies of Active Worlds as a medium for distance education. *British Journal of Educational Technology, 36*, 439-451.

Dimitrov, D. (2012). *Statistical methods for validation of assessment scale data in counseling and related fields.* Alexandria, VA: American Counseling Association.

Dobrynin, N. F. (1958). Voluntary and post-voluntary attention. *Uchenyye zapiski Moskovskogo gorodskogo pedagogicheskogo institute imeni V. P. Potyomkina, 81*, 5-65. (in Russian).

Dondlinger, M. J. (2007). Educational video game design: A review of the literature. *Journal of Applied Educational Technology, 4*(1), 21-31.

Dormashev, Y. (2010). Flow experience explained on the grounds of an activity approach to attention. (E. N. Osin, Trans.). In B. Bruya (Ed.), *Effortless attention* (pp.287-333). Cambridge, MA: The MIT Press.

Draper, J. V., Kaber, D. B., & Usher, J. M. (1998). Telepresence. *Human Factors, 40*, 354-374.

Drengner, J., Sachse, M., & Furchheim, P. (2009). Flow in consumer research: A novel approach. In A. L. McGill & S. Shavitt (Eds.), *Advances in consumer research*, (Vol. 36, pp. 670-671). Duluth, MN: Association for Consumer Research.

Duchowski, A. T. (2002).A breadth-first survey of eye tracking applications. *Behavior Research Methods, Instruments, and Computers, 34*, p. 455-470.

Duchowski, A. T. (2007). *Eye tracking methodology: Theory and practice* (2^{nd} ed). London, UK: Springer-Verlag.

Egenfeldt-Nielsen, S. (2005). *Beyond edutainment: Exploring the educational potential of computer games* (Doctoral dissertation). IT-University of Copenhagen, Denmark.

Eiben, C. B., Siegel, J. B., Bale, J. B., Cooper, S., Khatib, F., Shen, B. W., Foldit Players, Stoddard, B. L., Popovic, Z., & Baker, D. (2012). Increased diels-alderase activity through backbone remodeling guided by Foldit players. *Nature Biotechnology, 30*(2), 190-194. doi:10.1038/nbt.2109

Engeser, S., & Schiepe-Tiska, A. (2012). Historical lines and an overview of current research in flow. In S. Engeser (Ed.), *Advances in flow research* (pp. 1-22). New York, NY: Springer.

Ermi, L., & Mäyrä, F. (2005). Fundamental components of the gameplay experience: Analyzing immersion. In S. de Castell & J. Jenson (Eds.), *Proceedings of the DiGRA 2005 Conference: Challenging Views-Worlds in Play* (pp. 15-27). British Columbia, Canada.

Eysenck, M. W., & Keane, M. T. (2010). *Cognitive psychology: A student's handbook* (6^{th} ed.). New York, NY: Psychology Press.

Evans, J. St. B. T. (1984). Heuristic and analytic processes in reasoning. *British Journal of Psychology, 75*, 451-468. doi:10.1111/j.2044-8295.1984.tb01915.x

Evans, J. St. B. T. (2003). In two minds: Dual-process accounts of reasoning. *Trends in Cognitive Sciences, 7,* 454-459.

Evans, J. St. B. T. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annual Review of Psychology, 59*, 255-278. doi:10.1146/annurev.psych.59.103006.093629

Evans, J. St. B. T. (2009). How many dual-process theories do we need: One, two or many? In J. St. B. T. Evans & K. Frankish (Eds.), *In two minds: Dual processes and beyond* (pp. 31-54). New York, NY: Oxford University Press.

Evans, J. St. B. T., & Frankish, K. (Eds.). (2009). *In two minds: Dual processes and beyond*. New York, NY: Oxford University Press.

Evans, J. St. B. T., & Over, D. E. (1996). *Rationality and reasoning*. Hove, UK: Psychology Press.

Fan, X., Thompson, B., & Wang, L. (1999). The effects of sample size, estimation methods, and model specification on SEM fit indices. *Structural Equation Modeling, 6*(1), 56-83. doi:10.1080/10705519909540119

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*, 1149-1160. doi:10.3758/BRM.41.4.1149

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175-191.

Fenske, M. J., & Raymond, J. E. (2006). Affective influences of selective attention. *Current Directions in Psychological Science, 15*, 312-316. Doi: 10.1111/j.1467-8721.2006.00459.x

Fichtenholtz, H. M., & Labar, K. S. (2012). Emotional influences on visuospatial attention. In G. R. Mangun (Ed.), *The neuroscience of attention: Attentional control and selection* (pp. 250-266). New York, NY: Oxford University Press.

Finneran, C. M., & Zhang, P. (2005). Flow in computer-mediated environments: Promises and challenges. *Communications of the Association for Information Systems*, *15*(15), 82-101.

Fischer, B. (2007). *Looking for learning: Auditory, visual and optomotor processing of children with learning problems*. New York, NY: Nova Science.

Forgas, J. P. (2001). The affect infusion model (AIM): An integrative theory of mood effects on cognition and judgments. In L. L. Martin & G. L. Clore (Eds.), *Theories of mood and cognition: A user's guidebook* (pp. 99-134). Mahwah, NJ: Lawrence Erlbaum Associates.

Forgas, J. P., & East, R. (2008). On being happy and gullible: Mood effects on skepticism and the detection of deception. *Journal of Experimental Social Psychology, 44*(5), 1362-1367.

Frankish, K., & Evans, J. St. B. T. (2009). The duality of mind: An historical perspective. In J. St. B. T. Evans & K. Frankish (Eds.), *In two minds: Dual processes and beyond* (pp. 1-29). New York, NY: Oxford University Press.

Fu, F.-L., Su, R.-C., Yu, S.-C. (2009). EGameFlow: A scale to measure learners' enjoyment of e-learning games. *Computers & Education*, *52*(1), 101-112. doi:10.1016/j.compedu.2008.07.004

Gailliot, M. T., & Baumeister, R. F. (2007). The physiology of willpower: Linking blood glucose to self-control. *Personality and Social Psychology Review*, *11*, 303-327. doi:10.1177/1088868307303030

Gailliot, M. T., Baumeister, R. F., DeWall, C. N., Maner, J. K., Plant, E. A., Tice, D. M., Brewer, L. E., & Schmeichel, B. J. (2007). Self-control relies on glucose as a limited energy source: willpower is more than a metaphor. *Journal of Personality and Social Psychology*, *92*, 325-336. doi:10.1037/0022-3514.92.2.325

Gaudiosi, J. (2009, December 10). Gameworld: Video games take bigger role in education. *Reuters*. Retrieved from http://www.reuters.com

Gee, J. P. (2007). *What video games have to teach us about learning and literacy*. New York, NY: Palgrave Macmillan.

Gee, J. P. (2009). Deep learning properties of good digital games: How far can they go? In U. Ritterfeld, M. Cody, P. Vorderer (Eds.), *Serious games: Mechanisms and effects* (pp. 65-80). New York, NY: Routledge.

Ghani, J. A., & Deshpande, S. P. (1994). Task characteristics and the experience of optimal flow in human-computer interaction. *Journal of Psychology, 128,* 381-391. doi:10.1080/00223980.1994.9712742

Gilet, A.-L., & Jallais, C. (2012). Mood’s influence on semantic memory: Valence or arousal? In S. Masmoudi, D. Y. Dai, & A. Naceur (Eds.), *Attention, representation, and human performance: Integration of cognition, emotion, and motivation* (pp. 77-91). New York, NY: Psychology Press.

Godijn, R., & Theeuwes, J. (2003). The relationship between exogenous and endogenous saccades and attention. In J. Hyönä, R. Radach, & H. Deubel (Eds.), *The mind’s eye: Cognitive and applied aspects of eye movement research* (pp. 3-26). New York, NY: Elsevier.

Goldberg, J. H., & Helfman, J. I. (2010, March). *Visual scanpath representation*. Paper presented at the Eye-Tracking Research & Applications (ETRA) Conference, Austin, TX.

Green, C. S., & Bavelier, D. (2003). Action video game modifies visual selective attention. *Nature, 423*(6939), 534-537.

Gregory, E. (2008). Understanding video gaming’s engagement: Flow and its application to interactive media. *Media Psychology Review, 1*(1). Retrieved from http://www.mprcenter.org/mpr

Gudmundsen, J. (2006, May 19). Movement aims to get serious about games. *USA Today*. Retrieved from http://www.usatoday.com

Hau, K. T. & Marsh, H. W. (2004). The use of item parcels in structural equation modeling: Non-normal data and small sample sizes. *British Journal of Mathematical Statistical Psychology, 57*, 327-351. doi:10.1111/j.2044-8317.2004.tb00142.x

Hedley, N. R., Billinghurst, M., Postner, L., May, R., & Kato, H. (2002). Explorations in the use of augmented reality for geographic visualization. *Presence: Teleoperators and Virtual Environments, 11*(2), 119-133. doi:10.1162/1054746021470577

Henderson, J. M., & Ferreira, F. (Eds.). (2004). *The integration of language, vision, and action: Eye movements and the visual world*. New York, NY: Psychology Press.

Hilgard, E. R. (1980). The trilogy of mind: Cognition, affection, and conation. *Journal of the History of Behavioral Sciences, 16*(2), 107-117.

Hinrichs, R., & Wankel, C. (Eds.). (2011). *Transforming virtual world learning: Cutting-edge technologies in higher education*. Bingley, UK: Emerald.

Hoffman, B., & Nadelson, L. (2010). Motivational engagement and video gaming: A mixed methods study. *Educational Technology Research & Development, 58*, 245-270. doi:10.1007/s11423-009-9134-9

Hoffman, D. L., & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments: Conceptual foundations. *Journal of Marketing, 60*(3), 50-68. doi:10.2307/1251841

Hoffman, D. L., & Novak, T. P. (2009). Flow online: Lesson learned and future prospects. *Journal of Interactive Marketing, 23*(1), 23-34. doi:10.1016/j.intmar.2008.10.003

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & van de Weijer, J. (2011). *Eye tracking: A comprehensive guide to methods and measures*. New York, NY: Oxford University Press.

Hornbæk, K. (2006). Current practice in measuring usability: Challenges to usability studies and research. *International Journal of Human-Computer Studies, 64*(2), 79-102. doi:10.1016/j.ijhcs.2005.06.002

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1-55. doi:10.1080/10705519909540118

Huang, M. H. (2003). Designing website attributes to induce experiential encounters. *Computers in Human Behavior, 19*, 425-442. doi: 10.1016/S0747-5632(02)00080-8

IJsselsteijn, W., van den Hoogen, W., Klimmt, C., de Kort, Y., Lindley, C., Mathiak, K., Poels, K., Ravaja, N., Turpeinen, M., & Vorderer, P. (2008). Measuring the experience of digital game enjoyment. In A. J. Spink, M. R. Ballintijn, N. D. Bogers, F. Grieco, L. W. S. Loijens, L. P. J. J. Noldus, G. Smit, & P. H. Zimmerman (Eds.), *Proceedings of Measuring Behavior* (pp. 88-89). Maastricht, The Netherlands.

Immordino-Yang, M. H., & Damasio, A. (2007). We feel, therefore we learn: The relevance of affective and social neuroscience to education. *Mind, Brain, and Education, 1*(1), 3-10. doi:10.1111/j.1751-228X.2007.00004.x

Jackson, S. A. (2010). *The Flow manual*. Queensland, Australia: Mind Garden.

Jackson, S. A. (2012). Flow. In R. M. Ryan (Ed.), *The Oxford handbook of human motivation* (pp. 127-140). New York, NY: Oxford University Press.

Jackson, S. A., & Csikszentmihalyi, M. (1999). *Flow in sports: The keys to optimal experiences and performances*. Champaign, IL: Human Kinetics.

Jackson, S. A., & Marsh, H. W. (1996). Development and validation of a scale to measure optimal experience: The flow state scale. *Journal of Sport & Exercise Psychology*, *18*(1), 17-35.

Jacob, R. J. K., & Karn, K. S. (2003). Eye tracking in human-computer interaction and usability research: Ready to deliver the promises. In J. Hyönä, R. Radach, & H. Deubel (Eds.), *The mind's eye: Cognitive and applied aspects of eye movement research* (pp. 573-605). New York, NY: Elsevier.

James, W. (1890). *The principles of psychology* (Vol. 1). New York, NY: H. Holt & Co.

Jefferies, L. N., Smilek, D., Eich, E., & Enns, J. T. (2008). Emotional valence and arousal interact in attention control. *Psychological Science, 19*(3), 290-295. doi:10.1111/j.1467-9280.2008.02082.x

Jennett, C., Cox, A. L., Cairns, P., Dhoparee, S., Epps, A., Tijs, T., & Walton, A. (2008). Measuring and defining the experience of immersion in games. *International Journal of Human-Computer Studies, 66*, 614-661. doi:10.1016/j.ijhcs.2008.04.004

Jie, L., & Clark, J. J. (2007). Game design guided by visual attention. In L. Ma, M. Rauterberg, & R. Nakatsu (Eds.), *Entertainment Computing: ICEC 2007*, LNCS 4740, pp. 345-355. New York, NY: Springer. doi:10.1007/978-3-540-74873-1_41

Johnson, W. A., & Heinz, S. P. (1978). Flexibility and capacity demands of attention. *Journal of Experimental Psychology: General*, *107*, 420-435. doi:10.1037/0096-3445.107.4.420

Johnson, A., & Proctor, R. W. (2004). *Attention: Theory and practice*. Thousand Oaks, CA: Sage.

Jones, M. G. (1998). Creating electronic learning environments: Games, flow, and the user interface. *Proceedings of Selected Research and Development Presentations at the National Convention of the Association for Educational Communications and Technology (AECT)*, 205-214.

Just, M. A., & Carpenter, P. A. (1980). A theory of reading: From eye fixations to comprehension. *Psychological Review, 87*, 329-354.

Kafai, Y. B. (1995). *Minds in play: Computer game design as a context for children's learning*. Mahwah, NJ: Lawrence Erlbaum.

Kahneman, D. (1973). *Attention and effort*. Englewood Cliffs, NJ: Prentice-Hall.

Kahneman, D. (2011). *Thinking fast and slow*. New York, NY: Farrar, Straus and Giroux.

Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In T. Gilovich, D. Griffin, & D. Kahneman (Eds.), *Heuristic and biases* (pp. 49-81). New York, NY: Cambridge University Press.

Kara, P., & Jakob, N. (2009). *How to conduct eyetracking studies*. Fremont, CA: Nielsen Norman Group.

Ke, F. (2009). A qualitative meta-analysis of computer games as learning tools. In R. E. Ferdig (Ed.), *Handbook of research on effective electronic gaming in education* (Vol. 1, pp. 1-32). Hershey, PA: Information Science Reference.

Kearney, P., & Pivec, M. (2007, June). *Immersed and how? That is the question*. Paper presented at the Games in Action Conference, Gothenburg, Sweden.

Ketelhut, D. J. (2004). Assessing *science self-efficacy in a virtual environment: A measurement pilot*. Harvard University, Cambridge, MA, Unpublished qualifying paper.

Khatib, F., DiMaio, F., Foldit Contenders Group, Foldit Void Crushers Group, Cooper, S., Kazmierczyk, M., Gilski, M., Krzywda, S., Zabranska, H., Pichova, I., Thompson, J., Popović, Z., Jaskolski, M., & Baker, D. (2011). Crystal structure of a monomeric retroviral protease solved by protein folding game players. *Nature Structural & Molecular Biology*, *18*, 1175-1177. doi:10.1038/nsmb.2119

Kiili, K. (2005). Digital game-based learning: Towards an experiential gaming model. *Internet and Higher Education*, *8*(1), 13-24. doi:10.1016/j.iheduc.2004.12.001

Kirriemuir, J., & McFarlane, A. (2004). *Literature review in games and learning*. Bristol, UK: Futurelab.

Kivikangas, J. M. (2006). *Psychophysiology of flow experience: An explorative study* (Unpublished master's thesis). University of Helsinki, Helsinki, Finland.

Kivikangas, J. M., Ekman, I., Chanel, G., Järvelä, S., Cowley, B., Salminen, M., Henttonen, P., & Ravaja, N. (2010, January). *Review on psychophysiological methods in game research*. Paper presented at the DiGRA Nordic 2010: Experiencing Games: Games, Play, and Players Conference, Stockholm, Sweden.

Klasen, M., Weber, R., Kircher, T. T. J., Mathiak, K. A., & Mathiak, K. (2012). Neural contributions to flow experience during video game playing. *Social Cognitive and Affective Neuroscience, 7,* 485-495. doi:10.1093/scan/nsr021

Klopfer, E., Osterweil, S., & Salen, K. (2009). *Moving learning games forward: Obstacles, opportunities, and openness*. Cambridge, MA: The MIT Education Arcade.

Komogortsev, O. V., Gobert, D. V., Jayarathna, S., Koh, D., & Gowda, S. (2010). Standardization of automated analyses of oculomotor fixation and saccadic behaviors. *IEEE Transactions on Biomedical Engineering, 57*, 2635-2645.

Krapp, A. (1999). Interest, motivation and learning: An educational-psychological perspective. *European Journal of Psychology of Education, 14*(1), 23-40. doi:10.1007/BF03173109

Krapp, A., Hidi, S., & Renninger, K. A. (1992). Interest, learning and development. In K. A. Renninger, S. Hidi, & A. Krapp (Eds.), *The role of interest in learning and development* (pp. 3-25). Hillsdale, NJ: Lawrence Erlbaum.

Lachter, J., Ruthruff, E., Lien, M.-C., & McCann, R. S. (2008). Is attention needed for world identification? Evidence from the Stroop paradigm. *Psychonomic Bulletin & Review, 15*, 950-955. doi:10.3758/PBR.15.5.950

Lachter, J., Forster, K. I., & Ruthruff, E. (2004). Forty-five years after Broadbent (1958): Still no identification without attention. *Psychological Review, 111*, 880-913 doi:10.1037/0033-295X.111.4.880

Lamb, R. L., Annetta, L., Meldrum, J., & Vallett, D. (2011). Measuring science interest: Rasch validation of the science interest survey. *International Journal of Science and Mathematics Education*, Advance online publication. doi:10.1007/s10763-011-9314-z

Lamb, R., Annetta, L., Vallett, D., Cheng, R. (Accepted pending revision). Development of a short form measure of self-efficacy in science and technology. *Educational Research.*

Lambert, T. (2003). Visual orienting, learning and conscious awareness. In L. Jiménez (Ed.), *Attention and implicit learning* (pp. 254-275). Philadelphia, PA: John Benjamins.

Lang, P. J. (1995). The emotion probe: Studies of motivation and attention. *American Psychologist, 50*, 372-385. doi:10.1037/0003-066X.50.5.372

Lavie, N. (2005). Distracted and confused? Selective attention under load. *Trends in Cognitive Sciences*, *9*(2), 75-82 doi:10.1016/j.tics.2004.12.004

LeDoux, J. E. (1996). *The emotional brain*. New York, NY: Simon & Schuster.

LeDoux, J. E. (2000). Emotion circuits in the brain. *Annual Review of Neuroscience, 23*, 155-184. doi: 10.1146/annurev.neuro.23.1.155

Lee, J. J., & Hammer, J. (2011). Gamification in education: What, how, why bother? *Academic Exchange Quarterly, 15*, 146-151.

Leighton, J. P., & Gierl, M. J. (2011). The *learning sciences in educational assessment: The role of cognitive models*. Cambridge, UK: Cambridge University Press.

Lindley, C. A., Nacke, L., & Sennersten, C. C. (2008, November). *Disserting play: Investigating the cognitive and emotional motivations and affects of computer gameplay*. Paper presented at the International Conference on Computer Games: AI, Animation, Mobile, Interactive Multimedia, Educational & Serious Games (CGAMES), Wolverhampton, UK.

Malone, T. W. (1981). Toward a theory of intrinsically motivating instruction. *Cognitive Science: A Multidisciplinary Journal, 5*, 333-369. doi:10.1207/s15516709cog0504_2

Markoff, J. (2010, August 9). In a video game, tackling the complexities of protein folding. *New York Times*. Retrieved from http://www.nytimes.com

Masmoudi, S. (2012). Introduction: Toward an integrative understanding of cognitive, emotional, and motivational processes. In S. Masmoudi, D. Y. Dai, & A. Naceur (Eds.), *Attention, representation, and human performance: Integration of cognition, emotion, and motivation* (pp. xv-xxv). New York, NY: Psychology Press.

Matthews, G., Warm, J. S., Reinerman, L. E., Langheim, L. K., & Saxby, D. J. (2010). Task engagement, attention, and executive control. In A. Gruszka, G. Matthews, & Szymura, B. (Eds.), *Handbook of individual differences in cognition: Attention, memory, and executive control* (pp. 205-230). New York, NY: Springer. doi:10.1007/978-1-4419-1210-7_13

Mauri, M., Cipresso, P., Balgera, A., Villamira, M., & Riva, G. (2011). Why is Facebook so successful? Psychophysiological measures describe a core flow state while using Facebook. *Cyberpsychology, Behavior, and Social Networking, 14*, 723-731. doi:10.1089/cyber.2010.0377

McDougall, W. (1949). *An outline of psychology* (13th ed.). London, UK: Methuen.

Mermillod, M. (2012). Investigating the psychological and neural basis of emotional processing. In S. Masmoudi, D. Y. Dai, & A. Naceur (Eds.), *Attention, representation, and human performance: Integration of cognition, emotion, and motivation* (pp. 41-59). New York, NY: Psychology Press.

Mikropoulos, T. A., & Natsis, A. (2011). Educational virtual environments: A ten-year review of empirical research (1999-2009). *Computers & Education, 56*, 769-780. doi:10.1016/j.compedu.2010.10.020

Mitchell, A., & Savill-Smith, C. (2004). *The use of computer and video games for learning: A review of the literature*. London, UK: Learning and Skills Development Agency.

Moray, N. (1959). Attention in dichotic listening: Affective cues and the influence instructions. *Quarterly Journal of Experimental Psychology, 11*(1), 56-60. doi:10.1080/17470215908416289

Nacke, L., & Lindley, C. A. (2008, November). *Flow and immersion in first-person shooters: Measuring the player's gameplay experience*. Paper presented at the FuturePlay 2008 Conference. Toronto, Canada. doi:10.1145/1496984.1496998

Nacke, L., Lindley, C. A., & Stellmach, S. (2008). Log who's playing: Psychophysiological game analysis made easy through event logging. *Proceedings of Fun and Games, Second International Conference* (pp. 150-157). Berlin, Heidelberg: Springer-Verlag. doi:10.1007/978-3-540-88322-7-15

National Research Council. (2007). *Rising above the gathering storm: Energizing and employing America for a brighter economic future*. Washington, DC: The National Academies Press.

National Research Council. (2010). *Rising above the gathering storm, revisited: Rapidly approaching category 5*. Washington, DC: The National Academies Press.

National Research Council. (2011). *Learning science through computer games and simulations.* Washington, DC: The National Academies Press.

National Science Board. (2010). *Preparing the next generation of STEM innovators: Identifying and developing our nation's human capital*. Arlington, VA: National Science Foundation.

Niu, Y., Todd, R. M., Kyan, M., & Anderson, A. K. (2012). Visual saliency and emotional salience influence eye movements. *ACM Transactions on Applied Perception (TAP), 9*(3), 13. doi:10.1145/2325722.2325726

Noton, D., & Stark, L. W. (1971a). Scanpaths in eye movements during pattern perception. *Science, 171*(3968), 308-311. doi:10.1126/science.171.3968.308

Noton, D., & Stark, L. W. (1971b). Eye movements and visual perception. *Scientific American, 224*(6), 34-43.

Nunez, D. (2003). *A connectionist explanation of presence in virtual environment* (Unpublished master's thesis). University of Cape Town, Cape Town, South Africa. www.cs.uct.ac.za/~dnunez/dnunez_thesis.pdf

OECD (2011). *Lessons from PISA for the United States: Strong performers and successful reformers in education*. Paris, France: OECD Publishing. doi:10.1787/9789264096660-e

Olsen, R. K., Moses, S. N., Riggs, L., & Ryan, J. D. (2012). The hippocampus supports multiple cognitive processes through relational binding and comparison. *Frontiers in Human Neuroscience, 6*(146). doi:10.3389/fnhum.2012.00146

Orvis, K., Horn, D., & Belanich, J. (2006). *Videogame-based training success: The impact of trainee characteristics – Year 2* (Technical Report 1188). Arlington, VA: United States Army Research Institute for the Behavioral and Social Sciences.

Osborne, J., & Hennessy, S. (2003). *Literature review in science education and the role of ICT: Promise, problems and future directions* (Report 6). Bristol, UK: NESTA Futurelab.

Palladino, L. J. (2007). *Find your focus zone*. New York, NY: Free Press.

Pavlas, D. (2010). *A model of flow and play in game-based learning: The impact of game characteristics, player traits, and player states* (Unpublished doctoral dissertation). University of Central Florida, Orlando, FL. www.navistudios.net/Pavlas_Davin_A_201012_PhD.pdf

Peifer, C. (2012). Psychophysiological correlates of flow-experience. In S. Engeser (Ed.), *Advances in flow research* (pp. 139-164). New York, NY: Springer.

Pellegrino, J. W., Chudowsky, N., & Glaser, R. (Eds.) (2001). *Knowing what students know: The science and design of educational assessment.* Washington, DC: National Academy Press.

Plass, J. N., Underwood, J., Homer, B. D., Isbister, K., Goldman, R., Frye, J., Hendee, C., Case, J., & Perlin, K. (2010, June). *Defining and measuring engagement in educational games*. Poster presented at the Games, Learning, Society (GLS) Conference, Madison, WI.

Posner, M. I., & Peterson, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience, 13*, 25-42. doi:10.1146/annurev.ne.13.030190.000325

Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrated approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*, *17*, 715-734. doi:10.1017/S0954579405050340

Prensky, M. (2001). *Digital game based learning*. New York, NY: McGrawHill.

Privitera, C. M. (2006). The scanpath theory: Its definition and later developments. In B. E. Rogwitz, T. N. Pappas, & S. J. Daly (Eds.), *Proceedings of SPIE-IS&T: Human Vision and Electronic Imaging XI*, *6057*(60570A), 1-5. http://dx.doi.org/10.1117/12.674146

Psotka, J., & Davison, S. (1993). Cognitive factors associated with immersion in virtual environments. In *Proceedings of the 1993 Conference on Intelligent Computer-Aided Training and Virtual Environment Technology* (p. 285-297). Houston, TX: NASA.

Qin, H., Rau, P. P., & Salvendy, G. (2007). Player immersion in the computer game narrative. *Proceeding of the International Federation for Information Processing*, (Vol. 4740, pp. 458-461). Laxenburg, Austria: IFIP.

Raschke, M., Chen, X., Ertl, T. (2012). Parallel scan-path visualization. In *Proceedings of the 2012 Symposium on Eye Tracking Research and Applications* (ETRA), pp. 165-168. doi:10.1145/2168556.2168583

Raykov, T., & Pohl, S. (2013). Essential unidimensionality examination for multicomponent scales: An interrelationship decomposition approach. *Educational and Psychological Measurement*, *73*(2), 191-209. doi:10.1177/0013164412470451

Raykov, T., & Shrout, P. E. (2002). Reliability of scales with general structure: Point and interval estimation using a structural equation modeling approach. *Structural Equation Modeling*, *9*(2), 195-212. **doi:**10.1207/S15328007SEM0902_3

Rayner, K. (1978). Eye movements in reading and information processing. *Psychological Bulletin, 85*, 618-660.

Raz, A., & Buhle, J. (2006). Typologies of attentional networks. *Nature Reviews Neuroscience, 7,* 367-379. doi:10.1038/nrn1903

Reber, A. S. (1993). *Implicit learning and tacit knowledge: An essay on the cognitive unconscious*. New York, NY: Oxford University Press.

Reid, D. (2004). A model of playfulness and flow in virtual reality interactions. *Presence: Teleoperators & Virtual Environment, 13*, 451-462. doi:10.1162/1054746041944777

Renshaw, T., Stevens, R., & Denton, P. D. (2009). Towards understanding engagement in games: An eye-tracking study. *On the Horizon, 17*, 408-420. doi:10.1108/10748120910998425

Richardson, D. C., & Spivey, M. (2004). Eye tracking: Characteristics and methods. In G. Wnek & G. Bowlin (Eds.), *Encyclopedia of biomaterials and biomedical engineering* (pp. 568-572). New York, NY: Marcel Dekker.

Ritterfeld, U., Shen, C., Wang, H., Nocera, L., & Wong, W. L. (2009). Multimodality and interactivity: Connecting properties of serious games with educational outcomes. *Cyberpsychology & Behavior, 12*, 691-697. doi:10.1089/cpb.2009.0099

Royce, J. R., & Diamond, S. R. (1980). A multifactor-system dynamics theory of emotion. *Motivation and Emotion, 4*, 263-298. doi:10.1007/BF00993581

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology, 39*, 1161-1178.

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological Review, 110*(1), 145-172. doi:10.1037/0033-295X.110.1.145

Russell, J. A. (2009). Emotion, core affect, and psychological construction. *Cognition and Emotion, 23*, 1259-1283. doi:10.1080/02699930902809375

Ryan, R. M., Rigby, S., & Przybylski, A. (2006). The motivation pull of video games: A self-determination theory approach. *Motivation and Emotion, 30*, 344-360. doi:10.1007/s11031-006-9051-8

Salen, K., & Zimmerman, E. (2004). *Rules of play: Game design fundamentals*. Cambridge, MA: The MIT Press.

Saldaña, J. (2013). The coding manual for qualitative researchers (2nd ed.). Thousand Oaks, CA: SAGE.

Sas, C., & O'Hare, G. M. P. (2003). Presence equation: An investigation into cognitive factors underlying presence. *Presence, 12*, 523-537. doi:10.1162/105474603322761315

Sawyer, R. K. (2006). Introduction. In R. K. Sawyer (Ed.), *The Cambridge handbook of the learning sciences* (pp. 1-16). New York, NY: Cambridge University Press.

Sawyer, B., & Smith, P. (2008, February). *Serious Games Taxonomy*. Presentation at the Serious Games Summit, Games Developers Conference, San Francisco, CA. [Electronic version] http://www.seriousgames.org/presentations/serious-games-taxonomy-2008_web.pdf

Semrud-Clikeman, M., & Kutz, A. (2005). *Attention. In S. Lee (Ed.), Encyclopedia of school psychology* (pp. 29-33). Thousand Oaks, CA: SAGE.

Scherer, K. R. (2003). Introduction: Cognitive components of emotion. In R. J. Davidson, K. R. Scherer, H. H. Goldsmith (Eds.), *Handbook of affective sciences* (pp. 563-571). New York, NY: Oxford University Press.

Schoenau-Fog, H. (2011). *The player engagement process: An exploration of continuation desire in digital games*. Paper presented at the Fifth DiGRA Conference: Think Design Play, Hilversum, Netherlands. Abstract retrieved from http://www.digra.org/dl/db/11307.06025.pdf

Schubert, T., Friedmann, F., & Regenbrecht, H. (1999). Embodied presence in virtual environments. In R. Parton, & I. Neilson (Eds.), *Visual representations and interpretations* (pp. 268-278). London, UK: Springer-Verlag.

Sennersten, C., & Lindley, C. (2008, September). *Evaluation of real-time eye gaze logging by a 3D game engine*. Paper presented at the IMEKO TCI & TC7 Joint Symposium on Man Science & Measurement, Annecy, France.

She H. C., & Chen Y. Z. (2009). The impact of multimedia effect on science learning: Evidence from eye movements. *Computers & Education*, *53,* 1297-1307. doi:10.1016/j.compedu.2009.06.012

Shernoff, D. J., Csikszentmihalyi, M., Schneider, B., & Shernoff, E. S. (2003). Student engagement in high school classrooms from the perspective of flow theory. *School Psychology Quarterly, 18*(2), 158-176. doi:10.1521/scpq.18.2.158.21860

Shute, V. J., Ventura, M., Bauer, M., & Zapata-Rivera, D. (2009). Melding the power of serious games and embedded assessment to monitor and foster learning. In U. Ritterfeld, M. Cody, and P. Vorderer (Eds.), *Serious games: Mechanisms and effects* (pp. 295-321). New York, NY: Routledge.

Silvia, P. J. (2001). Interest and interests: The psychology of constructive capriciousness. *Review of General Psychology, 5*(3), 270-290. doi:10.1037/1089-2680.5.3.270

Skadberg, Y. X., & Kimmel, J. R. (2004). Visitors' flow experience while browsing a website: Its measurement, contributing factors and consequences. *Computers in Human Behavior, 20*, 403-422. doi: 10.1016/S0747-5632(03)00050-5

Slater, M., Usoh, M., & Steed, A. (1994). Depth of presence in virtual environments. *Presence: Teleoperators and Virtual Environments, 3*(2), 130-140.

Spires, H. A. (2008). 21st century skills and serious games: Preparing the N generation. In L. A. Annetta (Ed.), *Serious educational games* (pp. 13-23). Rotterdam, The Netherlands: Sense Publishing.

Squire, K. (2003). Video games in education. *International Journal of Intelligent Simulations and Gaming, 2*(1), 49-62.

Stanovich, K. E. (1999). *Who is rational? Studies of individual differences in reasoning*. Mahwah, NJ: Erlbaum.

Stark, L. W. (1994, July). *Why virtual reality works: Top-down vision in humans and robots*. Paper presented at the International Conference on Artificial Reality and Tele-Existence, Tokyo, Japan.

Steriade, M. (1996). Arousal: Revisiting the reticular activating system. *Science, 272*(5295), 225-226.

Sternberg, R. J. (2009). *Cognitive psychology*. Belmont, CA: Wadsworth.

Steuer, J. (1992). Defining virtual reality: Dimensions determining telepresence. *Journal of Communication, 42*(4), 73-93. doi: 10.1111/j.1460-2466.1992.tb00812.x

Styles, E. A. (2006). *The psychology of attention* (2nd ed.). New York, NY: Psychology Press.

Svahn, M. (2009, September). *Processing play: Perceptions of persuasion*. Paper presented at the Digital Games Research Association (DiGRA), Breaking New Ground: Innovation in Games, Play, Practice and Theory. London, UK.

Sweetser, P., & Wyeth, P. (2005). GameFlow: A model for evaluating player enjoyment in games. *ACM Computers in Entertainment, 3*(3), 1-24. doi:10.1145/1077246.1077253

Tai, R. H., Loehr, J. F., & Brigham, F. J. (2006). An exploration of the use of eye-gaze tracking to study problem-solving on standardized science assessments. International *Journal of Research & Method in Education, 29*(2), 185-208. doi:10.1080/17437270600891614

Takatalo, J. (2002). *Presence and flow in virtual environments: An explorative study* (Unpublished master's thesis). University of Helsinki, Finland. eve.hut.fi/Publications/ttalo_thesiswoa.pdf

Takatalo, J., Häkkinen, J., Komulainen, J., Särkelä, H., & Nyman, G. (2004). The experiential dimensions of two different digital games. *Proceedings PRESENCE 2004 at the seventh Annual International Workshop on Presence*, 274-278.

Tellegen, A. (1982). *A brief manual for the differential personality questionnaire*. Minneapolis, MN: University of Minnesota.

Tobii (2010). *Tobii Studio user manual: Software release 2.2.* Danderyd, Sweden: Tobii Technology AB.

Tobii (2011). *Tobii T60 & T120 Eye Tracker user manual: Revision 4.0*. Danderyd, Sweden: Tobii Technology AB.

Tobii. (2012). *User manual: Tobii Studio Version 3.2*. Danderyd, Sweden: Tobii Technology AB.

Trevino, L. K., & Webster, J. (1992). Flow in computer-mediated communication: Electronic mail and voice mail evaluation and impact." *Communication Research, 19*, 539-573. doi:10.1177/009365092019005001

Treisman, A. M. (1960). Contextual cues in selective listening. *Quarterly Journal of Experimental Psychology, 12*(4), 242-248.

Ulicsak, M., & Wright, M. (2010). *Games in education: Serious games*. UK: Futurelab.

Venkatesh, V. (1999). Creation of favorable user perceptions: Exploring the role of intrinsic motivation. *MIS Quarterly, 23*(2), 239-260. doi:10.2307/249753

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research, 11*, 342-365. doi:10.1287/isre.11.4.342.11872

Wadlinger, H., & Isaacowitz, D. M. (2006). Positive affect broadens visual attention to positive stimuli. *Motivation and Emotion, 30*, 89–101.

Wason, P., & Evans, J. St. B. T. (1975). Dual processes in reasoning. *Cognition, 3*(2), 141-154.

Webster, J., Trevino, L. K., & Ryan, L. (1993). The dimensionality and correlates of flow in human computer interactions. *Computers in Human Behavior, 9*, 411-426. doi:10.1016/0747-5632(93)90032-N

Weniger, S., & Loebbecke, C. (2010, December). *Cognitive absorption: Literature review and suitability in the context of hedonic IS usage*. Paper presented at the Annual SIG-IS Cognitive Research Exchange Workshop, St. Louis, MO.

White House, the, Office of the Press Secretary. (2010, January 6). *President Obama expands of "Educate to Innovate" Campaign for excellence in science, technology, engineering and math (STEM) education* [Press release]. Retrieved from http://www.whitehouse.gov/the-press-office/president-obama-expands-educate-innovate-campaign-excellence-science-technology-eng

Whitton, N. (2011). Game engagement theory and adult learning. *Simulation & Gaming, 42*, 596-609. doi:10.1177/1046878110378587

Wiebe, E. N. & Annetta, L. A. (2008). Influences on visual attentional distribution in multimedia instruction. *Journal of Educational Multimedia and Hypermedia 17*. 259-277.

Wiederhold, B. K., Davis, R., & Wiederhold, M. D. (1998). The effects of immersiveness on physiology. In G. Riva, B. K. Wiederhold, & E. Molinari (Eds.), *Virtual environments in clinical psychology and neuroscience* (pp. 52-60). Burke, VA: IOS Press.

Winkielman, P., and Cacioppo, J. T. (2001). Mind at ease puts a smile on the face: Psychophysiological evidence that processing facilitation elicits positive affect. *Journal of Personality and Social Psychology, 81*, 989-1000. doi:10.1037//0022-3514.81.6.989

Wirgley, W. J., & Emmerson, S. B. (2011). The experience of the flow state in live music performance. *Psychology of Music, 41*, 292-305. doi:10.1177/0305735611425903

Witmer, B. G., & Stinger, M. J. (1998). Measuring presence in virtual environments: A presence questionnaire. *Presence: Teleoperators and Virtual Environments, 7*(3), 225-240. doi:10.1162/105474698565686

Wojciulik, E., Kanwisher, N., & Driver, J. (1998). Covert visual attention modulates face-specific activity in the human fusiform gyrus: fMRI study. *Journal of Neurophysiology, 79*, 1574-1578.

Yarbus, A. L. (1967). *Eye movement and vision*. New York, NY: Plenum Press.

Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology, 18*, 459-482.

Young, M. F., Slota, S., Cutter, A. B., Jalette, G., Mullin, G., Lai, B., Simeoni, Z., Tran, M., & Yukhymenko, M. (2012). Our princess is in another castle: A review of trends in serious gaming for education. *Review of Educational Research, 82*(1), 61-89. doi:10.3102/0034654312436980

Zhang, P. (2013). The affective response model: A theoretical framework of affective concepts and their relationships in the ICT context. *MIS Quarterly, 37*(1), 247-274.

Zipf, G. (1949). *Human behavior and the principle of least effort*. Reading, MA: Addison-Wesley.

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