

CHARACTERIZING PERFORMANCE VIA BEHAVIOR CO-OCCURRENCES IN A 3D
COLLABORATIVE VIRTUAL LEARNING ENVIRONMENT:
AN EXPLORATORY STUDY OF PERFORMANCE AND DESIGN

A Dissertation
presented to
the Faculty of the School of Information Science and Learning Technologies
at the University of Missouri-Columbia

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

by

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JULY 2013



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COLLABORATIVE VIRTUAL LEARNING ENVIRONMENT:
AN EXPLORATORY STUDY OF PERFORMANCE AND DESIGN

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And hereby certify that, in their opinion, it is worthy of acceptance.

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Dr. Joi Moore

Dr. Janine Stichter (Outside Member)

DEDICATION

To my husband: You moved with me 3,650 miles, became a single parent while I focused on my studies, provided unwavering encouragement, and never once doubted me or my abilities.

To my parents: You have been my cheerleaders since birth, always confident and proud of whatever I have chosen to do.

To my son: You inspired me to finish. Let's go play!

With all my love and gratitude,

Thank you.

ACKNOWLEDGEMENTS

I have received encouragement and support from many individuals throughout the course of my Ph.D. work, especially this dissertation. While the acknowledgements are long, I like to think this is representative of how collaboration over distance serves to produce quality work and lasting friendships.

First and foremost, I express my deepest appreciation for my advisor, my supervisor, and my mentor, Dr. James Laffey. He provided me with rich opportunities for researching virtual worlds, online learning, and social computing. He continually helped me to see ideas or writing in an entirely different light with just a small comment, also becoming known as “The Yoda Effect.”

I also want to thank my committee members Dr. Gail Fitzgerald, who always had great timing with her advice and support, Dr. Joi Moore, who helped me to dig into research and writing early on in my Ph.D. program, and Dr. Janine Stichter and her SCI-A team, who were integral to the success of the iSocial project. The curriculum she and her team have developed is a large part of what made the iSocial 3D CVLE such an interesting and engaging project to research.

I also thank the iSocial 3D CVLE team making an engaging 3D CVLE for kids, and without their effort this work would not have been possible: Joe Griffin, Ryan Babiuch, Michael Haug, Tyler Derrick, Kaustubh Gadre, Xianhui Wang, Nan Ding, Mark Singer, Jaclyn Benigno, and former iSocial members Drs. Matthew Schmidt and

Carla Schmidt, two of the initial iSocial visionaries. I especially thank Joe Griffin for always lending an eager ear to my dissertation progress and thoughts; it was great to share with Joe an overall excitement about learning and research.

I also want to thank the University of Wisconsin Epistemic Games Group for creating this innovative method ENA, and for gladly mentoring and sharing papers, software, and ideas with others freely in order to advance research and learning. Specifically I want to thank Dr. David Hatfield for meeting with me initially and getting me on the right track by helping to frame my research with just a few simple questions, a book, and solid encouragement. I want to thank Golnaz Arastoopour for her unending support over email and Skype calls, always answering my next ENA question in thoughtful detail. I also want to thank Dr. David Shaffer for taking the time to walk me through the “big picture” ENA concepts. It was with all of this support in understanding how to apply ENA and using the ENA scripts and software that this dissertation was possible.

In addition, I thank Dr. Sean Goggins for allowing me to pick his brain periodically, wherever he was in the world at the time, on software, R, resources, and network ideas.

I also thank Karen Grace-Martin, the best statistical instructor and consultant there ever was. She can take something as abstract as Linear Mixed Modeling and make it as intuitive as possible.

For funding my positions, I also want to acknowledge the Institute of Education Sciences and the Department of Elementary and Secondary Education, without whom the field tests would not have occurred.

I want to share my deep appreciation to my close friends and colleagues, Dr. Camille Dickson-Deane and Dr. Holly Henry, who understood and could lend a sympathetic ear. As part of the “Three Musketeers”, they helped to push me through those last four months of analyzing and writing at all hours, and set me up with a goal that I could not say “no” to.

Lastly, I want to share my love and appreciation to my husband Jeff and my son Alexander. You never said a negative word. Thank you for being proud of me. We did it.

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Abstract

The iSocial 3D CVLE is an innovative design for addressing special needs at a distance that require social and active learning. This exploratory retrospective case study explored innovative methods of analyzing co-occurrences of behavior to gain insight into understanding and evaluating student performance and 3D CVLE design. Visualization techniques were employed to model student behavior within similarly structured activities. Linear mixed models revealed that student performance significantly differed across environments. In addition, environmental design attributes were identified through qualitative memos. General behavior patterns were associated with design environment attributes, warranting further study.

CHAPTER 1: INTRODUCTION

Overview

The purpose of this chapter is to introduce a study of performance in a 3D virtual learning environment. The chapter situates the study within the context 3D virtual learning, and provides a rationale and significance for the research questions and methods. The structure of this introduction is as follows: First 3D virtual learning in general and with students with autism spectrum disorders are reviewed. Next, 3D collaborative virtual learning environments (3D CVLEs) is discussed, including the iSocial 3D CVLE, the learning system for this study. The theoretical framework, statement of problem and significance of the study are described, followed by the research questions and design of the study. An overview of delimitations, limitations, and key terms follow.

3D Virtual Learning

Three-dimensional, virtual learning environments (3D VLEs) are gaining momentum as mediums for teaching and learning. Their natural affordances to immerse students in virtual worlds literally of any design allow students to experience places and interactions that they may not otherwise have the opportunity. They hold great potential for “learning by doing” by allowing the performance of embodied actions through an avatar in a 3D environment (Hew & Cheung, 2010), and are a safe place to experiment without incurring potential

serious consequences like those that could be incurred in the real world. Certain types of 3D VLEs can also allow distributed users to synchronously participate in a learning experience, which can provide access to instruction and information regardless of location.

Three-dimensional virtual learning environments are defined as “computer-generated, three-dimensional simulated environments that are coupled with well-defined learning objectives” (Schmidt, 2010, p. 4). These three-dimensional environments use an “Alice-in-Wonderland” style interface (Dede, 2005) in which the user enters a 3-dimensional world through their avatars using a networked computer, and can be single-user or multi-user. Single-user virtual environments facilitate the user to interact with items in the world or programmed non-player characters (NPCs, or “bots”), but do not see or interact with other real people within the virtual world. Multi-user virtual environments, known as MUVES or collaborative virtual environments, allow multiple users to enter at one time. Users can often see each other, chat, and sometimes speak to each other. When designed with learning objectives in mind, these become virtual learning environments (Mikropoulos & Natsis, 2011).

Some of the most heavily researched 3D CVLEs over the past decade have been (a) River City (Dede, Nelson, Ketelhut, Clarke, & Bowman, 2004; Ketelhut & Schifter, 2011; Metcalf, Clarke, & Dede, 2009); (b) Quest Atlantis (Barab, Thomas, Dodge, Carteaux, & Tuzun, 2005; Hickey, Ingram-Goble, & Jameson, 2009); and most recently (c) EcoMUVE (Metcalf, Kamarainen, Tutwiler, Grotzer, & Dede, 2011; Metcalf et al., 2009). All of these 3D CVLEs have a common goal of supplementing

late middle school-age curriculums through 3D virtual learning experiences. In addition to these environments, other 3D virtual learning research has encompassed a wide range of domains such as physics (Scheucher, Bailey, Gütl, & Harward, 2009), second language learning (Peterson, 2007), business computing (Dickey, 2005), healthcare training (Chodos et al., 2010), and special education (Cheng, Chiang, Ye, & Cheng, 2010; Schmidt, Laffey, Schmidt, Wang, & Stichter, 2012). Previous studies have shown that students can learn in these environments (Arici, 2009; Hickey et al., 2009; Ketelhut, Nelson, Clarke, & Dede, 2010; Metcalf et al., 2011) and they are highly engaging and motivating (Arici, 2009; Choi & Baek, 2011; Dede, Clarke, Ketelhut, Nelson, & Bowman, 2005).

Students with Autism Spectrum Disorder and 3D Virtual Learning

Individuals identified with Autism Spectrum Disorder (ASD) have qualitative impairments in three main areas: (1) social interaction; (2) communication; and (3) “restricted repetitive and stereotyped patterns of behavior, interests and activities” (American Psychiatric Association, 1994). Deficits in these areas manifest themselves as a lack of social competence, or inability to know how and when to appropriately use social skills when interacting with others (Stichter et al., 2010). Students with a diagnosis of autism can lie anywhere along a range of functioning in these core areas, thus the term “spectrum” in ASD. For students with high-functioning autism (HFA), they are known to have a desire to be social but do not yet have the knowledge or skills to successfully perform interactions in a complex and social environment (Myles & Simpson, 2002). The three core areas that are

particularly problematic for students with HFA/AS in regards to social competency are (1) theory of mind; (2) emotion recognition; and (3) executive functioning (Stichter et al., 2010).

Deficits in social competency can have severe and long-lasting consequences if left untreated. Immediate issues such as the inability to make and maintain friendships can result in social isolation (Eaves & Ho, 1997), inability to properly handle bullying (Stichter et al., 2010), low self-esteem (Myles & Simpson, 2002), and depression to name a few. Longer-term consequences such as instability of employment also point to the need for developing and maintaining social competency (Howlin, 2000; Howlin, Mawhood, & Rutter, 2000). Assisting students with ASD through social competency interventions is a need in order to improve the well-being and outcomes of youth with ASD. Unfortunately challenges of location and access limit the ability of youth to participate in high quality, evidenced-based interventions.

Three-dimensional learning environments have shown promise in developing social skills of students with ASDs. Research has demonstrated that individuals with ASDs can use and interpret virtual environments as well as learn targeted social skills such as enhanced empathy (Cheng et al., 2010), emotion recognition through avatar representations (Moore, Yufang Cheng, McGrath, & Powell, 2005), positive social behaviors such as eye contact and attending (Cheng & Ye, 2010), and social appropriateness in virtual social settings (Leonard, Mitchell, & Parsons, 2002; Parsons & Mitchell, 2002; Parsons, Mitchell, & Leonard, 2005; Rutten et al., 2003). In addition, research has also shown that these types of environments,

including electronic screen media in general, are highly engaging to students with ASD (Mineo, Ziegler, Gill, & Salkin, 2009).

3D Collaborative Virtual Learning Environments and iSocial

Three-dimensional collaborative learning environments are a type of 3D VLE that allow multiple users to be present in the world at the same time and interact with the world and with each other through their avatars, text chat, and sometimes voice. Many of the aforementioned studies of 3D VLEs were either usability or efficacy studies of a single user interacting with a researcher (Cheng & Ye, 2010; Cheng et al., 2010), or multiple users in the environment where the emphasis was not on collaboration with peers, but on individually performing certain tasks in world and either reporting back to a team or teacher through text chat or writing submissions (Barab et al., 2005; Dede et al., 2005; Metcalf et al., 2009).

What is performance?

Performance within a CVLE, as defined in this study, uses Hickey et al.'s definition of "close level" data, which are data collected at the level of the game or learning environment itself (2009, p. 188). It is from this performance, situated within the context in which it is learned, that data are gathered and analyzed. A performance, as defined in this study, is a summation of behaviors of observable avatar movement, verbalizations, or interactions within the 3D CVLE for a targeted unit of analysis. The targeted unit of analysis for this study is a student within a lesson activity.

The call to study performance

Research from these environments and others are stating there is a need to begin to study performance in 3D CVLEs in order to understand at a more detailed level what students are doing in the environment, how that relates to their distal learning outcomes, how design might influence learning behavior, and eventually be able to use student performances as one of several levels of assessment (Dede, 2012; Hickey et al., 2009; Quellmalz & Pellegrino, 2009; Quellmalz, Timms, & Schneider, 2009; Shute, 2009). Dede and Quellmalz call specifically for more advanced methods to study performance that are useful for identifying patterns in behavior, such as that found in network analysis (Dede, 2012; Quellmalz & Pellegrino, 2009). Currently the research on performance in 3D CVLEs is quite limited, primarily based on the frequencies of interactions with NPCs that can be found in the River City research (Ketelhut et al., 2010) or more proximal measures of behavioral performance such as ratings of in-world writing samples submissions from an inquiry learning in world as found in Quest Atlantis (Hickey et al., 2009). However, more advanced, pattern-oriented approaches are emerging to analyze complex behaviors in CVLEs by adopting techniques used in other fields such as text analysis to identify behavioral patterns (Thawonmas & Iizuka, 2008). For iSocial, in particular, the research on reciprocal interaction has used frequency analysis to describe collaborative performances of individuals, but identifies the need to look at behavior patterns using more advanced methods to represent and model user behavior. Understanding behavior patterns could more richly could characterize

both within-activity and across-activity performance as well as provide implications for design improvements (Schmidt et al., 2012, pp. 411-412).

The iSocial 3D CVLE

There is currently a dearth of research on student performance within richly collaborative learning tasks where the core components of the activity are synchronous and highly collaborative between multiple students. The strong affordances of collaborative virtual learning environments can allow students to synchronously collaborate and interact with each other in world, which is why this medium holds great promise for social competency instruction and practice.

iSocial 3D Virtual Learning (i.e., “iSocial”), the context for this study, is a 3D CVLE designed to deliver curricular content to youth. The current implementation is a translation of a social competency curriculum for youths with ASD ages 11-14 to synchronously learn together as a group within the 3D CVLE. iSocial is one of the only collaborative learning experiences that utilizes a 3D CVLE that requires and depends upon complex and extensive collaboration in the virtual world. Students are brought into the world along with an instructor to interact with each other through their avatars and voices, engage in synchronous discussions, interact with the environment as a group, and learn about and perform integrated, scaffolded, social competency skills and problem solving for a total of 31 curricular lessons of 45 minutes each. In addition, iSocial is not a supplement to classroom curriculum, but is the entire social competency curriculum delivered at a distance to distributed students. The level and type of collaboration present in iSocial is not present in the

aforementioned studies. The case of iSocial provided a unique opportunity to study student performance in world and how we can understand and characterize complex, open-ended social performances in a collaborative, synchronous virtual learning environment. The benefits of being able to characterize complex social performance in collaborative 3D virtual learning environments have many benefits. Some of these benefits can eventually lead to being able to provide formative assessments and feedback to teachers and learners, and helping designers to understand how design choices can affect learner behavior and overall performance in the virtual environment. However, in order to pursue to that end, we must first be able to identify and characterize virtual performances in the virtual environment in ways that go beyond simple counting of behaviors and that resonate with the complexity of behavior in a social context.

Theoretical Framework

The guiding theoretical framework of the study is that of situated learning (Brown, Collins, & Duguid, 1989). Situated learning theory posits that learning develops within a social context, and individuals use environment within that context to enact and support that learning (Lave & Wenger, 1991). Individuals learn by engaging in the process of performing, and it is through continued use of those skills in practice that those skills become crystallized (Brown et al., 1989). For example, students do not just learn about social competency skills in isolation, but learn by also using and practicing their social skills within an environment.

iSocial uses a social competency curriculum (see Chapter 3 for additional details) which has designed multiple authentic (aka “naturalistic”) practices into every unit. They are authentic and naturalistic in that while the situations may be fantasy, the social problem solving is real, negotiated, and student-led. The core idea for these naturalistic and situated practices is to embed the group of learners into a designed social context in which they need to use and integrate all the skills they have learned up until that point into an authentic social situation within the virtual world in order to accomplish something of value together (e.g., escape the ship and get to an island, build a restaurant, or help the king). It is within this sub-context in iSocial that the performances are understood and characterized. Because the learning, activity, and performance take place within a context and are inextricable from that context, this study also investigated how student performances varied between these design environments, or naturalistic practice activities, in order to understand how and in what ways environmental and activity design attributes are associated with behavior patterns.

Statement of the Problem

While we know that students, both with and without ASDs, can learn in 3D VLEs and 3D CVLEs, we do not yet know how to characterize (describe key features of) complex, open-ended social performances in a collaborative, synchronous virtual learning environment. We also do not yet know how to measure and characterize that type of performance when the goal is to integrate multiple behaviors

simultaneously to demonstrate competency in such a performance, or in other words, how to characterize a performance that takes into account co-occurring behaviors. We are also still learning how design attributes play a role in these collaborative performances, and how the design attributes may be associated with behavior patterns.

Purpose of the Study

The purpose of this study was to further our understanding regarding (a) characterizing complex, social student performance within iSocial 3D CVLE activities, (b) how behavior patterns may differ across iSocial 3D CVLE activities and design environments, and (c) how the activity and environmental design attributes are associated to student behavior patterns in world.

Significance of the Study

The significance of this study is threefold. First, by exploring and building our understanding of how to characterize student performance within the iSocial 3D CVLE context, this study's findings help to advance the methods and techniques used to characterize that performance in terms of its co-occurring behaviors. Once we can accurately characterize student performances, researchers can then work towards assessing that performance and providing formative feedback to students and teachers. Formative feedback has been found to assist in self-regulation of

learning (Nicol & Macfarlane-Dick, 2006), and is an important process of teaching and learning (Benson, 2003). In addition, once we can more accurately characterize performance and hone the methods to characterize that performance, researchers can also work towards which aspects of that performance might be able to be taken over by machine-based logging of actions for understanding performance.

The second significant aspect of this study is its contributions to 3D CVLE and human-computer interaction (HCI) design. By looking at characterized performances of individuals and how behaviors patterns may differ across design environments, as well as looking into how patterns of behavior are associated with patterns of design attributes, we were able to see how design and implementation choices can potentially contribute to and mediate student performance.

The third aspect with major significance for this study is related to the method itself. Traditionally, where performance was observed and evaluated, they were in the form of frequency studies. This study applies an innovative method to understand the unique characteristics of student performances by looking at the patterns of how the behaviors co-occur, or are performed together in the virtual world. For other studies where the performance needs to look at how and in what way users combine specific behaviors together in their social performance within a 3D CVLE, this case study can move that area of research forward. Additionally, this method also provides a means for understanding how design choices can be associated with changes in complex behavior patterns. If other studies need to investigate how design changes can impact the complex integration of behaviors

into a systematic whole performance, this study provides promise with the methods.

This study provides a way of characterizing student performance via co-occurrences of behavior within the iSocial 3D CVLE, both within and across design environments, as well as investigated how patterns design attributes are associated with patterns of behavior. In return, this study benefits design decisions and the implementation of iSocial. The study also explicates a particular method of study that has potential for broad application across 3D CVLEs.

Statement of the Research Questions

Based on the purposes mentioned above, the study is guided by the following research questions:

RQ 1: Can student performance within iSocial 3D CVLE naturalistic practice activities be characterized through co-occurrences of behavior? If so, how and in what ways?

RQ 2: Do characteristics of student co-occurring behaviors in iSocial 3D CVLE naturalistic practice activities differ across design environments? If so, how and in what ways?

RQ 3: Are design attributes associated with behavior patterns?

Design of the Study

This research is an exploratory, retrospective case study of student performance and 3D CVLE design within the iSocial naturalistic practice activities. This design was chosen due to the need to gain a better understanding of, explore and describe the co-occurring behaviors and patterns within the specific context of the iSocial 3D CVLE, and in turn, be able to gain insights into design from the characterized performances. Qualitative coding of behaviors combined with methods to achieve inter-rater reliability were used, and those coded behaviors were then analyzed using network analysis techniques and visualizations. The network analysis techniques were applied from epistemic network analysis studies (Hatfield, 2011; Orrill & Shaffer, 2012; Shaffer et al., 2009), where the core rationale is that how the student qualitative codes are used together (their relationship and pattern of use, or co-occurrence) provides insights beyond those gleaned from frequency counts alone or the behaviors in isolation, especially when the goal is to use concepts together rather than in isolation. This method does this by studying the co-occurrence of student performance codes and in turn being able to (a) characterize performances and compare those performances between students, (b) compare the performances and across design environments, and (c) investigate how patterns of behavior are associate with patterns of design attributes.

One type of iSocial learning activity structure was chosen as the context to study student performances. This specific learning activity structure is termed “naturalistic practice”, which is a type of student-led and teacher-facilitated activity in which students are to practice and integrate all of their previously learned skills

into a complex social performance aimed at accomplishing something of value as a group within the virtual world. For example, in one task the students were to work as a group and decide how to build a restaurant buffet for their restaurant. In another lesson, the task was to locate and find all of the king's missing items, find the king, and return them to him. By choosing the same activity structure, all comparisons of performance can then be more greatly attributed to individual differences and the remaining aspects of design environment and attributes.

In addition, performances across all design environments were compared. Linear mixed models were used to detect for significance of performance differences across levels of activity environment. Design attributes were identified through qualitative analysis, followed by the investigation of the association design attributes with patterns of behavior as described in the post-hoc multiple comparisons. This allowed us to build knowledge regarding how design attributes may play a role in student performance.

As stated, this case study is retrospective. The delivery of the lessons used in this study took place during the Spring of 2012 and was part of a larger study on the effectiveness of iSocial to produce gains in the social competency of students with ASD as observed by gains in the distal assessments in three core areas: theory of mind, emotion recognition, and executive functioning. A pilot study was conducted prior to this study on a small subset of this data, 7 students within 2 naturalistic practice activities, which served to create the coding scheme for this study.

Study Delimitations

In this study, the design is limited to a specific type of learning activity, which is the naturalistic practice activity (further described in Chapter 3). This was done for three reasons (a) to limit the scope of the study since the level of analysis is very detailed and nuanced; (b) to limit the confounding effects of activity type (e.g. a teacher-led review or teacher-led modeling activity) when comparing performance across design environments; and (c) the naturalistic practice activities have the richest opportunities for student-led, peer-to-peer interaction and performance. In addition, students or lessons with large dosage issues (where students miss a significant portion of the curriculum due to absence or technical issues) were also left out of the study to limit confounding effects of network or computer issues on performance when attempting to understand how the students' performances differ across design environments.

Summary

This chapter introduced the overview, rationale, and significance for this study. Students with ASD and HFA are in great need of social competency development for both short-term and long-term outcomes, no matter their location or immediate access to services. The iSocial 3D CVLE is such a system, and provides a unique context for researching and understanding student performance both within and across activities. There is currently a gap between the current predominant methods of counting behaviors and the need to understand patterns of

rich interactive performances that use simultaneous behaviors within those performances, such as found in iSocial. This study attempted to bridge that gap in order to facilitate improvement of designs as well as facilitate the ability to target students in regards to the types of co-occurring behaviors that are used. To that end, this study performed an exploratory, retrospective case study on characterizing performances via the co-occurrences of behavior within the unique context of iSocial 3D CVLE.

In the next chapter, the literature surrounding these issues is covered. Chapter 3 covers the specific attributes of iSocial in detail, followed by three chapters covering the methods, results, and discussion.

Key Terms

Terms Related to Autism

- **ASD:** Autism Spectrum Disorder, characterized by deficits in 1) social interaction, 2) communication, and 3) “restricted repetitive and stereo-typed patterns of behavior, interests and activities” (American Psychiatric Association, 1994)
- **HFA:** High-functioning autism

3D VLE-Related Terms

- **Avatar:** A visual representation of the user within a virtual environment, often in embodied form
- **Three-dimensional collaborative virtual environment (3D CVE):** “a distributed computer-based virtual space (or set of spaces) in which people can meet and interact with others via their avatars” (Moore et al., 2005, pp. 231-232). Also known as a multi-user virtual environment, or MUVE.
- **Three-dimensional collaborative virtual learning environment (3D CVLE):** A 3D CVLE is “designed to support learners’ achievement of specific learning objectives ” (Schmidt, 2010, p. 4)
- **Three-dimensional virtual learning environment (3D VLE):** “A computer-generated, three-dimensional simulated environment which is coupled with well-defined learning objectives and relies on the environment and

associated software affordances to mediate and facilitate achievement of those objectives” (Schmidt, 2010, p. 15)

Methods Terms

- **3D Point:** For the purposes of this study, a “3D point” is a point in 3-dimensional space, representing three scores, one score for each of the three principal components. Principal component 1 corresponds to the x-axis, principal component 2 corresponds to the y-axis, and principal component 3 corresponds to the z-axis.
- **Adjacency Matrix:** A matrix which defines the co-occurrences of behaviors within the same segment; if behavior x and behavior y are both present, then $Cell_{x,y} = 1$ and $Cell_{y,x} = 1$; otherwise the value is 0 for both. The adjacency matrix used in this study is a symmetrical, binary, square matrix.
- **Adjacency Vector:** A segment with a series of ones (1) and zeros (0) indicating presence or absence of the behavior. The adjacency vector is the numerical and matrix representation of the values coded in the segment.
- **Behavior:** A discrete and explicit coded unit of observable movement, interaction, or verbalization within the 3D CVLE. See Appendix D.
- **Behavior patterns:** Co-occurrences of behaviors that predominantly emerge for a user over time. Behavior patterns are used to characterize a student performance. One can discuss behavior patterns as a subset of the co-occurring behaviors of the overall user/student performance. See Appendix D.

- **Characterized performance:** A performance that is described based on its principal components and dominant co-occurrences of behaviors (behavior patterns)
- **Co-occurrence of behavior:** Behaviors which are used at the same time; i.e., within the same segment
- **Cumulative Adjacency Matrix:** A matrix that is a sum of all the binary adjacency matrices for that unit of analysis, (in most of our cases in this study, a student within an activity)
- **Cumulative Adjacency Vector:** A vector which is the cumulative adjacency matrix converted into vector form
- **Design attributes:** Properties and features of the activity and design environment, such as tool use, targeted learning area worldbuilding style, or whether it is a large group or small group activity.
- **Design environment:** For the purposes of this study, it is the equivalent to the activity content, structure, and rules as well as the environment in which the activity takes place. The design environment encompasses the elements of virtual world design, virtual tools, and activity content, structure and rules. Design attributes are a subset of properties that are used within activity and design environment.
- **Performance:** The sum of behaviors evaluated according to expectations or goals; in the context of the study's methods, performance is the co-occurrence of behaviors summed for a targeted unit of analysis, or a student within an activity

- **Score:** For the purposes of this study, a score is number between -1 and +1 that represents a student's summative performance for a unit of analysis on a particular principal component.
- **Segment:** A selected unit of time, also called a "slice", in which coded behaviors will be identified. The occurrence of behaviors within the same segment defines them as being "co-occurring." (See Rupp et al., 2009; Shaffer et al., 2009)

CHAPTER II: LITERATURE REVIEW

The purpose of this chapter is to provide a synthesis of literature related to this study of performance and design in the iSocial 3D CVLE. The central argument of this chapter is two-fold: (1) that there is a need to characterize complex, open-ended social performances in such a way that allows the portrayal of the behavioral complexity, especially when the expectations is for users to perform simultaneous (i.e. co-occurring) behaviors, and (2) that behavior can be used to understand and inform design. For example, a user's performance could be characterized by active orienting towards peers, and this behavior tends to co-occur with verbal initiations and verbal responses. Characterizing performance based on these behavior co-occurrences can allow representation and interpretation of patterns of behavior and the relationships between those behaviors within student performances. In doing so, characterizing performances via behavior co-occurrences can move forward our ability to analyze student performances within activities as well as look at the associations between behavior patterns and design attributes.

The structure of this literature review is as follows. First we review the call in the literature to (a) look at performance and behavior within 3D virtual environments, and (b) begin to analyze behavior in order to achieve a more authentic understanding of performance within 3D CVLEs. Second, we then review the literature regarding ways researchers have analyzed behaviors and performance in 3D VEs, 3D VLEs, and 3D CVLEs, both for the purposes of being able

to describe that behavior as well as to inform and iterate design. Third, I will review promising methods for characterizing complex, open-ended performance, methods which look at co-occurrences of behavior to characterize performances. Due to the context for this case study, I also will review the characteristics of ASD and HFA in regards to social competency, and what we currently know about individuals with ASD learning and performing social competency within 3D VLEs and CVLEs. After the review, we then summarize how the application of a technique of characterizing complex co-occurrences of qualitative codes, epistemic network analysis (ENA), is a promising method for analyzing patterns of co-occurring behaviors within a social competency performance such as those found within the iSocial 3D CVLE, both within and across design environments.

Why Research Virtual Performance?

The potential and ability for students to learn in well-designed 3D VLEs has been established. Student learning gains have been documented in 3D VLEs and 3D CVLEs targeting domains such as scientific inquiry (Barab et al., 2009; Dede et al., 2004; Hickey et al., 2009; Ketelhut, Dede, & Clarke, 2008; Ketelhut et al., 2010), history (Squire, Barnett, Grant, & Higginbotham, 2004; Squire & Barab, 2004), special education (Cheng & Ye, 2010; Cheng et al., 2010; Moore et al., 2005; Rutten et al., 2003), and self-care (Kafai & Giang, 2007). Learning gains have often been established using a pre-post assessment format. In turn, these out-of-environment data serve as proxies for their performance in the environment (Dede, 2012). While

the continued assessment of learning gains from these environments is important, many researchers in the 3D VLE fields are calling for more authentic means to describe and assess individuals' performances within the VLEs in order to inform both what students are doing in the VLEs (Dede, 2012; Quellmalz & Pellegrino, 2009) and in turn inform design (Hickey et al., 2009).

Ketelhut et al. (2010) in their study of the River City scientific inquiry environment analyzed results of over 2000 middle school-aged students across 61 classrooms, found pre-to-post gains in scientific inquiry based on a standardized "test-like" survey. However, by also conducting a related in-world performance assessment in which students were asked to write "Letters to the Mayor", students were able to demonstrate their learning processes within a similar context. Hickey (2009) call this form of assessment "proximal assessment", or learner performance on a task not the same as, but also not far removed from, the context in which it is learned. They found a wider variation and demonstration of what students understood and could do in their "letters to the mayor" than was demonstrated in the distal standardized assessments. Hickey calls this type of assessment "distal" because it is far removed from the context in which it is learned. While not an example of analyzing behavior in the VLE, it does demonstrate that different data used in tandem with other types of performance data serve to reveal a more in-depth and accurate picture of student learning and performance than distal standardized tests alone. Because of this, Ketelhut's observations of students showing a wider variation of what they understood in the proximal over distal tasks led them to conclude that distal assessments, such as standardized achievement

measures, used in isolation of other data could possibly lead to mis-categorization of student learning or lead researchers astray if not used in conjunction with other forms of data, like proximal and close data, such as the documentation of behaviors within authentic virtual world performance tasks.

Both Hickey and Dede from their respective research in Quest Atlantis (Barab et al., 2005; Hickey et al., 2009) and River City (Dede et al., 2004; Ketelhut et al., 2010; Metcalf et al., 2009), two of the most heavily researched 3D CVLEs in the past decade, also agree that virtual performance data are essential. Similar to what Ketelhut found, Hickey (2009) stated that multiple levels of analysis, in particular close, proximal, and distal, should be conducted in order to triangulate and inform our interpretation of what students know and can do, and in turn the multiple levels of data can inform design. Virtual performance data (close-level data) can be used to triangulate distal assessment data by looking for “echoes”, or patterns, between the performances and distal data. Hickey also points out that when echoes or patterns are seen across levels of assessment, it supports the idea that the distal results were less likely achieved by chance, and the close data can be analyzed for ways to inform and iterate the design. Dede and colleagues’ work and experience on the heavily-researched 3D CVLEs of River City and more recent EcoMuve (Metcalf et al., 2011; Metcalf et al., 2009), both 3D CVLEs for middle-school aged students, has led to Dede’s most recent report (2012) describing the directions that 3D CVLEs need to move in order to gain a more authentic understanding of student learning and performance within these worlds. While he states that these environments are indeed engaging, most of what we know about students are from proximal and distal

data, often multiple-choice or standardized assessments outside of the virtual world, what he terms “proxies” for the real world performance. Dede suggests that researchers need to move forward by gaining more authentic data on what the students are doing in world, not via proxies, but by gathering data on the actual performance within the virtual world.

There is a growing trend in analyzing complex behavioral data, both in and outside virtual environments via more complex models to represent patterns rather than only frequency counts. There is a growing number of researchers that are suggesting that the understanding of performance needs to adopt new techniques by having education researchers look to areas of computer science where “pattern analysis of complex data already exists” and adopt those techniques into virtual world performance analysis and assessment (Quellmalz et al., 2009). Such research is seen in the uses of Bayesian Networks (Shute, 2011; Shute & Ke, 2012), multidimensional scaling and cluster analysis (Hou, 2012; Thawonmas & Iizuka, 2008; Thawonmas, Kurashige, & Chen, 2007; Wallner & Kriglstein, 2012), looking at co-occurring patterns through networks (Thawonmas & Iizuka, 2008; Wallner & Kriglstein, 2012), and the adoption of text analysis techniques to virtual world behavior such as KeyGraphs (Thawonmas & Iizuka, 2008). Quellmalz suggests that the field of serious games, educational simulations, and 3D CVLEs needs to be able to understand complex student performance in context within 3D CVLEs in order to move forward in understanding how students are using and learning within 3D CVLEs.

Analyzing Virtual Performance within 3D VEs, VLEs, and CVLEs

Core commonalities and trends exist in the 3D VE behavior and performance analysis literature. Most of the recent literature analyzing behavior and performance in VEs uses visualization to represent the complex patterns that exist within the data. The data is then often used to understand user behavior and then in turn inform design iteration. Visualization is defined as “the use of computer-supported, interactive, and dynamic visual representations of data to gain new insights and form new hypotheses” (Dixit & Youngblood, 2008, p. 33). However, as researchers have explored the best methods to analyze performance in 3D VEs, they have identified a constellation of approaches. Many of the 3D VEs have specific goals for its users, different types of desired performances for the users and different virtual environment layouts. Because of this, there is a divergent set of approaches that have been used to analyze user behavior and performance in order to analyze those goals. Little research has been done on characterizing complex, open-ended, highly collaborative social performances within 3D CVLEs, especially performances that require the user to demonstrate co-occurring behaviors within that performance. In the following sections, empirical research in 3D VEs, CVEs, and CVLEs on the analysis of behaviors to describe performance patterns and iterate designs is reviewed.

Virtual Performance in 3D VEs

Many single-user 3D VEs have primarily been interested in the usability and playtrace patterns of its users in order to inform design. Many begin the analysis of usability and playtrace patterns by collecting telemetry data. Telemetry data are defined as the raw data that represents user behavior within the virtual environment (Drachen 2012), and this raw data is then converted into interpretable user metrics to understand performance and iterate design. For many 3D VEs, aggregated playtraces overlaying virtual environment maps were the dominant form of analyzing behavioral trends, such as “hot spots” or navigational flow patterns. Researchers perform this analysis to determine if users were using the environments as intended by designers (Dixit & Youngblood, 2008; Gagné, El-Nasr, & Shaw, 2011). These playtraces, heat maps, and bar charts were used to represent actions within certain locations in the environment over time and over many players (Dixit & Youngblood, 2008; Drachen & Canossa, 2009; Moura, el-Nasr, & Shaw, 2011).

As one case study, VU-Flow (Chittaro, Ranon, & Ieronutti, 2006), a visualization tool for analyzing navigational behavior in virtual environments, gathered telemetry data from navigation logs in Udine3D. Users were able to walk through Udine, Italy and explore one of the city squares. The logs captured and recorded user ID, position in the environment, orientation, timestamp, and session ID. A total of 23,000 log entries across 130 unique visits were collected. By analyzing the frequencies from the log data, they were able to study how long users

spent in various parts of the environment. In addition, overlaying the playtraces and frequencies of time spent onto a 2D map of the world, the data then were visualized in two ways, non-aggregated and aggregated. Non-aggregated allows comparison of users, and aggregated highlights dominant paths and averages among the users. They found when applying the VU-Flow tool to the environment of Udine3D, they could see patterns in time spent and navigational flow within the environment, indicating natural flow as well as navigational problems. For example, they saw some users did not understand the visual language in the world and would consistently attempt to walk through transparent walls and fail. They stated the visualizations of vast amounts of log data helped to identify usability issues and improve design. However, they stated it would be necessary to enhance their methods to include other types of interaction data. Specifically, they would like to correlate the navigational data with other interactional data, as they stated these correlations between user behaviors would make the data more meaningful. In other words, they stated it would be more informative and meaningful to represent relationships between the behaviors as a unified whole rather than simply the frequencies in isolation.

Visual analysis of data is a useful way to represent large amounts of data in order to uncover patterns. In addition, documenting movement and orientation is useful for documenting patterns of what is important for the user's attention while in the environment. While collecting playtraces are useful for uncovering navigational issues, when users are doing more than navigating, additional and possibly different types of data need to be collected and visualized. In addition,

when the virtual environment becomes collaborative in nature, then multiple users have the potential to interact together, often in more open-ended and unstructured ways than in single-user VEs. It is within 3D CVEs that data becomes much more complex.

Virtual Performance in 3D CVEs

The analysis of behaviors to understand performance in 3D CVEs have evolved over the past decade. While frequency analysis still continues due to its usefulness in analyzing certain types of patterns over time and space, more complex models are being used to model and cluster user behavior within these collaborative worlds. Table 1 lists a review of the literature on the type of data and methods for analyzing behaviors within 3D CVEs. While frequency analysis is useful and informative, the visual analysis can become complicated very quickly the more behaviors that are added to the analysis, especially when looking for trends or patterns of performance over time or space. In addition, frequency analysis does not do well with classifying users or identifying roles. Over the past few years, more complex methods of modeling student behavior within 3D worlds have developed.

Table 1. Type of data and methods of analyzing behaviors in 3D CVEs

Type of data	Behavioral data recorded	Methods: how behaviors analyzed	Environment	Authors
Qualitative codes from screen recordings	Interactions and to whom interaction is directed: communication, audio, text chat, Gesture, Navigation, Scanning environment	Frequency counts	COVEN Project CVE	(Tromp, Steed, & Wilson, 2003)
Telemetry	Public utterances and Gestures	Frequency analysis, Percentage charts, bubble graphs, histograms	Star Wars Galaxies	(Ducheneaut & Moore, 2004)
Telemetry	User ID, chat logs, screenshots	Task accuracy, distance travelled and group-to-target distance as a way to analyze performance scores and group dynamics to find information	StarWalker	(Chen & Börner, 2005)
Telemetry	Name, timestamp, world position, movement, clicking, teleporting, and chatting	Navigational playtrace data (heat maps and flow diagrams) of navigation Frequency analysis of chat utterances over time	ActiveWorlds Universe TombRaider: Underworld	(Penumarthy & Borner, 2004) (Börner, Penumarthy, DeVarco, & Kerney, 2005) (Penumarthy & Börner, 2006) (Drachen & Canossa, 2009)
Ethnographic data	Ethnographic descriptions	Qualitative analysis	Everquest Online Adventures	(Ducheneaut & Moore, 2005)

Table 1, continued. Type of data and methods of analyzing behaviors in 3D CVEs

Type of data	Behavioral data recorded	Methods: how behaviors analyzed	Environment	Authors
Telemetry	Length of stay, number of visits, chat utterances, gestures	Frequency analysis Bubble charts Histograms	Star Wars Galaxies	(Ducheneaut, Moore, & Nickell, 2007)
Telemetry (script)	Id, gender, interpersonal distance, mutual gaze, talking, location	Frequency and statistical analysis of frequencies between treatment groups (ANOVA)	Second Life	(Yee, Bailenson, Urbanek, Chang, & Merget, 2007)
Telemetry	Chat, walk, picking up object, among others	Multidimensional scaling, Keygraph based on data mining framework from DNA and text analysis. Uses co-occurrences of behaviors to detect clusters of items of behaviors among all users	ICE online game	(Thawonmas & Iizuka, 2008)
Not stated	Name, time on task	Frequency analysis of time on task	3D Puzzle task	(Octavia, Beznosyk, Coninx, Quax, & Luyten, 2011)
Telemetry	Telemetry data (actions from log files)	Multidimensional scaling, primary paths	DOGeometry and Team Fortress 2	(Wallner & Kriglstein, 2012)

Frequency Analysis

Frequency analysis has been used by the majority of researchers in looking at trends in user behavior, often analyzing frequencies of behaviors over space and time. Unlike many single-user 3D VEs, 3D CVE research has used telemetry data as well as qualitative coding and looks at interactions with other avatars in the environment (though most research has still focused on interactions with objects and NPCs). Qualitative coding appears more often when the researcher wants to capture a behavior that is not easily captured through telemetry data alone, such as the quality of an action or to whom a voice utterance or chat is intended.

Tromp (2003) used screen recordings to capture user perspectives and then qualitatively coded the smallest meaningful units of user behaviors in order to perform a usability evaluation of a 3D CVE. One of the scenarios they ran was the “WhoDo” game, a collaborative murder mystery environment that allowed users to explore collaboration processes in the 3D CVE. The following social behaviors were coded and categorized in the WhoDo experiment: communication (audio, text chat, and verifying events), Navigation, Scanning the environment for events, gesture, and external (talking to someone outside of the environment). They found that navigating into position took up the majority of the coded events through a visual percentage analysis using pie charts, and less than half of the communication acts are related to verifying being heard or seen by others. The frequency analysis revealed that most of the communication tasks were not about collaboration, as that only involved 29.8% of the communication tasks. By analyzing the makeup of the

frequency of qualitatively coded behaviors in the CVE, they found that collaboration was insufficiently supported, as much of the behaviors were not related to active collaboration. Since the environment mediated user behavior, they were able to see how user issues with navigation and interaction were affected by usability issues such as size of walkway and placement of spaces.

Penumarthy & Borner (2004) looked at social diffusion patterns within Active Worlds 3D CVE worlds. Like Chittaro, Moura and Gagne in their studies of navigation in 3D VEs, they overlaid typical path patterns (playtraces) over a map in several different 3D CVEs. Overall patterns in the behavior could be seen by looking at the dominant paths people took from location to location. They used symbols to display activity such as text chatting and the clicking of in-world objects with the playtrace data. This helped to reveal overall navigation and usage patterns within the worlds. They also looked at high-frequency words within the text chat and overlaid high-frequency words over time using a graphical time display graph. Through visual analysis, they were able to discover patterns of behaviors in space and time using diverse methods of visualization. Using the ActiveWorlds toolkit and playtrace data of the Comidas! world in LinkWorld, they were able to identify places that seemed “most exciting” based on the number of visits. However, they note that while this type of frequency analysis was useful in discovering space and time patterns, more complex forms of modeling of student behavior would be needed to be able to look at types or roles of students, such as identifying students as “leaders” or “followers” using forms such as clustering methods and network analysis.

Advanced Visualization Methods

Thawonmas & Iizuka (2008) described a visualization approach for analyzing multiple players' actions and interactions in a 3D CVE online game, ICE. A group of 20 undergraduate computer science students participated as players in the study. They were asked to play the game with the main game objects being NPCs. They were asked to begin playing the game starting in Town 1. Telemetry data were collected including interactions, timestamps, and locations. Thawonmas & Iizuka used classical multidimensional scaling (CMDS) and KeyGraph to discover clusters of players who used similar types of behaviors and then KeyGraph visualization to essentially "drill down" or display the particular relations of behaviors of the players via a network diagram. KeyGraph is a visualization tool for looking at relationships in text-based data. However, the researchers applied this tool to look at performance, each node representing a behavior or interaction or location, all data that are located in the telemetry data. These nodes were then labeled. After running KeyGraph on the cluster, black dots represented core associated behaviors with high frequency, red dots represented behaviors which were highly associated with those core behaviors, and the dotted lines represented associations between the core behaviors and highly-associated behaviors. Figure 1 represents an example of a KeyGraph visualization applied to the Thawonmas et al abstract.

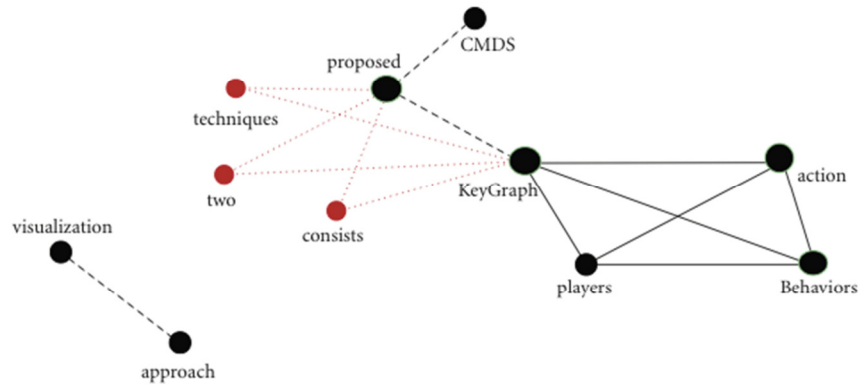


Figure 1. Keygraph visualization applied to the Thawonmas & Iizuka abstract (2008, p. 3)

The researchers used multidimensional scaling to identify clusters of students behaving in the same way. Then using KeyGraphs, the researchers could then drill down within those clusters to see dominant patterns of behaviors. They were hoping to find differences in the patterns of behaviors between achievers, socializers, and explorers. They found that achievers had interaction with “mission masters”, often stayed in Town 1, and completed many missions as their core behaviors; socializers had chatting as their central behavior; and explorers had interactions with remote objects and were not interested in pursuing missions.

Whereas Thawonmas used the nodes to represent core behaviors, interactions and locations, Wallner and Kriglstein (2012) used nodes to represent gamespaces and edges (connecting lines) that represented the individual connections and states (paths people took to get from A to B). The edges were combined into meta-edges, which allowed further clustering of the paths. The clustering was performed by multi-dimensional scaling, like Thawonmas, but performed in a very different way. By using telemetry data to log time and location,

the nodes represented the locations and meta-edges represented the clustering of the paths people took to get from location to location. Wallner looked at two different types of 3D CVEs, both games, and found that performance overall was good at the start of the game (users easily found the paths they were supposed to take), but after the first two locations, the pattern degraded into a web, indicating there was not a predominant pattern, and users were likely confused as to where to go.

Virtual Performance in 3D CVEs

Three-dimensional CVEs are spaces for individuals to collaborate at some level to accomplish an educational objective. Research to analyze performance in 3D CVEs has used qualitative as well as telemetry data; however the number of CVEs that have analyzed user behavior is quite low (see Table 2). Most CVEs such as Quest Atlantis, River City, and EcoMUVE have traditionally placed resources in analyzing pre- and post- test data (primarily proximal and distal) in order to provide evidence of learning gains as a result of the learning environment. River City (Ketelhut et al., 2010) did collect telemetry data, however, and analyzed student inquiry behavior trends over time of students as a whole. The inquiry behavior was measured as the frequency of structured interactions with NPCs, who represented residents of River City. Ketelhut was able to use this close behavioral data as evidence of student use of the environment, which was then connected to learning gains shown in the distal learning data.

Table 2. Type of data and methods used to analyze performance in 3D CVLEs

Type of data	Behavioral data recorded	Methods: how behaviors analyzed	Environment	Authors
Telemetry	Conversational interactions with bots (“inquiry behavior”)	Thematic analysis frequency analysis frequency over time trends	River City	(Ketelhut et al., 2008)
Qualitative analysis of quest submissions	Writing submissions	Submissions qualitatively coded in real time and returned to student; this was the only real-world behavior analyzed	Quest Atlantis	(Barab et al., 2005; Hickey et al., 2009)
Telemetry	All interactions and movements, followed by qualitative grouping	Frequency analysis Sequential analysis Cluster analysis	Talking Island	(Hou, 2012)

Quest Atlantis (Barab et al., 2005; Hickey et al., 2009) did analyze performance, but not at the granular behavior level of user telemetry that many researchers in this review have. Students submitted writing submissions to the Ranger Bartle and these submissions were qualitatively coded in real time and returned to the student. It is unknown if telemetry data were collected, but it was not discussed, and the writing submissions were the only virtual world behavior analyzed.

Hou (2012) explored behavioral patterns in an educational massively multiple online role playing game called Talking Island. Hou recorded telemetry data of 100 participants over 335 days, acquiring 379,681 behavioral units. The behaviors were categorized into 1 of 10 qualitative behavior codes, such as “fight,” “pets” (configuring a virtual pet), “Tools”, “Trading tools”, and “Learning in fighting.” Hou then performed three types of analysis on the data. The first analysis was a

behavior frequency analysis, which revealed which behaviors accounted for dominant forms of behavior, such as learning in fighting with flash cards accounted for 30% of the behavior codes in total. Hou then performed a behavior sequential analysis using the coded behavior data. Hou found that 21 significant sequences occurred during the entire length of the observation, which revealed dominant behavior sequences such as configuring pets and engaging in battle, or collaborative discussion and learning during team-work tasks. Hou was also able to look at the sequences according to desired performance, such as the expectation of sequential correlations between the learning-related behavior sequence sections. Seeing the lack of significant sequences in these patterns signaled a need for more optimized design for the instructional-specific tasks. As a third methodological strategy, Hou explored cluster analysis on the coded behaviors using the Ward Method and the dendrogram diagram to determine the number of clusters. Frequencies of each coded behavior was listed for each cluster and descriptively compared. Clusters of users fell into “hard-core gamers” (N=3) with the highest amount of discussion and collaboration codes; high participation gamers (N=14); and ordinary participation gamers (N=83). The cluster analysis assisted in distinguishing between the players and the patterns of behavior that make up that cluster. This technique of looking at frequencies within clusters was not as useful as Thawonmas & Iizuka’s technique of applying Keygraph to look at associated performances within the clusters.

Researchers are continuing to explore ways to address the needs stated by Dede and Quellmaz, and continue to explore the ways to best analyze behavior and

performance of users within CVEs and CVLEs, as evidenced by the Hou (2012), Thawonmas (2008), and Wallner & Kriglstein (2012). All categories of analysis in this review have revealed the following: the capturing small behavioral units, either through telemetry or qualitative coding, and then visualizing that complex data in order to reveal patterns and gain insights is important for learning about user performance and how the environment may mediate that performance.

The studies reviewed were predominantly concerned with revealing patterns across all users within the sample rather than drilling down into the data to look at patterns within a student, which is important when looking at students with idiosyncratic and diverse behaviors, as well as learning how we can build knowledge for formative feedback, evaluation, and assessment for students. As such, this literature review also looks at and reviews an additional method that has not yet been applied to 3D CVEs but looks at complex patterns of qualitative codes, is able to “drill down” to one student to observe patterns in those codes at a student level, and is able to use very small sample sizes within that analysis.

Epistemic Network Analysis: Analyzing Qualitative Code Co-occurrence Patterns in Small Samples

Epistemic network analysis (Shaffer et al., 2009) is a recent method that models the relationships of qualitatively coded data within a particular unit of analysis (Hat-field, 2011). It is often used to model coded data that originate from tasks such as writing samples or chat logs, via network analysis (Wasserman & Faust, 1994). Each “node” in the network represents a qualitative code and each

“link” or edge represents a connection between those two qualitative codes. A connection is defined as a “co-occurrence”, which means the user performed (or connected) those two ideas, or behaviors, together at the same time. Shaffer and colleagues use this type of network analysis to model a student’s demonstration of understanding within complex tasks, where mastery of individual skills are not a measure of expertise; rather, it is the concurrent use of specific skills in a given context, emerging as a whole, integrated expertise, that are more representative of learned skills in context (Shaffer et al., 2009).

Hatfield (2011) lists the usefulness of this form of network analysis in studying complex performance tasks, as this method allows researchers to (a) model a student’s mental model on a task by emphasizing the patterns, or linkages, that were used; (b) study the prominence of particular combinations of nodes, or elements; (c) study similarities and differences between networks, or student models; (d) study similarities and differences in networks or linkages, or student models, at different points of time or different settings; and (e) study both similarities and differences between individuals and as well as settings. This method has primarily been used to study epistemic games environments (Bagley, 2011; Hatfield, 2011; Rupp et al., 2009; Rupp, Gushta, Mislevy, & Shaffer, 2010), which are 2D web-based games designed to increase a student’s expertise within a STEM domain. The nodes are domain-specific categories that, for most of the ENA studies, represent the skills, knowledge, identity, values, and epistemology (SKIVE) elements represented by a user within the environment for that particular domain. Each node is a qualitatively coded “concept” that is mentioned by the individual, and

the links represent when the individual connects the use of those concepts together, or when they “co-occur”. ENA has not just been constrained to the meta-nodes of SKIVE, however; ENA has also been used to study teacher knowledge outside of epistemic game environments (Orrill & Shaffer, 2012), with each concept representing a particular math concept and the lines representing the teacher’s connecting those concepts together in the application of a math problem scenario task.

Epistemic Network Analysis in Science.net

Hatfield (2011) used epistemic network analysis to assess learning within journalism as a result of participating in a web-based journalism game, science.net, which simulated a professional reporting practicum experience. As part of this study, 12 middle school-aged users were asked, both before and after science.net, to complete a journalism-copyediting, interview-based task. The interviews were then segmented and coded using grounded theory techniques. Journalism expertise according to the SKIVE elements served as the lens to code the data. Each segment then represented a vector of 1’s and 0’s, meaning presence or absence of the particular journalistic code. This established the co-occurrences of qualitative codes, which formed the basis for the rest of the analyses. Cumulative adjacency matrices then represented all student qualitative co-occurrences in their performances for the entire unit of analysis, or performance. These networked data were then normed and principal component analysis using singular value decomposition (SVD) was run to emphasize the patterns and types of co-occurrences (structure) of

the student SKIVE elements represented within the task, rather than how often the students mentioned them. Each student then received a score on the first and second principal components, which were calculated as capturing the most variance in the data and best characterized the defining features of the coded SKIVE elements in that task. For example, on the first principal component, students were contrasted as critiquing writing through the lens of sourcing (journalistic expertise) vs. writing seen primarily through the lens of the reader (lack of journalistic expertise). All individuals received scores on first and second principal components in the pre- and post-interview tasks. Differences between the student networks were then compared by running a paired sample t-test on the principal component scores on the interview task. Statistically significant differences were found on the first and second principal components ($p < .01$) and showed progression towards writing in terms of sources rather than writing in terms of readers. This finding was triangulated by statistically significant differences on pre- and post-data frequency of skills use in other interview and writing tasks as well as qualitative excerpts pulled from purposefully sampled extreme scores on the principal components.

Epistemic Network Analysis in Math Teacher Education

Orrill and Shaffer (2012) used ENA techniques to explore three teachers' understandings and use of mathematics during an interview-based scenario problem-solving task in order to capture complex co-occurrences and patterns in teachers thinking and problem solving. Collected from data from a larger project, one interview-based performance task on ratio concepts was selected for analysis.

Interview participants were presented with a mathematical problem-solving task. A list of targeted math concepts and skills were identified a priori (math objectives) such as ratio concepts. Interviews were then coded for these targeted math concepts and skills. Cumulative adjacency matrices represented all the co-occurrences of codes (math concepts) for each person within an interview. Cumulative adjacency vectors were created from the cumulative adjacency matrices and were used to locate the segments in high-dimensional space. Principal component analysis using SVD was used to then decompose the data into a set of uncorrelated components, accounting for the most variation in the data. Maps of the individual teachers were then compared by looking at the connections between codes accounting for the most variance. They found that teacher' use of ratio concepts qualitatively differed between each other, with the teachers relying on different connections and ways of understanding the problem to make sense of ratios. They found the least expert teacher introduced many ideas that were not connected to any others, while the most expert teacher introduced a moderate amount of ideas that were strongly connected to each other.

Educational researchers have stated that the development of 3D VLE technologies have rapidly outpaced some of the methods traditionally used to study learning Quellmalz (2009), and often in 3D VLEs the rich stream of close behavioral data is not used. To begin to study this close behavioral data, we will need to borrow from other areas such as ENA to move the field forward and understand performance in context. One of the unique aspects of studying performance in

context is also the ability to look at how behavior changes across different contexts or design environments.

Summary of Performance in Virtual Environments

Many researchers in the 3D VLE fields are calling for better ways to understand student performance within these environments in order to inform both what students are doing in the virtual worlds (Dede, 2012; Hickey et al., 2009) and inform design (Hickey et al., 2009). Much of the research that has been done on users in virtual environments has primarily encompassed frequency studies, which reveal basic patterns of user behavior, frequently over space and time. While this type of analysis is useful, it is difficult to characterize user performance and groups of users based on co-occurrences of behaviors used over time, and to understand which types of behavioral co-occurrence patterns are drawn out in the particular design environment. More advanced methods that take into account patterns of co-occurring behavior over time and then use visualization can help researchers to characterize user performance based on the pattern of those behaviors. Epistemic network analysis is a promising yet evolving method for looking at co-occurrence of qualitative codes over time for small sample sizes of users. Just as Thawonmas applied a textual analysis tool to his larger dataset of qualitative behavior codes, ENA, while originally meant for interview and writing codes, could also be applied to qualitative behavior codes as well to reveal patterns in user behaviors. However, since it a new and still evolving method, it is important for anyone implementing

this method to work closely with ENA researchers to stay up-to-date regarding method refinements and research visualization tools.

In the next section, I review a pertinent topic related to the context of this study: ASD, its characteristics, and the social competence intervention for adolescents program. Each of these topics are reviewed and then followed by the review of 3D CVLEs for students with ASDs. That is followed by a summary which brings together the methods of analyzing complex, open-ended performances of co-occurring behaviors of students with the forms of behavior undertaken in the iSocial 3D CVLE.

ASD and Social Competence Intervention for Adolescents

Characteristics of ASD and HFA/AS

Individuals with ASD have impairments in social interaction, communication, and “restricted repetitive and stereotyped patterns of behavior, interests and activities” and manifest these behaviors in varying severity across a spectrum (American Psychiatric Association, 1994). In particular, students with ASD have a marked lack of knowledge of social skills and display inappropriate performance of those skills. This can lead to being judged by peers, bullying, and social isolation (Eaves & Ho, 1997; Stichter et al., 2010). For students with HFA, it is known that

they have a desire to be social, but do not have the knowledge or skills to do so appropriately (Myles & Simpson, 2002).

Students with HFA/AS in particular have difficulty with (a) theory of mind, (b) emotion recognition, and (c) executive functioning (Stichter et al., 2010). Theory of mind refers to “the ability to acknowledge that others’ thoughts and beliefs are distinct from one’s own, to make inferences about what others are thinking and feeling, and to predict behavior accordingly,” (Solomon, Goodlin-Jones, & Anders, 2004, p. 650). Emotion recognition is the ability to know one’s own feelings and emotions and knowing and recognizing the emotions of others (Solomon et al., 2004). Executive functioning is the “complex cognitive processing requiring the coordination of several sub-processes to achieve a particular goal” (Elliott, 2003, p. 49). According to Solomon et al., the list can include “planning, impulse control, inhibition of prepotent but irrelevant responses, set maintenance, organized search, and flexibility of thought and action” (2004, p. 651).

Deficits in these three core areas often manifest itself as a lack of social competence, or the ability to know and use the appropriate social skills in a given context. Students with HFA have “idiosyncratic ways” of understanding emotions of themselves and others, and they lack the reciprocal interaction and coordinated affective aspects necessary to engage in successful interactions and maintain those successful relationships (Solomon et al., 2004).

Social Competence Intervention for Adolescents

Social competency is defined as “a broad term that ideally manifests as the culminating outcome of effective interventions that target pivotal social behaviors” (Stichter, Randolph, Gage, & Schmidt, 2007, p. 230). One social competence intervention that has shown marked learning gains in areas that contribute to social competency is the social competence intervention for adolescents (SCI-A; Stichter et al., 2010).

Stichter and colleagues (2010) created and implemented a social competency curriculum for students age 11-14 with HFA. This curriculum targets the primary deficits of theory of mind, emotion recognition, and executive functioning by systematically teaching skills as part of an integrated whole by interweaving theory of mind and executive functioning throughout the teaching of emotion recognition and other reciprocal interaction and problem solving skills. The goal of this curriculum is for the students to experience greater social competency by using these integrated skills together in appropriate ways within a social context. The entire curriculum is 5 units in length, focusing on: (1) facial expressions, (2) sharing ideas, (3) turn taking, (4) feelings and emotions, and (5) problem solving. Each unit scaffolds on the next, with the students expected to integrate prior skills into the next unit, at the end emerging with increased social competence.

In their 2010 study, male students (N=27) age 11-14 participated in 20 hours of group intervention, twice a week for 10 weeks total. Participants were a part of 7 separate groups that took part in the intervention over 5 semesters. Learning gains

were measured by giving students a battery of tests 2 weeks before and 2 weeks after the intervention. These distal measures targeted social abilities, theory of mind, emotion recognition, and executive functioning. There were significant gains in social abilities ($t = 7.75, p < .001$) according to the Social Responsiveness Scale, parent form (see Constantino & Gruber, 2005). Students also demonstrated significant gains in theory of mind tests ($t = -2.38, p < .05$) but saw tests fall for the Pass/Fail tests of Sally-Anne (Baron-Cohen, Leslie, & Frith, 1985) and Smarties test (Perner, Frith, Leslie, & Leekam, 1989) producing overall mixed results. Students demonstrated significant gains in emotion recognition both in labeling an emotional or mental state by only looking at the eyes ($t = -2.66, p < .05$) on the Reading the Mind in the Eyes test (Baron-Cohen, Wheelwright, Spong, Scahill, & Lawson, 2001) and being able to identify the emotion of a pictured child ($t = -2.45, p < .05$) as measured by the DANVA-CF-2 (Nowicki & Carton, 1993). Highly significant gains were achieved in executive functioning ($t = 4.73, p < .001$) as measured by the Behavior Rating Inventory of Executive Function (BRIEF; Gioia, Isquith, Guy, & Kenworthy, 2000) as well as highly significant reduction in scores ($t = -3.37, p < .001$) on the Test of Problem Solving (TOPS-3; Bowers, Huisinigh, & LoGiudice, 2007).

In addition to SCI-A's effectiveness in producing significant gains in social competence for adolescents, it did so by "systematically teach[ing] discrete skills as parts of a whole, interconnected to emerge as social competence" (Stichter et al., 2010, p. 1075). Due to the need to provide successful instruction to students with ASD no matter what their access to services, this curriculum was then translated

and used as the core curriculum for a 3D CVLE for adolescents with autism, called iSocial (Goggins, Schmidt, Guajardo, & Moore, 2011, 2010; Schmidt et al., 2012; Schmidt, 2010).

Summary of ASD and SCI-A

Social competency is a core deficit for students with ASD. SCI-A targets those core social competency deficits through an integrated curriculum aimed at getting students to learn about and perform the social skills not in isolation, but as an integrated whole. SCI-A has been translated into the iSocial 3D CVLE, where users learn about and practice social skills. In light of what we know about analyzing performance, visualizing co-occurring behaviors of students within the 3D CVLE would reveal interesting patterns, such as which behaviors tend to co-occur together for certain students, and how co-occurring behavior patterns might differ across design environments. In addition, relating patterns of complex behavior with patterns of design attributes could in turn inform design iteration as well as design theory for similar 3D CVLEs. Applying the ENA techniques to iSocial performance would allow co-occurring behavioral patterns of interest to be revealed, which can then in turn be used to understand how design and performance are associated.

However, it is also important to look at how performance has been analyzed for students with ASDs in 3D VLEs and 3D CVLEs over the past decade. Next, social competency interventions that are delivered through 3D CVLEs are reviewed.

Analyzing Performance of Students with ASD in 3D VLEs and CVLEs

There has been limited work done on social competency interventions in 3D VLEs and 3D CVLEs for students with ASDs. In this section, this review looks at empirical research performed with individuals with ASD within 3D VLEs and CVLEs. Studies which looked at virtual reality (see Schroeder, Heldal, & Tromp, 2006), summarized prior research (see Parsons, Leonard, & Mitchell, 2006), or were 2D virtual learning environments used to inform 3D CVLE design (see Moore et al., 2005) were not used in this review.

Most of the work done up to this point has looked at targeted social behaviors, limited in scope, within a certain context. Table 3 lists the type of data and methods used to analyze behavioral performance of students with ASD within the 3D VLEs or CVLEs. The research reported in this table represents three projects spanning a decade; the first two represent the empirical reports by AS Interactive (Parsons et al., 2000), a project that took place between April 2000 and April 2003, and marks some of the first research done to assist students with ASD to enhance their social skills within 3D CVLEs. Two more recent studies by Cheng and colleagues at the National Changhua University of Education (Cheng & Ye, 2010; Cheng et al., 2010) look at teaching specific social competency skills to students with ASD within a 3D CVLE. These skills are targeted and the collaboration is more highly structured and scripted than what is found in the CVLEs mentioned earlier in this review. Additionally, the specific behaviors of students while they were engaged in the environment were not recorded. iSocial 3D CVLE, the last row of Table 3 and

Table 3. Type of data and methods used to analyze performance within the 3D VLEs or CVLEs, students with ASD focus

Type of 3D VE	Type of behavioral data	Behavioral data recorded	Methods: how behaviors analyzed	Environment	Authors
SUVE	Qualitative coding	Social appropriateness ratings of observed choices	Mixed design using frequency analysis	AS Interactive	(Leonard, Mitchell, & Parsons, 2002)
CVLE	Qualitative coding	Appropriateness or inappropriateness of performance on a given tasks: using a path, using a pedestrian crossing, and looking both ways, and bumps	Frequency of inappropriate behaviors, scatterplot of time versus executive functioning scores	AS Interactive	(Parsons, Mitchell, & Leonard, 2005) (Parsons, 2005)
CVLE	Telemetry	Not described	Not analyzed	Social Interaction System: social comp	(Cheng & Ye, 2010)
CVLE	Telemetry	Not described	Not analyzed	Social Interaction System: empathy	(Cheng et al., 2010)
3D CVLE	Video screen recordings, qualitatively coded	Interactions within a context and time, gestures, avatar movement, social interaction subcategories, timestamps	Frequency and duration analysis over time, Single subject design	iSocial	(Laffey, Schmidt, Wang, Henry, & Stichter, 2009) (Schmidt, 2010) (Schmidt & Laffey, 2012)

the most recent research regarding students with ASD in a 3D CVLE, is a 3D virtual learning experience for adolescents age 11-14 to develop social competency. Unlike the prior 3D CVLEs mentioned in this section, iSocial translates a full 5-unit curriculum encompassing 31 curricular lessons into a richly complex collaborative learning experience. There has been a great amount of effort put forth in understanding and developing the methods to understand the behaviors and performances that occur within this 3D CVLE and how that information can be used to understand and support students' performances.

AS Interactive

The AS Interactive project began their research with an exploratory study on single-user virtual learning environments (SVLEs). The exploratory study revealed that students with ASD could (a) make meaning from virtual environments; (b) learn rules about social skills from virtual environment sessions; and (c) generalize these rules to another medium such as video. Following this initial study of the 3D SVLE, they created two worlds within a 3D CVLE, (a) a meeting room to role-play more formal interactions such as business meetings; and (b) a social café to role play more informal interactions such as conversations with friends (Rutten et al., 2003). The social café was modeled after the SVLE and allowed users to interact with the other avatars.

AS Interactive's initial work involved using a single user virtual environment where users needed to find a place to sit on a bus (Leonard et al., 2002). Behavioral data encompassed qualitative codes of user avatar behavior, and was coded

according to appropriateness or inappropriateness of the behavior within those specified tasks. Frequency analysis was used in a mixed design and displayed in a tabular format. The data illustrated that most inappropriate actions were made in the first session and during the second session, inappropriate behaviors dramatically reduced across all students as sessions progressed.

Parsons et al (2005) later investigated 10 male and 2 female students with ASD and their ability to adhere to social conventions within a 3D VLE, such as using a path, using a pedestrian crossing, looking both ways, getting a drink at the cafe and finding a seat, and not bumping into other people in the virtual cafe. Two comparison groups were used. Students for these two groups were drawn from special needs schools, and they were individually matched with a student in the ASD group according to performance IQ (PIQ) and the second comparison group matched according to verbal IQ (VIQ). A standardized executive functioning assessment was given to the students with ASD, the Behavioral Assessment of the Dysexecutive Syndrome (BADS; Wilson, Alderman, Burgess, Emslie, & Evans, 1986). Behavioral data encompassed qualitative codes of user avatar behavior, and coded according to appropriateness or inappropriateness of the behaviors within their given tasks. They also captured the time it took for users to complete their assigned tasks. They found that individuals with ASD could use the CVLE with support from their teacher and other researcher, and found promise for high-functioning users to learn social skills within the 3D CVLE. Additionally, users that took the longest and had the most bumps also had lower executive functioning scores. Participants who took less time to get a drink tended to score higher on the executive functioning

scores. They found that students who did deviate the most from the tasks had the lowest VIQs, but that did not appear as a pattern across all users in the group. There was also a significant correlation between executive functioning scores and bumps into people in the cafe. They stated this could indicate either a lack of personal space or perhaps a lack of motor ability. However, further research connecting off-task or inappropriate performance to standardized assessment scores like executive functioning would be warranted.

CVLE Social Interaction Systems

The first pilot study (Cheng & Ye, 2010) investigated how a “CVLE-Social Interaction System” containing a 3D expressive avatar, an animated social situation, verbal and text communication can facilitate gains in social competency. A multiple-baseline single case design was used with three students with ASD, consisting of one teacher, a researcher, and just one student within each session. The student’s laptop was set in an empty room. During the session, there was one-on-one interaction via the CVLE-interaction system between the student and the researcher. Student performance was measured using the Social Situations Pictures (SPP; Howlin, Baron-Cohen, & Hadwin, 2000) and the Behaviors Checklist (BC ; Jeanie, Jack, Vicki, Linyan, & Eric, 2007). Scores measured baseline, intervention, and maintain for all three students. While all students had different levels of baseline, all showed marked in-crease during the intervention phase and ability to maintain the learned social interaction skills.

Cheng et al.'s second study (2010) investigated the ability for another 3D CVLE to teach empathy to adolescents with ASD using a multiple-baseline method with three students over a 5-month period. Student performance on the Empathy Rating Scale (ERS; Lin, 2008) was used to measure the system's effectiveness by randomly sampling selected questions for each session probe. Like the first study, the intervention used one-on-one interaction between the researcher and student (with real-world, in-room teacher support) to understand whether the system increased aspects of empathy (kindness, toleration, and respect). Two of the students increased their scores dramatically while the third increased moderately during intervention. All were able to maintain performance after intervention. This study shows that students with ASD can learn aspects of empathy within 3D CVLEs, but more research is warranted.

The two works by Cheng and colleagues bring some of AS Interactive's work up to date, but only take limited advantages of the affordances of a 3D CVLE. For example, most of the system is not focused on the student's collaboration through an avatar within virtual space, but the collaborative nature seems to be in watching videos, speaking through the 3D CVLE to the researcher, and utilizing 2D interfaces on top of the 3D display. As such, most of the performance seems to be clicking on the 2D interface of the 3D environment. In addition, while Cheng states in both studies that interactions with the 3D CVLE system (telemetry data) were logged and input into a database system via MySQL, those logged details were not discussed or analyzed in those works.

The iSocial 3D CVLE

Laffey et al. (2009) and Schmidt et al. (Schmidt et al., 2012) examined reciprocal interaction behaviors of 4 adolescents with ASD in groups of 2 within one turn-taking unit of iSocial during the Fall of 2008. The unit's topic was "turn taking", where they build upon the previous units of facial expressions and sharing ideas and then learn and practice how to have complete and continued reciprocal interactions. Students worked in a lab but were physically separated by rooms while synchronously engaging with each other and an online guide (teacher) in the virtual world. The online guide followed lesson plans that were translated from Stichter et al.'s (2010) SCI-A curriculum to the 3D virtual world. Video recordings were collected of their physical environments as well as screen recordings of their computer screen to capture their perspective from their avatar in the virtual world. All videos were merged into one video called an "all-views" video (Goggins et al., 2010). Reciprocal interaction coding (McEvoy et al., 1988) was performed along with IOA. In order to capture aspects of the environment that might influence those behaviors, multiple levels were coded (a) the context (e.g. "starting activities-poster" or "Verbal practice-organization"); (b) the reciprocal action (e.g. initiating or responding); and (c) the means of action (e.g. gestures or voice), also called the "interaction mode." Coding was conducted by first labeling interaction mode and then coding action and context. The interaction model captured inappropriate and appropriate initiations, responses, and continuations, as well as coded interruptions and overlaps.

Frequencies were visualized by displaying the interaction modes as columns in a stacked histogram and the interaction model frequencies as a line chart overlaying the interaction modes chart. Using this method, findings indicated that different contexts could draw out different behaviors. One user's aggregate reciprocal interactions across contexts within a single lesson were displayed through a combination of histograms and line charts. For one of the users, researchers were able to describe how different activities, for example practice and finishing activities, drew out only verbal behavior while other activities, like starting the activity, drew out verbal, movement, and gestures. In addition to the visualizations, percentile means allowed the researchers to determine that the dominant interaction was response and the dominant mode of interaction was verbalization. In addition, a comparison of two individuals over time within a lesson saw how one user's initiations rose and fell throughout but another users' initiations were consistently lower throughout all sessions, revealing how just averaging the frequencies may tend to obscure patterns.

Schmidt et al. state several future directions for understanding social behavior in 3D CVLEs. First, they state that additional codes could be used which represent different or additional social goals of users within the environment. Second, they also note that more advanced ways to represent behavior would be needed, especially to look at behavioral or interactional patterns. Third, they state there is a need to be able to compare youth behaviors within and across activities or design settings, and they state there is a need to look at types of learner engagement across various types of environments that would be more than simple frequency

studies. Comparing across activities or design settings, they note, could assist in detecting how the design (lesson and environment) may invite or constrain certain patterns of behavior. In addition, while their method is exceptional at providing detailed information on what students performed in which context how many times, it does not provide us with a more nuanced view of how students integrate those skills together. For example, in the starting activities that drew out verbalizations, movement, and gesture, we do not know if the verbalizations were in concert with the gestures and movement (e.g. the user moves towards a student to verbalize), or if they were each performed separately (e.g. the user verbalized and then later on in the activity moved and gestured towards the end of the lesson). In the first example, the student integrates those skills, in the latter the student is able to display those skills in isolation but they are not integrated with the other skills. In addition, it is important to note that this study focused on forms of active interaction (aside from non-response), just as speaking or gesture or movement use, and did not focus on more passive forms of participation (what SCI-A would label the “listening” role), such as orienting towards the speaker.

Summary of Analysis of Performance of Students with ASDs

There has been little research of students with ASDs in 3D VLEs and CVLEs, and even less that analyze their behavior within the environment in a systematic way. The primary means of analysis has been through frequency analysis, although over the past decade the visualizations for portraying the complexity over space and time has matured to the complex visualizations that can be seen in the Schmidt and

Laffey work performed with iSocial. However, the frequency visualizations used do not allow an easy way to classify users or connect co-occurrences of behavior over time in order to look at patterns of co-occurring behaviors. Co-occurring behaviors are an important feature in social competency, and being able to drill down at a single-user level to visualize the co-occurrences of behavior and characterize that user's overall performance over time would be a step forward in performance analysis of students with ASDs learning social competency within 3D CVLEs. In addition, by being able to capture the complex social behaviors and relate them to design attributes, it would also be a step forward to then iterate designs based on complex performances as well as generate design theory for similar contexts and 3D CVLEs.

Attributes of design environments and performance

In the previous sections, this literature review has described the different ways behaviors were analyzed, both in general 3D CVEs and 3D CVLEs as well as 3D CVLEs for individuals with ASD. The purpose of analyzing the behaviors was often twofold: (a) to gain insight into what users were doing within the environment, and (b) to use that information to then iterate the learning environment design.

We understand from activity theory (Vygotsky, 1978; Leont'ev, 1981; Nardi 1996) that the context in which learning takes place cannot be entirely separated from the learning activity itself. Design environments encompass both the activity design (instruction) and the virtual world design (tools and components of the

world). The two are integrally linked, and according to situated learning theory, are inseparable from each other when the user is participating in such a system {Brown 1989a; Lave 1991; Dede 2004}. The unit of analysis is the student within the setting and the relationship between them {Barab 2002e; Dede 2004}. In turn, it is a natural approach to not only look at behavior but also analyze the context of the VLE, or the attributes of the design in which the activity takes place. Researchers have stated that there is a need to understand how activity design supports learning in virtual worlds {Dickey 2005}. Indeed, Shaffer & Gee (2011) go so far as to state that understanding how learners perform in relation to their context would address “one of the most elusive concepts in education: the opportunity to learn” (p. 20).

In this section, we briefly review attributes of design that have been shown to produce user engagement in designed environments across a variety of genres. The purpose of this section is not to be an exhaustive list or literature review on attributes of 3D CVLE design. However, the purpose of this review section is to build an understanding of what constitutes “attributes” of design, and to provide an overview of common attributes discussed in the literature.

Many attributes of design

There is no current consensus regarding attributes of design. For example, in Wilson et al.’s (2009) literature review studying the relationships between game attributes and learning outcomes, over 18 game attributes were identified. Many of those eighteen attributes were overarching categories with multiple levels and distinctions, such as the attribute of “Locations” including type of setup, story

behind the location, and boundaries of space. Staalduinen and de Freitas (2011) identified 25 serious game design attributes to develop a design framework. They separated the attributes into four main categories: learner specifics, pedagogy, representation, and context. Amory (2007), identified over 50 attributes that could be used to develop, design and evaluate games and serious games. Indeed, researchers are still questioning what, and which attributes may facilitate engagement and ultimately learning within a game (Staalduinen & de Freitas, 2011; Dickey, 2007; Dickey, 2005; Kiili, 2005). In the following sections, we provide a brief overview of attributes of design, followed by a summary of the literature review.

An Overview of Design attributes

In Malone's seminal work on user engagement in intrinsically motivating instructional environments, he provided a framework for intrinsically motivating instruction. The framework involves a challenge (uncertain about ability to attain the goal), fantasy, and curiosity (novelty and ability to arouse curiosity). Since then, work has been done to further explicate these motivating aspects of user engagement. Dickey et al. (2005) point to some of the key features, five of which are: narrative, interactivity, choice, challenge, and mystery.

Narrative provides the background story and situates the user in the world (Barab, 2010), often with a goal-oriented focus and linear in nature (Dickey, 2007). Often these narratives have fantasy elements, which are something that does not exist in real life and conjures up images in the player's mind that do not exist

(Wilson et al., 2009). The narrative provides the backstory that gives rise to the environment around them, and a purpose for their activity in the virtual world.

Interactivity is the ability for the user to interact with others as well as with the world, also called “interactive participation” (Barab, 2010), with most separating the interactivity into its two separate components. The interactivity (social) is also what Wilson et al. (2009) term “pieces or players”. The attributes would include objects (such as NPCs) or people being included in the scenario or activity. This would include such scenarios as interacting with NPCs, interacting with small groups, or the number of people required to interact in the game or activity. The interactivity (environment/tool) attribute is when the user interacts with the environment itself. It can be menus and interactive components that then have cause-and-effect results within the world. The level of interactivity is described as the level of “manipulability” (Wilson et al., 2009) and also varies on a range of level of embodiment and immersion. Interactivity, along with choice, help the learners to be producers and not just users, a core principle that Gee mentions in his elements of game design and how they can teach us about learning (Gee, 2007).

Choice is also central to gameplay and activity design: who to be, what to do, where to go, and what to choose (Dickey, 2005). In game design, these choices are called “hooks”, as they hook the user into the game or activity. In more sophisticated games, users need to utilize previously learned skills in complex ways in order to accomplish the goal at hand, which coincides with what learning environments are aiming to do (Dickey, 2005). Choices can be range from somewhat restrictive to

widely open, to “right” or “wrong” choices with consequences, or the freedom to make or build from whatever is in front of them.

The **challenge** of the activity needs to be difficult enough that it does not bore users but not so difficult as to induce frustration (Dickey, 2007). This often involves careful planning and scaffolding of users’ skills. Most often games do this automatically; instructional design often does this a priori by designing the curriculum in a scaffolded manner.

In addition, elements of **mystery** are brought into play when there is a gap between available and unknown information. The mystery is often enhanced by surprise or unpredictability, and mystery triggers curiosity in the players (van Staalduinen & de Freitas, 2011).

Wilson et al. (2009) discuss the notion of **location**, which is the virtual world that the learning takes place in, which then influences the types of interactions that take place. The authors describe how the world elements placements, orientation, size, shape, and “story” can potentially influence the way that the players, or in our case students, are able to carry out a performance within the virtual world. In the context of iSocial, it could be the size and shape of learning spaces, the size of the worlds, and the boundaries that the world then creates for social interaction and movement.

Summary of attributes of design environments

While reviewed design attributes are far from all encompassing, they are some of the most prominently discussed design attributes both in game design and

instructional design. Previous iSocial research has noted how frequencies of behaviors can change across different design environments within lessons (Schmidt et al., 2012), as noted earlier in this review. Some of these potential contributors to the behavior changes could be design attributes, such as tool use in the environment as well as its usability, how the world is shaped and the need for movement (or lack thereof) due to environmental design or task.

Summary

This literature review covered analyzing performance within 3D VEs, 3D CVEs, and 3D CVLEs. There is a need to analyze and characterize patterns of performance both to inform and eventually to assess students' behaviors within the 3D VLE. This can also serve to inform design and how that design can mediate virtual performances. For students with ASD, social competency is of great importance. As the SCI-A literature illustrates, competency is not demonstrated by performing a skill in isolation, but is demonstrated by performing and integrating the skills into a whole, unified performance. This requires not just a frequency count, but necessitates connecting demonstrated skills that are being used simultaneously, or co-occurring at the same time. For example, a user would be facing the speaker, having eye contact, and nodding their head. Beginning to understand how design can mediate and draw out co-occurrences of behavior, or conversely constrain certain co-occurrences of behavior, would be of great

importance to designing worlds that can effectively support targeted human to human via avatar interactions in the virtual world.

Much of the teaching of social behavior to users with ASD is done in small numbers, thus the sample size can be extremely small. In addition, there is a need to “drill down” and look at individual performance, both the “passive” as well as the “active” performance. ENA is a valuable technique that can be applied to study qualitative co-occurrences of codes, which would be a good fit for studying co-occurring behaviors of social performance within a 3D CVLE such as iSocial. The nodes would represent the behaviors of interest, and each link would represent a co-occurrence of that behavior with another. Over time a user’s dominant co-occurring behavior patterns would be revealed. In addition, by also looking at the context in which the behavior is performed, we can gain further insight into student performance.

In this next chapter, we discuss the background of the iSocial 3D CVLE.

CHAPTER III: THE iSOCIAL 3D CVLE

The purpose of this chapter is to describe the iSocial 3D CVLE and delivery model (how iSocial is delivered). In this section, the background and overarching goals of iSocial are described, which includes describing the units, activities, and lesson structure. Following the background is a description of the iSocial environment, how the virtual world is built across the five units and a sample screenshot of one of the naturalistic practice activities. This is then followed by a description of iSocial's delivery model.

iSocial Background

iSocial (see Laffey, Schmidt, Stichter, Schmidt, & Goggins, 2009) is a 3D collaborative virtual learning environment designed to deliver an evidence-based social competency curriculum (see Stichter et al., 2010; Stichter, Herzog, O'Connor, & Schmidt, 2012; Stichter, O'Connor, Herzog, Lierheimer, & McGhee, 2012) to youth aged 11-14 diagnosed with high-functioning autism spectrum disorders. Students are pre-screened and need to meet the requirement of full-scale IQ of 75 and above, and diagnosed with ASD according to scores on the Autism Diagnostic Observation Schedule (ADOS; Lord et al., 2000) or Autism Diagnostic Interview-Revised (ADI-R; Lord, Rutter, & Couteur, 1994). iSocial uses a translation of the evidence-based social competency curriculum, SCI-A, by Stichter and colleagues. SCI-A is shown to

have positive impacts on the three core deficits of HFA/AS (Stichter et al., 2010) as well as evidence of generalization of those skills to other environments. (Schmidt, Stichter, Lierheimer, McGhee, & O'Connor, 2011). iSocial is built using the Open Wonderland toolkit for creating virtual worlds (About OpenWonderland, n.d.). A range of 3 to 6 students age 11-14 can participate in the 5-unit, 34-lesson program aimed at increasing their social competency skills both in the virtual and real worlds. The students synchronously participate together (as a cohort) in every 45-minute lesson on designated days and times, commonly 2-3 times a week, until the program is complete. Table 4 lists the content of the program.

Table 4. iSocial curriculum content

Unit	Content	# of Lessons
Orientation	Orientation to the iSocial 3D CVLE, Rules, and Expectations	2
Unit 1	Facial Expressions	5
Unit 2	Sharing Ideas	6
Unit 3	Turn Taking	6
Unit 4	Feelings and Emotions	7
Unit 5	Problem Solving	7
Fun Day	One lesson of fun social activities not related to unit content	1

The Online Guide (OG) leads and facilitates each of the lessons with the support of an Online Helper (OH), who assists with technical needs as they may arise. The OG follows a strict protocol for how to lead and facilitate the lesson and

provide feedback to the students. The students stay together in world (avatars are proximate to each other) for all of the activities, as interactions with each other in world are core to the program.

Within the lessons are specific teaching behaviors, or ways that the activities are structured so that they scaffold from teacher-directed introductions, to modeling, structured practice, naturalistic practice, and review. In this study, the focus is on analyzing student performance via co-occurrences of behavior in naturalistic practices, as naturalistic practice activities are the primary time where students practice the learned social skills in order to promote increased competency and generalization. Naturalistic practices are student-led activities facilitated by the online guide (OG). Each unit follows a common structure of delivering the teaching behaviors shown in Figure 2. Not every lesson has all the teaching behaviors listed in Figure 2; often a lesson will have two or three maximum. For example a lesson might have a review and preview with one or two other teaching behaviors listed. Thus, naturalistic practice appears approximately 2 or 3 times as activities within each unit. Figure 2 presents and describes each of these teaching behaviors within lessons.

The iSocial Environment

The iSocial curriculum has 5 units, which are built as separate worlds within the iSocial environment. Figure 3 shows the top-down views of the iSocial worlds. Within each world, the lessons take place in different parts of the world as they

progress from the first lesson to the last lesson in each unit. Just as each unit builds on the previous units, the lessons also build on each other and are structured in such a way to scaffold student learning and practice. Because of this the design of the environment also represents the design of the curriculum in that the curriculum scaffolds from one skill to another.

Teaching Behavior Within Each Unit

Introduction:	<ul style="list-style-type: none"> • Review of background knowledge • Didactic instruction/ Discussion-verbal practice of skills
Modeling:	<ul style="list-style-type: none"> • Articulate and provide practice didactic instruction materials
Structured Practice:	<ul style="list-style-type: none"> • Opportunities to practice, receive support and feedback
Naturalistic Practice:	<ul style="list-style-type: none"> • Opportunities to practice skills to promote generalization • Provide opportunity for natural peer feedback/post practice support
Review and Preview:	<ul style="list-style-type: none"> • Evaluation of objectives through culminating activity • Scaffolded skill sets to connect the skills and preview

Figure 2. Teaching behaviors within each unit. The focus of this study is on student performance in naturalistic practice.

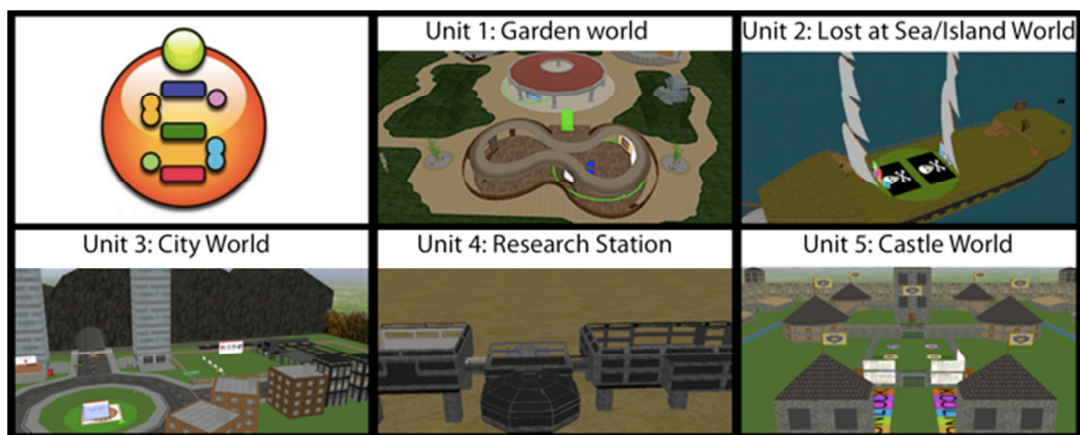


Figure 3. iSocial worlds across the five curricular units

The activities are designed to facilitate social interaction and social communication according to the curricular framework. Figure 4 shows an example of students in the Unit 3 environment, naturalistic practice activity: “Restaurant Buffet.” Here they build a restaurant buffet collaboratively. Tools are displayed to the student to control the restaurant choices. The student avatar can also turn left and right to orient to other users, move, speak to others through their headset, and use gestures from a pre-set gesture list window.



Figure 4. iSocial in action: students building a restaurant in Unit 3 Lesson 6 naturalistic practice activity

The iSocial Delivery Model

The purpose of iSocial is to reach students who would not normally have access to a trained education specialist in Autism to deliver this curriculum. As such, iSocial is set up as an entirely synchronous, distance-education program inside

of a 3D CVLE. The delivery model includes four main roles to successfully deliver at a distance: real world helpers, the online guide, the online helper, and the designated cohort of students.

Real world helpers

Each site has designated real world helpers (trained adults to assist with technical needs as they occur), though the ratio of real world helpers (RWHs) can vary from site to site depending upon the school's ability to supply personnel. The RWHs assist with real-world needs (like helping to login, restart, setup audio, or notify the OG of real-world behavior issues), but the RWHs are not directly involved in the lessons. Figure 5 displays what a typical setup with a student with a RWH looks like. In the next sections, the settings for the OG and each cohort are described in more detail.



Figure 5. The real-world helper (RWH, right) assists with any real-world needs but is not directly involved with the lessons

Online Guide and Online Helper

The online guide (OG) and online helper (OH) are located at the University of Missouri for this study, but future implementations could feasibly be located anywhere with appropriate bandwidth and Internet connection. The OG is the trained instructor that synchronously logs in, delivers and facilitates the curriculum delivery with the students while they are logged in world. The OH assists with technical support, such as starting the virtual worlds, testing audio with the RWHs at the start of each lesson, and problem solving any technical issues as they might arise during lesson delivery.

The OG and OH sit at their own computers with dual monitors within the iSocial development lab and they both wear a noise-canceling headset to communicate with the students. The OH does not directly interact with students during lesson delivery unless necessitated by a technical issue.

Students

Individual cohorts of students comprise three to six students. In the current study (which was a pilot study for iSocial) cohorts came from within single school districts, but the expectation for eventual use is for cohorts to span across multiple school districts addressing the needs of small and rural districts. Each student has his or her own computer with a headset. The students are either in separate rooms or in a large room facing away from each other. Students attend iSocial through their local schools by going to a pre-determined location and computer and logging in at designated days and times with the assistance of their real-world helper.

Summary

This section described the iSocial 3D CVLE and its delivery model. iSocial delivers a translated evidence-based social competency program (SCI-A) to students age 11-14 with ASDs within a 3D CVLE. In this section, the instructional and delivery model were described in order to provide additional context for this study. In the next section, the methods are described.

CHAPTER IV: METHODS

The overall goal of this research study was to build knowledge about how to characterize complex student performance via co-occurrences of behavior and how those behavior patterns can differ across 3D CVLE design environments containing different design attributes. This was done by exploring the case of iSocial 3D CVLE in the following ways: (a) characterizing complex, social student performance by analyzing behavior patterns within iSocial 3D CVLE naturalistic practice (NP) activities, and (b) exploring how those behavior patterns and performances in the iSocial 3D CVLE differ across design environments, and (c) exploring how design attributes are associated with behavior patterns. To achieve this goal, an exploratory, retrospective case study was performed using video screen recordings of student performance collected from a larger iSocial research study conducted during the spring of 2012.

This chapter describes the participants, materials, data collection, and data analysis procedures. Qualitative methods were used to code performance and network analysis and statistical methods analyzed the co-occurrence of codes and principal component scores to (a) characterize individual performance within a single design environment, and (b) understand and detect differences in overall student behavior patterns across design environments, and (c) explore how design attributes were be associated with behavior patterns.

Research Questions

Based on the stated purpose above, the following research questions guided this case study:

RQ 1: Can student performance within iSocial 3D CVLE naturalistic practice activities be characterized through co-occurrences of behavior? If so, how and in what ways?

RQ 2: Do characteristics of student co-occurring behaviors in iSocial 3D CVLE naturalistic practice activities differ across design environments? If so, how and in what ways?

RQ 3: Are design attributes associated with behavior patterns?

Research Design

Participants

A total of 11 student participants were in this study. Principal Investigators contacted school districts and after school districts agreed to participate, student recruitment began. Students were recruited by providing the school district with information on the minimum student eligibility requirements for iSocial. Eligibility requirements included the following; the student needed to:

- 1) Have an HFA according to Autism Diagnostic Interview-Revised (ADI-R) or Autism Diagnostic Observation Schedule (ADOS);
- 2) Have a minimum IQ of 75 or above;
- 3) Attend a participating middle school or junior high;
- 4) Have parent consent to participate; and
- 5) Be between the ages of 11 to 14 at the beginning of the field test.

School districts then provided iSocial with student information once parent consent was received. A total of 12 students were recruited and 11 students completed the iSocial curriculum. One student dropped the course prior to receiving any curriculum due to personal issues and never received instruction in the iSocial 3D CVLE.

All 11 student participants were involved in this study. The students were located across three school districts, termed “cohort.” Four students were in Cohort A, three students were in the Cohort B, and four students were in Cohort C. Each cohort name represents the location of their district, which will be discussed further under “Setting.” As the term “cohort” represents, the students stayed with the group they started with at the beginning of the semester and did not attend any lessons with any other cohort. The mean student age at the start of iSocial was 12.58 years, mean IQ was 99.55, and all students were white males.

Fidelity

The online guide was the same for all three cohorts during the field test, and had strong fidelity to the intent of the curriculum for content, process, behavior system use, specific verbal feedback, and timing across all units and cohorts (see Appendix A for specific data tables). Fidelity is defined as “the degree to which an intervention...is delivered as intended” (Carroll, et al., 2007).

The process of obtaining iSocial fidelity occurred as follows (see Stichter, Laffey, Galyen, Herzog, in press, p. 15):

1. Graduate students used an a priori fidelity checklist for each lesson
2. Teaching behavior was organized into four categories:
 - a. content (skill, concepts, and activities)
 - b. process (instructional methods like facilitation and response clarification)
 - c. behavior management (use of the designated behavior management system)
 - d. specific verbal feedback to students
3. Graduate students scored teaching behavior on a 0-2 scale:
 - a. 0: teaching behavior did not occur
 - b. 1: teaching behavior did occur but needed improvement
 - c. 2: full and accurate implementation of teaching behavior

Appendix A fidelity results indicate that while overall fidelity varied across cohorts slightly, all cohorts received accurate and similar teaching behaviors.

Setting

The three cohorts (Cohorts A, B, and C) were located in three areas, each a different town within the state of Missouri. As per the iSocial model described in the previous chapter, the OG and the OH were located at the University of Missouri.

Field Test

The iSocial 2012 spring field test with the above three cohorts began during January 2012 and ended at the end of April or beginning of May 2012 (depending on the cohort). The lessons occurred approximately every other day, and were recorded using screen capture software on each participant's computer and transferred to iSocial staff via FTP software immediately following the completion of the lesson, at which time the all-views videos were created.

Materials

Screen recordings of participants

The screen recordings collected from all participant computers comprise the data source for all virtual-world performance data. Upon receiving the screen recordings, they were exported from their native format into a compressed QuickTime format (.mov) then combined to create an "all-views video" (Goggins et al., 2011, 2010), which shows all perspectives of cohort participants and the OG. See Figure 6 for a sample view of an all-views video. The all-views cohort videos for the lessons were trimmed to start and end of the activity prior to coding.

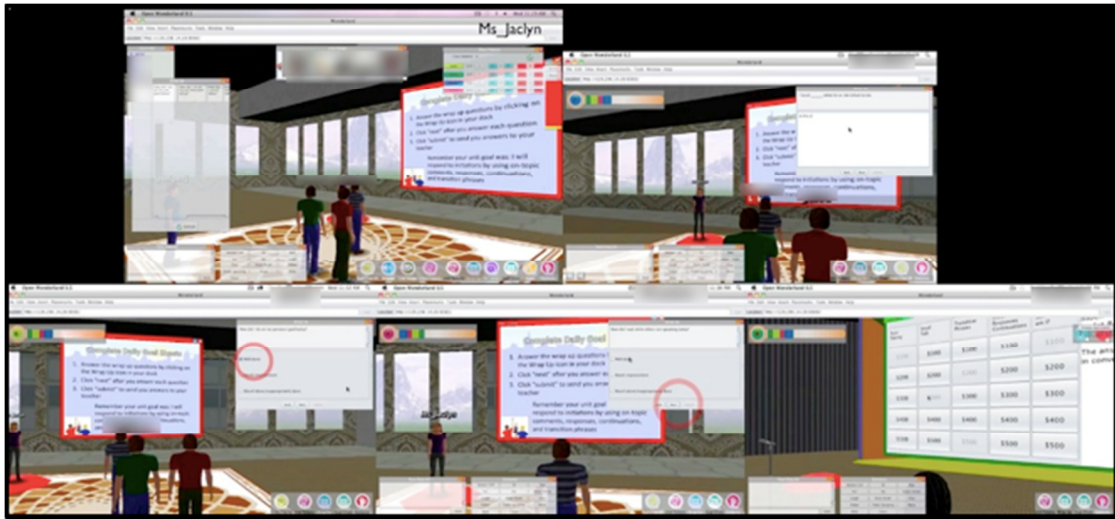


Figure 6. All-views qualitative analysis
 This method merges all screen recordings into one video. In this figure, 4 students and one OG view is merged into one all-views video.

List of Naturalistic Practice Activities

Table 5 lists the 11 student-led naturalistic practice activities of iSocial. These 11 activities include 121 student-within-activity units (the unit of analysis). Two naturalistic practice activities were discarded from analysis (22 student-within-activity units): U3L4 was discarded due to the short duration of the activity (approximately 3-4 minutes only), and U3L6 was discarded due to an entire cohort having technical issues and their data being dropped. The remaining nine naturalistic practice activities represent the data set for this exploratory study (see Table 6). Of the remaining 99 student-within-activity units, 11 additional units of analysis were dropped due to absence, technical issues, and video screen recording issues. The reasons for exclusion from the study are (a) student absence (most

common), (b) technical issues affecting ability to fully participate in the curriculum for the majority of the lesson activity (e.g, inability to speak or hear, freezing or restarting their computer), (c) behavior issues in the real world preventing participation, not common, and (d) video screen recording issues, in which the screen recording was lost, and behavior could not be seen from other videos at all times due to the nature of the lesson.

Table 5. List of student-led, naturalistic practice activities in iSocial

Name of activity	Unit and Lesson (Lesson # / time)	Length of Time, Total (minus intros)	Description
Facial expression scenarios	U1L4 (4)	20 (16-17)	Split into small groups, students are given social scenarios and they are to display the facial expression and emotion that most appropriately relates to that scenario. They discuss as a small group how to use their bodies and voice to show the emotion described in the scenario. They then take a picture of their faces in world and display them on an in-world pane called a “mediaboard”.
Lost at Sea: take items	U2L4 (9)	25 (19)	The students are given a narrative that they are on a boat and it is sinking. They are tasked with taking only 8 items from the cargo hold with them on the lifeboat. As a whole group, they need to work together to decide who will do what, which item they are going to take with them to the deserted island, and why. Users have roles that facilitate this activity.
Lost at Sea: go to island	U2L5 (10)	25 (20)	This is a continuation of U2L4. On this day they appear in the lifeboat and are tasked with deciding where to go on the island. As a whole group, they must decide where they want to land on the island, and once on the island, they need to decide who is tasked with which island chore by discussing and sharing ideas. Users have roles that facilitate this activity.
Restaurant buffet roles	U3L4 (15)	6 (3-4)	Students are informed in the previous lesson that they are building a restaurant together. One of the largest components of the restaurant activity is choosing which buffet and food items to serve at the restaurant. On this day, students decide as a whole group who will take on the roles for leading the buffet activity at various points over the next two lessons. They are to discuss and come to a consensus.
Restaurant buffet 1	U3L5 (16)	33 (26)	Based on the decisions made in U3L4, students enter into their restaurant building as a whole group and choose the buffet styles and begin deciding on foods such as main design and appetizers. While one student leads the interactivity of food changing in world, students need to discuss with each other to choose their food items collaboratively as a group.
Restaurant Buffet Completion	U3L6 (17)	10 (8)	Students continue the remaining buffet food items from U3L5.

Table 5, continued. List of student-led, naturalistic practice activities in iSocial

Emotional Status Activity	U4L4 (21)	12 (10)	Students are given three scenarios with three sticky notes, which are interactive writing tools suspended in air in world. Students are to work in small groups collaboratively and discuss and identify key components necessary to interpret emotional situations involving others. They discuss the situation and then one or more of them write a sample situation that they had previously been involved in that is an example of emotional status and range.
Emotional Role Play	U4L5 (22)	25 (23)	Students are to work collaboratively in groups to create a role-play involving displaying a range of emotions. They are given a scenario such as “There is a tornado siren at school”. As a small group, the students need to decide on the events of their role play, who will do what, practice the role play, and then perform it for in-world recording.
Role Play Planning and Taping	U4L6 (23)	25 (22)	Students work collaboratively in small groups. Rather than being given a scenario, each individual is given an organizer via a mediaboard to then plan out a scenario of his own. The small group then reads the scenarios and then discusses which role play they would like to practice and then record. The role plays are then recorded.
Plan Quest	U5L5 (29)	10 (7)	Students are in a medieval-looking castle world. In this whole-group activity, they are given a scenario that a King has lost many items, and they are tasked with finding them and returning them to the king. Given the scenario, the students use the hints to plan out their route via a mediaboard. They will use their plan to help navigate and locate items around the castle in order to find and return the king’s missing items. They need to use all their tools in order to solve the quest-planning problem. They perform the quest in the next lesson.
Quest	U5L6 (30)	30 (24)	In this lesson, the students as a whole group perform the quest activity. Following the plan they created from the previous lesson, they need to navigate the world together as a group, discuss, and use appropriate social skills to find and return all of the king’s missing items.

Table 6. Student dosage in all student-led, naturalistic practice activities

#	Name of activity	Unit & Lesson (#/t)	Time, Total (minus intros)	Dosage Cohort A				Dosage Cohort B			Dosage Cohort C				# Coded Units
				A01	A02	A03	A04	B05	B06	B07	C08	C09	C10	C11	
1	Facial expression scenarios	U1L4 (4)	20 (16-17)	+	+	A	A	+	+	+	+	+	+	+	9
2	Lost at Sea: take items	U2L4 (9)	25 (19)	+	+	+	+	+	+	+	+	A	A	+	9
3	Lost at Sea: go to island	U2L5 (10)	25 (20)	+	+	+	+	+	+	+	+	+	+	+	11
4	Restaurant buffet roles	U3L4 (15)	6 (3-4)	+/x	+/x	+/x	+/x	+/x	+/x	+/x	+/x	T	A	+/x	0
5	Restaurant buffet 1	U3L5 (16)	33 (26)	+	+	+	+	+	A	+	+	+	+	+	10
6	Restaurant Buffet Completion	U3L6 (17)	10 (8)	+/x	+/x	+/x	+/x	+/x	+/x	+/x	T	T	T	T	0
7	Emotional Status Activity	U4L4 (21)	12 (10)	+	+	+	+	+	+	+	+	+	+	+	11
8	Emotional Role Play	U4L5 (22)	25 (23)	+	+	+	+	B	+	+	+	A	+	+	9
9	Role Play Planning and Taping	U4L6 (23)	25 (22)	+	+	+	+	+	+	+	+	+	+	+	11
10	Plan Quest	U5L5 (24)	10 (7)	+	A	+	+	+	+	+	+	+	+	+	10
11	Quest	U5L6 (25)	30 (24)	V	+	+	+	+	+	+	+	V	+	A	8
Coded Units				8	8	8	8	7	7	9	9	7	8	9	88

+ = Student received full dosage of activity as outlined in lesson plan (+/- 2 minutes)

+/x = Student received full dosage of activity, but lesson is dropped from study

A = Student was absent and as such missed the entire activity (0 dosage)

B – Student was absent from world due to real-world behavior issues (non-compliance, etc.)

T = Student experienced major dosage issue due to technical issues in the environment

V = Student received full dosage; however, student’s screen recording was lost; due to nature of lesson, student could not accurately be coded via OG or other student screen recordings.

Exploratory Research Framework

The framework used to inform the coding of performances was based on the previous work done by Schmidt (2010), Schmidt et al. (2012), which was based on the SCI-A curriculum work done by Stichter et al. (2010), the curriculum used with iSocial. For example, codes of performance from Schmidt (2010) included appropriate and inappropriate verbal initiations, responses, and gestures. The framework that was used to understand and analyze student performance came from the epistemic framework (Hatfield, 2011; Orrill & Shaffer, 2012; Shaffer et al., 2009), which has the assumption that the connection, or relationship, among behaviors provides insights beyond those gleaned from frequency counts alone or the behaviors in isolation. In our example of social skills, the assumption is that the connection and how the individual behaviors are used together, or the co-occurrence of those behaviors is more important and indicative of social competency skills than the individual components mastered in isolation. For example, it is more indicative of social competency for the user to have a strong relationship, or co-occurrence, between orienting towards his peers while speaking to them than merely counting the number of times the user oriented towards his peers and the number of times he spoke. The ENA method used in this research is an application of Hatfield, Shaffer, and Orrill's works using epistemic network analysis that analyzes the content of written or spoken behavior co-occurrences using specific techniques (Hatfield, 2011; Orrill & Shaffer, 2012; Shaffer et al., 2009). The targeted behaviors, concepts, or demonstrated learning objectives become the

codes which are analyzed for co-occurrences, and as such, is applicable across many domains which seek to study the relationships between qualitative codes (behaviors) and how they are used together. This is especially true when the domain mastery is concerned with how a student uses the codes together and when, rather than the frequency of those codes in isolation. Whereas ENA has traditionally focused on mapping learners' epistemic frames either across times or settings, this study applies ENA to map learners' complex performances across settings.

This study examined the co-occurring behavior patterns through the methods of ENA as a way to understand the complex patterns of student performance in the 3D virtual learning environment targeting social performance, and how those patterns of behavior may change (what behavior relationships emerge) depending on the design environment and its attributes. However, this research differs from previous ENA work that analyzed qualitative codes from interview transcripts, writing samples, and chat logs in that the iSocial study focuses on qualitative codes derived from student performance and behaviors partially mediated by a 3D virtual world.

Characterizing student virtual world performance via behavior co-occurrences

Establishing Inter-Rater Reliability

Using an a priori coding scheme and codebook as a guide (see Appendix B), the student-led, naturalistic practice activities were qualitatively coded. The a priori codes were established through a previous pilot study (Galyen, 2012) and its

recommendations, grounded in SCI-A (Stichter et al., 2010) and previous iSocial work by Schmidt (2010) and Schmidt et al. (2012). A main coder and two inter-rater coders performed the coding, with the inter-raters coding a minimum of 20% of the data. One inter-rater coded verbal codes and the other inter-rater coded non-verbal codes. Coding verbal and non-verbal separately lessened coder error. Inter-rater reliability was calculated using Cohen's Kappa (1960), a commonly used measure that takes into account the rate of agreement expected by chance. Pooled Cohen's Kappa was used to calculate the overall Kappa, rather than averaging the individual Kappa codes, as Pooled Cohen's Kappa was found to be a more accurate representation of reliability when coding few subjects with a high number of codes (De Vries, Elliott, Kanouse, & Teleki, 2008). The significance of the Kappa value is interpreted as follows: $<.50$ = poor agreement, $.51-.60$ = fair agreement, $.61-.80$ = good agreement, and $>.80$ = excellent agreement. This takes into account the suggestions from the literature (Cicchetti, 1994; Fleiss, 1971; Landis & Koch, 1977; Miles & Huberman, 1994). Landis suggests $.61 - .80$ represents "substantial agreement" and $.81 - 1.0$ represents "almost perfect" agreement. Cicchetti and Fleiss have similar suggestions in that $.60 - .75$ represents good agreement and $.75 - 1.0$ represents excellent agreement.

Inter-rater agreement was initially calibrated using videos from the same field test and students but were not a part of the final dataset. Disagreements were resolved with negotiation, modification of the codebook, and recoding. For low-incidence codes in which Kappa could not be calculated, percentage of agreement was reported. Once the coders established greater than $.8$ agreement on the Kappa

(across all codes as well as pooled), the main coder then coded the remaining data with an inter-rater coding at least 20% of all data along with the main coder. If the Pooled Kappa for the session fell below .80 or if any individual Kappa fell below .61, the main rater and the inter-rater resolved the disagreements by negotiation and re-coded. This rule of thumb and Kappa guidelines were established by taking into account both the subjectivity of the codes and the probability at which coders were likely to agree. Given the nature of our coding all behaviors as “0” or “1” across all segments (thus many segments had either many zeroes in sequence or ones in sequence), the likelihood of agreement was extremely high in most cases, which severely penalizes the Kappa. In addition, while some codes were more subjective, other codes were much more objective, as such, the Pooled Kappa was expected to be higher than the lower individual Kappa limit. After calibration, IRR was checked at six intervals throughout the coding process to ensure against coder drift. These codes served as the core data for all other analyses. Table 7 summarizes the IRR across all six coding sessions.

Table 7. Inter-rater reliability
Inter-rater reliability of nonverbal and verbal codes

Code	Percentage of Agreement	Pooled Cohen's Kappa
Facing Learning Objects	94.9%	0.756
Facing Online Guide, not speaking	94.5%	0.839
Facing Online Guide, speaking	95.2%	0.836
Facing Peer/s, not speaking	97.0%	0.767*
Facing Peer/s, speaking	97.9%	0.848*
Facing Inappropriate	100.0%	1.000*
Orienting to Learning Object/s	88.0%	0.746
Orienting to Online Guide, not speaking	97.9%	0.789
Orienting to Online Guide, speaking	98.7%	0.867
Orienting to Peer/s, not speaking	98.8%	0.907*

Orienting to Peer/s, speaking	98.5%	0.820*
Orienting to Inappropriate	100.0%	1.000*
Moving towards or around Learning Object/s	94.7%	0.776
Movement towards group	95.2%	0.787
Movement Inappropriate	100.0%	-
Gesture: Clap, Laugh, Cheer	100.0%	1.000*
Gesture: Yes/No	100.0%	-
Gesture: Raise Hand	99.8%	0.837*
Gesture: Wave	100.0%	-
Tool use: Restrictive	99.0%	0.955*
Tool use: Unrestrictive	99.3%	0.927*
Verbal: Initiation	97.1%	0.880
Verbal: Initiation, inappropriate	99.9%	0.971*
Verbal: Response	94.9%	0.881
Verbal: Response, inappropriate	99.2%	0.900
Verbal: Non-response	100.0%	1.000*
Verbal: Undirected Talk	99.8%	0.929*
Overall	98.0%	0.835

Note: Empty Kappa cells remain for codes whose Kappa could not be calculated due to lack of variation (e.g., no presence of code).

*Kappa value does not include units where 100% agreement was reached but Kappa could not be calculated due to lack of variation in the code (all present or all absent).

Coding Student Virtual World Performance

The coding began at the end of each activity introduction and ended at the start of each activity review, thus only the “core” activity was coded. This was to reduce any influence of dominance of review or introduction on the interpretation of design environment in association with individual performance. Each video, representing a student within a lesson, was partitioned into 10-second segments. Student performance codes were then applied to each 10-second segment for presence or absence of behaviors. This segmentation was chosen to reflect both co-occurring behaviors as well as context immediately before and after that behavior. The ten-second segment was chosen to also represent a small span of time to allow behaviors to co-occur but not too much time so that many behaviors co-occur and the interpretation becomes meaningless and does not represent “co-occurrence.”

The pilot study revealed that spanning across a small period of time provided context for how the student was using the behaviors in relation to others. Due to the nature of the 3D CVLE that was used for example, students could never move and orient at the same time. Additional time allowed many codes to co-occur and too little time allowed for fewer codes to co-occur with loss of data.

Within the 88 video units coded, 9,083 ten-second excerpts were created. Of these excerpts, an additional 208 excerpts were removed from analysis: 88% (n=183) of the excerpts removed were due to student freezing and restarting issues and 9% (n=20) were due to audio issues, such as inability to vocally participate. If the student was not able to participate in the majority of the segmented lesson, they were dropped for technical reasons from the study as can be seen in Table 6.

Additionally, gestures were then merged into one code (a total of 68 gestures). This was done because students used gestures extremely infrequently and also used gestures in ways that distorted the intended meaning of the gesture code. In turn, this invalidated the code's interpretation. For example, students raised their hands or waved in order to perform a "high-five" with another student. While this is rather interesting, the meaning of the particular gesture codes became lost and not necessarily interpretable, so gestures were merged to represent just one code.

For the final dataset, a total of 8,875 ten-second excerpts remained containing a total of 33,345 coded behaviors. These coded behaviors and segments formed the basis for the remaining analyses.

Design environments

Throughout the qualitative coding phase, the researcher kept memos on attributes of the activity design environments and implementation. These memos assisted with answering research question 3, which investigates how design attributes are associated with behavior patterns. While the purpose of this study was not to develop a grounded theory on attributes of a design environment, the memos served as a tool for the researcher to further discuss attributes of these environments after a statistical analysis on the differences between the behavior patterns across design environments was performed.

Analysis

This section describes the analysis of the student performance data using applied epistemic network analysis to characterize student performance and behavior patterns within naturalistic practice activities and linear mixed modeling to detect differences of overall student behavior patterns between the design environments. Qualitative purposive sampling of students was used to describe characteristics of behavior patterns within single activities, followed by linear mixed modeling to analyze differences of behavior patterns between design environments.

Processing Data for Use in Network Analysis

Each 10-second segment for a student within an activity contained codes, representing the presence or absence of behaviors as a series of 1's and 0's ("1"

representing the presence of a behavior, and “0” representing the absence of a behavior). Each student’s activity performance was constructed of individual student qualitative behavior codes, b_i . For any student, s , in a given naturalistic practice activity, a , each segment of coded video performance $P_{s,a}$, provided evidence of whether student s was using one or more of the behaviors in his performance (P). Relationships between these behavior codes were defined as co-occurrences (presence) of these qualitative codes within the same 10-second segment. The performance segment was the core data unit by which all co-occurrence and network analyses followed. Each segment, or adjacency vector, of coded video performance $P_{s,a}$ was then converted into an adjacency matrix, A (see equation 1).

$$A^{s,a}_{i,j} = 1 \text{ if } b_i \text{ and } b_j \text{ are both in } P^{s,a} \quad (1)$$

Each coded adjacency matrix, $A^{s,a}_{i,j}$, was then summed into a single cumulative adjacency matrix. This cumulative adjacency matrix was then converted into a vector, called the cumulative adjacency vector. There was no loss of information, but it was used to place the points of the unit of analysis into high-dimensional space. This vector represented each student s for each naturalistic practice activity a , $U_{s,a}$, or in other words, for each unit of analysis, or student within an activity (see equation 2).

$$U^{s,a} = \sum A^{s,a} \quad (2)$$

The cumulative adjacency vectors were then normalized to a unit hypersphere (see equation 3) to control for the variation in vector length, or in other words, the variations of student frequencies. This emphasized the similarities in the types of co-occurring code pairs (the structure of the relationships) rather than the frequencies of the codes. In other words, norming the data in this manner helps to differentiate students more by what types of behavior patterns students were using rather than by how frequently they did those behaviors. In addition, this also controlled for variation in lesson duration. This was important when looking at what structure and patterns of performance were drawn out and characterizing those performances based on what types of co-occurrences of behaviors the students were making in their performances. This norming was done by dividing each value by the square root of the sum of squares of the vector (see equation 3).

$$nU^{s,a} = U^{s,a} / \sqrt{\sum (U^{s,a})^2} \quad (3)$$

The University of Wisconsin Epistemic Games Group (GAPS) has developed an ENA script for the R statistical computing environment (R Core Team, 2012) along with a GUI interface to run visual analyses on the above data. This was done to lessen the human error in processing and readying data for analysis, as well as add

in functionality for analyzing through interactive visualizations. The ENA script for R (which additionally controls the associated GUI interface) was used to apply the network analysis technique on the data. See Appendix C for a visual example of the series of ENA steps in this section.

Characterizing Student Performance via Behavior Co-occurrences

After processing the data, the characterizing of student performance of co-occurring behaviors was accomplished by looking at the patterns of co-occurrences rather than the frequencies in isolation. As stated earlier, this type of network analysis measures the relationships between a set of elements (codes, and in our case, behaviors) within a particular unit of analysis (student within a naturalistic practice activity).

Applying ENA to characterize student performances

Using the ENA R script, principal component analysis using singular value decomposition (SVD) was performed to understand the structure and characterize the student performances within the activity. All units of analysis were run together using the ENA script. The purpose is to reduce a high-dimensional dataset down to a set of uncorrelated components, “fewer in number than the number of dimensions yet still account for as much of the variance in the data as possible” (Hatfield, 2011, p. 51). Bartholomew, Steele, Moustaki, and Galbraith (2008) provided recommendations for choosing the number of principal components to interpret, and all primarily rest on choosing those that capture the most variance in the data

as well as those which most assist in providing meaningful interpretations. The principal component was interpreted by looking at the pattern of component loadings. Specifically, the two to three most positive and negative component loadings (behavior codes) guided the characterization of student performance on each component (Bartholomew et al., 2008). The positive and negative loadings themselves are inherently random, but the positive and negative loadings tend to be negatively correlated with each other when taking each code's total co-occurrences into account. The primary loadings on the principal component represent the types of behaviors that accounted for the most variation in student performance, and as such, are what are used to characterize student performances. The primary loadings on these components do not necessarily mean that those codes co-occur together for the student; they only mean that the student has one or more of those codes that could co-occur with each other, but do co-occur with other codes.

The number of principal components kept to interpret student performance was determined using the Scree Plot method, a visual analysis whereby a "bend" in the plot of principal components is determined and all principal components above, but not including, the bend are included in interpretation (Bryant & Yarnold, 1998). This served to include as many components that account for the greatest amount of variance yet also maintain parsimony when possible.

The principal components then served as the axes on which to plot the student performance. Positions, or scores, for each unit of analysis (student within an activity) on the principal components were determined by multiplying the student's normalized cumulative adjacency vector by the principal component

loadings, and binding the results of that matrix with the meta data, thus each score was labeled with student ID and additional meta data.

Principal component loadings, primary co-occurrence patterns, student scores, and scores along with a visual analysis of those scores on the principal components were used to support the interpretation of the activities and students within the lesson and their primary performance patterns.

Differentiating Group Performance Patterns Between Design Environments

Applying Linear Mixed Models to compare student behavior patterns between activities

Differences of behavior patterns between design environments (i.e., naturalistic practice activities) were determined using linear mixed models (LMM; see West, Welch & Galecki, 2006) approach on student performance scores. A linear mixed models approach was chosen due to its flexible nature to accommodate missing data points within a repeated measures or longitudinal design, unlike a repeated measures ANOVA (West et al., 2012).

In this set of analyses, the primary dependent variable was behavior score. The analysis is composed of a series of five steps. First, prior to running LMM, within-subject behavior scores on PC 1, 2 and 3 were plotted across time to look at overall descriptive trends in the data. Time was treated as a continuous variable representing the number of the lesson, and the purpose was to get an overall idea of

the patterns in the data, as well as to see if there may be a linear effect of time on the data that should be considered in the model.

Second, an empty model with student as the random effect was run in order to evaluate goodness of fit of following models and validity of adding additional fixed effects in the model. The empty model is specified in equation 4. In this model, β_0 represents the overall mean, u_i is the residual which represents the distance between each student's mean from the overall mean, and is also known as the random effect that is associated with the intercept for each student (West et al., 2012, p. 61). And lastly, ε_{ij} is the residual that represents the distance between each student's score and that student's mean. Interclass correlation was calculated for the null model using the formula in equation 5. In this null model, the ICC represents the proportion of variation that is due to subjects, or the between-subject variation. The remaining variation left from the ICC would be due to variation among the subject's 9 activity observations.

$$\text{Score}_{ij} = \beta_0 + u_i + \varepsilon_{ij} \quad (4)$$

$$\frac{\text{Var}(u_i)}{\text{Var}(Y_{ij})} = \frac{\text{Var}(u_i)}{\text{Var}(u_i) + \text{Var}(\varepsilon_{ij})} = \frac{\sigma_0^2}{\sigma_0^2 + \sigma^2} \quad (5)$$

Third, *time* was added as a continuous fixed effect (covariate) within the model in order to test if there was a significant linear effect of time on behavior score. This model is termed the random intercept model and is seen in equation 6.

$$\text{Score}_{ij} = \beta_0 + \beta_1 \text{Time} + u_i + \varepsilon_{ij} \quad (6)$$

REML-based model fit data, including Akaike's Information Criterion (AIC), -2 Restricted Log Likelihood Ratio, as well as Type III Test of Fixed effects together were used to evaluate whether the model (for each of the Principal Component scores) had better fit as compared to the Empty Model, as well as if time had a significant linear effect. Since time did not have a linear effect across scores and adding time did not increase model fit, time was rejected as part of the model; details are in Chapter 5.

Fourth, *environment* was added as a categorical fixed effect (factor) within the original null model in order to test if there were significant differences between the means of behavior score between environments. This model is also termed the random intercept model, and this model is specified in equation 7. Adjusted ICCs, which are based on the variance components used in the model containing both random intercepts and fixed effects (West, 2012), can again be interpreted. Changes in variance parameters can be used to interpret how the fixed effect contributed to the model, in addition to AIC, -2LL, and Type III Test of Fixed effects.

$$\text{Score}_{ij} = \beta_0 + \beta_1 \text{Environment} + u_i + \varepsilon_{ij} \quad (7)$$

At this point, no additional parameters were able to be added to the model due to too few subjects (such as adding parameters for a random intercept and slope model).

After the model was confirmed and interpreted, post-hoc Sidak-corrected paired comparisons, considered a moderate post-hoc test, (Meyers, Gamst & Guarino, 2005 p. 427) were conducted to determine significant differences between lesson environments.

Again it should be emphasized that these statistical tests are meant to reveal patterns in the complex multivariate sample data rather than to generalize to a population. What these data reveal is to what extent design environment, separate from issues of time, may contribute to behavior patterns seen in student performances within this iSocial case study.

Identifying potential design patterns and their associations with patterns of behavior

Memos using grounded theory techniques (Corbin & Strauss, 1990) were used in order to let salient design attributes emerge from the data. Memos were taken both on a whole-lesson level (after watching a video) as well as tagging segments of video linking memos regarding those attributes. The memos were then analyzed and using axial coding techniques, created categories and attributes based on the data. The categories were refined into more abstract constructs in order to

compare and contrast and discover similarities and differences between some of the underlying design attributes and related behavior.

Once the attributes were identified, the attributes were placed in a table, described, and marked as high, medium, low, or nonexistent according to the design attribute. Results from the post-hoc multiple comparisons as well as the table were used to guide and look for large patterns that resulted in significant differences in group performance patterns in the data. Due to the number of post-hoc multiple comparisons, a graph visualization was created to aid in the visual analysis of patterns between design attributes and behavior patterns. The patterns serve to focus and warrant interest in further study, rather than to identify definitive causes or influence on behavior.

Summary

This section described the methods that were used for exploring three research questions regarding (a) characterizing complex, social student performance via behavior co-occurrences, and (b) exploring how behavior co-occurrences patterns in student performances might differ across design environments, and (c) exploring how design attributes are associated with behavior patterns. The primary methods used to analyze these behavior co-occurrences was applying a new and innovative method, ENA, on the behaviors within the iSocial 3D CVLE. Linear Mixed Models were then used to determine whether these behavior patterns differed significantly across design environments, which enable us to

further examine the design environment's role in student behavior within the iSocial 3D CVLE. Further visualizations aided in analyzing the patterns of behavior as they relate to design environment attributes. As stated in Chapter I, this is an exploratory, retrospective case study and as such the methods applied are meant to explore and reveal patterns as well as gain insight about the unique context of iSocial 3D CVLE. Following this chapter is Chapter 5, which presents the results of this research study, followed by Chapter 6, the Discussion.

CHAPTER V: RESULTS

The purpose of this study was to build knowledge on (a) how to characterize complex student performance through co-occurring behavior patterns, (b) how those behavior patterns might differ across iSocial 3D CVLE design environments, and (c) how the design environment attributes may differ or are similar in relation to the emergent student behavior patterns. The research questions for this study are as follows:

RQ 1: Can student performance within iSocial 3D CVLE naturalistic practice activities be characterized through co-occurrences of behavior? If so, how and in what ways?

RQ 2: Do characteristics of student co-occurring behaviors in iSocial 3D CVLE naturalistic practice activities differ across design environments? If so, how and in what ways?

RQ 3: Are design attributes associated with behavior patterns?

Overview of Findings

This section presents an overview of findings, with more detailed results following.

For the first research question, it is clear that student performance can indeed be characterized through behavior patterns. By looking at student scores and where they lie on the interpreted principal components, we can see (a) variation in performance among the students, and (b) drill down into the data to then visualize their characteristic behavior patterns within the environment.

For research question 2, linear mixed model with post-hoc Sidak-corrected tests showed the design environment had a statistically significant effect on behavior scores for PC 1, PC 2, and PC 3. Additionally, time was ruled out as having a significant linear effect on behavior scores for PC 1, 2, and 3. Thus, we can assert that student behavior patterns do vary across design environments.

Research question 3 addressed the association between identified environmental design attributes and the behavior patterns as resulting from research question 2. General behavior patterns were associated with design environment attributes; this indicates warranting further study.

**RQ1: Characterizing student performance within iSocial 3D CVLE
naturalistic practice activities through co-occurrences of behavior**

The data for the three research questions utilizes data based on student co-occurrences of behavior. The student 10-second segments, representing presence or absence of behavior, was run through the ENA R script which performed PCA using

SVD on the data as described in Chapter 4. The principal components that most substantially represent the student variance in activity performance were chosen, interpreted, and then scores plotted. The following describes the selection of components and the interpretation of components, followed by a detailed drilling down into each activity for purposefully sampled students.

Selecting the Components

Three principal components were found to substantially explain the variance in student activity performance. A visual analysis of the scree plot (see Figure 7) shows that after the third principal component there is a substantial drop in percentage of variance accounted for by subsequent principal components. Principal component 1 accounted for 32% of the variance in behavior scores, principal component 2 accounted for 17% of the variance in behavior scores, and principal component 3 accounted for 14% of the variance of behavior scores.

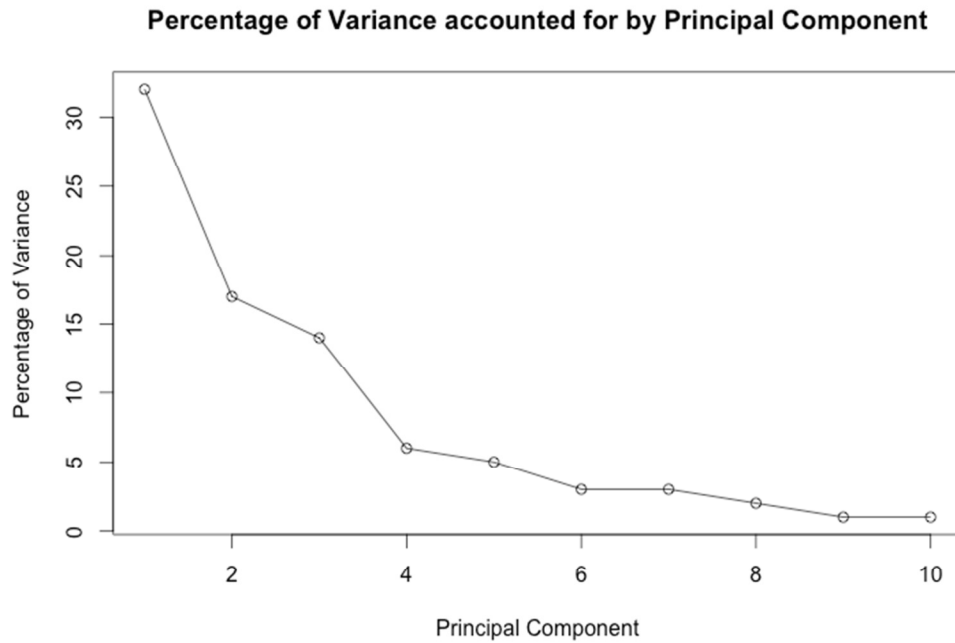


Figure 7. Percentage of variance accounted for by principal components (first ten listed)

Behavior scores on principal components 1, 2, and 3 were then plotted in 3-dimensional space, the x axis representing principal component 1 (PC 1), the y axis representing principal component 2 (PC 2), and the z axis representing the principal component 3 (PC 3). Figure 8 illustrates the direction of these axes in the graph.

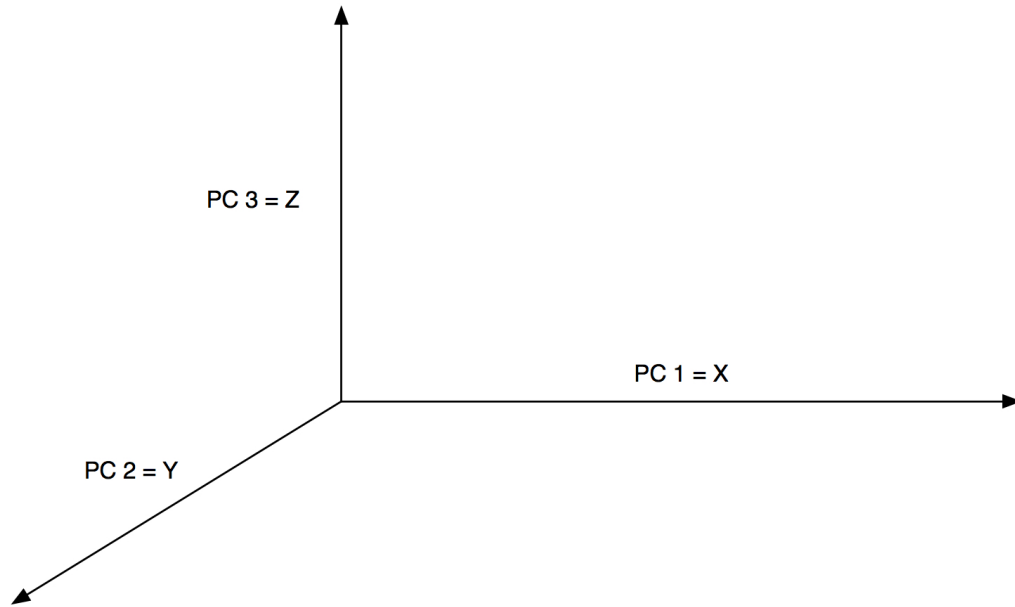


Figure 8. Behavior scores are plotted in 3D space according to PC 1, PC 2, and PC 3 scores to represent one 3D Point

All 10-second segment data, which represented presence or absence of a behavior, was processed according to the ENA process as outlined in chapter 4, resulting in three scores per unit of analysis, or student within an activity, visualized as one point within a 3-dimensional graph ("3D point"). Each score is an outcome measure that represents that student's score on a particular principal component, which is then interpreted by the loadings and dominant co-occurrences with those loadings (also as outlined in chapter 4). By looking at a student's scores on PC 1, PC 2, and PC 3 together (represented by a single dot in a 3-dimensional graph, or the 3D point), we begin to get a rich picture of the key characteristic behavior patterns of that student within the activity.

Interpretation of Components

As stated in chapter 4, the interpretation of the principal components is determined by (a) the coded behaviors which load most heavily on the principal component (specifically 2 to 3 of the most positive and negative as recommended by Bartholomew et al., 2008) and (b) the primary behavior co-occurrences connected to those behaviors which are heavily loaded onto the component of focus. Table 8 lists the top two positive and negative loadings for each of the three principal components. Table 9 lists the primary co-occurrence patterns for all students in all student-led naturalistic practice activities. Taking these behaviors and interpreting them onto the 3-dimensional graph gives Figure 9.

Table 8. Top loadings on principal components.

Top loadings for all students in all student-led naturalistic practices

Principal component	Percentage of Variance	Top positive loadings	Top negative loadings
PC1 (x axis)	32%	Orienting to the learning objects Movement to/around learning objects	Facing Online Guide: non-speaking Facing Online guide: speaking
PC2 (y axis)	17%	Facing online guide speaking Facing online guide non-speaking	Verbalizations greater than 5 words Verbal responses
PC 3 (z axis)	14%	Facing peers speaking Facing peers non-speaking	Orienting to learning objects Movement to/around learning objects

Table 9. Primary Co-occurrence patterns

Primary co-occurrence patterns for all students in all student-led naturalistic practice activities

Loaded onto PCs	Coded behavior	Primary co-occurrence
(PC1+)	Orienting to the learning objects	Facing and moving to/around learning objects
(PC1+)	Movement to/around learning objects	Orienting to learning objects
(PC1-)	Facing Online Guide: non-speaking	Facing learning objects, Facing online guide speaking
(PC1-)	Facing Online Guide: speaking	Facing learning objects, facing online guide non-speaking
(PC2+)	Facing online guide speaking	Facing learning objects, Facing online guide not speaking
(PC2+)	Facing online guide non-speaking	Facing online guide non-speaking
(PC2-)	Verbalizations greater than 5	Facing learning objects, Verbally responding
(PC2-)	Verbal responses	Facing learning objects
(PC3+)	Facing peers speaking	Facing learning objects, Facing peers non-speaking
(PC3+)	Facing peers non-speaking	Facing learning objects, facing OG non-speaking
(PC3-)	Orienting to learning objects	Facing learning objects
(PC3-)	Movement to/around learning objects	Orienting to learning objects

Interpreting Principal Component 1: Characterizing orientation and movement

Principal component 1, the x-axis, is generalized as “general orientation and movement”, major components of nonverbal behavior. PC 1 primarily divides student performance across static (negative scores) and active (positive) nonverbal behaviors. Negative scores on PC 1 are characterized by being nonverbally static (“facing”) while looking at the online guide speaking as well as while the guide was not speaking, as well as looking at the learning objects. Positive scores on PC 1 were

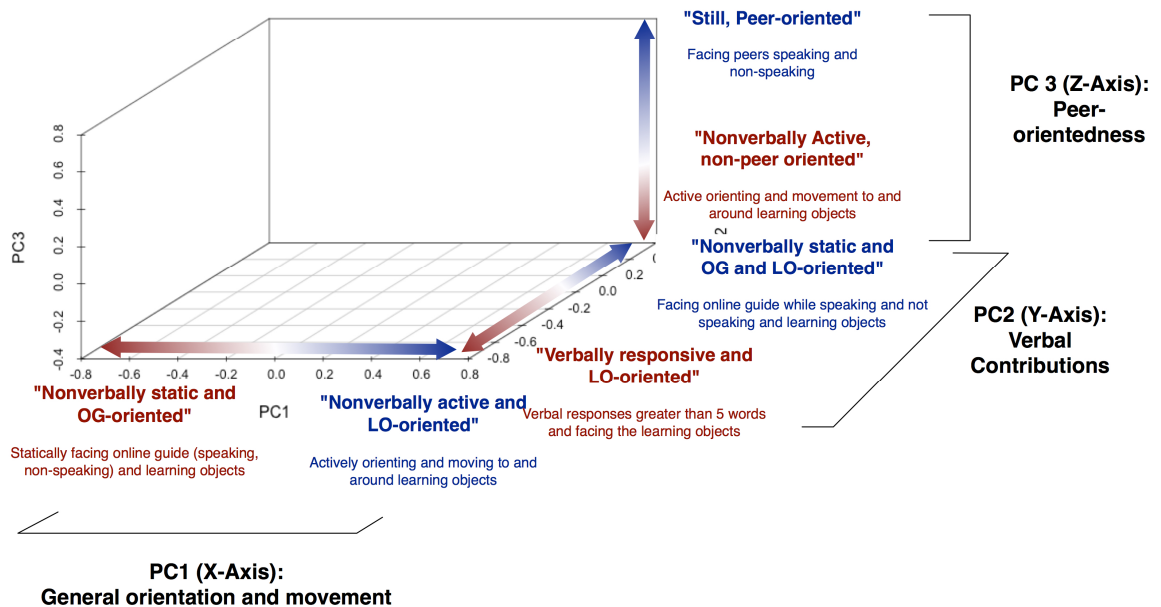


Figure 9. Interpretation of principal components overlaid onto a 3-dimensional graph

nonverbally active by orienting and moving around learning objects while also orienting to the learning objects and moving to and around the learning objects. So in summary, Principal component 1 characterizes a student's orientation and movement as varying between (1) static while OG and learning object-oriented and (2) active while learning object-oriented. Students whose performances were **negative and farther toward the static extreme** could be described as avatars being still, they did not orient or move to others, and stood facing the online guide both while she was speaking as well as when she was not the one speaking. Students whose performances were **positive and farther toward the active extreme** could be described as avatars actively orienting and moving to and around the learning objects and then repeatedly pausing to stop and face the learning objects.

Interpreting Principal Component 2: Characterizing Verbal contributions

Principal component 2, the y-axis, is generalized as “verbal contributions.”

Principal component 2 primarily divides student performance across verbally responsive (negative scores) and not having those verbal responses while facing the online guide (positive scores). Negative scores on PC 2 are characterized by verbal responses that are greater than 5 words while also facing towards a learning object. Positive scores on PC 2 are not characterized by verbal behaviors at all, but by statically facing the online guide while she is speaking or not speaking as well as facing learning objects. So in summary, Principal component 2 characterizes a student’s general verbal participation in an activity, ranging from verbally responsive and static behavior to nonverbal and static OG-focused behavior.

Students whose performances were **negative and more towards the verbal extreme** could be described as avatars who were responding in depth (more than 5 words) to the online guide or peer about a topic and were most likely also facing a learning object. Students whose performances were **positive and more towards the static, OG-focused extreme** could be described as avatars who were not speaking, standing still, facing the online guide while she was speaking as well as when she was not speaking, and were standing still facing a learning object.

Interpreting Principal Component 3: Characterizing Peer Orientation

Principal component 3, the z-axis, is generalized as “peer orientation.”

Principal component 3 primarily divides student performance across peer orientation and other nonverbal activity. Negative scores on PC 3 are characterized by non-peer active orientation and movement to and around learning objects.

Positive scores on PC 3 are characterized by facing peers who are speaking and facing peers who are not speaking. Students characterized as strongly positive have avatars that statically face peers, while those in the neutral or slightly positive range on PC 3 may be dividing their orientation between peers and learning objects in a more active manner. Students who were highly negative on PC 3 would be very active nonverbally but not peer-focused, such as looking at objects or transitioning to and around many different learning spaces and objects. So in summary, Principal component 3 characterizes a student’s general peer orientation (or lack thereof) within an activity. Students whose performances were **negative and farther toward the non-peer extreme** could be described as avatars moving and orienting to and around learning objects and then coming to stand still and face that learning object of focus. Students whose performances were **positive and farther toward the peer-oriented extreme** could be described as avatars standing still, facing their peers while they were speaking and while they were not speaking as well as most likely also facing the learning objects. Students whose performances were **more neutral, balancing the peer-oriented and learning object-focused elements**

could be described as both moving to and around learning objects while also stopping to face their peers while they were speaking or not speaking.

Overview of All Student Activity

With the interpretations of the 3 principal components in mind, Figure 10 is a representation of all students across all student-led naturalistic practice activities included in this study. It is a 3-dimensional scatterplot of all units of analysis, or students within activities, with the mean represented by a blue square.

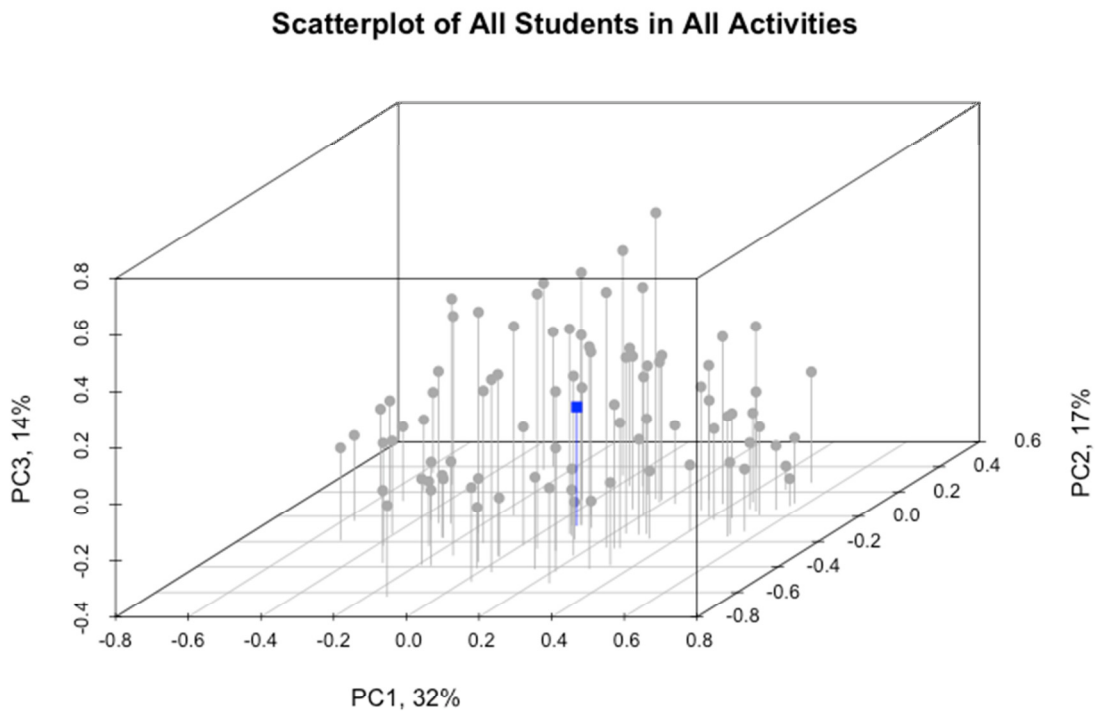


Figure 10. 3D Scatterplot of all students in all activities
Dots represent student scores for individual students within student-led NP activities
Note: The mean score is shown with a blue square

As Figure 10 illustrates, student behavior varies across nonverbal movement (PC 1, the x axis) and accounts for the most variance in student behavior across the activities (32%). Students vary from static (negative) to active (positive) on this principal component. Students also vary across verbal contributions (PC 2, the y axis), and this accounts for the second most variance in student behavior across activities (17%). Students vary from verbal (negative) to less verbal (positive) on this principal component. Students, in combination with how they vary across those two principal components, also vary across peer orientation (PC 3, the z axis), and this accounts for the least amount of variance (of the principal components that were retained; 14%). Students are seen to vary from more active and learning object focused (negative) to static and peer focused (positive).

Summary of interpreting principal components

As one can see, labeling principal components requires interpretation and can be somewhat complicated, but does serve as a way of characterizing complex student behavior within an activity performance with the use of scores. In addition to having scores and relative placement it is important to drill down into the data to explore what the activity looks like for a particular student in order to learn more about the meaning of the scores and to more precisely characterize student behavior within activities. In the next section, all nine student-led naturalistic practice activities are reviewed, with purposefully sampled students based on maximum variation to look at their primary behaviors and co-occurrences within the lesson. Maximum variation was determined by (1) selecting both for variation of

students across all nine activities (thus choosing different students across activities) as well as (2) variation across students within an activity by selecting students who varied from each other across two or more principal components. This drilling down process and case reports will further explicate how co-occurrences of behavior can characterize student performances within an iSocial 3D CVLE activity.

Each drilling down case report will have the following elements: a brief description of the activity, overview of student performance given the scores, a drilling down into the primary co-occurring behaviors of 2 sampled students within the activity, and a summary of overall student performance within the NP activity given the scores and advanced drill-down descriptions. The case reports revealed that students performed distinctly from each other within activities, and often differed from each other across two or more principal components. In addition, patterns of some students to verbally dominate or lead can be seen across activities. In addition, certain activities skewed all students towards certain types of performances and commonalities across students, such as less overall avatar movement and more verbal, or less peer-orientation and greater verbal behaviors.

Drilling down: Student performance within the U1L4 NP activity

Description of activity

Unit 1 Lesson 4 naturalistic practice activity, seen in Figure 11, is an activity in which students are to discuss as a small group (in a group of 2 or 3) how to use all three clues to show an emotion described in the scenario and then display facial

expressions using a cognitive strategy for facial expressions called the triangle scanning method.



Figure 11. A small group in cohort A discusses a situation in U1L4 NP activity

Overview of U1L4 NP student performance

Student scores were obtained and graphed, as shown in Figure 12. In addition, Table 10 lists the scores for each student on each component, and also assists with visual analysis by color-coding the positive and negative scores, with 0 being white, negative trending towards deep red, and positive trending towards deep blue. Again, “negative” and “positive” are randomly assigned and do not hold any inherent value in relation to “desirable” and “undesirable” behaviors.

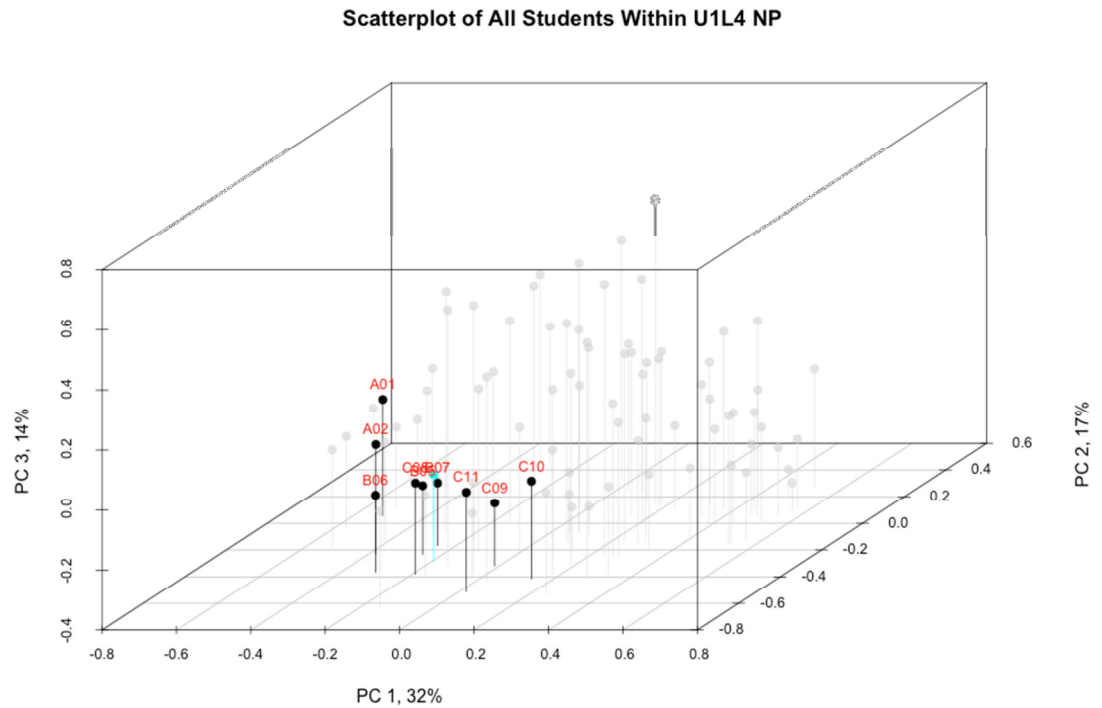


Figure 12. Scatterplot of all students within the U1L4 NP activity
Scores are shown within the context of the remaining 3D points representing all activities (greyed out), mean is shown with a blue square

Table 10. Scores of Students in U1L4 NP

Student	PC1	PC2	PC3
A01	-0.520	0.056	-0.012
A02	-0.382	-0.228	-0.037
B05	-0.254	-0.232	-0.171
B06	-0.307	-0.364	-0.144
B07	-0.250	-0.166	-0.191
C08	-0.191	-0.380	-0.096
C09	-0.012	-0.318	-0.191
C10	0.130	-0.412	-0.076
C11	0.019	-0.512	-0.068
Mean	-0.195	-0.284	-0.110
Median	-0.250	-0.318	-0.096
SD	0.207	0.166	0.067
N=9			

As can be seen in Figure 12 and Table 10, students' avatar behaviors were primarily static in nature (negative on PC 1; mean score of -0.195), which meant that they were primarily facing the online guide while she was speaking as well as when she was not speaking. Because "facing learning objects" is a primary co-occurrence to these behaviors, we know that they were primarily statically facing the online guide while also facing the learning objects, which in this instance are mediaboards (as can be seen in Figure 11). For PC 2, students are also overwhelmingly negative on this component (mean score of -0.284), aside from one student, which means that although they were rather static (negative on PC 1), they were verbally contributing in the environment with verbal responses and verbalizations greater than 5 words in length. Because facing learning objects and verbal responses are also primary co-occurrences to these behaviors, we also know that while verbalizing, they were also primarily facing learning objects, and when they were verbalizing greater than 5 words in length they were most often replying to another person in the environment. For PC 3, students are relatively similar to each other compared to the prior principal components; this is reflected both in the height of the 3D points in Figure 12, the lack of color and score differentiation in the PC 3 column in Table 10, and the standard deviation (SD = 0.067). They are all neither peer-oriented nor active in the environment, with a slightly negative score, meaning they are likely standing still as we can interpret from the other two principal components.

Student C10 and C11 are two students that were far more active than the other students, as can be seen by their 3D points being more to the positive extreme

of PC 1. They were also the most verbal, as their 3D points are the farthest towards the negative extreme of PC 2. For example, Student C10 can be seen talking to his peers, looking at the mediaboard, and often moving his avatar back and forth in a “jittery” fashion. In contrast, student A01 had the most static avatar behavior of all the students, being to the left-most extreme of his peers on PC 1, meaning he often just stood statically, facing the online guide as well as the learning objects. However, in addition to being nonverbally static, he was also the least verbal of all the students, as can be seen by his 3D point being the farthest towards the positive extreme of the PC 2 compared to any of the other students.

Drilling down: looking at specific student behavior patterns

Students A01 and C10 were sampled for this activity to further examine their co-occurring behavior patterns within this U1L4 NP activity. Figure 13 shows all student scores within the ENA visualizer for this activity; this is similar to Figure 12 but shown here for context when looking at student scores.

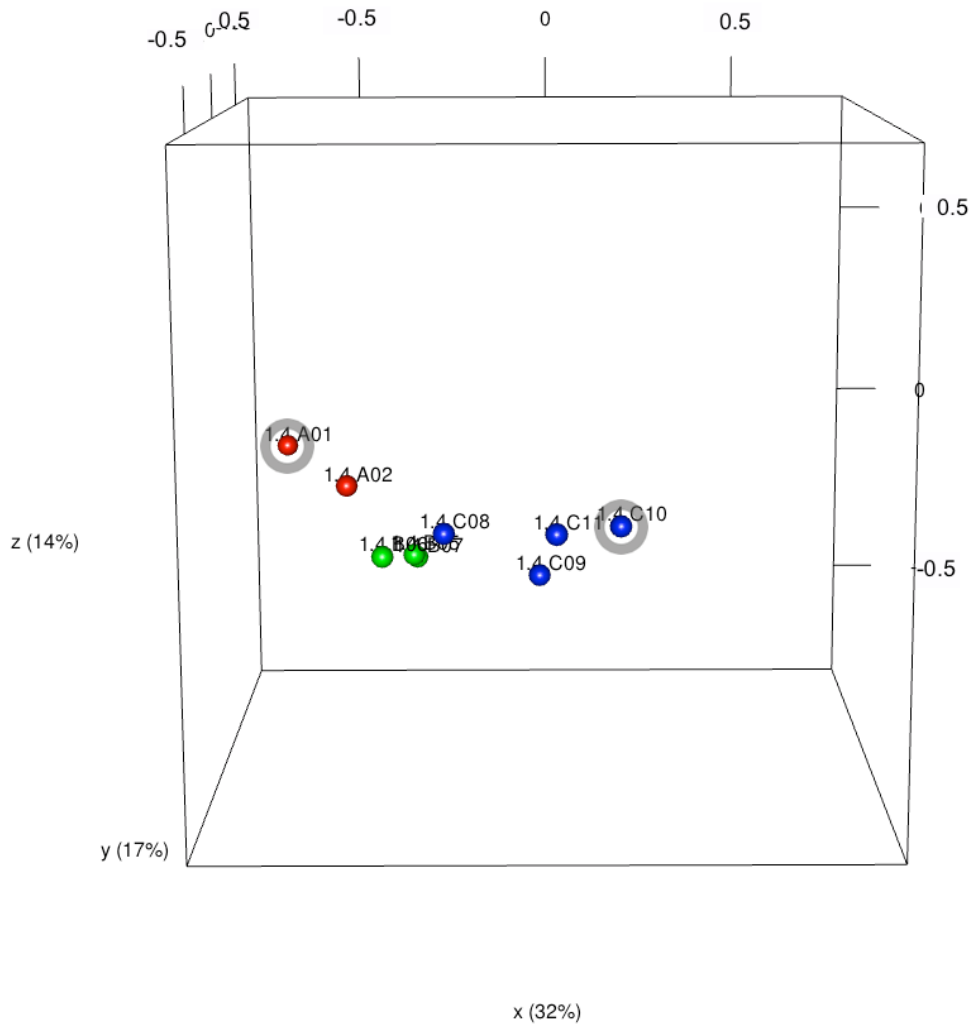


Figure 13. All students within the U1L4 NP activity as seen through the ENA visualizer. Red represents cohort A, Green represents cohort B, Blue represents cohort C; Students A01 and C10 are circled grey.

The following examples show drilling down to the level of data to take a look at individual co-occurrence patterns that were prevalent in their activity performance. These images were created with the ENA visualizer, zoomed in and cropped in order to feature the primary details of co-occurrence patterns (thus providing figures like shown in 13 for visual and space context). A green line between two behaviors indicates that those behaviors co-occurred together within a

10-second segment; see Appendix B for references to code labels and definitions. Thicker lines indicate a greater frequency of co-occurrence; thinner lines indicate less frequency of that behavior co-occurrence within that activity for that student.

Two individuals, A01 and C10, were purposefully sampled for maximum variation based on their scores in PC 1, PC 2, and PC 3, and will be used to drill down further into describing their primary co-occurring behavior patterns for each of them within this activity.

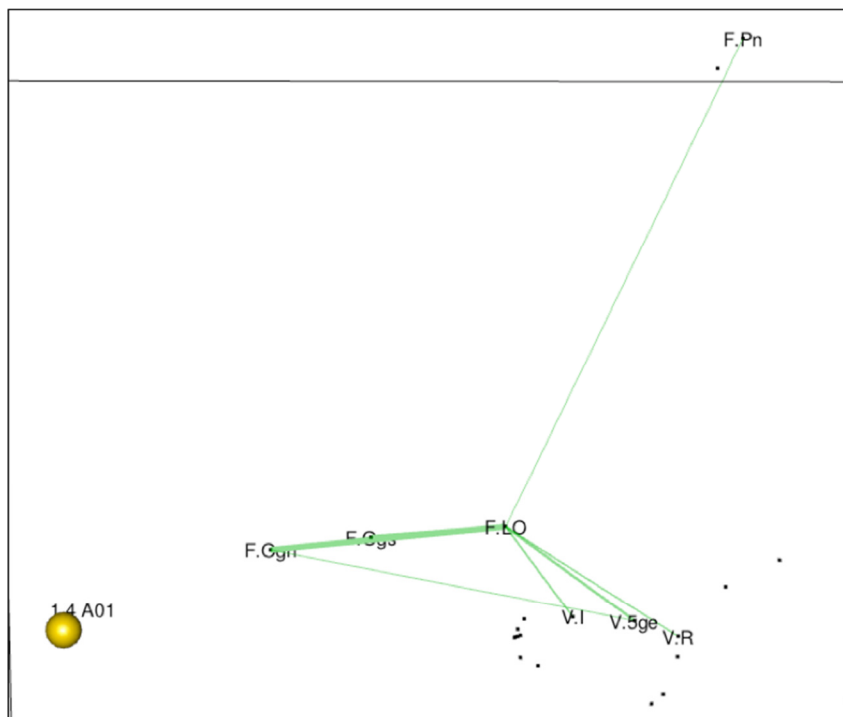


Figure 14. Student A01's primary co-occurring behavior patterns in U1L4 NP

Student A01

Student A01's primary co-occurring behavior patterns (Figure 14) are primarily statically facing the online guide, both when the online guide was talking

(F.OGs) as well as when she was not talking (F.OGn) while facing the learning object (F.LO; in this instance, a mediaboard). In other words, student A01 had little movement or orientation towards various speakers. These actions represent the majority of A01's behavior patterns, as shown by the thickness of the green lines. However, when A01 did choose to verbally contribute, he contributed primarily in the form of responses and initiations greater than five words in length while facing learning objects or online guide. He was not primarily facing his peers while he was speaking, although there is a small occurrence of him facing his peer while his peer was not speaking while A01 was also facing the learning object (in this instance, the mediaboard). If the student were to be going back and forth between orienting towards and facing his peers, talking to his peers, and orienting and facing the learning objects, there would be evidence of those primary patterns in his behavioral network diagram. However, he is primarily static in regards to his avatar behavior, and compared to his peers, is more of a listener than a speaker. However, it is important to note that when he is speaking, which is not often given that this is a small-group activity, he is showing evidence of initiations and responses that are greater than 5 words in length.

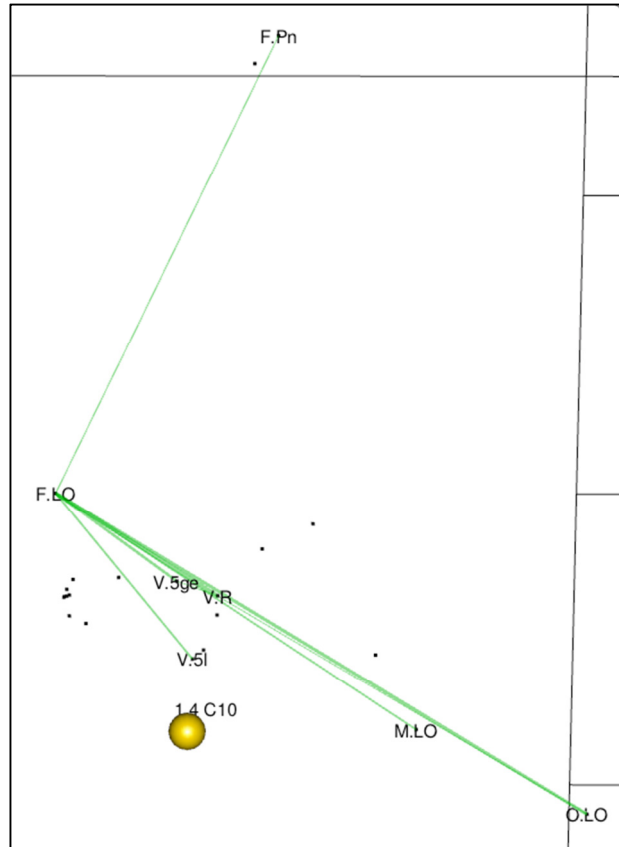


Figure 15. Student C10's primary co-occurring behavior patterns in U1L4 NP

Student C10

Student C10 (Figure 15) had different behavior patterns than A01, and as shown in the graph and table had much more active avatar behavior than the others. Student C10's primary behavior patterns were moving (M.LO) and orienting to and around learning objects (O.LO), as well as using verbal responses (V.R) using primarily longer utterances that are greater than or equal to 5 words in length (V.5ge). His behaviors are all co-occurring with facing the learning object (in this lesson, it is the mediaboard), meaning that C10 often oriented and stopped and faced the learning object, and then might move and then stop again. However, his

primary form of movement was not to orient towards his peers, and he was also not facing the online guide (unlike student A01). Student C10, unlike student A01, can be seen moving back and forth in a “jittery” fashion, orienting towards learning objects and moving his avatar body back and forth, often coming to a stop facing the learning object, and then responding to an online guide or peer while not facing them.

Summary of student performance within the U1L4 NP activity

In general, students within this activity spent the most time using more static avatar behavior, facing the online guide and the mediaboard learning object. In addition, while also talking to each other, they were primarily doing so without looking at each other. However it is important to note that there is a range of this type of behavior, as evidenced by drilling down into C10’s and A01’s behavior co-occurrences. This behavior might range from what could be deemed as inappropriate behavior co-occurrences on each end of an extreme (inappropriate due to never orienting, or inappropriate due to orienting and moving in a “jittery” fashion and not standing still). However, labeling a student’s performance would need further validation in order to confirm that those scores were indeed representative of inappropriate behavior co-occurrences for this activity. This type of range is often present in many of the activities, and is also discussed in future directions in Chapter 6.

Drilling down: Student performance within the U2L4 Activity

Description of activity

In the unit 2 lesson 4 naturalistic practice activity, students are given the scenario that their boat is sinking, and they must work together to decide what items they are going to take with them to a deserted island. Figure 16 shows a screenshot of this activity with some of the items in the background, and the online guide “Ms. Jaclyn” to the side.

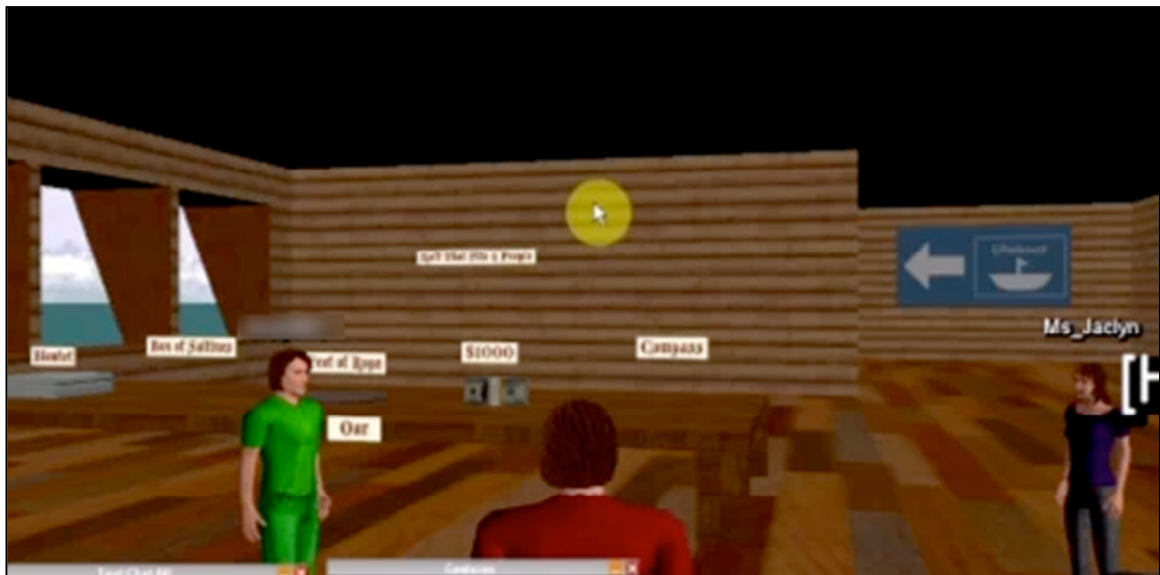


Figure 16. Students from Cohort C discuss which items to take in the U2L4 NP activity

Overview of U2L4 NP student performance

Student scores are graphed in Figure 17 and listed in Table 11. Overall, student performance differs from their performance in the U1L4 NP activity in that students are more nonverbally active (their avatars are orienting and moving more), as can be seen by the overall 3D points being more to the positive extreme on

PC 1 as well as their mean score on PC 1 (0.227 in this activity versus -0.195 in activity U1L4). Student verbalizations in this activity vary, as can be seen in Table 5.4, as scores range from very verbal (C11; -0.306) to the opposite end of the verbal extreme (A01; 0.334). When looking at the patterns of verbalization in Table 5.4, there are individuals that stand out as the most verbal within their cohorts: student A02 for cohort A, B06 for cohort B, and C11 for Cohort C. In this lesson, students were tasked with “leading” the items choosing activity, and none of these three aforementioned students were the leaders, which further emphasizes their verbal tendencies were not simply due to being assigned a task, but were due to their own social behavior choices.

In addition, in this activity compared to U1L4, students have a greater range of peer-orientation (PC 3 SD = .177). While in U1L4 the peer orientation had all negative scores (mean of -0.110), U2L4 ranges from more negative scores on PC 3 (less peer-oriented and actively moving) as can be seen by student B06 (score -0.159) to very positive scores on PC 3 (more peer-oriented) as demonstrated by student A01 (score 0.394).

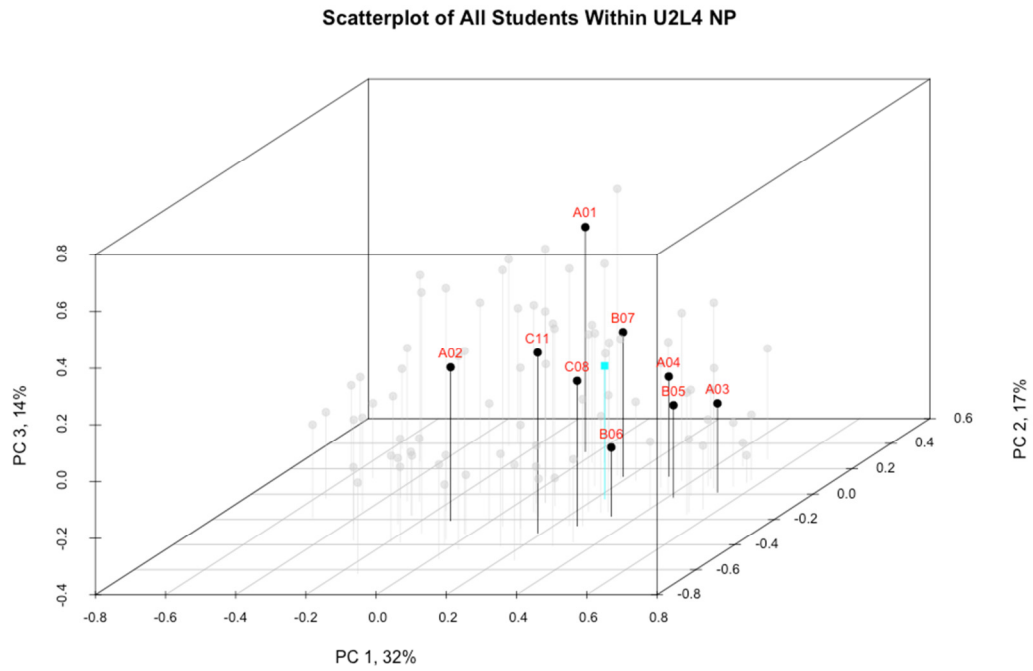


Figure 17. Scatterplot of all students within the U2L4 NP activity. Scores are shown within the context of the remaining 3D points representing all activities (greyed out), mean is shown with a blue square

Table 11. Scores of Students in U2L4 NP activity

Student	PC1	PC2	PC3
A01	-0.0346	0.334	0.394
A02	-0.117	-0.208	0.140
A03	0.519	0.015	-0.086
A04	0.311	0.140	-0.047
B05	0.417	-0.025	-0.075
B06	0.321	-0.172	-0.159
B07	0.182	0.138	0.111
C08	0.266	-0.249	0.110
C11	0.185	-0.306	0.236
Mean	0.227	-0.037	0.069
Median	0.266	-0.025	0.110
SD	0.202	0.214	0.177
N=9			

Drilling down: looking at specific student behavior patterns

Students A04 and B06 were sampled for this activity to further examine their co-occurring behavior patterns within this U2L4 NP activity. Figure 18 shows all student scores within the ENA visualizer; this is similar to Figure 17 but shown here for context when looking at student scores.

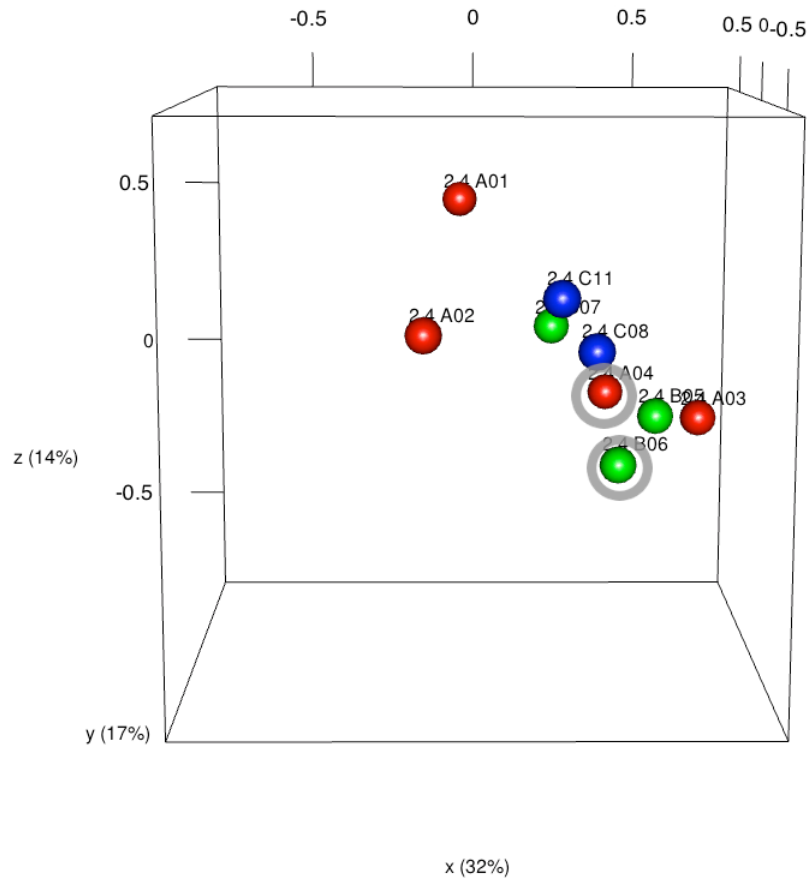


Figure 18. All students within the U2L4 NP activity as seen through the ENA visualizer. Red is cohort A, Green is cohort B, Blue is cohort C; Students A04 and B06 are circled grey

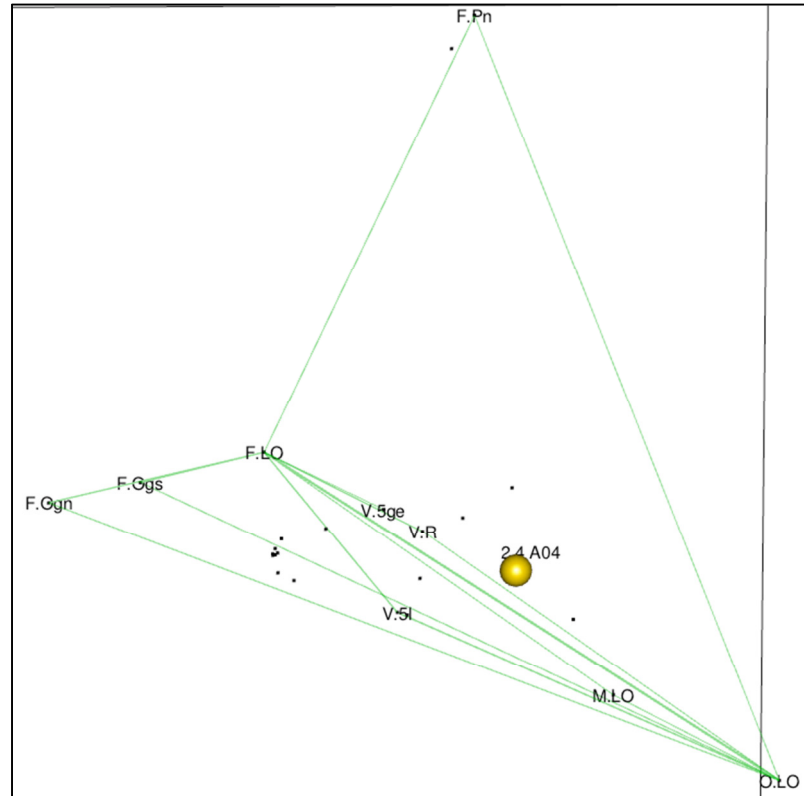


Figure 19. Student A04's primary co-occurring behavior patterns in U2L4 NP

Student A04

Student A04's primary co-occurring behavior patterns (see Figure 19) are (1) centered around orienting towards learning objects (O.LO) while then stopping to then face those learning objects (F.LO), as seen by those co-occurrences having the thickest green line, (2) followed by facing the online guide speaking (F.OGs) and not speaking (F.OGn) while facing the learning objects, as well as (3) verbal responses (V.R) that are greater than or equal to 5 words in length (V.5ge). The thinner lines represent less-frequent co-occurrences, with most of them co-occurring with orienting to learning objects: moving to and around learning objects (M.LO),

verbally speaking less than five words (V.5l), and facing peers none of whom were speaking (F.Pn). In other words, student A04 was focused on objects, and primarily stopped and oriented to look at the online guide while she was speaking, but did not stop to face his peers while they were speaking. In addition, while he was speaking there were co-occurrences with facing the learning objects, orienting, and movement, but he did not turn towards his peers while he was speaking to talk to them. He did have varying lengths of verbalizations (both less than 5 words and greater than 5 words per utterance), but his stronger co-occurrences of utterances, especially greater than 5 words, are while facing the learning objects (as can be seen by the thicker lines).

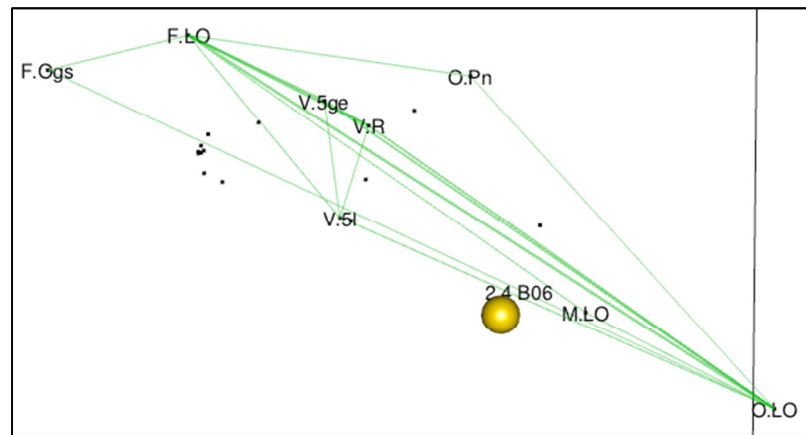


Figure 20. Student B06's primary co-occurring behavior patterns in U2L4 NP

Student B06

Student B06's primary co-occurring behavior patterns have his strongest co-occurrences between verbalization behaviors. As seen in Figure 20, the thick line

represents verbal responses greater than 5 words in length co-occurring with facing learning objects. His verbalizations also co-occur with orientation towards learning objects. In other words, he is orienting to the objects and stopping, then orienting and stopping again within these ten-second segments while he is also talking with his peers. There is some evidence of him orienting towards his peers, who were not speaking at the time, but that behavior did not occur often, and time spent facing his peers while they were speaking were not a primary behavior occurrence. In addition, when looking at Table 5.4, we can see that B06's verbal score is quite negative, more so than the rest of his cohort, meaning that of the group he was in, he was talking more than the rest of his group and could possibly be dominating the conversation (with B07 verbally contributing the least).

Summary of student performance within the U2L4 NP activity

Students within the U2L4 activity had a fair amount of movement and orientation to the learning objects, which were often small interactive objects that served as points of discussion for sharing ideas and collaboratively negotiating a solution. Many students seemed to be very focused on the learning objects, orienting to and around the learning objects while not orienting or facing towards their peers to speak or to listen. However, the peer-orientation is greater than that in U1L4 even though it is not high across all students. Students also varied between verbalizing a lot and verbalizing very little, and within cohorts we can see individuals who might be dominating that conversation, and the co-occurring behaviors of those potential verbal "dominators", such as A02, B06 and C11.

Drilling down: Student performance within the U2L5 Activity

Description of activity

Unit 2 Lesson 5 naturalistic practice activity, seen in Figure 21, is an activity in which students are to discuss where to go on the island and who has which chore. Certain individuals are assigned roles such as “chore manager” who then leads the discussion.



Figure 21. Cohort B discusses who should take which chore in U2L5 NP activity

Overview of U2L5 NP student performance

Referencing Figure 22 and Table 12, it can be seen that students overall are highly active with their avatars, moving and orienting (PC 1 mean score = 0.400), with the entire range of students' general orientation and movement patterns having a positive score. Verbal behavior is rather neutral (mean = 0.010). Verbal ranges vary, as the scores range from highly verbal (A02; -0.410) to lacking strong

verbal patterns (A04; 0.277). In addition, the verbal tended to be dominated by an individual within each cohort (A02, B06, C11), seen as red within the table PC 2 scores, with others being less verbal (seen in blue). This perhaps is either partly due to a peer's domination of verbal, or on a more desirable note, partially due to their leadership role. While in Cohort B and C the strong verbal scorer corresponds to the chores manager leading the chores discussion for this activity, Cohort A was again dominated verbally by student A02, which was confirmed by qualitative note memos of the online guide reprimanding him for over-talkative behavior, as it was not his duty to lead. Principal component 3 shows much more peer-oriented behavior than previous naturalistic practice activities (U2L5 mean score=0.137).

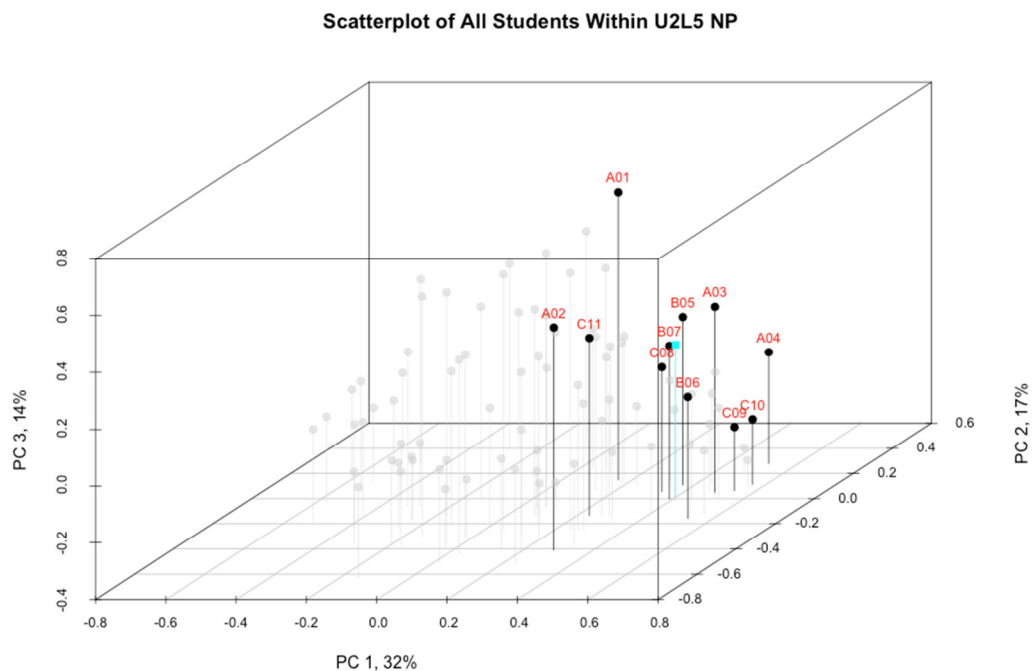


Figure 22. Scatterplot of all students within U2L5 NP; Scores are shown within the context of the remaining 3D points representing all activities (greyed out), mean is shown with a blue square

Table 12. Scores of Students in U2L5 NP

Student	PC1	PC2	PC3
A01	0.160	0.148	0.611
A02	0.287	-0.410	0.384
A03	0.490	0.049	0.253
A04	0.516	0.277	-0.008
B05	0.366	0.108	0.191
B06	0.527	-0.157	0.027
B07	0.389	-0.003	0.138
C08	0.335	0.056	0.037
C09	0.538	0.063	-0.175
C10	0.561	0.113	-0.170
C11	0.234	-0.133	0.224
Mean	0.400	0.010	0.137
Median	0.389	0.056	0.138
SD	0.136	0.184	0.233

N=11

Drilling down: looking at specific student behavior patterns

Two students were chosen for analyzing their behavior patterns in this lesson: A02 and C09. Figure 23 shows plots of student scores via the ENA visualizer tool for context.

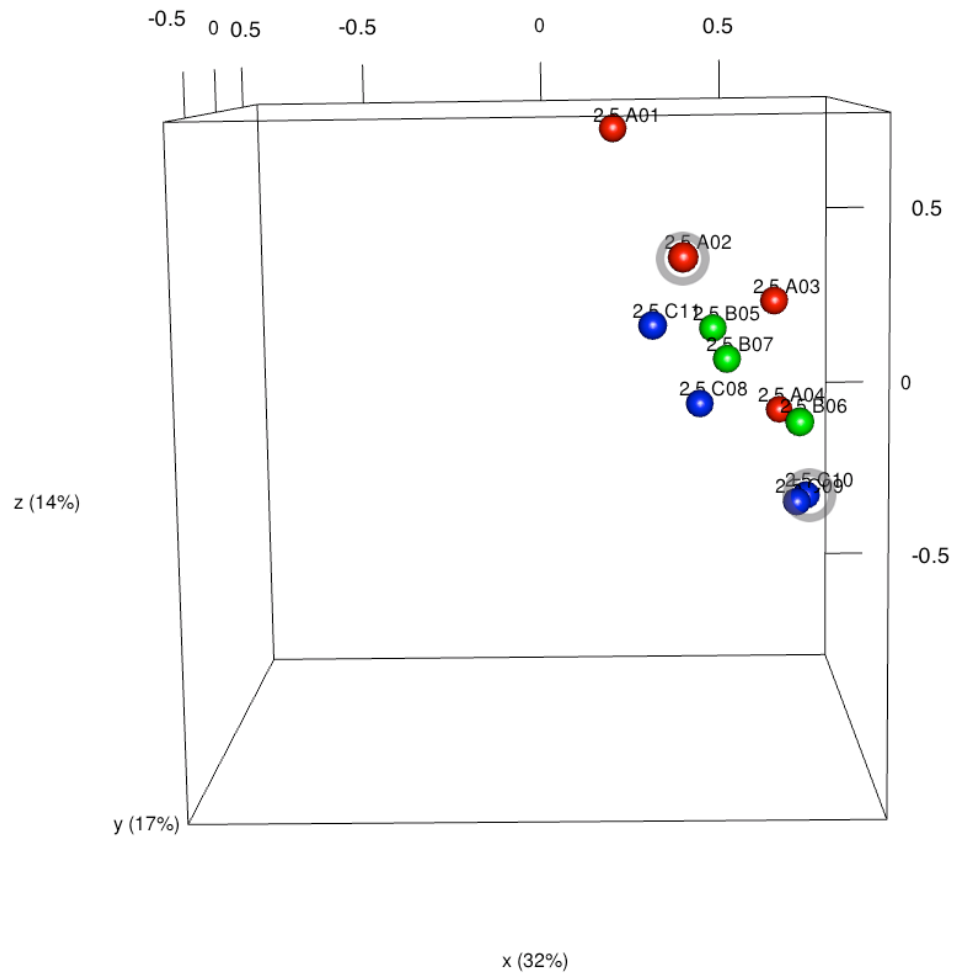


Figure 23. Scores of all student performances in U2L5 via ENA visualizer. Red is cohort A, Green is cohort B, Blue is Cohort C. Students A02 and C09 are circled grey.

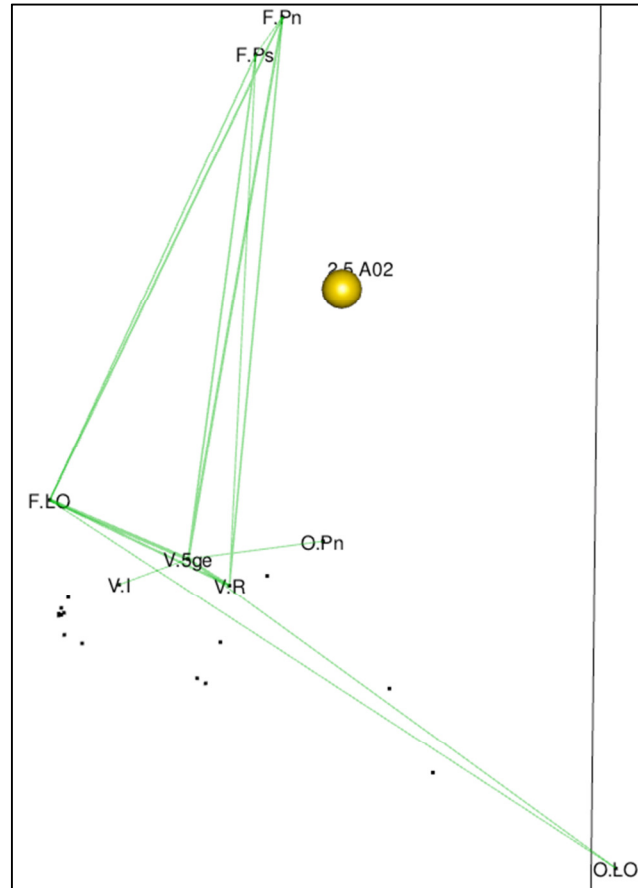


Figure 24. Student A02's primary behavior patterns in U2L5 NP Activity

Student A02

Student A02's primary behavior patterns (see Figure 24) were all heavily connected with (1) verbal responses (V.R) greater than or equal to 5 words in length (V.5ge) while facing learning objects (F.LO), and (2) to a lesser degree while facing his peers while they were both speaking and not speaking (F.Pn, F.Ps). As stated earlier, it was noted in the memos that this was also the student that "got in trouble" for dominating the conversation verbally and not pausing to let anyone speak. His primary co-occurrence patterns with his verbalizations were to face towards his

peers while they were speaking and not speaking, orienting towards his peers, and orienting towards learning objects. His “stand out” differences on the verbalizations principal component relative to his peers shows that his behavior was very different from his peers, likely due to his domination of the conversation. However, he was able to orient and then statically face his peers while speaking to them in this activity, which is absent from many other students’ behavior co-occurrences while they are speaking.

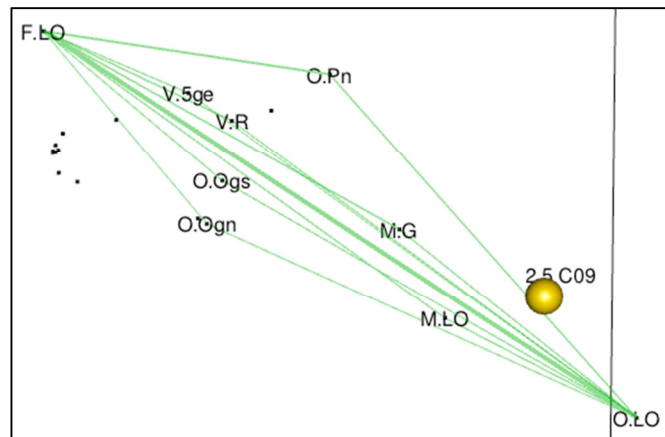


Figure 25. Student C09's primary behavior patterns in U2L5 NP activity

Student C09

Student C09’s primary behavior patterns (see Figure 25) center around facing, orienting, and movement to and around learning objects (F.LO, O.LO, and M.LO, respectively). Student C09’s behavior patterns primarily are him (1) orienting to learning objects and then (2) standing to face those learning objects, and then to a lesser extent, (3) orienting to the learning objects and to his non-speaking peers

(O.Pn). Student C09 does have some verbalizations, primarily in the form of verbal responses (V.R) greater than 5 words in length (V.5ge). However, though his verbalizations were primarily while facing learning objects or while he was orienting, unlike A02, he was not facing his peers or OG while speaking and was more object-focused when he was talking. Student C09 was a nervous and anxious student, and in this lesson, could be seen orienting and walking his avatar back and forth, looking at the learning objects. He would often walk up to the learning objects and not orient himself in a way that allowed his avatar to view his peers and instead focused, oriented, and moved to and around the learning objects in world.

Overall, student C09 was not very still and did not have what was called a “calm avatar” in the environment; his verbalizations primarily were done while he was still and facing the learning object rather than people in the environment.

Summary of student performance within the U2L5 NP activity

Students within the U2L5 NP activity overall had a greater amount of movement and orientation paired with greater peer-orientation compared to previous activities. Overall students would orient and move to and around learning objects and then stop and face their peers, as can be seen in A04’s drill-down descriptions. A04 was highly active but only moderately faced his peers in comparison to many of the other more positive scorers on PC 3 like A01, A02 and C11. Students also varied in their verbalizations, some according to assigned leadership roles and others such as A02 likely due to their verbal tendencies to

dominate, or like A01 or A04 to not speak or contribute as much to the conversation.

Drilling down: Student performance within the U3L5 Activity

Description of activity

In the unit 3 lesson 5 naturalistic practice activity (see Figure 26), students must decide together which items they want available on the buffets for the restaurant they have been building the last few lessons.



Figure 26. Students discuss which main dish items they want for their restaurant in U3L5 NP activity

Overview of U3L5 student performance

Overall, students in general were neither highly negative nor positive on principal components 1 and 2 with the mean scores on both principal components near 0 (mean scores -0.030, 0.043 respectively). While not overly static nor overly

active in this lesson on PC 1, students also do not have strong verbal or nonverbal patterns on PC 2, although there does seem to be a bit of a cohort-specific pattern with cohort A being less verbal than the other two cohorts. For PC 3, students tended to be slightly peer-oriented in this activity (mean score = 0.108), which is slightly less peer-oriented than is seen in U2L5 but more than in U1L4 and U2L4 NP activities. However, the peer orientation also has a cohort trend, with Cohort B students both having negative scores. This could potentially be a function of only having 2 students in the environment, in that there were fewer opportunities to face a peer with 2 students than when there were 4 students. See Figure 27 and Table 13 for visuals.

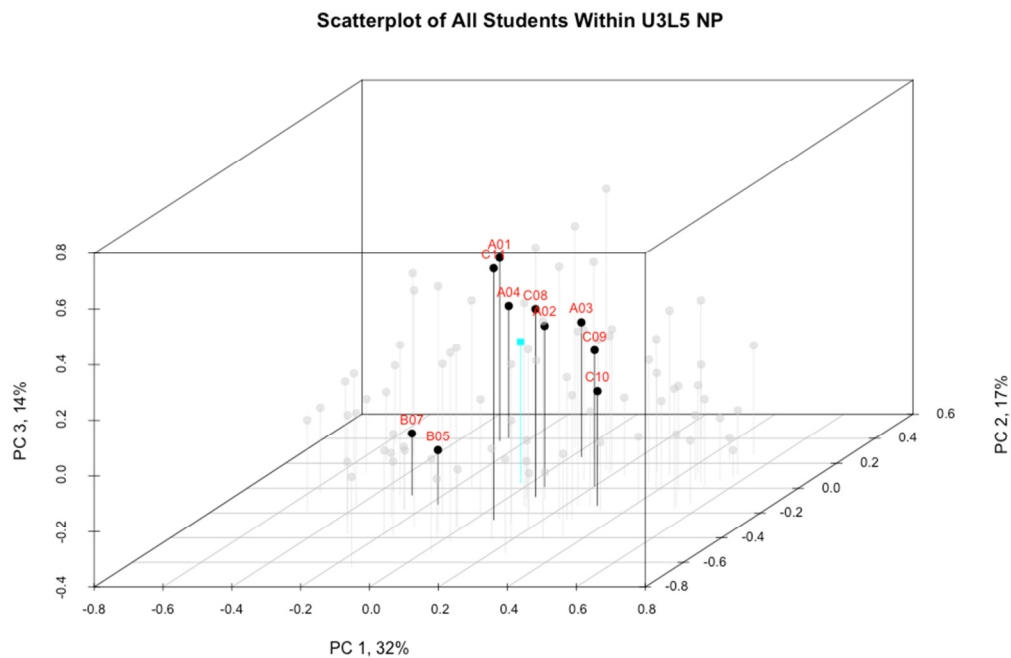


Figure 27. Scatterplot of student behavior scores in U3L5 NP activity

Table 13. Student scores in in the U3L5 NP activity

Student	PC1	PC2	PC3
A01	-0.278	0.380	0.259
A02	0.056	0.013	0.178
A03	0.030	0.251	0.085
A04	-0.266	0.406	0.075
B05	-0.175	-0.127	-0.206
B07	-0.291	-0.053	-0.179
C08	0.074	-0.067	0.274
C09	0.198	0.017	0.089
C10	0.293	-0.136	0.009
C11	0.055	-0.250	0.502
Mean	-0.030	0.043	0.108
Median	0.042	-0.020	0.087
SD	0.208	0.255	0.211

N=10

Drilling down: looking at specific student behavior patterns

Two individuals, students B07 and C22, were purposefully sampled to look at specific student behavior patterns within the U3L5 naturalistic practice activity.

Figure 28 displays the scores as seen through the ENA visualizer for context.

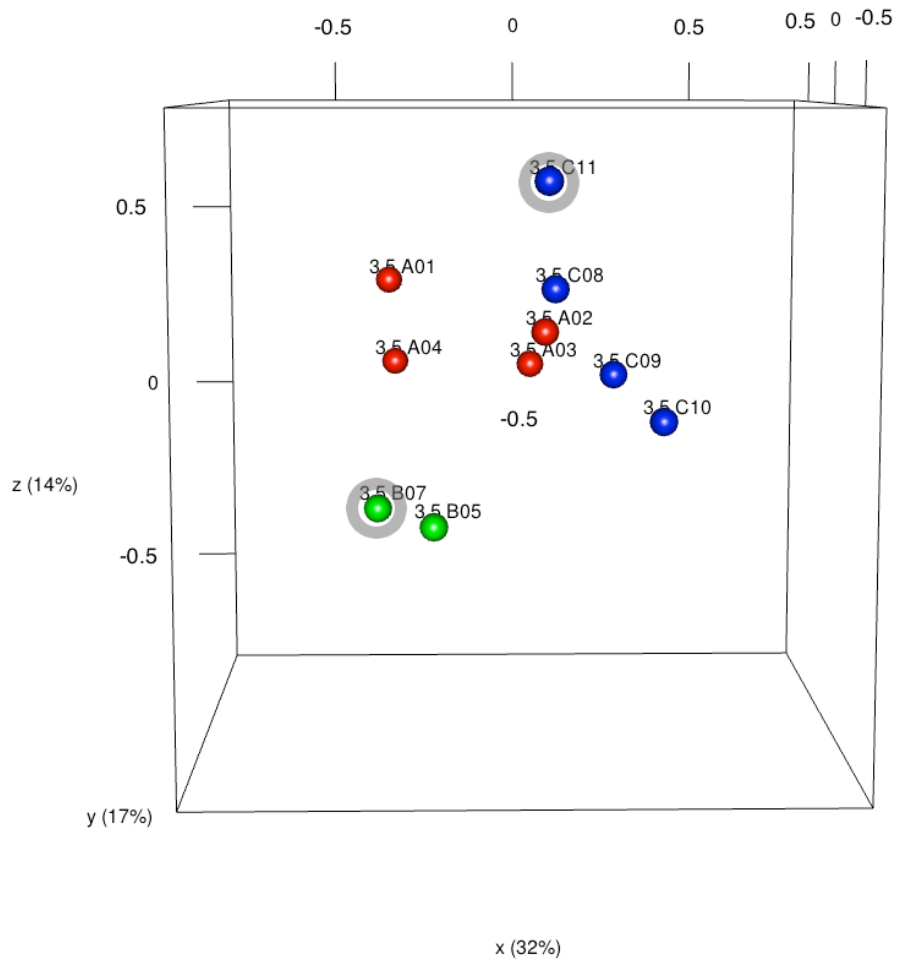


Figure 28. Student scores in U3L5 within the ENA visualizer; Red is cohort A, Green is cohort B, Blue is Cohort C. Students A02 and C09 are circled grey

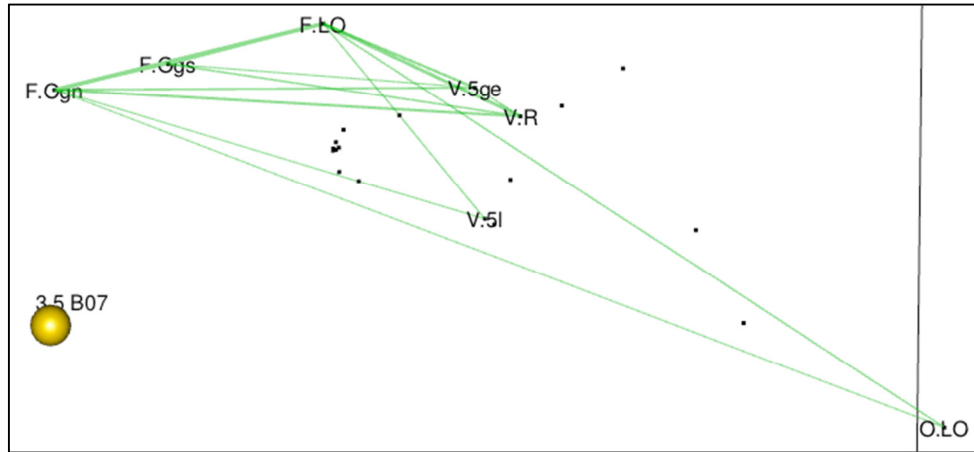


Figure 29. Student B07's primary behavior patterns in the U3L5 NP activity

Student B07

Student B07's primary behavior patterns (see Figure 29) were (1) primarily facing the online guide while the online guide was either speaking (F.OGs) or not speaking (F.OGn) while facing the learning objects (F.LO; in this case the buffet tables), and (2) verbalizing responses (V.R) that were greater than 5 words in length (V.5ge) while facing the learning objects as well as facing the online guide. Of much less frequency was orienting to learning objects (O.LO) and then stopping and facing the buffet tables as well as the online guide who was not speaking. Student B07's performance is primarily static in nature, with moderate verbal contributions that are not performed while facing his peers, but towards the guide and the learning objects.

Within the activity, student B07 can be seen to orient towards learning objects during transition, but then stands in front of the buffet so close that he is also no longer standing beside his peer but in front of his peer. His verbalization

patterns show that he is verbalizing at the learning objects and the online guide. It is important to note that the online guide often oriented stood behind the buffet and then oriented herself towards the students, so the students are automatically facing the online guide while they are facing the learning objects. Student B07 did not often, if at all, turn towards his peers, whether to speak or listen, during this activity.

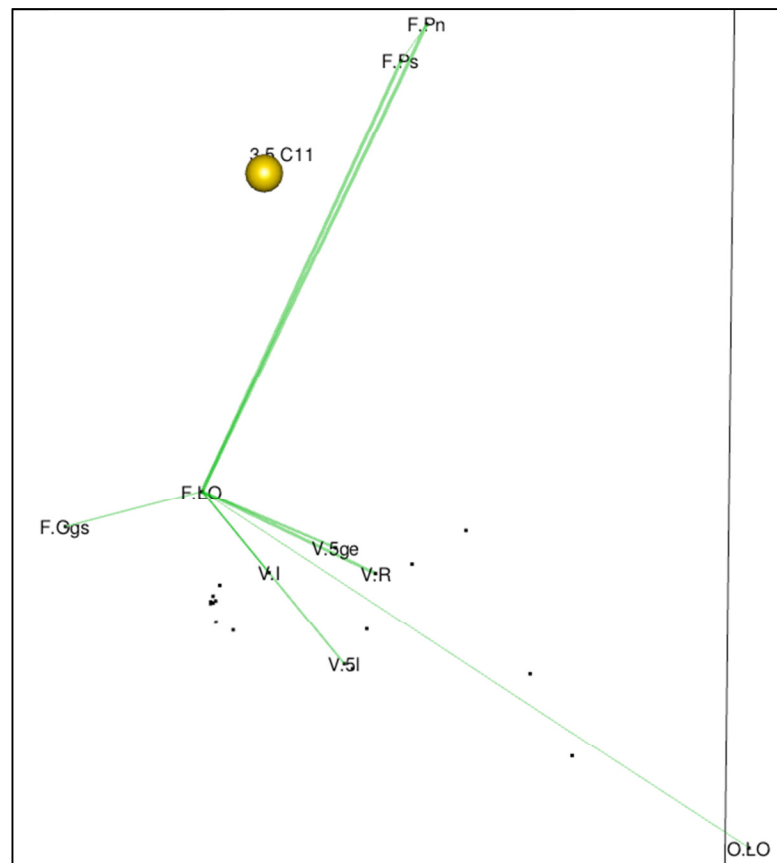


Figure 30. Student C11's primary behavior patterns in the U3L5 NP activity

Student C11.

Student C11's primary behavior patterns (see Figure 30) were (1) facing his peers, both while they are speaking (F.Ps) and not speaking (F.Pn) while facing the

learning objects (buffets), and (2) verbal responses (V.R) greater than or equal to five words in length (V.5ge) while facing learning objects. He was primarily static in this lesson, but he did not face the online guide much in the lesson in comparison to how much he faced his peers and the learning objects as well as how much he participated verbally.

In this activity with Cohort C, the online guide stood more off to the side, perhaps inviting some of the other students to go around to the other side of the buffet since she was not standing there. In doing so, this allowed for more opportunities for peer orientation for this student as well as others within his cohort. However, it could also be noted that it was “passive facing” in that the student may not have chosen to orient but someone oriented to him, and as a consequence he was facing his peer. However, student C11 could also be seen orienting and positioning himself appropriately so that he could see both his peers as well as the learning objects at the same time.

Summary of student performance within the U3L5 NP activity

Students within the U3L5 NP activity had moderate general movement and orientation, relatively moderate verbalization patterns, and oriented towards their peers. Students tended to orient and stand facing the restaurant buffets, often all on one side of the buffet with the online guide standing on the other side of the buffet. Some of them turned to orient towards their peers or stand in a way that allowed them to see the buffet as well as their peers. The cohort with the fewest number of students (Cohort B, N=2) had the least amount of peer orientation, perhaps due to

fewer opportunities to orient towards peers due to the small number of students in the environment.

The U3L5 NP activity has variations in peer orientation that are of interest. While cohort B had the least peer orientation, Cohort A had moderate-to-high peer orientation and cohort C had the highest. C11's instance of peer orientation is one example of peer orientation being a collaborative effort (meaning the other person needs to be facing you as well), rather than solely an individual behavior. In addition, it displays the complexity of how an online guide acting differently (moving off to the side in Cohort C rather than standing directly behind the buffets in front of the students as in Cohort A) might have been what invited students to gather around the buffet in cohort C and in turn allow for additional opportunities for peer orientation within that group that might not have been present for other cohorts.

Drilling down: Student performance within the U4L4 Activity

Description of activity

Unit 4 Lesson 4 naturalistic practice activity has students break into groups (of 2 or 3) and discuss emotional range in relation to three separate scenarios. They then need to discuss together as a group and come up with an answer, with one of members typing the answer on a "sticky note" in world, as seen in Figure 31.

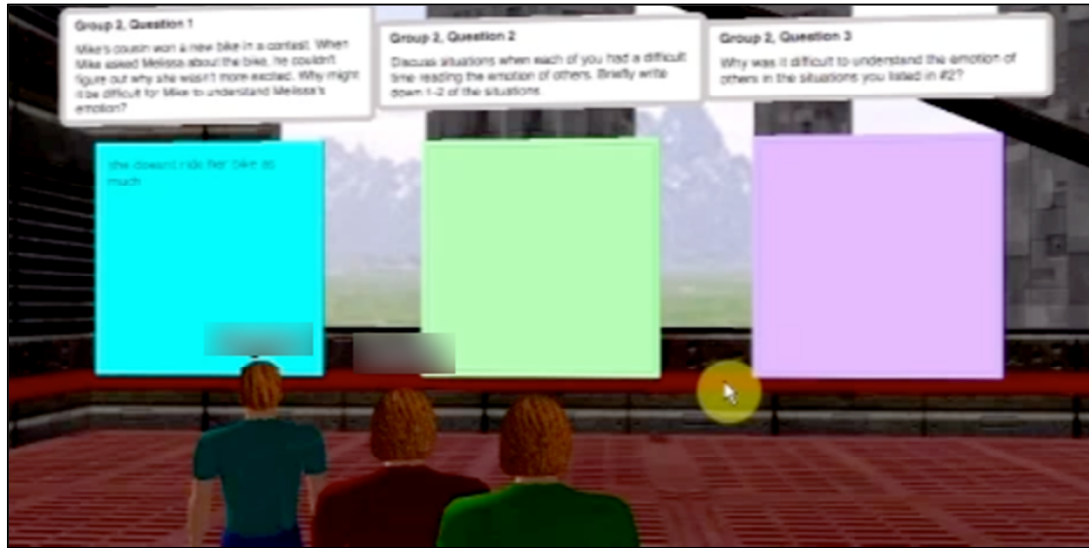


Figure 31. Students in cohort C discuss questions and answer them for the U4L4 NP activity

Overview of U4L4 NP student performance

Student scores were graphed as can be seen in Figure 32 and Table 14. Overall, performance in U4L4 is similar to that in U1L4: Student avatars were (1) more static (PC 1 mean score = -0.404), slightly less verbal (PC 2 mean score = -0.018), and not very peer-oriented (PC 3 mean score = -0.128). Figure 31 is a good example of this type of orientation and static-facing behavior pattern. Also again with verbal, as can be seen in Table 14, we see that there was one individual per cohort that stood out as the strong verbalizer in the group (A02, B06, and C08), and could reflect either verbal leadership or domination. In addition, there were no roles assigned for this activity to influence who might take a verbal leadership role in the activity. PC 3 shows a relative lack of peer orientation. Overall there is also a lack of variation among the students regarding peer orientation, as is seen in the scoring and standard deviation (SD = 0.051) and is reflected in the relatively equal height of the scores on the z-axis in Figure 32. Overall, the students are seen as standing still,

facing the online guide and/or learning object, moderately verbalizing and doing relatively little peer orientation.

It can also be seen (more easily from Figures 33 and 34) that there is a slight cohort grouping, in that Cohort A, seen in red, has slightly more verbal and has more dispersion across PC 1 general orientation and movement, whereas Cohorts B and C, seen in green and blue, are more static in nature with less strongly verbal scores. This may reflect that the OG chose to group the students differently, while maintaining curricular fidelity, and in doing so Cohort B and C did not break into groups and the Online Guide stayed with the group. In doing so, the students who stayed in one group tended to be exposed to a greater number of questions from the online guide than the small groups in Cohort A, as the online guide then needed to transition back and forth between the groups to facilitate discussion. We can see slight differences in both PC 1 and PC 2 behavior patterns as well as opportunities for behavior when the students experience breaking into small groups of 2 versus staying in one group of 3.

It is also interesting to note that one student stands out from the rest: Student A03 in regards to PC 1. It was noted in the memos that A03, parting from his peers on PC 1, was looking around the environment while his partner was filling out the sticky note with information. As such, he was sampled for the drill-down analysis.

Scatterplot of All Students Within U4L4 NP

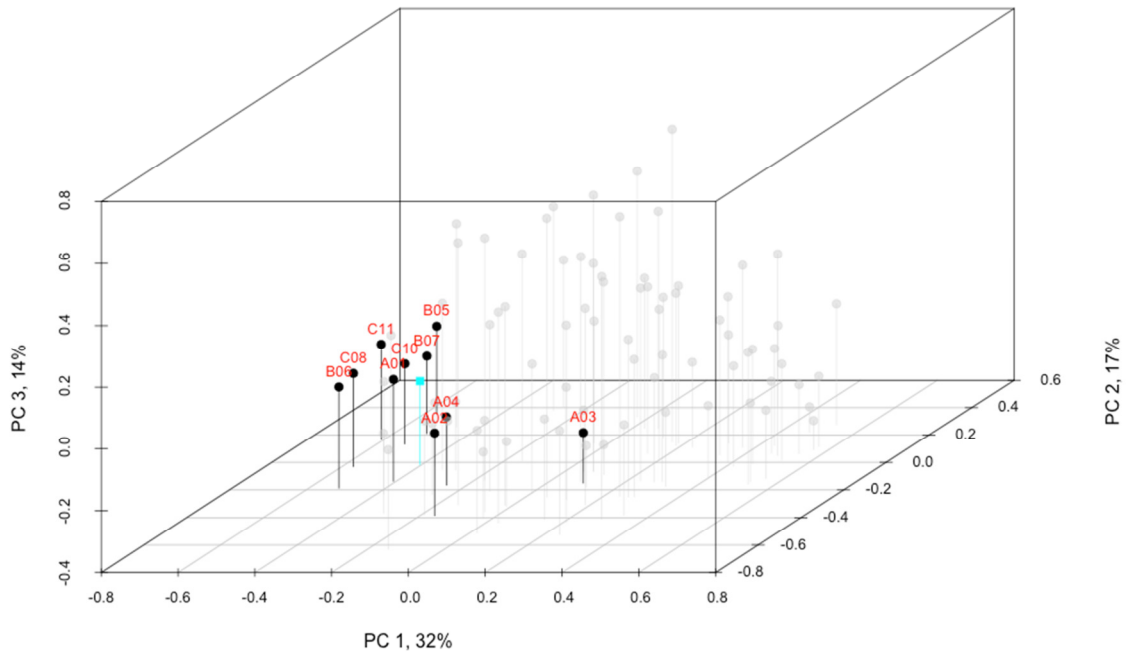


Figure 32. Scatterplot of all student performance within U4L4 NP; Scores are shown within the context of the remaining 3D points representing all activities (greyed out), mean is shown with a blue square

Table 14. Scores of Students in U4L4 NP

Student	PC1	PC2	PC3
A01	-0.407	-0.136	-0.069
A02	-0.162	-0.384	-0.133
A03	0.094	-0.150	-0.236
A04	-0.254	-0.164	-0.179
B05	-0.569	0.357	-0.116
B06	-0.521	-0.186	-0.072
B07	-0.514	0.212	-0.148
C08	-0.570	-0.031	-0.096
C10	-0.527	0.132	-0.138
C11	-0.607	0.166	-0.089
Mean	-0.404	-0.018	-0.128
Median	-0.518	-0.084	-0.125
SD	0.227	0.227	0.051
N=10			

Drilling down: looking at specific student behavior patterns

Students A03 and B06 were purposefully sampled for further examination of their behavior patterns within the U4L4 NP activity. Figures 33 and 34 show all student scores within the ENA visualizer for context (Figure 34 is a top-down view since student scores were too close together to visualize well in Figure 33).

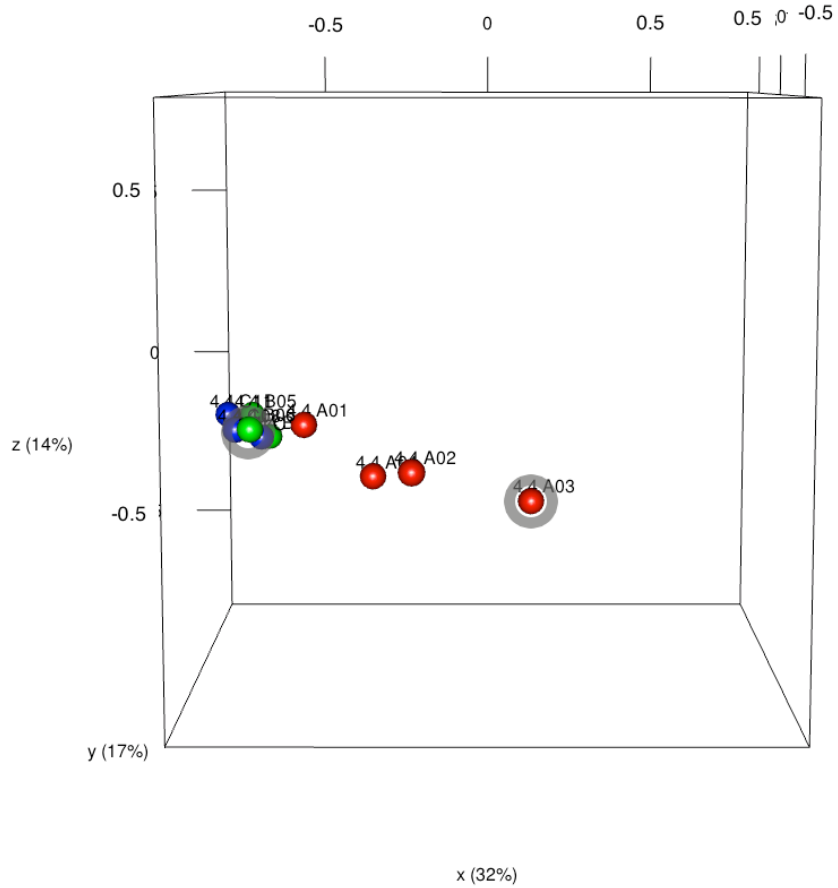


Figure 33. All students within the U4L4 NP activity as seen through the ENA visualizer; Red is cohort A, Green is Cohort B, Blue is Cohort C. Students A03 and B06 are circled grey

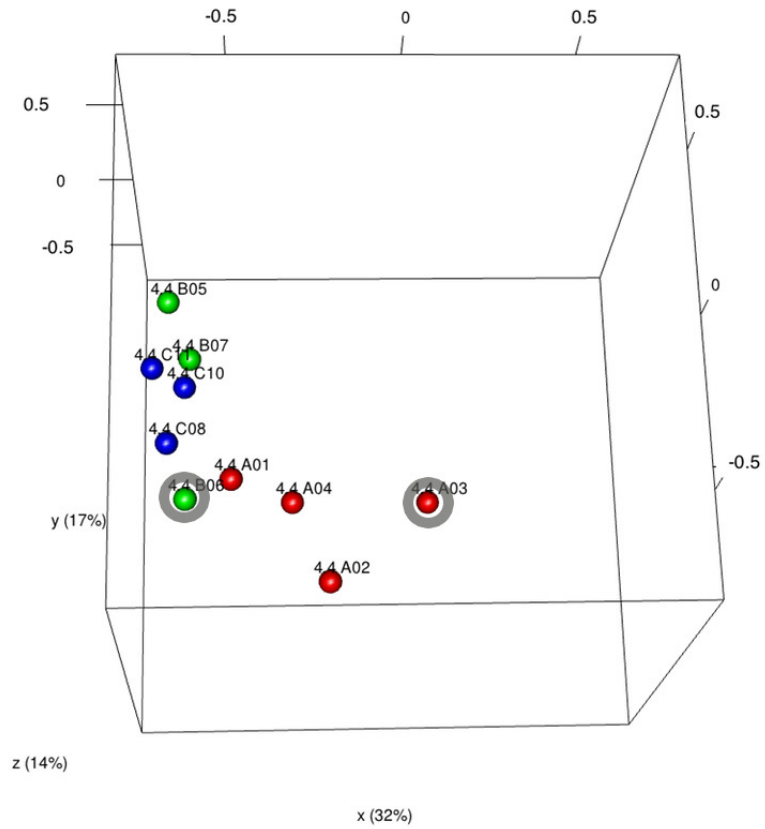


Figure 34. Top-down view of students within U4L4 NP activity as seen through ENA visualizer; Red is cohort A, Green is Cohort B, Blue is Cohort C. Students A03 and B06 are circled grey

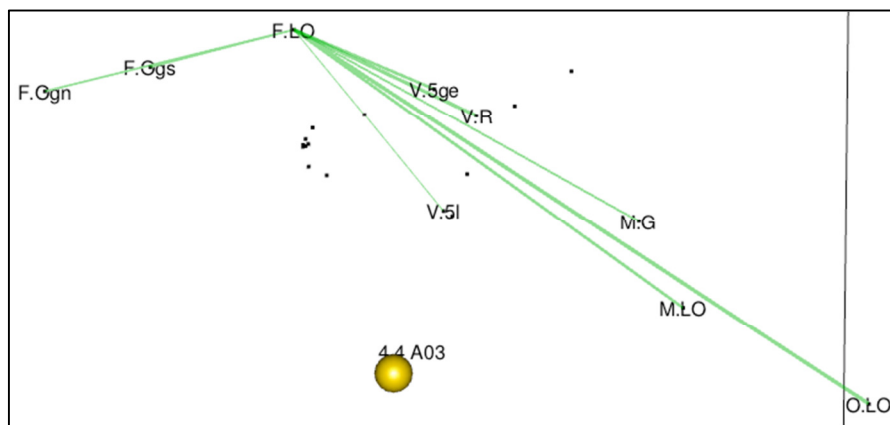


Figure 35. Student A03's primary behavior patterns in U4L4 NP activity

Student A03

Student A03's primary behavior patterns (see Figure 35) again are focused on (1) facing learning objects (F.LO) while orienting to learning objects (O.LO), (2) moving to and around the learning objects (M.LO), and (3) verbalizing with responses (V.R) greater than or equal to 5 words in length (V.5ge). These are all co-occurring with student A03 performing those behaviors while either facing the learning object (sticky notes) or orienting and moving to them and then stopping to face the sticky notes. To a lesser degree, student A03 did face the Online Guide while she was speaking and when she was not speaking, but it was to a lesser degree than the movement, orientation, and verbalization patterns, as demonstrated by the line thickness.

Because student A03 was not performing any writing on the sticky note, his partner A02 was doing most of the work. Student A03 was often seen moving and orienting to different learning objects, and then coming back to the sticky note to face that learning object. He was not positioning himself to orient towards his partner while speaking but could often be seen talking to his partner's back.

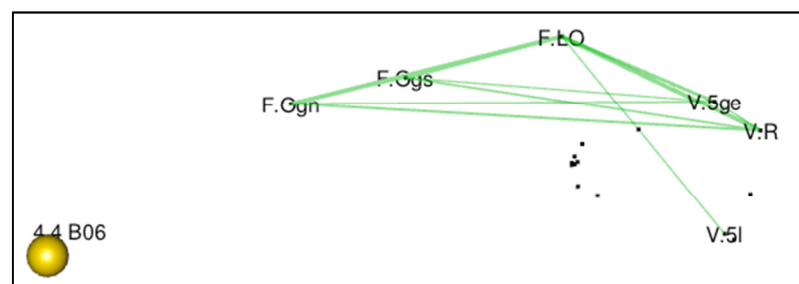


Figure 36. Student B06's primary behavior patterns in U4L4 NP activity

Student B06

Student B06's primary behavior patterns (see Figure 36) centered around (1) verbally responding (V.R) with greater than or equal to 5 words in length (V.5ge) while facing learning objects (F.LO) and to a lesser extent the online guide (F.OGn, F.OGs), as well as (2) facing the online guide while she was speaking and when she was not speaking (F.OGs, F.OGn), while also facing the sticky note learning objects. Verbalizing while standing still is a strong behavior pattern for B06 in this activity, though not the norm for him in other lessons. The norm for B06 has been strong verbalization patterns combined with strong movement and orientation patterns; however in this lesson he is standing still. However, B06's strong verbalization patterns overall, meaning the degree at which he was speaking, is still present in this lesson. This pattern corresponds to Table 14, which showed student B06 as continuing to be a dominant verbalizer in his cohort (PC 2 score = -0.186). He was not actively orienting towards his peers while speaking, and was primarily facing the learning object (sticky note) while talking to his peers and online guide. However, since his group did not break up into small groups, he primarily was facing the online guide and learning objects while she assisted in facilitating the conversation and practice.

Summary of student performance within the U4L4 NP activity

Students within the U4L4 NP activity overall had strong static avatar behavior (little active orientation and movement within the environment), varied in verbalizations and had relatively little peer-oriented behavior. Overall they stood

facing the sticky note learning objects while talking toward the sticky notes rather than turning and talking periodically towards each other. There were differences in general avatar behavior and verbalizations between Cohorts A (broke into 2 small groups) and Cohorts B and C (stayed as one large group of 3). They were reflected in the small groups being slightly more verbal with slightly more active orientation and movement, perhaps due to the fact that they had more opportunities to speak as well as the need to move to their small group locations. The groups that stayed as one large group of 3 tended to stay in one spot with the online guide standing in front of them the whole time, perhaps constraining the opportunities to speak and the lack of need to move around the environment to a small group location.

Aside from cohort and grouping differences, the U4L4 activity overall is relatively static and seems to constrain peer-oriented behavior patterns.

Drilling down: Student performance within the u4I5 Activity

Description of activity

In the unit 4 lesson 5 naturalistic practice activity (see Figure 37), students need to plan and practice a role play in which they show varying levels of emotions. Each small group (groups of 2 or 3) is to work together to decide on a role play to then be recorded by the in-world Helper.



Figure 37. Students in cohort A practice their role play in U4L5 NP activity

Overview of U4L5 student performance

Figure 38 and Table 15 provide a view of student scores for the U4L5 NP activity performance. Overall the major behavioral difference within this activity for the students was their peer-orientation. Aside from the usual behavior of student A01 being rather still and OG-oriented, students varied somewhat in the moderate range for general orientation and movement (PC 1 mean score = 0.038), meaning they were not overly static but they were not moving and orienting a lot of the time either. Students also varied along PC 2, demonstrating a range of verbalizing with some of the normal “high verbalizers” in their cohorts again emerging with one exception being A01. (A01’s partner, A04, ran off--both virtually and in the real world--and therefore the Online Guide helped A01 practice his role play.) Scores on principal component three were all skewed in the positive direction, indicating behavior patterns that lean towards facing their peers. Again in PC 2 one can see an individual who was more verbal than the rest; interestingly enough for Cohort A it

Scatterplot of All Students Within U4L5 NP

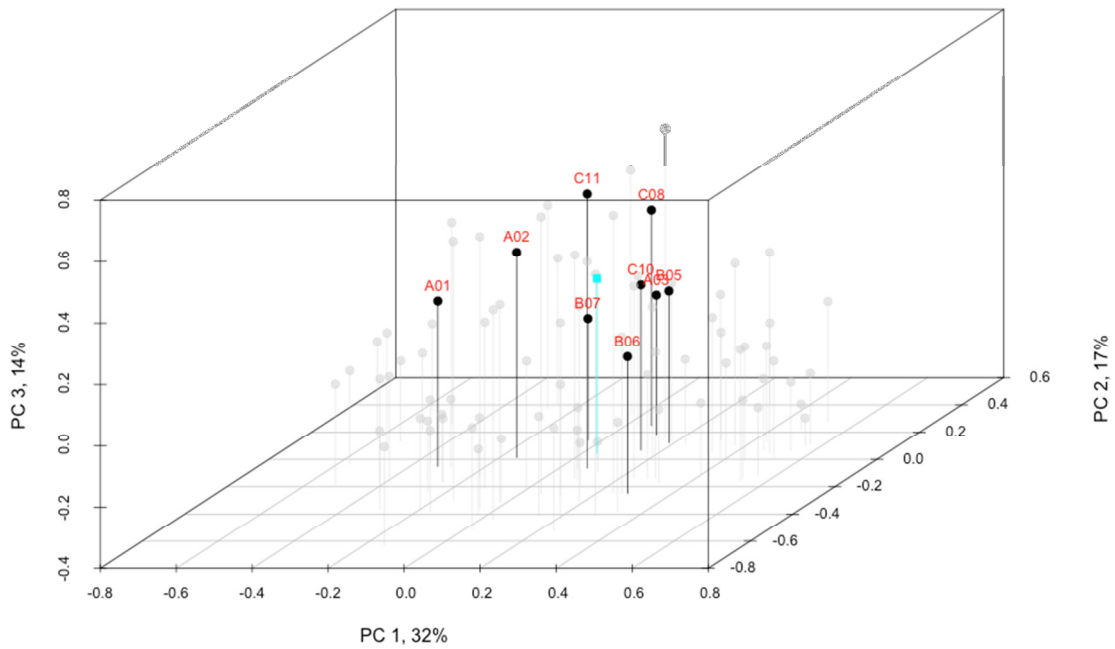


Figure 38. Scatterplot of student performance within the U4L5 NP activity; Scores are shown within the context of the remaining 3D points representing all activities (greyed out), mean is shown with a blue square

Table 15. Scores of Students in U4L5 NP

Student	PC1	PC2	PC3
A01	-0.326	-0.052	0.139
A02	-0.155	0.012	0.270
A03	0.117	0.183	0.054
B05	0.185	0.120	0.095
B06	0.280	-0.247	0.044
B07	-0.039	0.140	-0.003
C08	0.066	0.250	0.301
C10	0.141	0.066	0.139
C11	0.073	-0.064	0.493
Mean	0.038	0.045	0.170
Median	0.073	0.066	0.139
SD	0.185	0.151	0.157
N=9			

was student A01 who often was less verbal; however in this lesson the Online Guide paired with him during his role play activity since student A04 had behavior issues and was not present in the environment. Overall students were not overly active with their avatars but not overly static and were facing their peers more in this activity.

Drilling down: looking at specific student behavior patterns

Students A01 and C08 were purposefully sampled for this lesson to describe their behavior pattern co-occurrences within the U4L5 NP activity. Figure 39 shows the students' scores within the ENA visualizer for context.

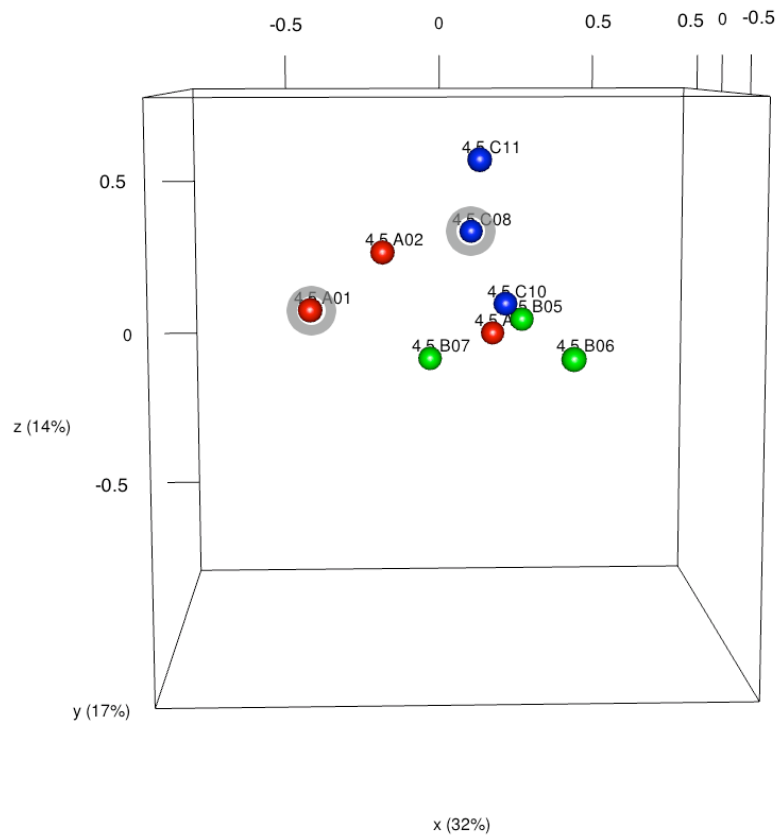


Figure 39. Scatterplot of student scores within the ENA visualizer for U4L5 NP activity; Red is Cohort A, Green is Cohort B, Blue is Cohort C, Students A01 and C08 are circled grey

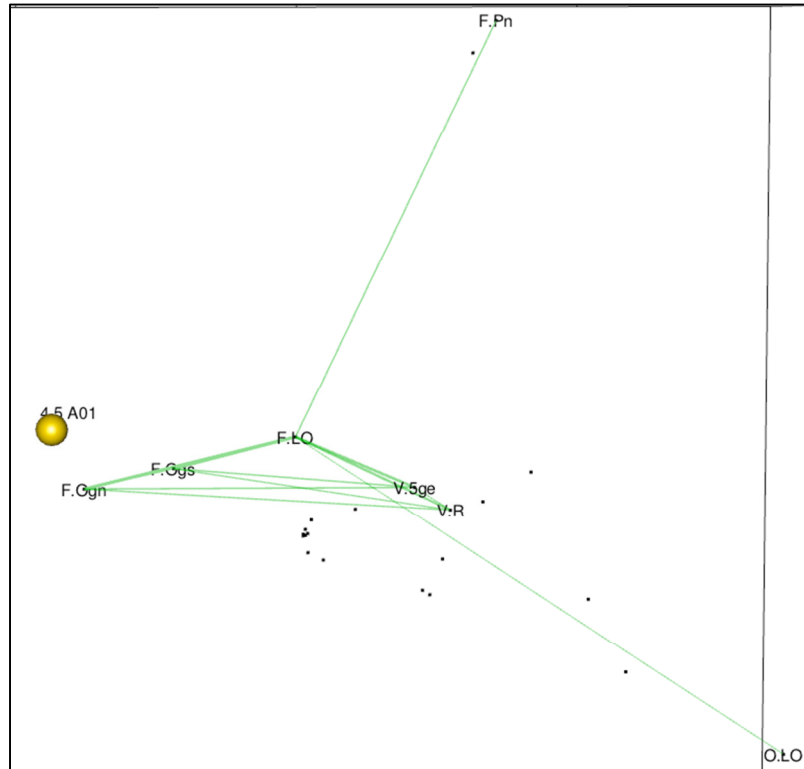


Figure 40. Student A01's primary behavior patterns within the U4L5 NP activity

Student A01

Student A01's primary behavior patterns (see Figure 40) were (1) facing the online guide while she was speaking and not speaking (F.OGs, F.OGn) while facing a learning object, and (2) verbally responding (V.R) with greater than or equal to 5 words in length (V.5ge) while facing a learning object, and (3) to a lesser degree verbalizing while also facing the online guide while she was speaking as well as when she was not speaking, and finally (4) facing his non-speaking peers (F.Pn) while also facing the learning object. As stated earlier, this corresponds to the fact that Student A01 partnered with the online guide for his role play practice, so most of his verbalizations and responses during this activity were directed to and with

the online guide. However, overall student A01 was still quite static in his nonverbal behavior but did verbalize much more in this activity than in other activities.

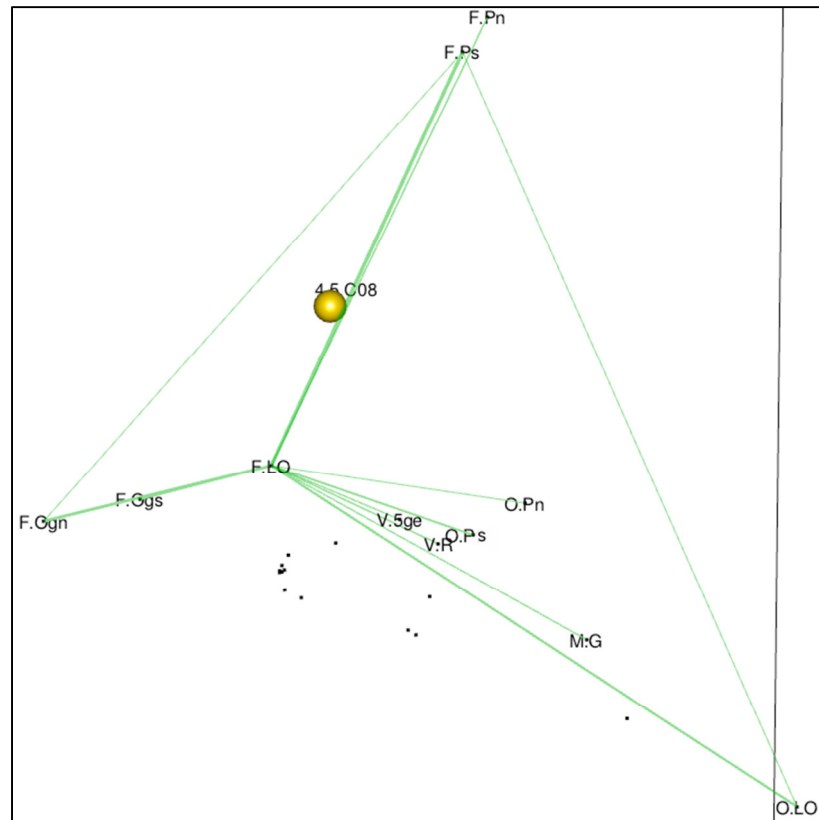


Figure 41. Student C08's primary behavior patterns within the U4L5 NP activity

Student C08

Student C08's primary behavior patterns (see Figure 41) were (1) facing his peers who were speaking (F.Ps) while also facing learning objects (F.LO), and to a lesser degree facing his peers while they were not speaking (F.Pn) while still focused on facing learning objects, (2) Facing the online guide while she was speaking (F.OGs) and while she was not speaking (F.OGn) while also facing the

learning objects, and (3) Orienting to learning objects (O.LO) and then stopping to face those learning objects. To a lesser degree he also demonstrated movement to and around learning objects (M.LO), verbally responded (V.R) and had utterances greater than or equal to 5 words in length (V.5ge), and oriented to his peers, both while they were speaking (O.Ps) and not speaking (O.Pn). The prevalence and diversity of patterns here is rich for this student, showing that while most of his performance in this activity was nonverbal in nature (PC 2 score was positive, 0.250 indicating a lack of strong verbal behavior), he was an active participant in other ways. One way in which C08 was highly active was his pattern of facing his peers while they were speaking (F.Ps).

While C11 and C10 were actively coming up with a story for their role play, C08 either could have felt left out or was simply quieter that day, or was less in tune with how to contribute to the brainstorming. However, C08 could be seen orienting and facing C11 and C10 during the brainstorming and participating as an active listener with his nonverbal behavior, as can be seen in the diagram.

Summary of student performance within the U4L5 NP activity

Students within the U4L5 NP activity had moderate movement and verbalizations, but relatively high peer-orientation. The peer orientation was highest in Cohorts C and A. Students can be seen in the environment gathering in a small group to discuss their role-play plan and then acting out that plan. The U4L5 NP activity, rather than having students directing their focus on learning objects in the environment and directing their discussion about those objects, had students

focus on each other and their interactions. While this did not seem to affect orientation and verbalizations to a great degree, this might have contributed to the high degree of peer orientation.

Drilling down: Student performance within the U4L6 Activity

Description of activity

In the U4L6 role play planning activity, students planned emotional range role plays using mediaboards. This differs from U4L5 in that in U4L6, they are to discuss and come up with two ideas for their scenarios and write their plans on the mediaboard, wherein in U4L5 they were given the scenarios and they simply discussed their role plays without any writing tools. In U4L6 they are to individually write and plan their role plays and then together as a small group (in groups of 2 or 3) and act out and record their role plays in the virtual world (see Figure 42).

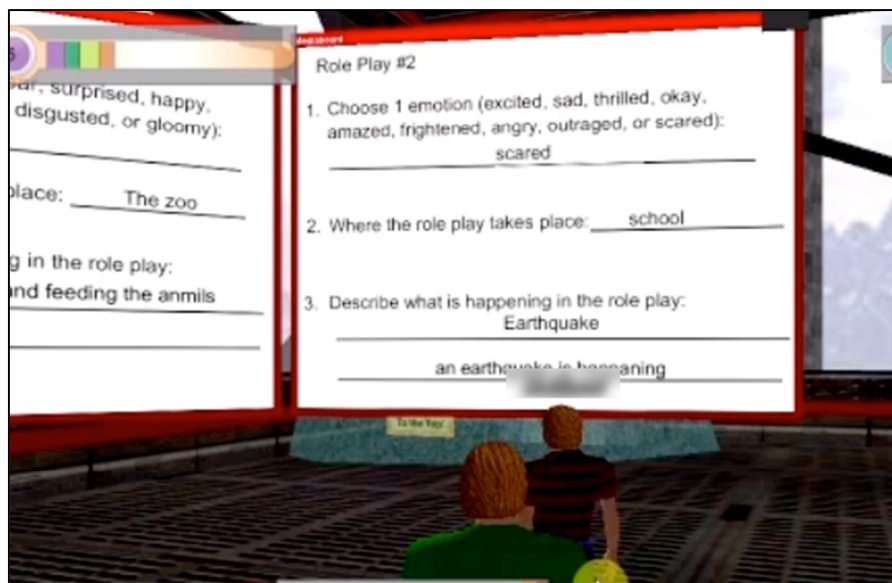


Figure 42. A small group in cohort C plans out two role plays in U4L6 NP activity

Overall summary of U4L6 NP activity student behaviors

Student scores are graphed in Figure 43 and listed in Table 16. In the U4L6 activity, students vary in their level of orientation and movement, though they are slightly skewed to the positive, or more active side of PC 1 (mean score = 0.127). Students who do fall slightly towards the negative extreme of PC 1 (A02, C08, C11) are only slightly negative, representing only slightly static nonverbal behavior. For PC 2, students are overwhelmingly verbal, with all students in the negative range and a mean score of -0.309. However for PC 3, many of the students were much more toward the positive, peer-facing end of PC 3 (mean score = 0.197) aside from all students within cohort B and C09.

Most of the variation in the student behavior for this activity seems to center around PC 3 and how and to what extent they oriented and faced their peers in the activity, given that they also needed to write on a mediaboard for their planning.

Scatterplot of All Students Within U4L6 NP

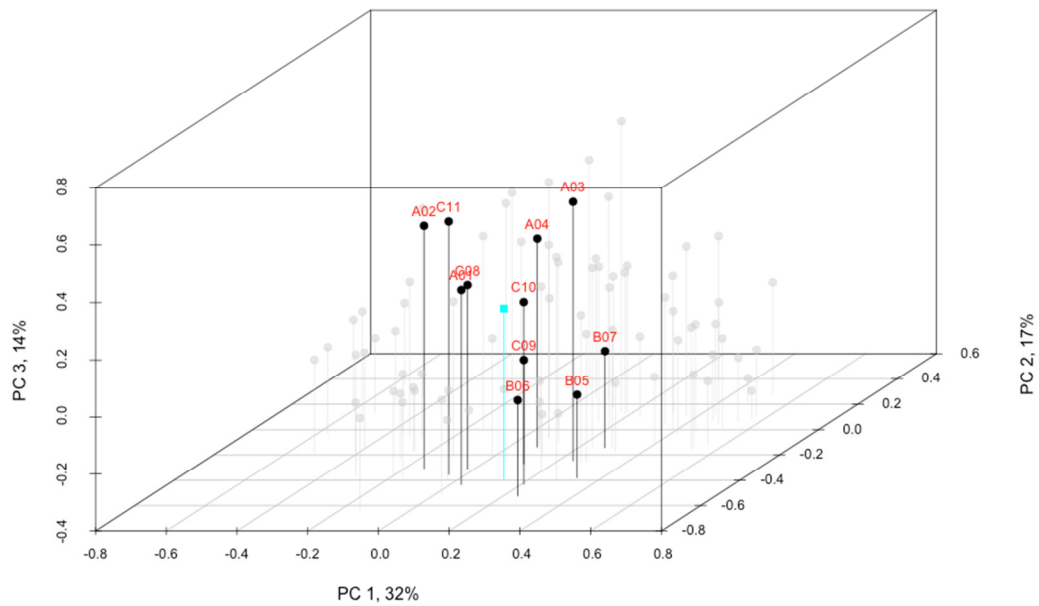


Figure 43. Scatterplot of all students within the U4L6 NP activity; Scores are shown within the context of the remaining 3D points representing all activities (greyed out), mean is shown with a blue square

Table 16. Scores of Students in U4L6 NP

Student	PC1	PC2	PC3
A01	0.032	-0.435	0.281
A02	-0.145	-0.305	0.447
A03	0.241	-0.244	0.504
A04	0.080	-0.136	0.327
B05	0.329	-0.381	-0.108
B06	0.240	-0.523	-0.064
B07	0.274	-0.141	-0.061
C08	-0.021	-0.308	0.242
C09	0.115	-0.268	-0.036
C10	0.206	-0.432	0.238
C11	-0.048	-0.355	0.484
Mean	0.127	-0.309	0.197
Median	0.161	-0.307	0.240
SD	0.152	0.121	0.234

N=11

Drilling down: looking at specific student behavior patterns

Student A02 and B05 were purposefully sampled for describing their behavior patterns within this U4L6 activity. Figure 44 illustrates student scores within the ENA visualizer for context.

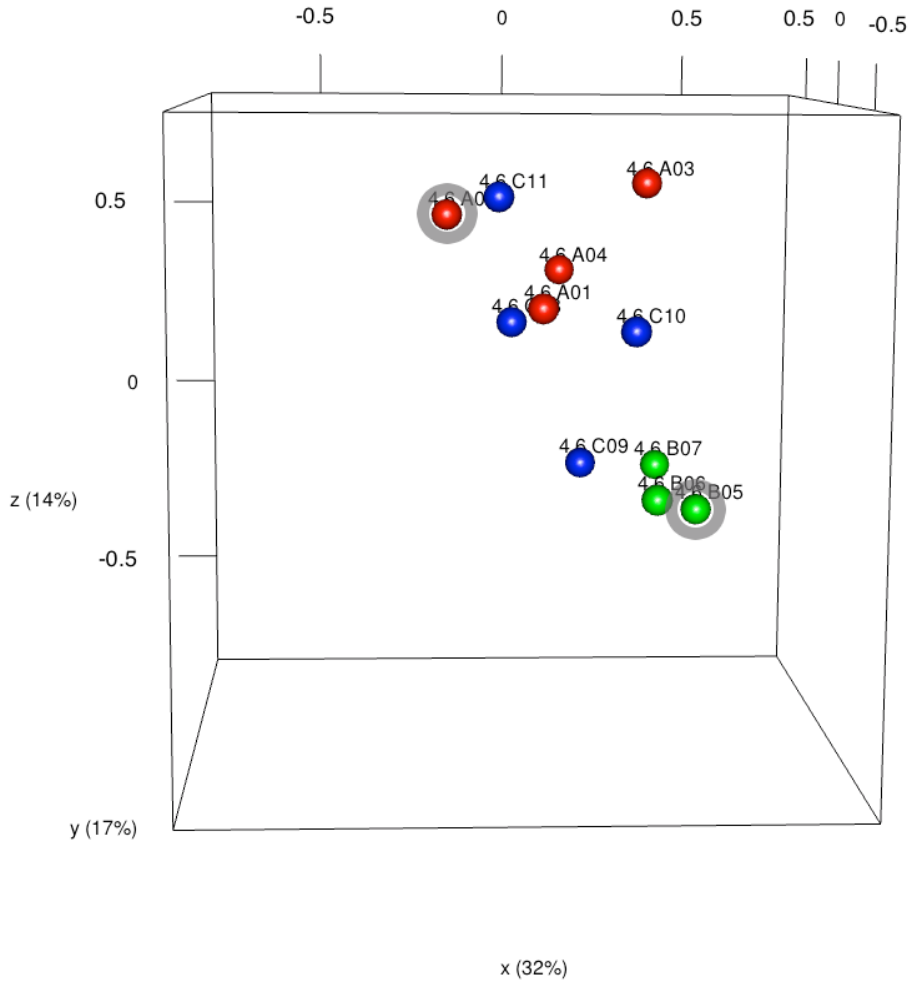


Figure 44. All students within the U4L6 NP activity as seen through the ENA visualizer; Red is Cohort A, Green is cohort B, Blue is Cohort C, A02 and B05 are circled grey

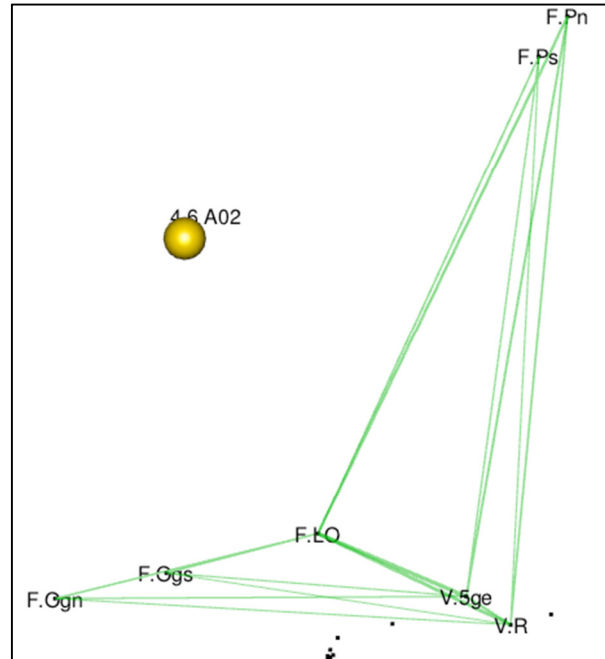


Figure 45. Student A02's primary behavior patterns within the U4L6 NP activity

Student A02

Student A02's primary behavior patterns (see Figure 45) within the U4L6 NP activity were (1) Verbally responding (V.R) with greater than or equal to 5 words (V.5ge) while facing learning objects (mediaboards) while also (2) facing peers while they were speaking (F.Ps) and facing peers while they were not speaking (F.Pn). To a lesser degree he also verbally responded while facing the online guide while she was speaking (F.OGs) and when she was not speaking (F.OGn). Student A02 was highly peer-oriented and verbal. In many activities up to this one, he is often the "verbal dominator" of the group and this again shows that while he is not actively moving his avatar in nonverbal manners, he is mostly standing still but being highly verbal and peer-oriented. Student A02 is facing the mediaboards, and

his partner in the striped shirt has oriented himself and moved himself in front of the mediaboards to speak to A02. Note that again, peer orientation is a collaborative effort, and A02's high peer orientation score in this lesson could be in large part due to his partner orienting, moving, and standing in front of A02, which in turn then facilitates A02's high peer orientation score.

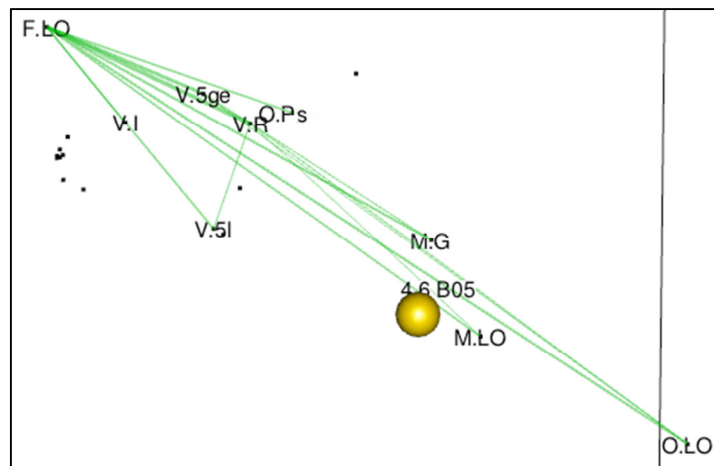


Figure 46. Student B05's primary behavior patterns within the U4L6 NP activity

Student B05

Student B05's primary behavior patterns (see Figure 46) within the U4L6 NP activity were highly active in nature. There is not a strong pattern of behavior, but a mix of (1) several active nonverbal actions such as movement to and around learning objects (M.LO), orienting to the learning objects (O.LO), movement to and with his group (M.G) and orienting to his peers while they are speaking (O.Ps), and (2) verbal initiations (V.I) and responses (V.R) of varying length (V.5ge, V.5l). These are also co-occurring with facing learning objects, but also there are some lesser-

degree co-occurrences with the other behaviors, meaning he is orienting and verbalizing, and moving and verbalizing.

Student B06, often the verbal leader of the group, often helped to direct the direction of the role play, both in planning and in execution. In doing so, he would often lead and facilitate discussions as well as play a major role in the play in which there were both active nonverbal and verbal components.

Summary of student performance with in the U4L6 NP activity

Students within the U4L6 NP activity performed a similar activity in U4L5 but in L6 had to collaboratively come up with their own scenarios by using mediaboards as organizers and then role play those scenarios together. This resulted in similar overall peer orientation, slightly greater general avatar orientation and movement, but much stronger verbalization patterns among all the students. The pattern of increased verbalization seems to rise when tools are inserted into the environment in which students need to write (see U1L4, U4L4) and collaborate. However unlike U1L4 and U4L4, the overall activity seems to be greater since the lesson also included the role play scenario in which the students needed to act out their situation in order to display emotional range.

Drilling down: Student performance within the U5L5 Activity

Description of activity

In the U5L5 NP activity, students were to plan the steps of their quest that they would then pursue in the next lesson. They were given a scenario with hints, and together they had to discuss, compromise, and come to a solution regarding their steps, and then place those steps, in order, onto the mediaboard (see Figure 47 below).



Figure 47. Students in cohort A are planning the sequence of their quest activity in the U5L5 NP activity

Overall summary of U5L5 NP activity student behaviors

Student U5L5 NP scores are graphed in Figure 48 and listed in Table 17. In the U5L5 activity, students vary considerably across their nonverbal and verbal

behaviors, but overall skewed negative on PC 3. For general nonverbal behavior, students vary from being extremely OG-oriented and static (A01; PC 1 score -0.464) to highly nonverbally active (A03; PC 1 score 0.458). While the mean score of PC 1 is neutral (-0.001), the standard deviation (SD = 0.271) also reflects this variance in student orientation and movement in this activity. For PC 2, variations range from highly verbal (B05; PC 2 score = -0.630) to less verbal (A01; PC 2 score = 0.261). For PC 3, while variations range from little peer orientation (C09; PC 3 score = -0.303) to relatively high peer orientation (A01; PC 3 score = 0.256), overall there is relatively little peer orientation (PC 3 mean score -0.110) though the level to which they are peer oriented varies (SD = 0.163).

In this lesson, student B05 led his cohort in helping to decide what the plan of action for finding the king's items would be. However, in A01's cohort, A01 took a bit of a "back seat" role and watched everything unfold with few contributions.

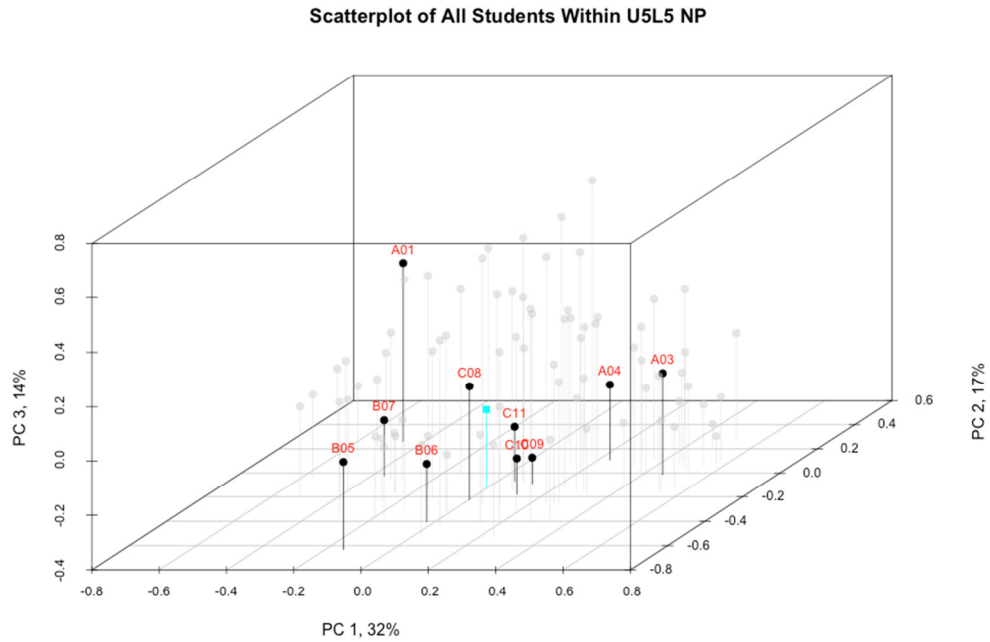


Figure 48. Scatterplot of all students within the U5L5 NP activity; Scores are shown within the context of the remaining 3D points representing all activities (greyed out), mean is shown with a blue square

Table 17. Scores of Students in U5L5 NP

Student	PC1	PC2	PC3
A01	-0.464	0.261	0.256
A03	0.458	-0.011	-0.026
A04	0.233	0.109	-0.122
B05	-0.146	-0.630	-0.079
B06	-0.024	-0.405	-0.186
B07	-0.362	-0.024	-0.194
C08	0.002	-0.224	0.019
C09	0.113	-0.088	-0.303
C10	0.117	-0.179	-0.266
C11	0.049	-0.068	-0.199
Mean	-0.002	-0.126	-0.110
Median	0.026	-0.078	-0.154
SD	0.271	0.253	0.163
N=10			

Drilling down: looking at specific student behavior patterns

Students A01 and B05 were purposefully sampled to look at individual student behavior patterns prevalent within their activity performances. Figure 49 is given for context.

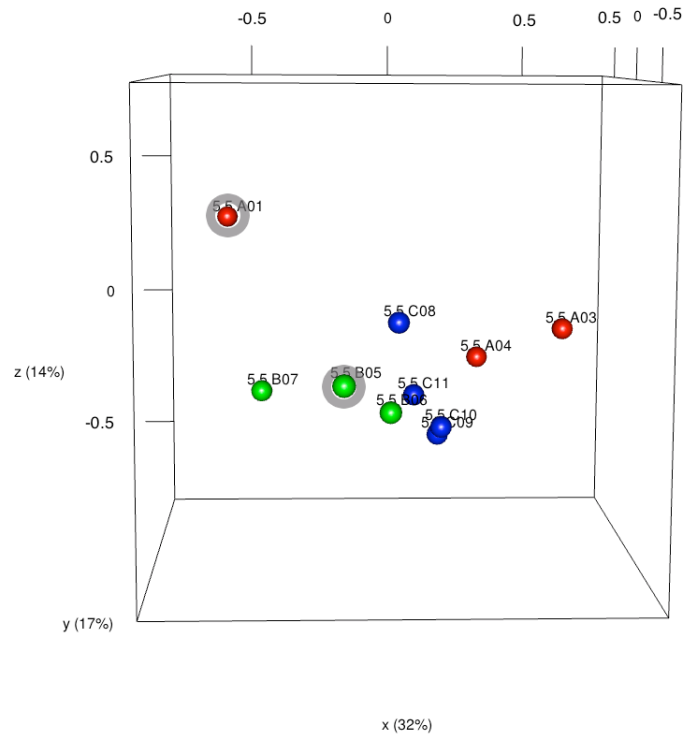


Figure 49. All students within the U5L5 NP activity as seen through the ENA visualizer; Red is cohort A, Green is cohort B, and Blue is cohort C; A01 and B05 are grey circles

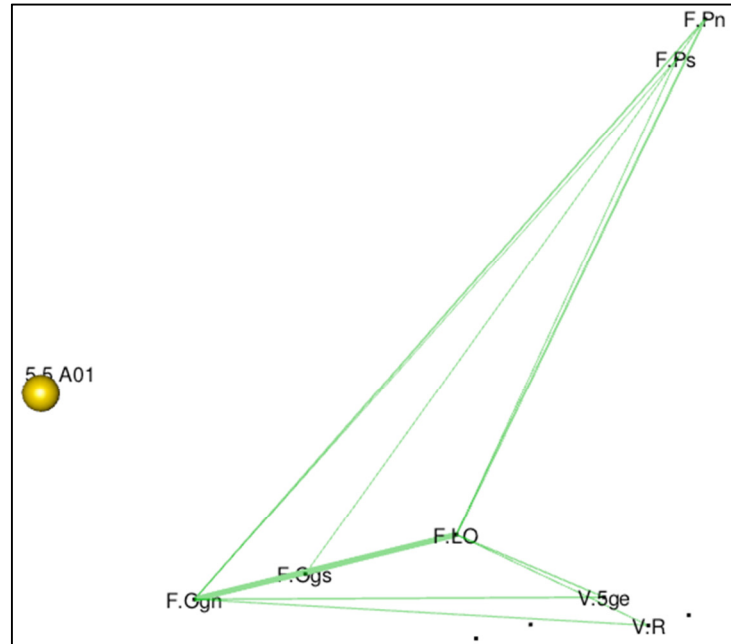


Figure 50. Student A01's primary behavior patterns within the U5L5 NP activity

Student A01

Student A01's primary behavior patterns (see Figure 50) within the U5L5 NP activity were (1) facing the online guide while she was speaking (F.OGs) and not speaking (F.OGn) while also facing the learning object and (2) facing peers who were both speaking (F.Ps) and not speaking (F.Pn) while also facing the online guide and learning objects. To a lesser degree, A01 contributed verbal responses that were greater than five words while facing the learning object as well as the online guide. Overall, student A01's behavioral patterns show that he was highly static in nature, but he oriented himself in such a way so that he could see the mediaboard map learning object as well as his peers and the online guide. He also did contribute

through verbal responses, but they were predominantly facing the online guide rather than his peers.

Throughout this activity, student A01 can be seen facing the mediaboard map, with some of his peers orienting to face others. In this sense, some of his “facing peers” codes were passive in nature, and the peers and environment allowed him to face his peers while they were speaking and not speaking, but he was not fully active in orienting towards peers that were speaking.

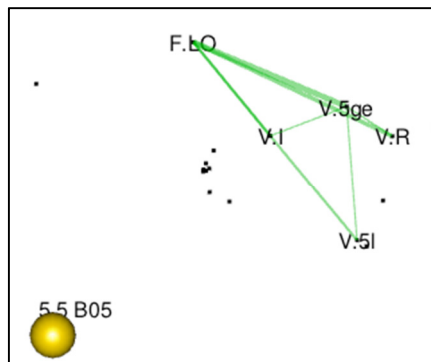


Figure 51. Student B05's primary behavior patterns in U5L5 NP activity

Student B05

Student B05's primary behavior patterns (see Figure 51) were highly verbal in nature, all revolving around what types of verbalizations and facing the learning object (the mediaboard quest map). His verbalization patterns were (1) verbally responding (V.R) with greater than or equal to 5 words (V.5ge) while facing the learning object, and (2) verbal initiations (V.I) that varied in length (V.5ge, V.5l) while facing the learning object. He primarily faced only the learning object and did

not face his peers while he was speaking, whether it was to the online guide or his peers.

Student B05 led his cohort with the map as a tool, and in doing so responded to his team members and asked questions regarding how they were to plan their quest for finding the King's items. He often asked students what they thought so he could assist in placing the numbers in the right sequence, and this role was a bit unusual for student B05, as often B06 is the student that takes the verbal leadership role. However, B06 also did have a high verbal score (PC 2 score = -0.405), so it shows that although B06 was also talking a lot, B05 was not orienting or facing his peer while they were talking about the map.

Summary of student performance within the U5L5 NP activity

Students within the U5L5 NP activity varied greatly across all three principal components. Depending on whichever self-appointed role they took on in leading the group (like B05 did in leading his group in the map placements), how and where they chose to stand to see others in the environment, and to what extent they chose to move around in the environment, the behaviors emerged differently for each individual within the environment, moreso than other activities as can be seen in the standard deviations across all three principal components. Self-appointing themselves to use the mediaboard, a tool which locks an avatar in place, would affect their ability to move, thus B05's score is very static and negative in nature on PC 1 and lacking peer orientation on PC 3 even though he was highly verbal. This could also contribute to the variation among the behavior patterns in this lesson.

Drilling down: Student performance within the U5L6 Activity

Description of activity

In the U5L6 NP activity, students are to use their plan from U5L5 NP activity and execute that plan. They are to find the lost items around the entire lesson environment and return them to the king. They need to discuss, collaborate, share ideas, and compromise in order to come to multiple solutions that will find all the items as well as lead them to the king (see Figure 52).



Figure 52. Students in cohort B discuss which amulet most likely belongs to the king in the U5L6 quest NP activity

Overall summary of U5L6 NP activity student behaviors

As can be seen in Figure 53 and Table 18, the variance among students for this lesson is limited, mainly for general nonverbal orientation and movement on PC 1 and peer orientation on PC 3. This low variance is shown in the low standard

deviations on PC 1 (SD = 0.089) and PC 3 (SD = 0.081). As can be seen by the 3D points being almost all to the positive extreme on PC 1 (mean score = 0.462), all students are highly mobile and active with their avatars. This represents a lot of the orientation, movement, and transitioning they are doing throughout the world in performing the quest activity. On PC 2, students vary their verbal a bit more, though none are highly verbal (PC 2 mean score = 0.068), and the only student that “stands out” is A04, who is relatively nonverbal compared to the rest of the students. However, for PC 3, students are all skewing towards the more active and less peer-oriented end of PC 3 (mean score = 0.081) with little variation among the scores (SD = 0.081). Overall, students are highly active, moderately verbal, and are not orienting towards their peers and are orienting more towards the learning objects in the environment as they move throughout the environment to find the quest items for the king.

Scatterplot of All Students Within U5L6 NP

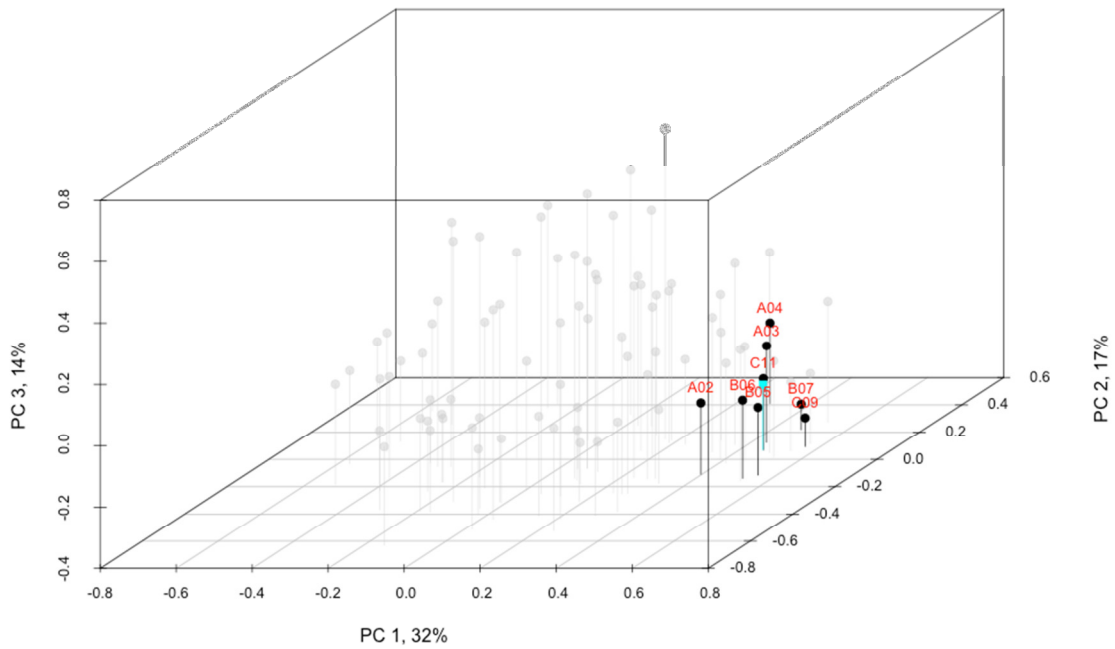


Figure 53. Scatterplot of students within the U5L6 NP activity; Scores are shown within the context of the remaining 3D points representing all activities (greyed out), mean is shown with a blue square

Table 18. Scores of Students in U5L6 NP

Student	PC1	PC2	PC3
A02	0.397	-0.109	-0.167
A03	0.441	0.122	-0.084
A04	0.289	0.411	-0.137
B05	0.550	-0.115	-0.178
B06	0.523	-0.138	-0.144
B07	0.477	0.220	-0.317
C09	0.559	0.092	-0.305
C11	0.463	0.066	-0.166
Mean	0.462	0.068	-0.187
Median	0.470	0.079	-0.166
SD	0.089	0.189	0.081

N=8; students in environment=10, 2 removed from data set due to screen recording loss

Drilling down: looking at specific student behavior patterns

Three students (Students A04, B06, and C09) were purposefully sampled in the U5L6 set of students to further describe behavior patterns present. Figures 54 and 55 are there for context; a top-down view is given due to scores being visually close together.

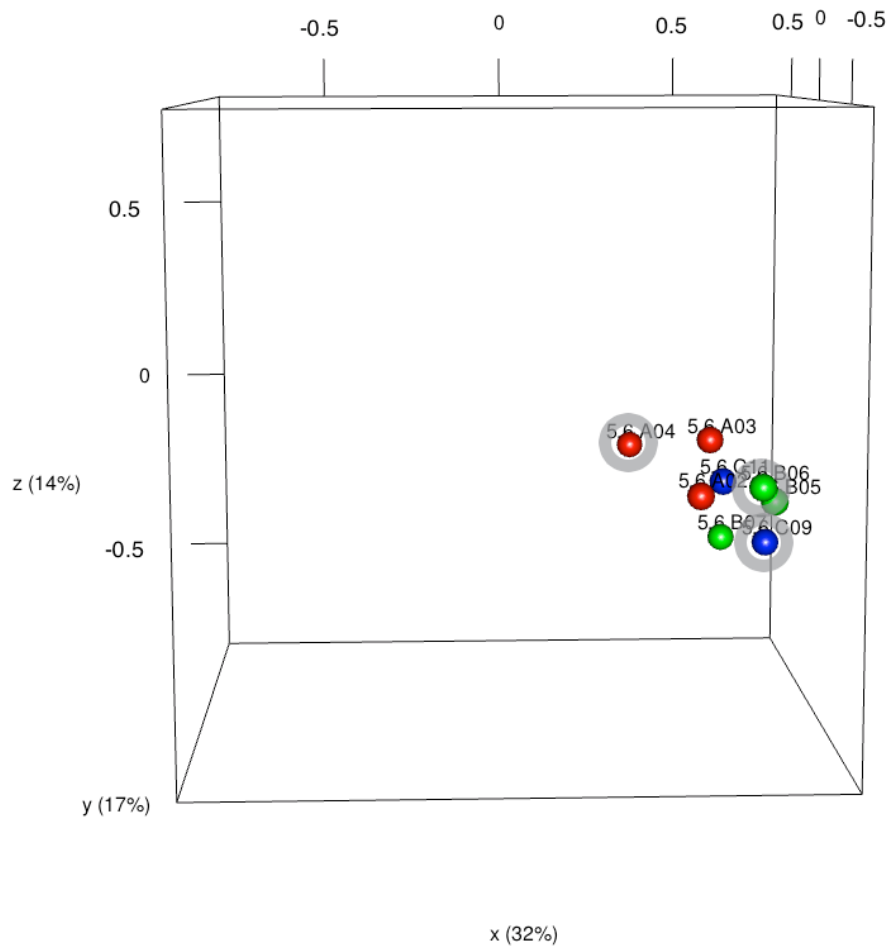


Figure 54. All students within the U5L6 NP activity as seen through the ENA visualizer (front view); Red is cohort A, Green is cohort B, Blue is cohort C, A04, B06 and C09 are circled grey

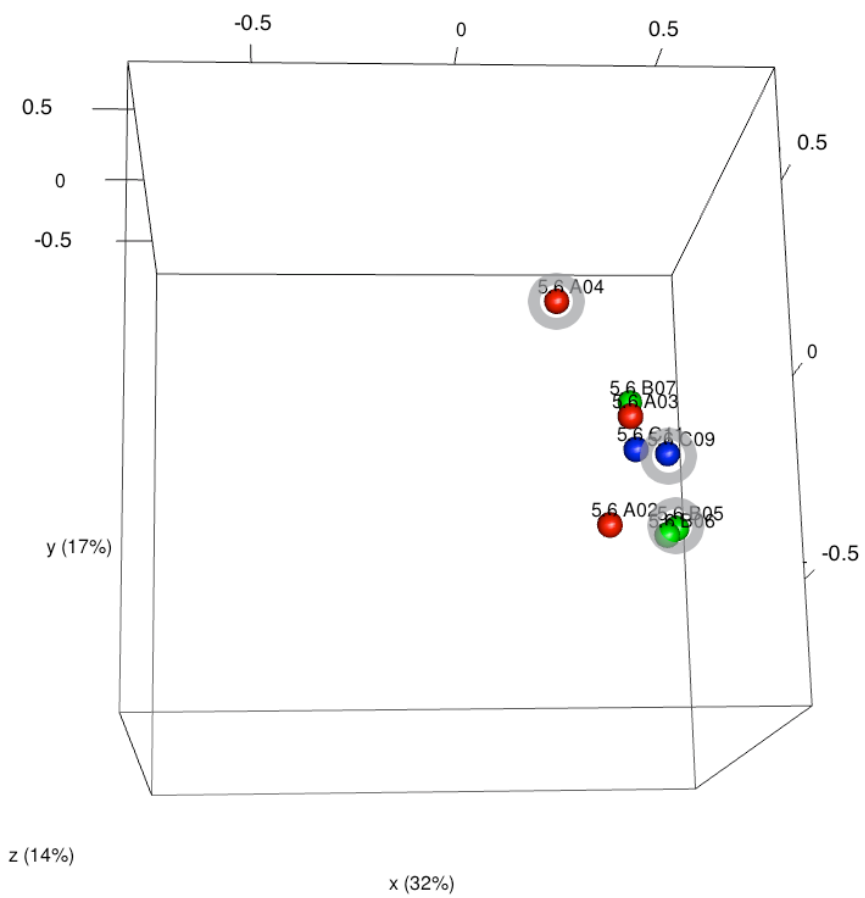


Figure 55. Top-down view, U5L6 NP activity through the ENA visualizer; Red is cohort A, Green is cohort B, Blue is cohort C, A04, B06 and C09 are circled grey

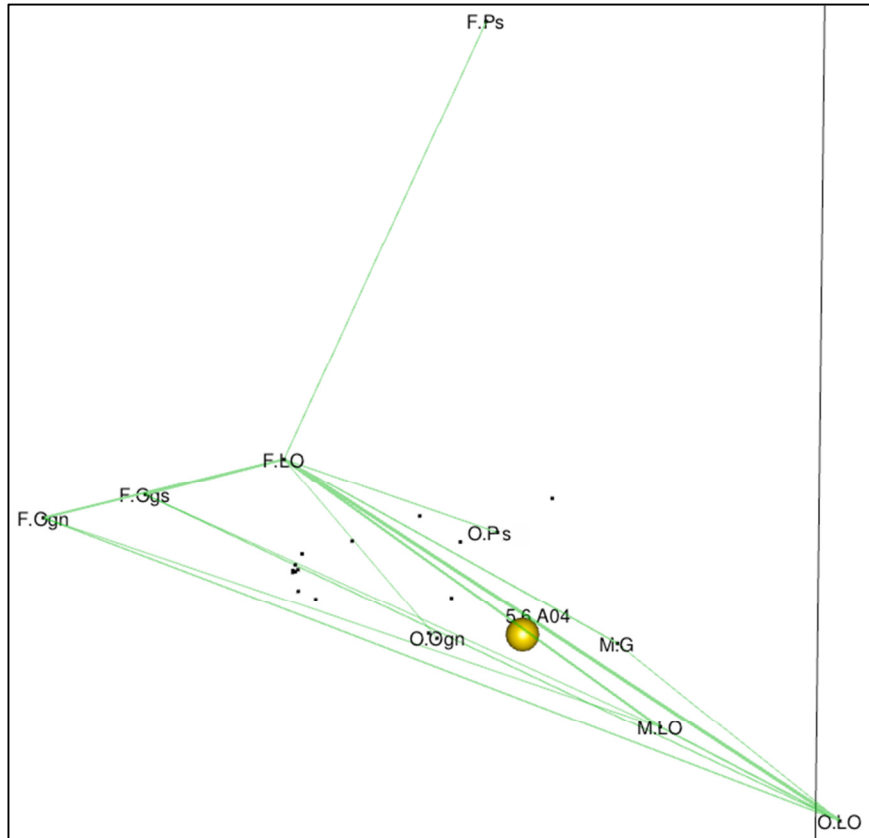


Figure 56. Student A04's primary behavior patterns in the U5L6 NP activity

Student A04

Student A04's primary behavior patterns, seen in Figure 56, in this lesson are both static and active in nature. Just as the table and graph showed he had the lowest verbal score, his primary patterns do not even register verbal behavior as one of his primary behaviors within this activity. Student A04's primary co-occurring behavior patterns are (1) Facing the online guide while she is speaking (F.OGs) and not speaking (F.OGn) while facing the learning object(s), and (2) Orienting to learning objects (O.LO), moving to and around learning objects (M.LO), and moving to and with the group (M.G). To a lesser degree he is also orienting

towards his peers who are speaking (O.Ps) and the online guide (O.Gn) as well as facing his peers who are speaking (F.Ps). Unlike some others in this lesson, he is also facing his peers while they are speaking, demonstrating that he is able to orient and look at his peers during a discussion. However, this does not take place often, even though he and A03 are the highest peer orienteers in this lesson.

A04 can often be seen in this lesson following others, and performing a simple verbal agreement at the end of choosing the learning object, thus making his verbalizations not a primary pattern for his behavior. He also would often try to say something, often a half a word in order to interject, but did not know how to do so appropriately in order to be heard by the group.

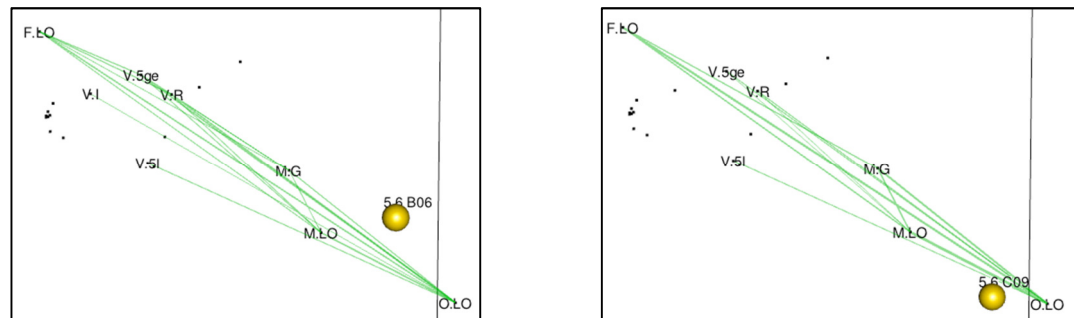


Figure 57. Student B06's and C09's behavior patterns in the U5L6 NP activity

Student B06 and C09

Both student B06 and C09 (see Figure 57) were chosen to describe side-by-side in this instance due to their similarity. There were many students with similar patterns throughout all nine activities, but this pairing of students is highlighted here to demonstrate that in addition to being able to summarize student behavior

patterns, we can also take a look at similarities in those patterns across cohorts, or groups of students. While these two students were in two separate cohorts, their behavior patterns were very similar in this lesson. Their primary behavior patterns in this lesson were (1) orienting to learning objects while also (2) moving to and around learning objects, while also (3) moving with the group and (4) verbalizing using responses and greater than 5 words per utterance while then (5) stopping to look at and face the learning object(s). Many of their co-occurrences were similar and indeed many of the students co-occurrence webs look rather similar within this activity. However, student B06 and C09 were not verbalizing while facing or orienting to their peers, but were verbalizing while facing learning objects or orienting to those learning objects.

Students B06 and C09 can be seen running and moving and orienting in transition from object to object within the U5L5 NP activity. When they get to a learning object, they will often stop, look at and discuss the learning object while not turning to orient towards each other to speak about the learning object at hand.

Summary of student performance within the U5L6 NP activity

Students within the U5L6 NP activity were required to move around the environment in order to locate the King's items as part of a quest to then return those items to the King. Because the activity took place across the entire environment, student scores for general avatar orientation and movement are extremely high, with low variation among those scores. Students had moderate verbalizing, neither high verbalizing or low verbalizing, perhaps due the fact that

there is a large portion of the activity where movement (and specifically, “running”) from place to place is taking place and students are not able to speak to each other clearly when this is occurring. The large amount of orienting and movement towards learning objects could also serve to explain the lower peer orientation towards peers, given that there is then less time spent facing peers and more time spent running from one environment to another and looking at learning objects. Activity U5L6 is by far the most extreme activity sampled insofar as activity and movement is concerned, and overall the high level of physical activity may possibly have an impact on the opportunities students may then have to verbalize and face their peers within the environment.

Overall performance: Characterizing student performance within all naturalistic practice activities

The overall behavior patterns are depicted in Figure 58 and Table 19. One can see a trend as some of the most nonverbally active students (as reflected in high PC 1 scores) are also some of the students who were the least peer-oriented (B05, B06, C09). Student A01 stands out from the group as one who is static in his avatar nonverbal behavior (PC 1), not highly verbal (PC 2), yet is facing towards his peers, but in a static manner (if he is facing them, he does not turn his avatar to look at other things or orient towards others; PC 3). Naturally, the more someone orients in the environment, the less “facing peers” they might be doing. However, this does indicate that a balance might be struck by students A02, C08 and C11 wherein they move and orient, but they also stop to look at peers as well as have a fair amount of

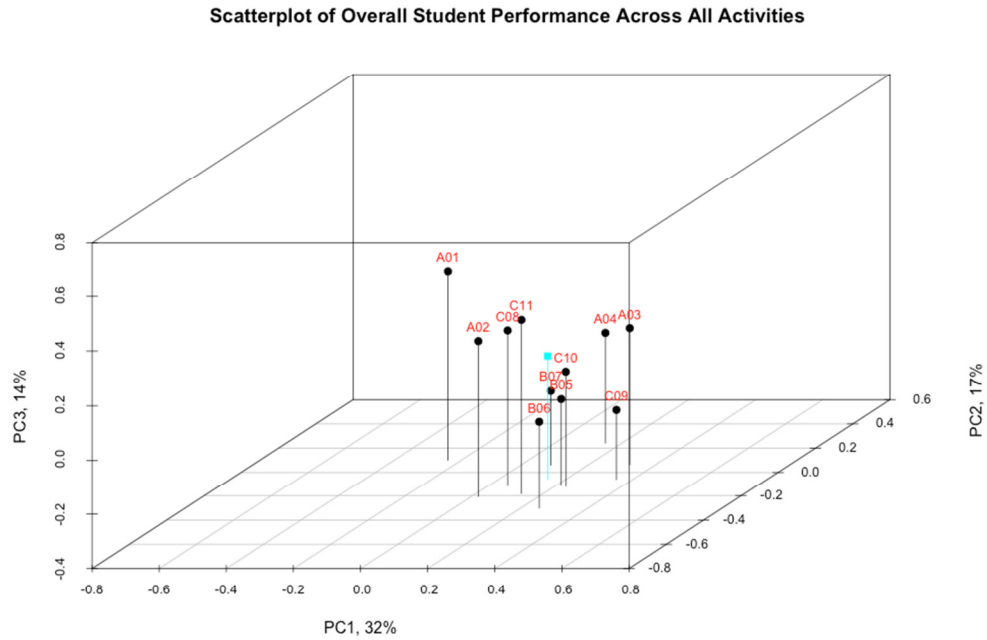


Figure 58. Scatterplots of student scores for all NP activities studied within the iSocial 3D CVLE; Mean is shown with a blue square

Table 19. Scores of Students across all NP Activities within iSocial 3D CVLE

Student	PC1	PC2	PC3
A01	-0.240	0.101	0.295
A02	0.020	-0.204	0.171
A03	0.321	0.064	0.099
A04	0.150	0.243	0.002
B05	0.216	-0.112	-0.08
B06	0.254	-0.300	-0.080
B07	0.089	0.060	-0.127
C08	0.058	-0.115	0.171
C09	0.350	-0.058	-0.145
C10	0.233	-0.119	0.021
C11	0.136	-0.182	0.239
Mean	0.144	-0.056	0.051
Median	0.150	-0.112	0.021
SD	0.165	0.158	0.152

N=11

nonverbal activity. In addition, the verbal scores of A02 and B06 were more negative (meaning being more verbal). When compared to others in their cohort, it is likely from the scores (and supported through the qualitative memos) that they were verbal dominators within their group.

In addition to being able to look at overall performance of students across all activities, we can also look at the behavior patterns that emerged within an activity across all students, and each activity then receives a score on each principal component. As seen in Figure 59 and Table 20, the behavior patterns were different in each lesson, with many of the activities varying from each other on elements of nonverbal behavior patterns, verbal behavior patterns, or peer-oriented behavior patterns. For example, student behavior patterns in NP activities U1L4, U4L4, U5L5, and U5L6 all have similar behavior patterns on PC 3 (peer orientation) but differed in terms of overall patterns of avatar verbal and nonverbal activity. Students within NP activities U3L5 and U4L5 had, in general, very similar behavior patterns.

Scatterplot of Overall Performance within Each Activity

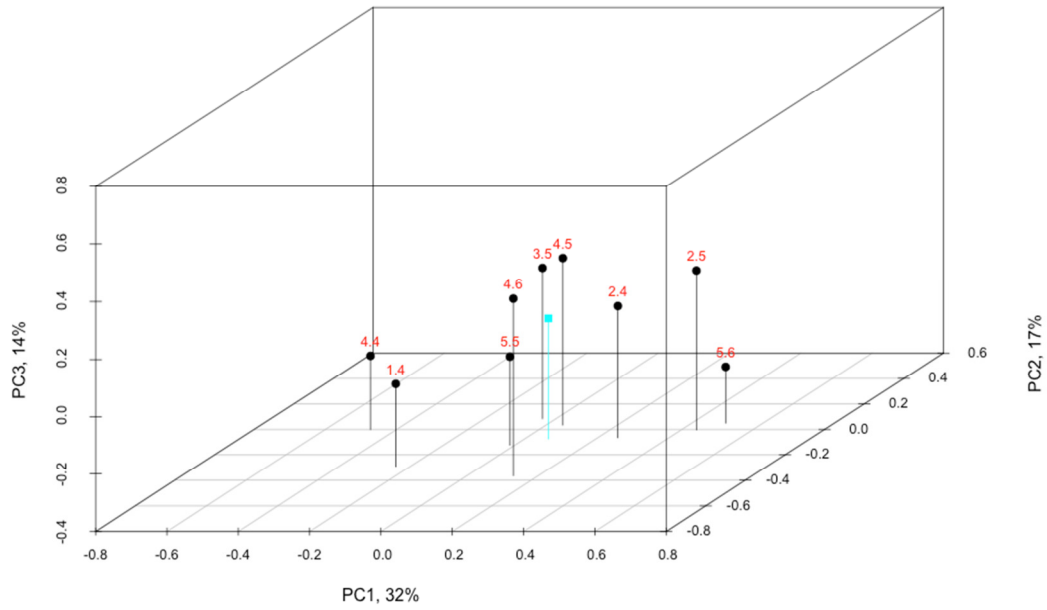


Figure 59. Scatterplot of activity scores for all 9 NP activities; Mean is shown with a blue square

Table 20. Scores of Activities across All Students within iSocial 3D CVLE

NP Activity	PC1	PC2	PC3
U1L4	-0.240	-0.291	-0.111
U2L4	0.256	-0.065	0.058
U2L5	0.442	-0.003	0.154
U3L5	-0.038	0.084	0.124
U4L4	-0.473	-0.000	-0.142
U4L5	0.047	0.033	0.180
U4L6	0.130	-0.366	0.217
U5L5	-0.013	-0.123	-0.090
U5L6	0.495	0.049	-0.202
Mean	0.067	-0.075	0.020
Median	0.047	-0.003	0.058
SD	0.309	0.156	0.157

Number of NP activities sampled = 9

Summary for RQ 1: Characterizing student performance based on co-occurrences of behavior

Research question 1 asked “Can student performance within the iSocial 3D CVLE be characterized through co-occurrences of behavior? If so, how and in what ways?” In this section, it was demonstrated that student performance within the iSocial 3D CVLE naturalistic practice activities can be characterized through co-occurrences of behavior (termed “behavior patterns”). Visuals of overall behavior patterns can indicate both general variance in student behavior across movement, verbalizations, and peer-orientation, both at the student-activity unit level, the student level overall, as well as at the activity level overall. The last set of results, those that looked at activity patterns overall, indicated that behavior patterns may differ across design environments.

However, to more accurately and objectively detect patterns of differences of behavior across environments, which has the potential to shed light on design of that environment, research questions 2 and 3 look at the differences of behavior between the environments and what patterns exist across those environments that could help to explain those differences (or lack of difference).

RQ 2: Do characteristics of student performance (co-occurrences of behavior) in iSocial 3D CVLE naturalistic practice activities differ across design environments? If so, how and in what ways?

Student scores for their behavior patterns within an activity were used to test whether behavior patterns differed across design environments. In this section, first the descriptive statistics were graphed and explored in order to more fully understand the data and what was happening with the data over activities and over time prior to analysis. This is then followed by a linear mixed model analysis of the data. A linear mixed model was chosen over repeated measures ANOVA due to its ability to accommodate missing data points as well as add in additional random effects, if needed, without severe penalties in degrees of freedom. Linear mixed model does this by treating time or repeated measurements as categorical, continuous, or both (Krueger & Tian, 2004). Additionally, time was tested as a potential factor in the model. Post-hoc Sidak-corrected paired comparisons were conducted to test for differences of behavior patterns between design environments.

Descriptive statistics for all student behavior pattern scores

Table 21 represents the same data described in the tables through the previous section covering research question 1. The means of the environments vary widely across all three principal components.

Table 21. Descriptive statistics for student behavior pattern scores across PC 1, PC 2 and PC 3

PC 1 Scores					
Environment	Mean	N	St. Deviation	Min	Max
1.4	-.195	9	.207	-.520	.130
2.4	.227	9	.202	-.117	.519
2.5	.400	11	.136	.160	.561
3.5	-.030	10	.208	-.291	.293
4.4	-.404	10	.227	-.607	.094
4.5	.038	9	.185	-.326	.280
4.6	.127	11	.152	-.145	.329
5.5	-.002	10	.271	-.464	.458
5.6	.462	8	.089	.289	.559
PC 2 Scores					
Environment	Mean	N	St. Deviation	Min	Max
1.4	-.284	9	.166	-.512	.056
2.4	-.037	9	.214	-.306	.334
2.5	.010	11	.184	-.410	.277
3.5	.043	10	.255	-.2501	.406
4.4	-.018	10	.227	-.384	.357
4.5	.045	9	.151	-.247	.250
4.6	-.309	11	.121	-.523	-.136
5.5	-.126	10	.253	-.630	.261
5.6	.068	8	.189	-.138	.411
PC 3 Scores					
Environment	Mean	N	St. Deviation	Min	Max
1.4	-.110	9	.067	-.191	-.012
2.4	.069	9	.177	-.159	.394
2.5	.137	11	.233	-.175	.611
3.5	.108	10	.211	-.206	.502
4.4	-.128	10	.051	-.236	-.069
4.5	.170	9	.157	-.003	.493
4.6	.197	11	.234	-.108	.504
5.5	-.110	10	.163	-.303	.256
5.6	-.187	8	.081	-.317	-.084

Note: environment number maps to NP activity, e.g. 1.4 = U1L4, 2.4 = U2L4, etc.

Behavior scores were charted across NP activities as seen in Figures 60, 61, and 62. This allowed for the visual inspection of patterns and potential time trends in the data to emerge. Missing data is marked with “//” within the graphs. Overall there does not initially seem to be a strong trend across lesson progression for PC 1, PC 2, or PC 3 scores.

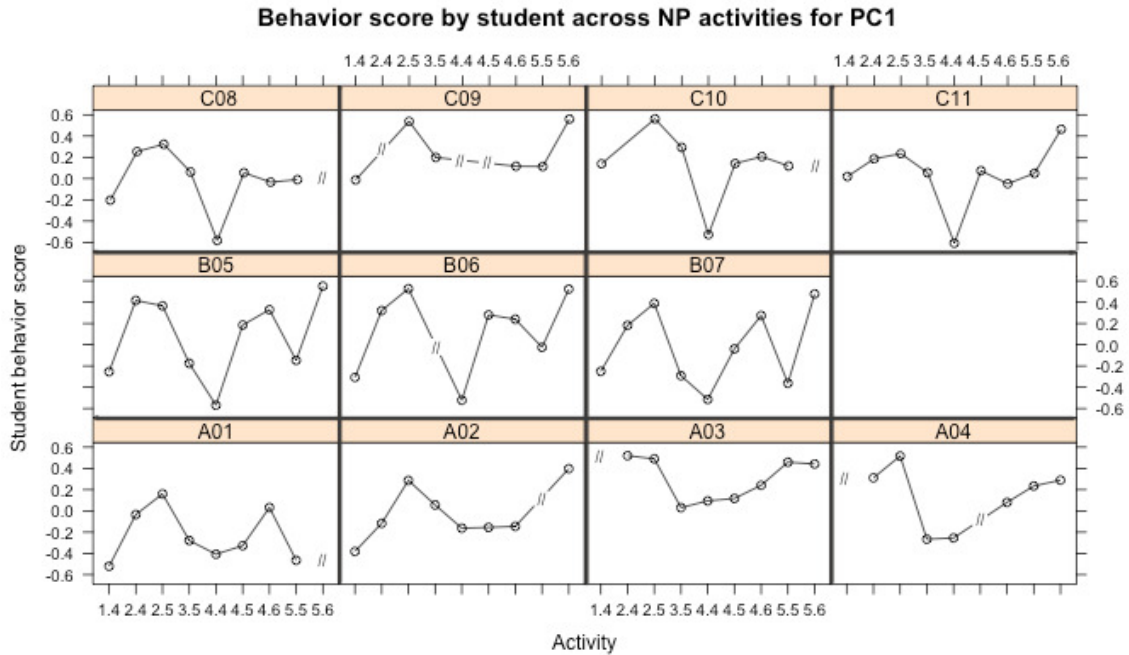


Figure 60. Behavior pattern scores by student across NP activities for PC 1, 2, and 3; “//” symbol used to represent missing data

For PC 1, there does seem to be an overall trend across activities. For example, students rise in PC 1 score for the first three activities and then their scores fall over the next two scores, and then rise again with their highest score often in U5L6. This could indicate that environment design has an influence on general orientation and movement score.

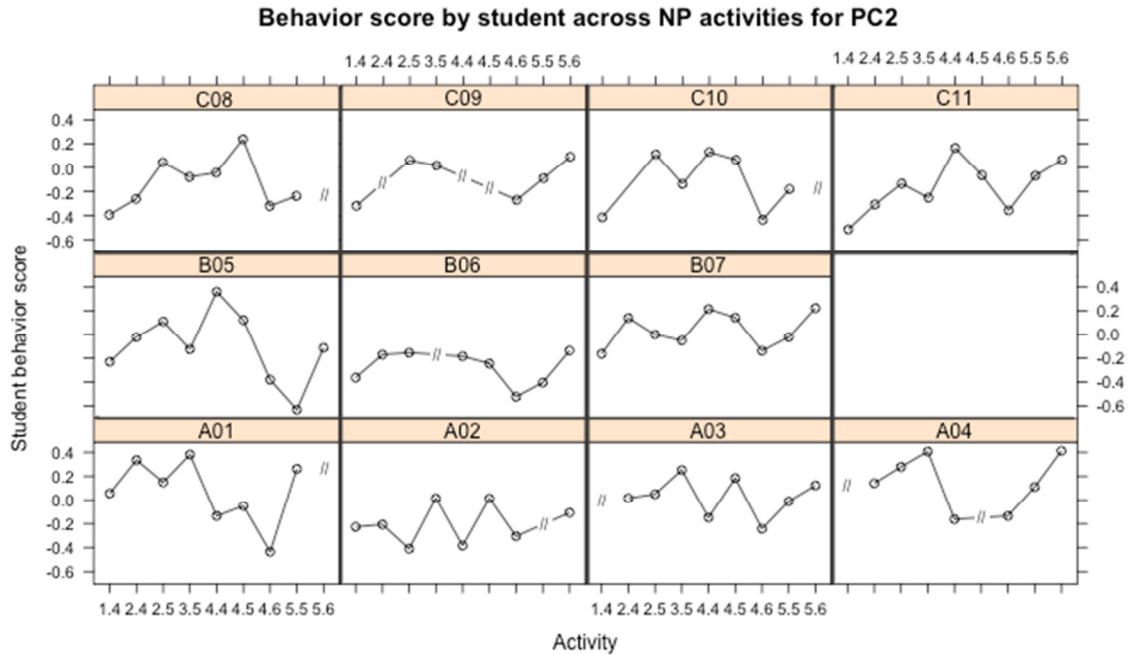


Figure 61. Behavior pattern scores by student across NP activities for PC 1, 2, and 3; “//” symbol used to represent missing data

For PC 2, there is less of a clear visual trend than was seen in PC1, although many of the activity patterns start low and get higher for the next one or two activities. This less clear pattern could indicate that PC 2, which is about verbalization, tends to be a quality that is more about students than environment compared to orientation and movement (PC1).

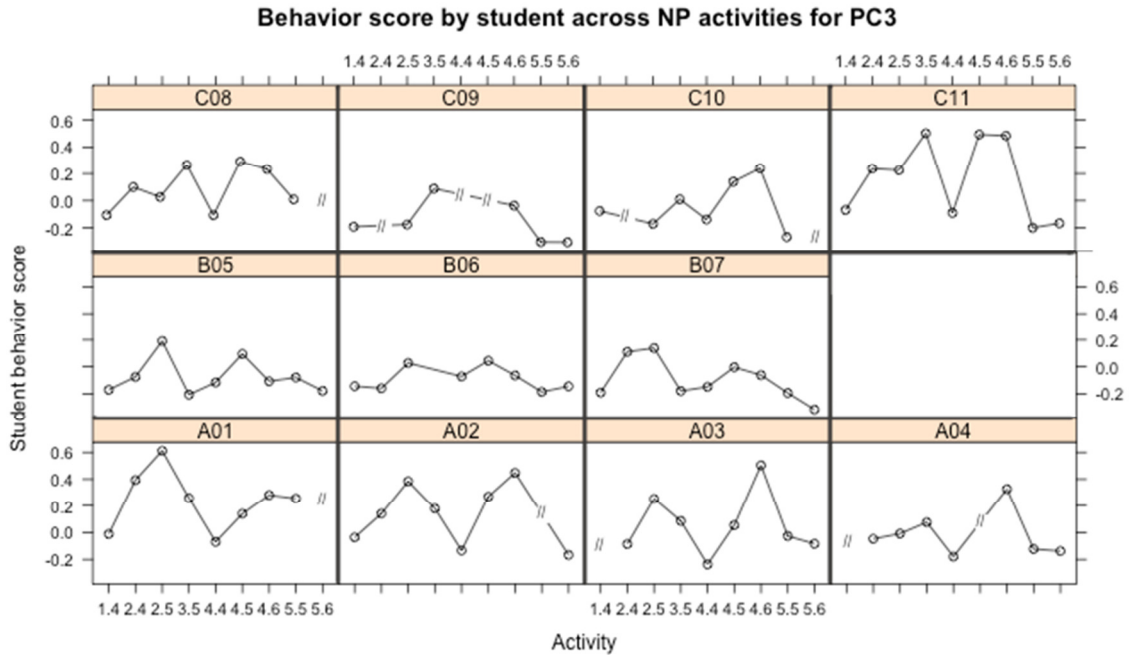


Figure 62. Behavior pattern scores by student across NP activities for PC 1, 2, and 3; “//” symbol used to represent missing data

The behavior scores for PC 3 seem somewhat similar to PC 1 in that there are patterns (though not as strong) across students. Student scores rise in the first two or three activities, then go lower, with often their lowest scores in the U4L4 or U5L5 NP activity. In addition, there does seem to be a possible cohort-trend for PC 3 especially in cohort B, which could indicate that the number of students within the environment could contribute to the opportunities for orienting to their peers; however it is not entirely clear. However, what is clear is that student scores go up and down dramatically throughout time, indicating changes in behavior patterns across all three principal components as they move throughout the activities.

Mean scores over time

Within this study, “activity” has been separated from “time”, as activity (for this study) is a categorical variable (as in a repeated measures study), and “time”, for the purpose of this study, is a continuous variable (as in a longitudinal study). Due to the observational nature of this study, and activity being confounded with time, it was important to address whether time was a significant predictor to behavioral pattern scores, and if so, it should be placed into the model. The value of time for each lesson can be seen in Tables 5 and 6. Figure 59 shows the changes over across activities of average student behavior pattern scores. There is not a clear trend from the average scores across activities over time.

To further descriptively look at trends over time, additional descriptive trends over time were plotted, but given Figures 60 through 62 and their indication of the large and sometimes opposing shifts in student behavior across time (rather than a trend to increase or decrease in certain behaviors), a statistical analysis of the contribution of time on behavior score would be more meaningful. The purpose of Figure 63 is to serve as a descriptive exploration of how student behavior scores may or may not be trending over time and if time would be a potential confound to design environment. It should be noted, however, that there is no basis for believing that the activities in between the NP activities (for example, teacher-led reviews and direct instruction) would lie on the path of these lines. The lines only serve as a visual tool for seeing change in between NP activities. In addition, time was graphed in order to look at change over time since the time in between NP activities was not

equal. For example, the time between U1L4 and U2L4 was different than U2L4 and U2L5.

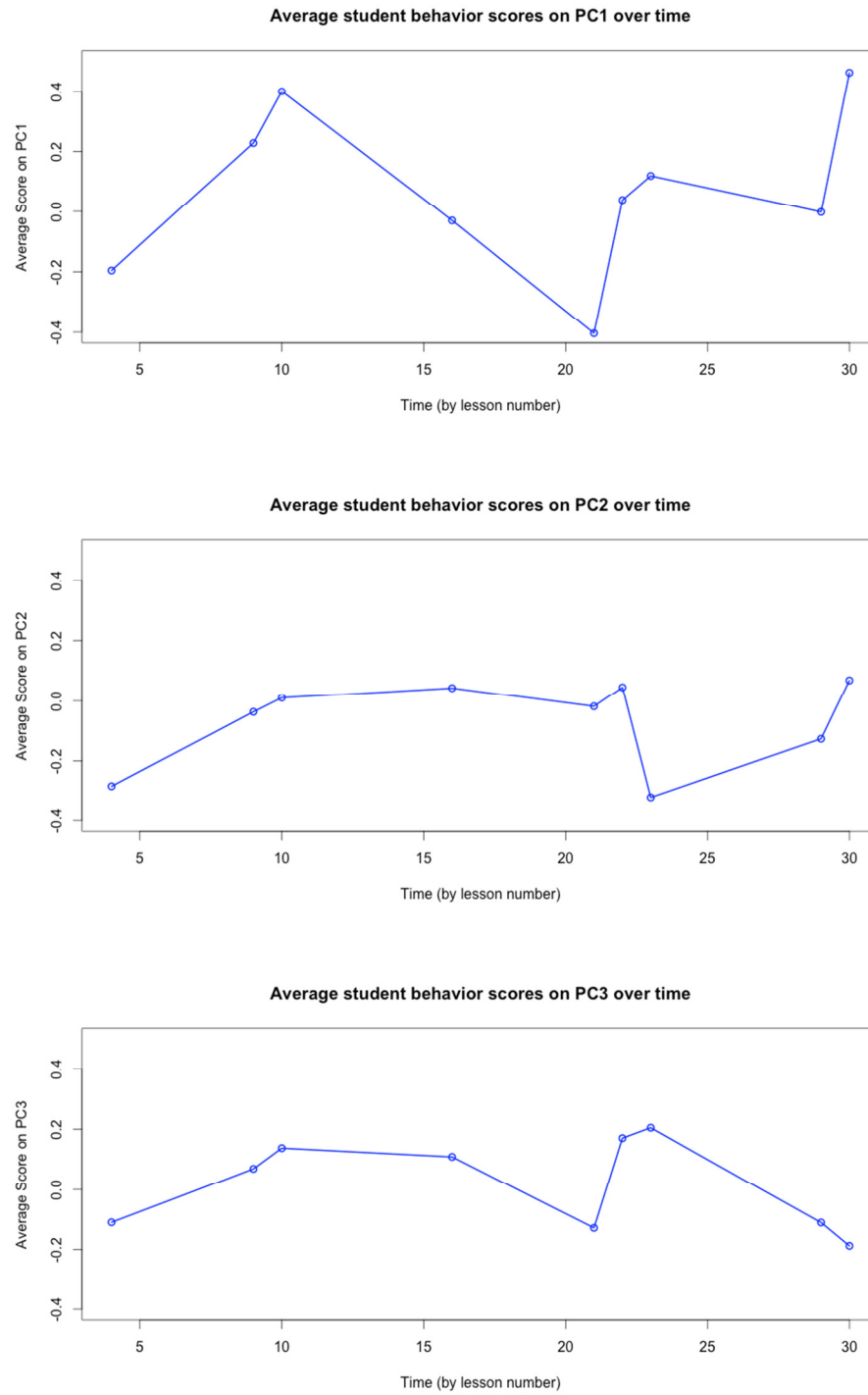


Figure 63. Mean student behavior scores for PC 1, PC 2 and PC 3 over time

Figure 63 indicates that there is likely no significant trend over time for solely NP activities.

Building and Testing the Model

Three models were tested as described in Chapter 4 Methods section. They are as follows:

Model 1:

$$\text{Score}_{ij} = \beta_0 + u_i + \varepsilon_{ij}$$

Model 2:

$$\text{Score}_{ij} = \beta_0 + \beta_1\text{Time} + u_i + \varepsilon_{ij}$$

Model 3:

$$\text{Score}_{ij} = \beta_0 + \beta_1\text{Environment} + u_i + \varepsilon_i$$

Normality of the residuals was also confirmed by plotting the expected values against the residuals. By not seeing any general linear trend in the visual plot, other than a slight grouping, normality can be assumed (Winter, 2011). PC 1 scores, PC 2 score, and PC 3 residuals demonstrate no linear trend, demonstrating normality (see Figures 64 – 66 for plots for Model 3 normality tests).

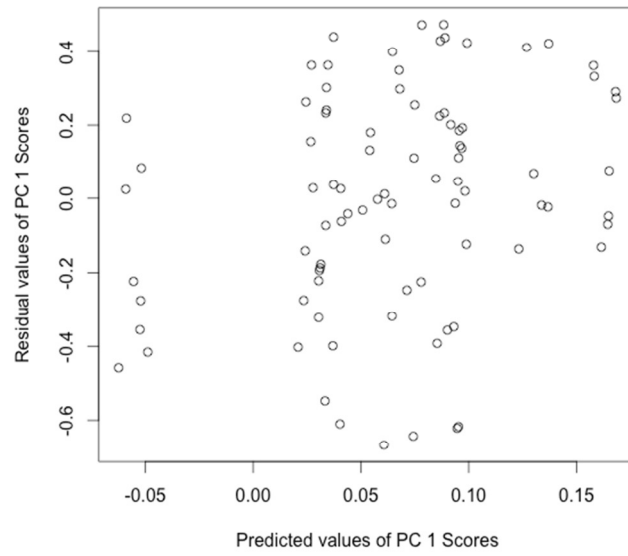


Figure 64. Plot of predicted values against residuals for PC 1

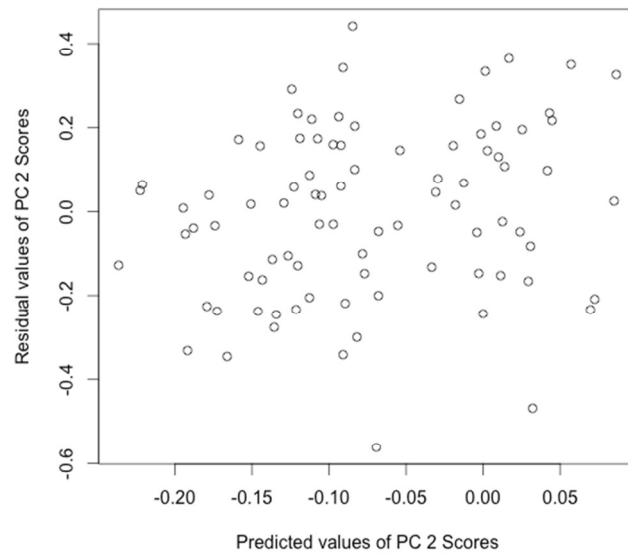


Figure 65. Plot of predicted values against residuals for PC 2

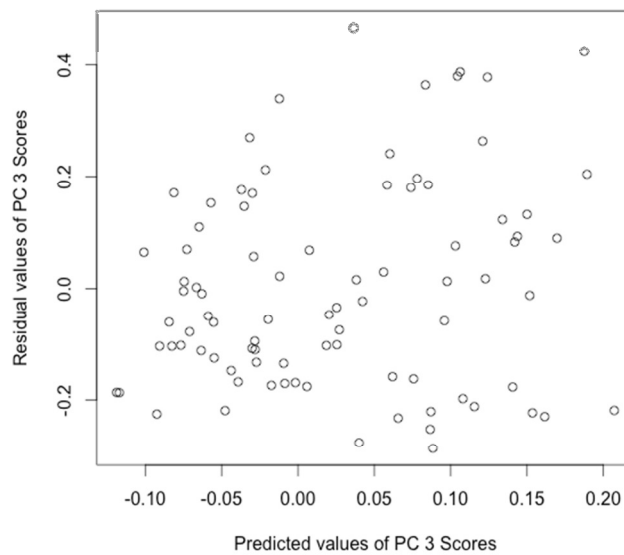


Figure 66. Plot of predicted values against residuals for PC 3

Model 1 was run using the MIXED procedure in SPSS in order to obtain model fit statistics for PC 1, PC 2, and PC 3 student behavior scores using a step-up approach. A step-up approach starts with the null model and adds fixed effects, testing for model fit (West et al., 2012). Students were set as random effects with a random intercept, also known as the random intercept model with no fixed effects present. The covariance parameters are listed in Table 22, which are the variance parameters which are used to calculate ICC. Type III Test of Fixed Effects for the empty model, which tests if the intercept is significantly different from zero, was not included as it is not of interest in this study for the null model.

For the second model, *time* was added as a fixed effect covariate (continuous predictor) within the model and tested. As Tables 22, 23, and 24 indicate, time did not increase model fit for PC 1, PC 2, or PC 3 behavior scores as evidenced by a

significant increase, rather than decrease, in AIC and -2LL scores. In addition, *time* was also not a significant predictor for PC 1, PC 2, or PC 3 behavior scores according to the Type III Test of Fixed effects. This means that *time* (a) did not serve as a better predictor than the simple overall mean score for predicting student behavior scores, and (b) did not have a significant linear effect for any of the PC behavior scores. Thus time was rejected from inclusion in the model for PC 1, PC 2, and PC 3 behavior scores.

The third model was tested using *environment* as a fixed effect factor (categorical predictor). As Tables 22, 23, and 24 indicate, design environment significantly increased model fit according to the reduction in -2LL and AIC across PC 1, 2 and 3. In addition, design environment was a significant predictor ($p < .001$) for PC 1, PC 2, and PC 3 behavior scores in that the means significantly differed from each other according to the Type III Test of Fixed Effects. This random intercept linear mixed model design was equivalent to a repeated measures ANOVA and thus the significant F test indicates that the variance between the students within environments was less than the variance between the students across environments.

Table 22. Model fit and significance test of fixed effects for PC 1

Model	Model Fit		Type III Test of Fixed Effects		
	-2LL	AIC	F	Sig	ICC
Model 1	49.87	53.87	-	-	.085
Model 2	59.03	63.03	.08	.777	.079
Model 3	-29.62	-25.62	27.11	.000	.343

Table 23. Model fit and significance test of fixed effects for PC 2

Model	Model Fit		Type III Test of Fixed Effects		
	-2LL	AIC	F	Sig	ICC
Model 1	-8.17	-4.17	-	-	.189
Model 2	1.30	5.30	.51	.480	.184
Model 3	-25.49	-21.49	7.41	.000	.309

Table 24. Model fit and significance test of fixed effects for PC 3

Model	Model Fit		Type III Test of Fixed Effects		
	-2LL	AIC	F	Sig	ICC
Model 1	-22.99	-18.99	-	-	.219
Model 2	-14.54	-10.54	1.72	.194	.231
Model 3	-52.55	-48.55	10.85	.000	.378

Interclass correlations (ICC) were also calculated for each model. When using the empty model, for PC 1, student variation only accounted for approximately 8.5% of the variance in the dataset, which is not high, meaning that 92% of the variation in PC 1 was unaccounted for in the empty model. Looking at Table 25, we can see that by adding environment as a fixed effect, this reduced the random error in the model (ϵ_{ij}) by 73%. Model 3's adjusted ICC is .343, meaning that 34% of the variation in the full model is accounted for by student individual differences, which supports the validity of controlling for student when also looking at environment as a fixed effect. For PC 2, students accounted for approximately 18.9% of the variance in the data in the empty model, which is significant and warrants the validity of controlling for student as well. Referring again to Table 25, we can see that by adding environment as a fixed effect, this reduced the random error in the model

(ϵ_{ij}) by 40%. For PC 3, students accounted for approximately 21.9% of the variance in the data within the empty model. We can see that by adding environment as a fixed effect, this reduced the random error in the model (ϵ_{ij}) by 51%. These ICC scores show that in this data set, individual student individual variation accounts most for peer orientation, followed by verbalization, with individual variation accounting least for general orientation and movement. In addition, since model 3 shows significant F test results across all three PC scores, in this data set environment accounts for the most variance in regards to general orientation and movement (73% reduction in the residual term), followed by peer orientedness (51% reduction in the residual term) with the environment accounting for the least amount of variation in verbalization (40% reduction in the residual term). These findings coincide with the descriptive graphs in Figures 60-62 in that PC 2 scores tended to have the least amount of detectable patterns between students across environments when compared to Figures PC 1 and PC 3.

Table 25. Estimate of covariance parameters in models 1 vs. 3

PC 1 Scores		
Parameter	Estimate, Model 1	Estimate, Model 3
Residual	.093	.025
Intercept ^a	.008	.013
PC 2 Scores		
Parameter	Estimate, Model 1	Estimate, Model 3
Residual	.045	.027
Intercept ^a	.010	.012
PC 3 Scores		
Parameter	Estimate, Model 1	Estimate, Model 3
Residual	.037	.018
Intercept ^a	.010	.011

a. subject = student

Testing for differences between the environments

Post-hoc Sidak-corrected pairwise corrections revealed a number of significant differences in PC 1, PC 2 and PC 3 scores between environments (see Tables 26, 27, and 28). On PC 1, which represented the non-verbal behavior patterns, 21 design environment pairs were significantly different from each other on the nonverbal behavior score outcomes. On PC 2, which represented the more verbal behavior patterns, 10 design environment pairs were significantly different from each other on those behavioral pattern outcomes. And finally, for PC 3, which represented the more peer-oriented behavior patterns, 16 design environment pairs were significantly different from each other.

In order to understand what patterns in design environment might exist with these differences, we come to the third and final research question.

Table 26. Pairwise comparisons for PC 1

Behavior scores across environments

(I) Env	(J) Env	Mean Difference (I-J)	Std. Error	df	Sig. ^a	95% Confidence Interval for Difference ^a	
						Lower Bound	Upper Bound
1.4	2.4	-.427*	.076	68.886	.000	-.678	-.176
	2.5	-.577*	.072	68.314	.000	-.815	-.339
	3.5	-.150	.073	68.508	.811	-.394	.094
	4.4	.218	.073	68.623	.138	-.026	.462
	4.5	-.227	.075	68.422	.121	-.477	.023
	4.6	-.295*	.072	68.314	.004	-.533	-.057
	5.5	-.165	.073	68.508	.633	-.409	.079
	5.6	-.624*	.078	69.038	.000	-.884	-.364
2.4	2.5	-.150	.072	68.389	.772	-.388	.088
	3.5	.277*	.073	68.601	.012	.033	.522
	4.4	.645*	.073	68.151	.000	.403	.888
	4.5	.200	.075	68.406	.292	-.049	.450
	4.6	.132	.072	68.389	.925	-.106	.370
	5.5	.262*	.073	68.601	.024	.018	.506
2.5	5.6	-.197	.078	68.669	.390	-.455	.062
	3.5	.427*	.069	68.095	.000	.197	.658
	4.4	.795*	.069	68.184	.000	.564	1.026
	4.5	.350*	.072	68.392	.000	.112	.588
	4.6	.282*	.068	67.932	.003	.057	.506
	5.5	.412*	.069	68.095	.000	.181	.642
3.5	5.6	-.047	.074	68.521	1.000	-.294	.200
	4.4	.368*	.071	68.374	.000	.131	.605
	4.5	-.077	.073	68.602	1.000	-.321	.167
	4.6	-.145	.069	68.095	.768	-.376	.085
	5.5	-.016	.071	68.268	1.000	-.252	.221
4.4	5.6	-.474*	.076	68.732	.000	-.727	-.222
	4.5	-.445*	.073	68.152	.000	-.687	-.202
	4.6	-.513*	.069	68.184	.000	-.744	-.282
	5.5	-.383*	.071	68.374	.000	-.620	-.147
4.5	5.6	-.842*	.076	68.867	.000	-1.095	-.589
	4.6	-.068	.072	68.392	1.000	-.306	.170
	5.5	.062	.073	68.602	1.000	-.183	.306
4.6	5.6	-.397*	.078	69.162	.000	-.657	-.137
	5.5	.130	.069	68.095	.913	-.101	.360
5.5	5.6	-.329*	.074	68.521	.001	-.575	-.082
5.5	5.6	-.459*	.076	68.732	.000	-.711	-.206

*. The mean difference is significant at the .05 level.

^a Adjustment for multiple comparisons: Sidak.

Table 27. Pairwise comparisons for PC 2
Behavior scores across environments

(I) Env	(J) Env	Mean Difference (I-J)	Std. Error	df	Sig. ^a	95% Confidence Interval for Difference ^a	
						Lower Bound	Upper Bound
1.4	2.4	-.222	.078	69.044	.190	-.482	.037
	2.5	-.271*	.074	68.411	.017	-.517	-.025
	3.5	-.289*	.076	68.627	.011	-.541	-.036
	4.4	-.243	.076	68.750	.071	-.496	.009
	4.5	-.325*	.078	68.528	.003	-.583	-.067
	4.6	.061	.074	68.411	1.000	-.186	.307
	5.5	-.123	.076	68.627	.985	-.375	.129
	5.6	-.338*	.081	69.217	.003	-.607	-.069
2.4	2.5	-.049	.074	68.491	1.000	-.295	.198
	3.5	-.066	.076	68.727	1.000	-.319	.186
	4.4	-.021	.075	68.227	1.000	-.272	.230
	4.5	-.103	.078	68.511	1.000	-.361	.156
	4.6	.283*	.074	68.491	.010	.037	.529
	5.5	.099	.076	68.727	1.000	-.153	.352
	5.6	-.116	.080	68.803	.998	-.383	.152
2.5	3.5	-.018	.072	68.166	1.000	-.256	.221
	4.4	.028	.072	68.262	1.000	-.211	.266
	4.5	-.054	.074	68.494	1.000	-.300	.192
	4.6	.332*	.070	67.984	.000	.099	.564
	5.5	.148	.072	68.166	.794	-.091	.387
	5.6	-.067	.077	68.641	1.000	-.322	.188
3.5	4.4	.045	.074	68.474	1.000	-.200	.290
	4.5	-.036	.076	68.729	1.000	-.289	.216
	4.6	.349*	.072	68.166	.000	.111	.588
	5.5	.166	.074	68.360	.636	-.079	.410
	5.6	-.049	.079	68.877	1.000	-.311	.212
4.4	4.5	-.082	.075	68.228	1.000	-.333	.169
	4.6	.304*	.072	68.262	.003	.065	.543
	5.5	.120	.074	68.474	.983	-.125	.365
	5.6	-.095	.079	69.022	1.000	-.356	.167
4.5	4.6	.386*	.074	68.494	.000	.139	.632
	5.5	.202	.076	68.729	.296	-.050	.454
	5.6	-.013	.081	69.350	1.000	-.282	.256
4.6	5.5	-.184	.072	68.166	.370	-.422	.055
	5.6	-.399*	.077	68.641	.000	-.654	-.144
5.5	5.6	-.215	.079	68.877	.248	-.476	.046

*. The mean difference is significant at the .05 level.

^a Adjustment for multiple comparisons: Sidak.

Table 28. Pairwise comparisons for PC 3
Behavior scores across environments

(I) Env	(J) Env	Mean Difference (I-J)	Std. Error	df	Sig. ^a	95% Confidence Interval for Difference ^a	
						Lower Bound	Upper Bound
1.4	2.4	-.158	.065	68.806	.472	-.373	.058
	2.5	-.247*	.061	68.296	.005	-.451	-.043
	3.5	-.211*	.063	68.467	.046	-.419	-.002
	4.4	.032	.063	68.572	1.000	-.177	.241
	4.5	-.263*	.064	68.394	.004	-.477	-.049
	4.6	-.314*	.061	68.296	.000	-.518	-.110
	5.5	-.008	.063	68.467	1.000	-.217	.201
	5.6	.059	.067	68.936	1.000	-.163	.282
2.4	2.5	-.089	.061	68.365	.997	-.293	.114
	3.5	-.053	.063	68.552	1.000	-.262	.156
	4.4	.189	.062	68.152	.117	-.018	.397
	4.5	-.106	.064	68.379	.982	-.320	.108
	4.6	-.157	.061	68.365	.372	-.361	.047
	5.5	.150	.063	68.552	.516	-.059	.359
	5.6	.217	.067	68.612	.061	-.005	.438
2.5	3.5	.036	.059	68.102	1.000	-.161	.234
	4.4	.279*	.059	68.184	.000	.081	.477
	4.5	-.016	.061	68.367	1.000	-.220	.188
	4.6	-.067	.058	67.959	1.000	-.260	.125
	5.5	.239*	.059	68.102	.005	.042	.437
	5.6	.306*	.064	68.478	.000	.095	.518
3.5	4.4	.242*	.061	68.351	.006	.040	.445
	4.5	-.053	.063	68.553	1.000	-.262	.156
	4.6	-.104	.059	68.102	.960	-.301	.094
	5.5	.203*	.061	68.254	.050	.000	.405
	5.6	.270*	.065	68.664	.003	.053	.486
4.4	4.5	-.295*	.062	68.153	.000	-.503	-.087
	4.6	-.346*	.059	68.184	.000	-.544	-.148
	5.5	-.040	.061	68.351	1.000	-.242	.163
	5.6	.027	.065	68.788	1.000	-.189	.244
4.5	4.6	-.051	.061	68.367	1.000	-.255	.153
	5.5	.255*	.063	68.553	.005	.046	.465
	5.6	.322*	.067	69.050	.000	.100	.545
4.6	5.5	.306*	.059	68.102	.000	.109	.504
	5.6	.373*	.064	68.478	.000	.162	.585
5.5	5.6	.067	.065	68.664	1.000	-.149	.283

*. The mean difference is significant at the .05 level.

^a Adjustment for multiple comparisons: Sidak.

RQ 3: Are design attributes associated with patterns of behavior?

Research question 2 revealed that student behavior patterns do emerge differently across design environments. Research question 3 attempts to take that data and understand what design elements could be contributing to those patterns of behavior, which in turn makes up the student performance within the environment. As stated earlier, environment design, for the purposes of this study, takes into consideration curricular design and world design together as one set of attributes, since it would not be possible to tease them apart.

Describing differences between design environments

In this section, we describe (1) how the attributes were determined and provide examples of each, (2) compare attributes across environments in order to look for patterns, followed by (3) analyzing behavior pattern results from RQ 2 and how they might be associated with environmental design attributes.

Table 29 describes the category and attribute definitions used to describe the design of the environments. In the next section, how the attributes were determined and defined are reviewed.

Table 29. Design environment categories, attributes, and definitions

Design Environment Attributes and Definitions	Levels defined
Category: Engagement	
Definition: Salient attributes from literature review shown to promote intrinsic motivation and engagement in learning environments	
Engage: World interactivity Environment is interactive; models and attributes of the world can appear, disappear, move, etc.	H: Interactivity was present throughout the lesson, 3D world objects are interactive M: Interactivity in small parts of the lesson, 3D objects are interactive L: Interactivity is limited to 2D elements on or within 3D world
Engage: Choice Level of choice students have to enact decisions in environment	H: No right or wrong answers, students free to make choices and act them out M: Students free to make choices but only given limited options to choose from L: Students can make choices but there are right or wrong choices, and corrected if wrong
Category: Tool use	
Definition: type of tools students use in the environment	
Tool use: Restrictive Tools which lock one's avatar in place while they are being used. Orientation and movement are not allowed while one is "in control" of the tool.	H: All students needed to use at some point in the lesson for a substantial period of time M: Used throughout but not required by all students
Tool use: Unrestrictive Tools which do not lock one's avatar in place while they are being used. Orientation and movement are allowed while one is "in control" of the tool.	L: Used for very little time during the lesson

Table 29, continued. Design environment categories, attributes, and definitions

Category: Object Position	
Definition: Worldbuilding setup of targeted learning spaces	
<p>Position: Circular Learning objects are positioned so that (a) students are able to surround learning objects easily, and (b) learning objects are low enough so that if students were to surround the learning objects, they could see each other at the same time (below head avatar height).</p>	<p>H: Students were exposed to position setup majority of time</p> <p>M: Students were exposed to position setup half of the lesson</p> <p>L: Students were exposed to position setup less than 25% of time</p>
<p>Position: Wall Learning objects are positioned so that (a) students cannot surround learning object easily (for example it is placed up against a wall) and/or (b) learning object is tall enough that if students were to surround the learning object(s), they could not see each other at the same time.</p>	<p>-: Students were not exposed to that position setup (not in activity)</p>
<p>Position: Open There are no central learning objects that the students surround. They are immersed in the learning objects and surrounded by them rather than the students surrounding or looking at the objects.</p>	
Category: Groups	
Definition: Group is designed to stay as a whole group or break into small groups. <i>Note: this is the only design attribute which changes depending on number of people in the environment.</i>	
<p>Group: Cohort/Large All students in environment together.</p>	<p>H: Cohort was together majority of time; not split up</p> <p>M: Group split some the time</p>
<p>Group: Small Students broken up into small groups for activity]</p>	<p>L: Group was in group type only a small portion of time</p> <p>- : Students were not in that group type</p>
Other	
Definition: Other elements as observed	
<p>Other: Movement Level of movement designed in activity, if students were designed to move from space to space or stay within a small space</p>	<p>H: Movement around the entire environment for much of the lesson</p> <p>M: Movement allowed in a larger space</p> <p>L: Little to no movement designed within activity</p>

Identifying the attributes

Engagement: World Interactivity and Choice.

As discussed in the literature review, interactivity and choice are two of many elements found by Malone (1981) and Dickey et al. (2005a) to promote engagement and intrinsic motivation in instructional environments. While narration, challenge, and mystery were also considered, interactivity and choice emerged as the most salient for the contexts within this exploratory case study. For example, Unit 1 Lesson 4 NP activity is defined as having low interactivity and low choice. The environmental design is limited in world interactivity to 2D elements within the 3D world. The 2D elements are described as low world interactivity due to less immersion and larger-scale cause-and-effect virtual world interaction. In addition, the “choice” is listed as “low” in that the students are given a scenario, in which they are to perform a facial expression that is within a spectrum of right and wrong. They are corrected based on that behavior and then move on to the next scenario and facial expression. “High” does not necessarily correspond to more desirable, but for this study serves as a way to help categorize level of choices as designed into the curricular activity. For example, in activity 4.6 they create a role play, and each student chooses any character, any location, any emotion, and acts out that scenario with their peers.

In addition to engagement attributes based on the literature review regarding designing engaging environments, the design environments were also labeled with four additional attributes emerging from the memos: tool use, position,

group, and movement. While there are likely more attributes of the design environments, the ones chosen here appear most salient based on the literature review and qualitative memo notes.

Tool Use: Restrictive and Unrestrictive tools

Often tools were placed within the environment for students to use either (a) as needed and as they chose, (b) as assigned by role of activity, or (c) as assigned to everyone by the activity design. The tools themselves had two major distinctions between them, categorized as restrictive or unrestrictive tools. Restrictive tools, were tools which disabled a student's ability to orient and move their avatar when they took control over the tool. Unrestrictive tools were tools which still allowed a student's avatar to move freely even when they still "had control" over the tool. Examples of restrictive tools were mediaboards and sticky notes. Examples of unrestrictive tools are the Quest inventory tool, restaurant menu tool, and popup pod tools.

Position: Circular, Wall, and Open

The *position* category emerged as behavior patterns in targeted learning spaces setup were examined. A targeted learning space is defined as a space where students are intended to gather for part of the lesson activity. For example, while the U5L6 environment is quite large, some of the far reaches of the environment are there for visual purposes, but are not intended for students to stop and engage in curricular discussions. An example of a memo note from one of the U5L6 NP activity videos stated:

“Students gathered around this table [tagged segment where students were gathering around a table with several chalices] and therefore were orienting towards each other. Having the items low with walkable space around for them [students] to gather may assist in opportunities for student peer orientation.”

The three types of positions emerged through the axial coding after memos were completed. A “circular” position is described as a targeted learning space that allows students to gather around the learning objects. This does not mean that the students *do* gather around the learning objects, but would be able to, and in addition, would be able to see each other as well. Figures 67 and 68 show examples of the “circular” position setup within NP activities U2L4 and U5L6.



Figure 67. Students from Cohort A gather around a circular-positioned setup in U5L6 NP activity



Figure 68. Students from Cohort C are near a circular-positioned setup in the U2L4 NP activity, but do not gather around the table like other cohorts in this example

The “wall” position describes a setup where the learning objects are either placed against a wall or placed in such a way that students cannot circle around the learning objects, or if the students were to circle around the learning objects they would not be able to see each other. Figures 69 and 70 show the wall position in iSocial.

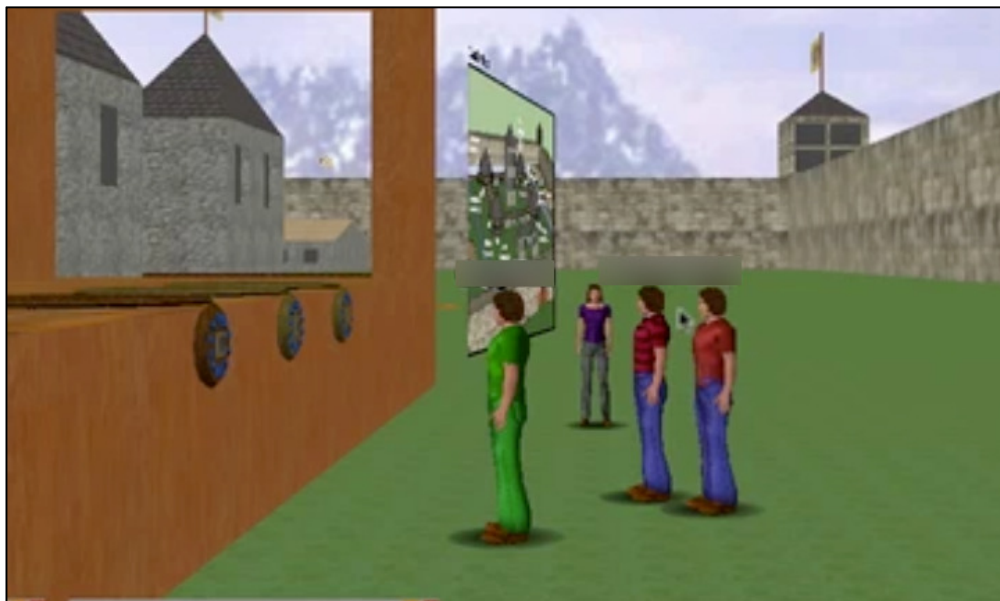


Figure 69. Students from Cohort A discuss which necklace might be the King's in this wall-positioned setup

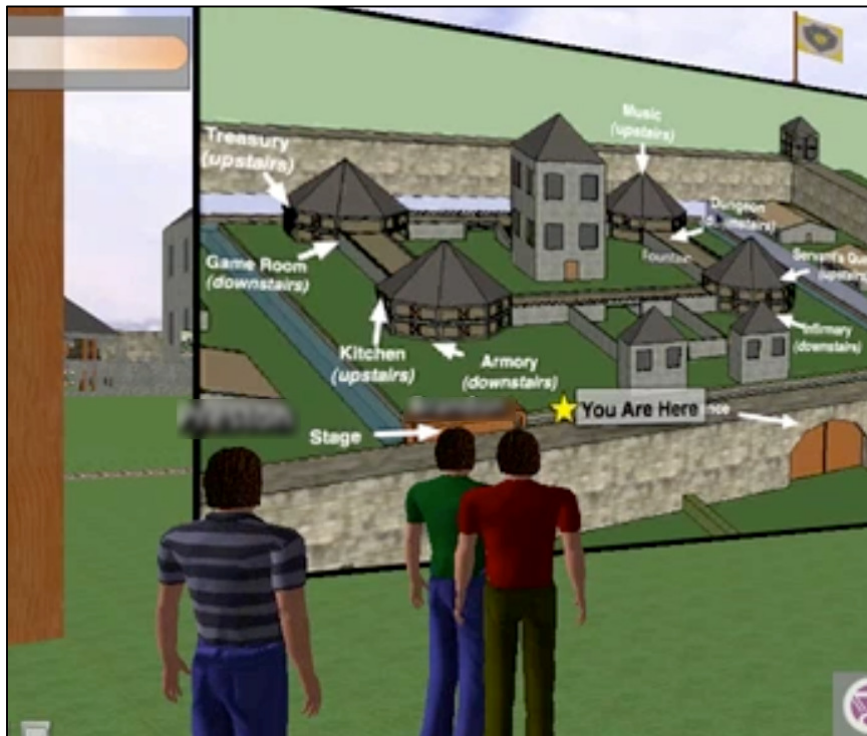


Figure 70. Students from Cohort A discuss how to get to their next location by looking at the map, a wall-positioned setup

The “open” position describes a setup that has no central learning object, rather describes a more immersive setup wherein the learning object(s) surround the students and the students are central, rather than the learning objects. Figure 71 shows an example from the U2L5 NP activity where they are in the center of a chores activity and surrounded by and standing on top of the chores learning objects to facilitate their discussions.



Figure 71. Students in Cohort A discuss who should do which chore in this open-positioned setup of U2L5

Group: Cohort/Large and Small

The next category that emerged for environmental design was group, which describes how the activity was designed, whether it was large group (group stayed together) or small group (group separated). This is the only attribute that changed depending on the number of people in the environment. If there were only 3 or fewer students in the environment, then the activities, which were designed as “small group”, were performed as large group for those cohorts (sometimes less movement to group locations, online guide staying with the group). Thus in the table, “cohort/large” and “small” may be listed as “high” for both large and small group.

Other: Movement

In addition to the level at which students choose to move their own avatars within the environment, there is also a level of movement designed into the activity. This would include designing whether students moving from A to B, the size of the

environment and how much they need to move from part of the activity to the next portion of the activity. For example, in U4L4 NP activity, the environment is designed for students to stand by their sticky notes and it is not designed to for students to move extensively around the environment. However, U5L6 NP activity is designed for them to move around the entire environment.

To determine if there was an association between behavior and environments, first the design attribute patterns that exist across the environments (Table 29) were identified. Table 30 lists to what extent each design environment had the following attributes. They are not mutually exclusive, and were labeled according to the definitions listed in Table 29. It should be noted that due to the exploratory nature of this study, these are not expected to be the only types of attributes that may be important but rather are a starting point for analyzing the role of environmental attributes and subsequent student behavior. This was done as a first step to determine if there was an association between behavior and environments.

Next the results from the paired comparison tests were used to identify patterns that may exist between the paired comparison tests and the design attributes table.

Table 30. Design environment attributes of iSocial 3D CVLE NP activities

Design Environment Attribute	NP Activities								
	1.4	2.4	2.5	3.5	4.4	4.5	4.6	5.5	5.6
Tool use: Restrictive	H	-	-	-	H	L	H	L	-
Tool use: Unrestrictive	-	L	H	M	-	-	-	-	M
Position: Circular	-	H	M	M	-	-	-	-	M
Position: Wall	H	L	M	M	H	L	H	H	M
Position: Open	-	M	M	-	-	H	L	-	L
Engage: Interactivity	L	M	L	H	L	L	L	L	M
Engage: Choice	L	H	H	M	L	H	H	M	M
Group: Large	H	H	H	H	H	H	H	H	H
Group: Small	H	-	-	-	H	H	H	-	-
Other: Movement	L	M	H	M	L	L	L	-	H

H=High; M=Moderate; L=Low; - = Not present

Comparing design attributes across environments

Looking at Table 30, two activity groupings emerge that distinguish between environments. The first group, Type I, contains activities U1L4, U4L4, U4L5, U4L6, and U5L5. The second group, Type II, contains activities U2L4, U2L5, U3L5, and U5L6. Another table was recreated grouping Type I and Type II NP activities together.

Table 31. Design environment attributes of iSocial 3D CVLE NP activities

Design Environment Attribute	NP Activities								
	Type I					Type II			
	1.4	4.4	4.5	4.6	5.5	2.4	2.5	3.5	5.6
Tool use: Restrictive	H	H	L	H	L	-	-	-	-
Tool use: Unrestrictive	-	-	-	-	-	L	H	M	M
Position: Circular	-	-	-	-	-	H	M	M	M
Position: Wall	H	H	L	H	H	L	M	M	M
Position: Open	-	-	H	L	-	M	M	-	L
Engage: Interactivity	L	L	L	L	L	M	L	H	M
Engage: Choice	L	L	H	H	M	H	H	M	M
Group: Large	H	H	H	H	H	H	H	H	H
Group: Small	H	H	H	H	-	-	-	-	-
Other: Movement	L	L	L	L	-	M	H	M	H

H=High; M=Moderate; L=Low; - = Not present

Type I

The Type I group has common patterns: use of restrictive tools (such as mediaboards or sticky notes), no use of circular positioning regarding worldbuilding design, and are the only environments that use High levels of the wall-type of positioning regarding worldbuilding design. They also have fewer open positioning present compared to the Type II group, and have the lowest level of movement within the environment. With the exception of U5L5, all of the activities also break into small groups (some cohorts or days with low numbers of students do not break into small groups when there are only 2 or 3 students present, thus the use of “high” on both large and small groups).

However, within the Type 1 group exist subsets. U1L4 and U4L4 design environments contain exactly the same design attributes listed in Table 5.20 (this does not mean they are designed exactly the same as there are likely more design attributes to look at than what is listed in the table). The environments U4L5 and U4L6, unlike the other environments in the group, have the open positioning present, with U4L5 having a high level of open positioning. The environments U4L5 and U5L5 both have low levels of restrictive tool use, but differ in that U4L5 has low wall positioning and U5L5 has high use of wall positioning and no circular or open positioning.

Type II

The second group, Type II, contains activities U2L4, U2L5, U3L5, and U5L6. They all contain no restrictive tool use, use unrestrictive tools, and with the

exception of U3L5, contain all three types of positioning in their environments to some degree. They are also all large group activities, with no students breaking up into small groups across the cohorts. They all contain moderate to high levels of choice in their activity designs as well.

The Type II environments do have varying levels of movement, levels of interactivity, and degree of unrestricted tool use.

Associations between design attributes and behavior patterns

To further investigate the patterns that existed in the paired comparisons on PC 1, PC 2, and PC 3 results, visualizations were created using Gephi software to look at dissimilarity patterns. To accomplish this, a network graph was created in Gephi with a force-based layout. Each paired comparison which demonstrated a lack of statistical dissimilarity regarding behavior patterns was coded as “1”, thus “pulling” the environment nodes closer together, and each paired comparison which demonstrated statistically significant differences was coded as a “0”, and thus the graph then “pushed” those nodes further apart.

Patterns in paired comparisons on PC 1.

As seen in Figure 72, the paired comparisons show that there was somewhat of a Type I / Type II difference between the overall nonverbal orientation and movement patterns of the students. Type II Environments U2L4, U2L5, and U5L6, while the least dissimilar to each other, were different from all of the Type I environments, including U3L5 (the other Type II environment). Environment U2L4

was not different in regards to movement from environments U4L5 and U4L6 and it was U2L4 that “bridged” the environmental differences between most of the Type II and Type I environments.

Referencing the mean differences between the paired comparisons, the graph also reveals another trend: the nodes with higher movement scores are to the right-hand side of the graph, and as one moves left, the mean differences become less and less with the environment U4L4 having the lowest behavior score (and most still behavior patterns) of all of the environments.

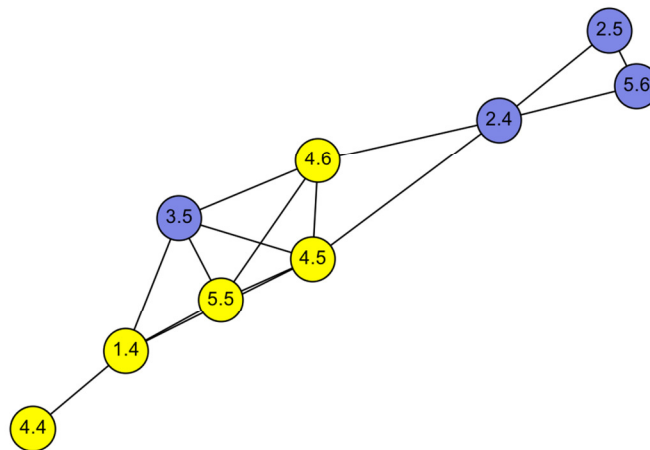


Figure 72. Visualization of dissimilarity from paired comparisons on PC 1

The activity U3L5, while dissimilar in movement from U4L4, U2L4, U2L5, and U5L6, comes from the Type II group initially due to its use of unrestrictive tool use and positioning, was also the only one of its group to lack the “open” positioning. Both U2L4 and U3L5 had only moderate amounts of movement placed into their design environment, with U2L5 and U5L6 incorporating high levels of movement.

Patterns in paired comparisons on PC 2

Figure 73 demonstrates how the paired comparisons show that there was somewhat of a Type I / Type II difference between the overall verbal patterns of the students, but they were not as pronounced between Type I and Type II environments on PC 2 than they were with PC 1. In addition, just as there was a pattern in Figure 72 with scores on PC 1, there are also patterns with scores on PC 2. The right-hand nodes represent (in general) higher scores on PC 2 and as one moves left, the scores on PC 2 are lower; keep in mind that a strong negative scores means strong verbal patterns and higher scores mean less verbal patterns.

Overall the verbal scores of U1L4 and U4L6 are quite strong in the verbal range, and are different from the other design environment verbal scores. Specifically, U1L4 and U4L6 are both different from U2L5, U3L5, U4L5, and U5L6. In addition, U4L6 is also different from U2L4 and U4L4 as well. In comparing environments U4L5 and U4L6 for example, both Type I environments, they were significantly different on verbal patterns, with activity U4L6 having more strong verbal patterns than U4L5. The design elements in environment U4L6 had high restrictive tool use (compared to low in U4L5), high wall positioning regarding the worldbuilding environment (compared to low wall positioning in U4L5), and low open positioning (compared to high open positioning in U4L5).

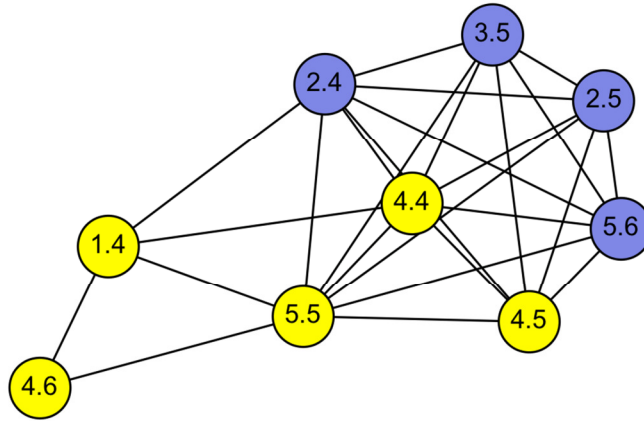


Figure 73. Visualization of dissimilarity from paired comparisons on PC 2

Patterns in paired comparisons on PC 3

Figure 73 demonstrates how the paired comparisons show that there exist quite strong differences between peer orientation patterns on PC 3. Environments U2L5, U3L5, U4L5 and U4L6 are not significantly different from each other regarding the peer-orientation, and on the opposite end of the spectrum, U1L4, U4L4, U5L5, and U5L6 are also not significantly different from each other regarding peer orientation. These two groups, made up of both Type I and Type II environments, are all significantly different from each other according to the paired comparisons. Environment U2L4 again acts as a “bridge” between the two groups as it is more similar to most of both groups in regards to peer-orientation.

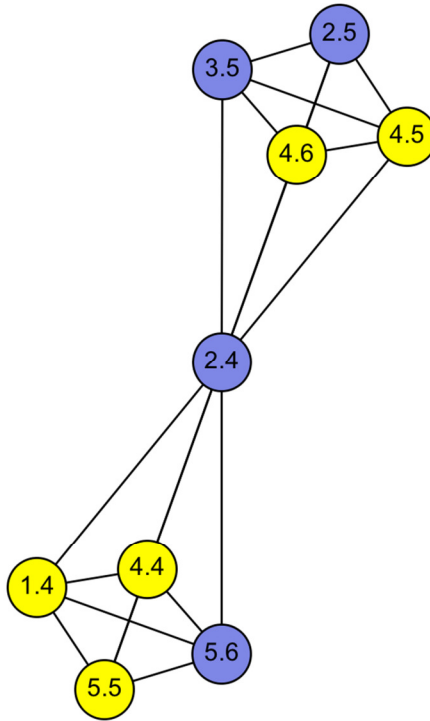


Figure 74. Visualization of dissimilarity from paired comparisons on PC 3

The grouping towards the top of Figure 74 has higher peer-orientation than the grouping in the lower part of the figure. Figures U1L4, U4L4, and U5L5 all have wall positioning with restrictive tool use, being a part of the Type I group, whereas environment U5L6 in fact has the lowest mean score in regards to peer-orientation. Environments U3L5, U3L5, U4L5, and U4L6 all have higher scores on peer orientation, with U4L5 and U4L5 having the highest mean score for peer orientation. It is also important to note that these two activities involve a role play in which students are to “act out” their emotions with another peer.

Patterns in paired comparisons on across all three PCs

Figure 75 shows environments which never reached statistically significant difference across any of the three PCs (thick black lines) and those that were different across two of the PCs (brown lines); those that were different only on one PC are not shown to retain visual simplicity. There are not large separations between groups like we saw in the other graphics, but there is still somewhat of a separation between Type I and Type II environments, with activity U4L5 embedded within the Type II environments graphically, and activity U2L4 is not significantly different from any of the other activities on 2 or 3 principal components.

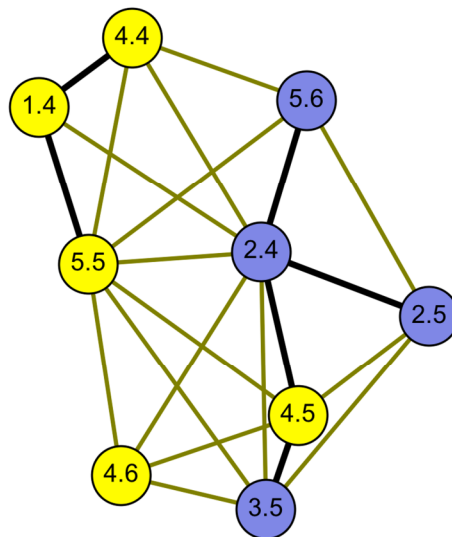


Figure 75. Visualization of overall dissimilarity from paired comparisons on PC 1, PC 2, and PC 3

Looking at the environments that have the greatest amount of dissimilarity, environments U1L4, U2L5, U4L4, U4L6, and U5L6 are five environments that tend to stand out as the most “unique” environments in that they have the most significantly

different paired comparisons across 2 or more of the principal components as indicated in the graph (seen as the least number of edges).

Figure 76 graphs the activity scores on all three principal components with Type I and Type II environments color-coded. In general, Type I environments are the design environments which used restrictive tools (often used for writing), used the wall-type positioning, paired off into small groups or were in groups of 3 or fewer, designed less movement into the activity design and had students who would then verbalize more and orient to their peers less.

In general, the Type II environments used unrestrictive tools, used additional positioning like open and circular in addition to wall, kept as whole groups, designed more movement throughout the activity design, and had students who would then verbalize less but be more peer-oriented.

The above descriptions of Type I and Type II environments are extremely general, and as such, there are activities that deviate from that description. For example, environments U4L5 and U4L6 are highly peer-oriented but have Type I attributes. It is important to note that both of these activities are role plays in which students are asked to act out an emotional role play with each other. This could lend itself to greater peer orientation for activity U4L6 as the students use each other, rather than the world, essentially as learning objects in the activity. Environment U5L6 is clearly low on peer-orientation and low on verbal, even though it is a Type II environment. It is possible that the high amount of movement (running around the environment) lessens the students time and ability to orient to his or her peers.

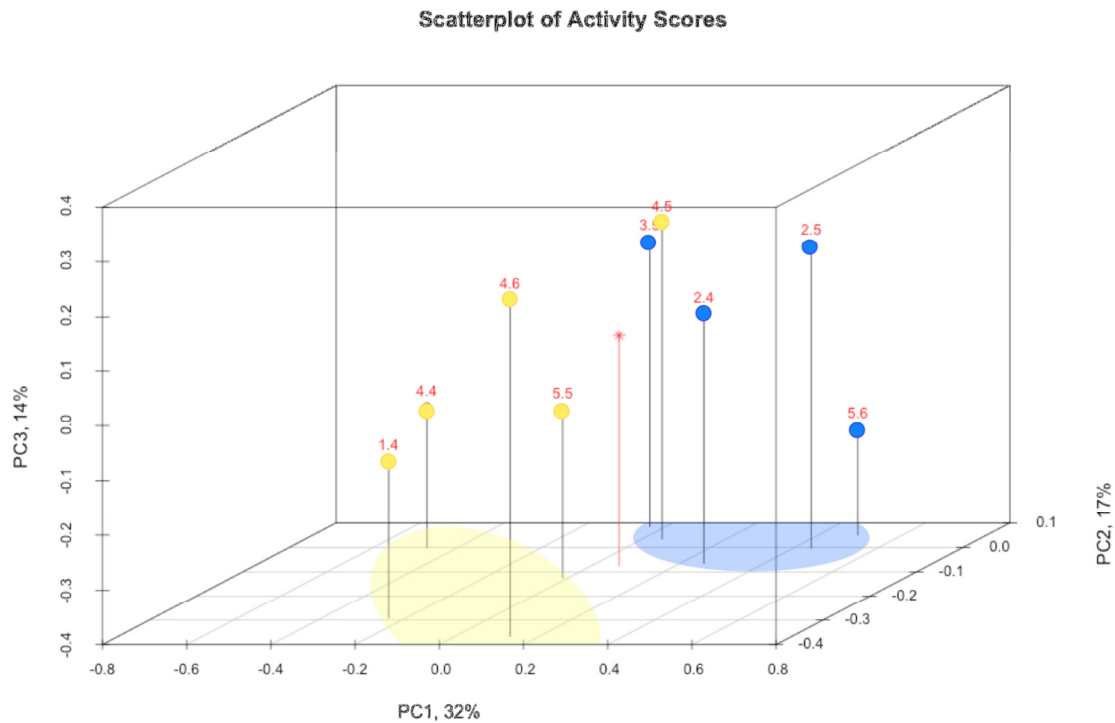


Figure 76. Scatterplot of Type I (yellow) and Type II (blue) activity environments across PC 1, PC 2 and PC 3

Summary of associating environment design attributes with behavior patterns

In summary of the results for RQ 3, the question asked how design attributes might be associated with patterns of behavior. The results indicated that there are indeed differences in design environment attributes and there are general patterns that exist in the design environments and how they relate to behavior patterns of the students. However, design environments contain many potential variables, and the ones identified in this study are potentially only a few of those that may be found salient through future study. The analysis here regarding the environments

was not meant to be all-inclusive, but be an exploratory beginning to help understand potential design contributors to student behavior patterns within the iSocial 3D CVLE.

Following this chapter is the Discussion, followed by limitations and future directions for research.

CHAPTER VI: DISCUSSION AND CONCLUSION

The purpose of this study was to build knowledge on (a) how to characterize complex student performance through co-occurring behavior patterns, (b) how those behavior patterns might differ across iSocial 3D CVLE design environments, and (c) how design attributes are associated with patterns of behavior. Three-dimensional virtual learning environments hold great potential for “learning by doing” by allowing the performance of embodied actions through an avatar within a 3D environment (Hew & Cheung, 2010). Users are not only immersed in these worlds, but can enact complex, social performances within them.

However, there is currently a call from those who study virtual learning environments and serious gaming to understand at a more detailed level what students are doing within the environment, or gather what Hickey et al. (2009) defines as close-level data. Up to this point, most data collected on students within virtual worlds have been at the proximal or distal levels, which are then utilized as proxies to overall student performance in world (Dede, 2012). In other words, if students did well on the proximal and distal assessments, then it is assumed that they did what they needed to be doing within the environment in order to learn. However, the proximal or distal data do not provide the information necessary to (1) evaluate student virtual performance, or (2) inform design decisions and iterations. Proximal and distal data, while important for evaluating learning outcomes, are not directly measuring student behaviors in world. There is a need to

characterize and describe performance within environments where there are many options for action, rather than simple multiple-choice interactions. Close-level data on behavior and performance and the ability to characterize these complex performances, like those found in richly collaborative environments, are what is needed to (1) close the gap regarding formatively evaluating student performance in 3D CVLEs student performance, and (2) use that data to iterate designs, generate design theory, and design environments with intention, which are key components of design-based research (DBRC, 2003).

The target of research question 1 was to see how a method of characterization added meaningful description and insight into a complex, richly collaborative performances within a 3-dimensional world. In doing so, expose the usefulness as a method to characterize and evaluate student performances. Research questions 2 and 3 took the data collected to address research question 1 and examined it for understanding how student performance, as characterized by the methods, is associated with design attributes within the iSocial 3D CVLE.

What follows is a discussion on the study's three research questions regarding characterizing performance via behavior co-occurrences, assertion of findings, and the implications for understanding performance within the iSocial 3D CVLE. Future directions, limitations, and conclusions follow.

Research Question 1: Characterizing student performance through co-occurrences of behavior

Research question one asked, “Can student performance within iSocial 3D CVLE naturalistic practice activities be characterized through co-occurrences of behavior? If so, how and in what ways?”

There has been a call from researchers within the 3D VLE fields for more authentic means to describe, evaluate, and eventually assess individuals’ performances within the VLEs (Dede, 2012; Quellmalz & Pelligrino, 2009), and to cease using solely proximal and distal data as proxies for understanding how students are performing within and using the 3D CVLEs (Quellmalz, 2009; Dede 2012). This study follows in the footsteps of other researchers building knowledge and applying methods from other areas to understand complex performances in 3D CVLEs.

Findings from characterizing performances of students within activities

This study applied ENA techniques (Shaffer et al., 2009; Hatfield, 2011) to analyze the behavior co-occurrences of complex student performances within the iSocial 3D CVLE. This study demonstrated that across all nine iSocial naturalistic practice activities within a highly social and collaborative 3D CVLE, co-occurrence behavior and analysis led to derivation of performance scores, characterizations enabling in-depth descriptions, a visual differentiation between students, and the ability to evaluate student performance within the iSocial 3D CVLE.

Scores were derived for each student, and these scores were interpreted by using major loadings and primary co-occurrences across the three principal components. These components accounted for the greatest amount of variation in behavior data: general orientation and movement (PC 1; 32%), verbalization (PC 2; 17%), and peer orientation (PC 3; 14%). Each student's performance score within an activity was then mapped to a 3D graph and plotted, with 3 scores represented by one 3D point. Each 3D point then represented a rich description of complex co-occurring primary behaviors performed by each student within an activity. This analysis moved forward techniques into virtual world performance analysis as suggested by Quellmalz et al. (2009) and helps to fill the gap described by Dede (2012) and Quellmalz & Pellegrino (2009) for more authentic ways to describe and evaluate individual performances within 3D VLEs.

This study's use of co-occurrence analysis highlighted how behaviors were used together within an activity (or unit of analysis). This analysis modeled user behavior by looking at the primary co-occurrences, with the underlying assumption being that the behaviors students perform together is more informative about performance competency than the frequency counts of the behaviors in isolation. What follows next are several examples from the research question 1 analysis. This serves to highlight the findings that reveal rich characterization and the ability to evaluate student performance.

Example 1

In the U1L4 NP activity example, most of the students' 3D Points resided in the bottom-left-front octant of the graph, negative scores across all three principal components. This meant that the majority of the students were less active, OG-facing, verbal, and non-peer and learning-object-oriented. We can see that A01 spoke the least and should have turned to speak to his peers more (as well as speak more overall). C10 was moving the most, and drill-downs revealed C10 was moving back and forth, with his video recording confirming inappropriate movement while speaking and listening. In addition to characterizing these two students, this co-occurrence analysis of behavior revealed that all of the students should have been more peer-facing, and should have been orienting back and forth between their peers and the facial expressions mediaboard learning object. Rather, the students were talking while almost exclusively facing towards their learning objects and the OG rather than alternating between each other and their learning objects. This characterization of students performing x while doing y is what co-occurrence analysis brings to understanding performances. This integration of behaviors in a performance is often what demonstrating competency in a complex skill requires, as noted in Stichter et al. (2010) regarding integrating behaviors and competencies into a "unified whole" performance for social competency.

Example 2

In the U4L4 NP activity, most of the students' 3D Points spanned across two octants, the bottom-left-front and the bottom-left-back octants. This is represented

by negative scores on PC 1 and PC 3 and having decreased verbalization as a whole group on PC 2. This meant that the students were still very static and OG-facing and learning object-facing, moderately to not very verbal, and not peer oriented. We saw that A03 moved the most and his behavior patterns were extremely distinct from the rest of his peers. Upon drilling down into his behavior and inspecting the video, it can be seen that A03 is off-task compared to the rest of his peers. Even while the rest of the peers were on-task, their social performance was less than ideal. As a whole group, the students should have oriented more between their learning objects and peers, spoke *towards* their peers rather than speaking towards their sticky note learning objects, and in general spoken more overall.

Both the U1L4 and U4L4 NP activities are prime examples of how both formative tracking, evaluation, and feedback could serve both the student as well as the OG in world. Students could potentially receive formative feedback based on their co-occurrences of behavior (for example, talking while facing the learning object as a primary behavior pattern). A feedback system could alert the student to “Remember to turn to your peers while speaking”, or “Remember to keep a calm avatar.” In addition, data given to instructors either while in world or after the session could characterize student performance and alert instructors to behavior patterns that might need verbal correction or specific prompting.

Example 3

In the U2L4 NP activity, all of the students’ 3D Points were positive on PC 1, spanned across PC 2, and mostly positive on PC 3. This meant that students overall

were actively orienting and moving, were orienting and stopping to face their peers, but varied in the amount of verbalizations that they did when they were performing these behaviors. Students A02, B06, and C11 stand out as what could be termed “verbal dominators” in their cohort. Given these rich co-occurrence analyses, we know that there was a verbal dominator in each group with the remaining students in each cohort speaking less; however overall the students were orienting to their peers rather than solely focused on the learning objects. Formative feedback could potentially be given to the verbal dominators, such as “Have you given your other peers a chance to speak?” The analysis could be provided to the online guide to reflect how of the 11 students, 2 were not orienting towards their peers (C09, C10), so prompting could be performed there as well. In addition, the co-occurrence analysis provides a rich context in which to understand behaviors: to what extent, and with what other behaviors it occurred. Based on this characterization, we can then begin to describe and evaluate the behaviors in order to provide formative feedback.

Example 4

The U5L5 NP activity demonstrates that some activities lend themselves to high variability in student performances. Based on each of the students’ 3D Points, an interesting and in-depth characterization can be made about the student’s performance in world. The co-occurrences not only serve to describe what the student performed together or in sequence, but the co-occurring behaviors serve to provide context for the behaviors. For example, we know that in U5L5 student A01

was standing still and not moving. While simply collecting the frequency of movement would describe his behavior, it does not tell us standing still and *something else*. Yet with the co-occurrence analysis, we know that he was standing still *while* facing the online guide *while* not speaking but *while* facing his peers. This type of analysis gives both (a) a rich description as well as (2) a firmer foundation for providing formative feedback, especially when the demonstration of competency requires behaviors to be performed together.

The students in iSocial were learning and practicing to gain skills in social competency. The types of co-occurrences observed that are not ideal involve not turning towards peers while speaking or not facing peers while speaking. The codes used in this study documented movement and orientation, useful for documenting what is important for the student's attention while he is in the environment. However, for the subpopulation of students with ASD, it is concerning that in many situations for many of the students, their primary attention is not shared with others in the environment. Co-occurrence analysis helped to bring this style of behavior to light that might otherwise be more difficult to identify out of context.

Implications of RQ 1

The results from research question one have five important implications to studying performance within 3D CVLEs, listed here: (1) Rich behavioral descriptions at multiple levels of analysis, (2) Ability to differentiate and compare units of analysis such as a student within an activity, (3) Seeing echoes and similarities

within these units of analysis such as students within an activity, (4) Performance and learning assessment triangulation and (5) Methods for understanding complex 3D CVLE performances.

(1) Rich behavioral descriptions across multiple levels of analysis

The results demonstrated that characterizing student performance based on co-occurring behaviors provides rich behavioral descriptions at multiple levels of analysis. In this study, the 3D point represented how and to what degree students performed in general orientation and movement, verbalization, and to what extent they were peer oriented, along with their primary co-occurrences. The visualizations represented hundreds and sometimes thousands of codes. The visualizations also allowed for patterns to be intuitively observed through the display of 3D points in space, though the interpretation of the observed patterns can be somewhat cumbersome. Whereas prior studies in iSocial have displayed complex behavior via histograms for each student (see Schmidt, 2010; Schmidt et al., 2012), the 3D Points convey a rich set of behavior patterns that a student performed within an iSocial activity.

This 3D Point can then be drilled down and analyzed further into another level of analysis of the 3D point. Here the ENA visualizer was able to display the primary behavior co-occurrences within that student's performance. This allowed for further descriptions and analysis, as well as which co-occurrences were happening most often for that student within the activity.

Our primary unit of analysis within this study was a student within an activity, but units of analysis can easily be changed and superimposed on the principal components of interest. The units of analysis are flexible, and can be used to analyze various “groupings” of the data: student performance, cohort performance, or other performances with like-meta data. Any type of meta-data (e.g., represents the same codes) that can be used to group segments together can be used to then describe performance across the multiple levels of analysis. This is done by taking the raw cumulative co-occurrence matrix of interest and multiplying it by the rotation matrix of interest. Because of this flexibility, in this study we were able to also look at units of analysis which represented overall student performance over all activities, as was shown in Figure 58. We were also able to represent the activities themselves as the unit of analysis (see Figure 59). The progression from 3D point to 3 PC scores to drill-down primary co-occurrences is a useful set of multiple levels of analysis of rich performance data, each revealing unique insights about the performance in order to understand and describe what was done in the activity.

It should be noted that all of these descriptions were based on qualitative coding of data, and the ability to describe a performance is not only about the network analysis methods used to create the student scores, but it also relies on quality of that coded data. The codes need to be discrete enough to allow for differentiation as well as be substantive enough as stand-alone descriptors to add value to a performance characterization. A variety of codes is also needed in order to create meaningful differentiation. For example, if only verbal responses and

orientation were coded, the description would not be as rich as our study that used 30 codes.

It is important to note that the codes represent the researcher capturing the behaviors of interest to describe student performance. In addition, the researcher was highly experienced with the setting and the sets of behavior from prior studies and personal experience of watching students in world. These codes are based both on the conceptual understandings of what is important as well as the experiential understanding of what the students do in world. Due to the interest in social performance, our codes captured behaviors like orientation, and distinguished the orientation from orienting to peers or to teachers. We also captured orienting to learning objects as a means to understand *to where* the students were directing their behavior. Our verbalization codes captured more than just when the student spoke, but it also captured whether the verbalizations were appropriate or inappropriate, how many words were used, and whether the verbalization was an initiation, response, or a continuation. These codes were also chosen due to the fact that we were observing students performing within a naturalistic practice. In this NP setting, the expectation is that students demonstrate, rather than simply talk about, social behavior. Together through the combination of the codes and the co-occurrence analysis, we were able to gain a rich understanding of performances within these naturalistic practices.

However if we were to study teacher-led activities where the focus was less on student demonstration of embodied skills and more on cognitive understanding of concepts, the codes could also include verbal content. This would in turn result in

a visual of the student mental model of core concepts, or what is also termed an epistemic network (Shaffer et al., 2009).

Our behavior codes led to interesting and useful descriptions, but many of the more detailed verbal codes were “hidden” due to being present beyond the third principal component. Thus behaviors that do not account for the greatest amount of variation in student behavior may not show in these graphs. However, this can be resolved by (a) looking beyond the principal components that make the cutoff point according to the scree plot, or (b) performing a second analysis with a subset of segments which only include the behavior of interest (for example, verbalization). For example (a), the fourth principal component in this study actually included to what extent students were speaking (did they only speak a few words like “I agree”, “Yes,” or “No”), or did they speak in longer utterances (e.g. “I agree, let’s go with the brick restaurant.”). However, due to the scree cutoff point to maintain parsimony, it was not included in the model. A better way to delve into details of verbalizations, for example, would be through alternative (b) of performing a second analysis with a subset of segments. For example, we could run a second analysis with only the segments that show one of the verbal codes as present; if no verbal codes were present, that segment would be excluded from the analysis. We would receive new PCs and interpretations of those PCs. We would then see details of what the students were doing *while they were speaking*. This would then highlight some of the less frequent behaviors (such as length of verbalizations, inappropriate responses, or inappropriate orientation or gestures while initiating) that do not surface when analyzing all behaviors together.

(2) Differentiate and compare units of analysis

Throughout all students within the nine naturalistic practice activities analyzed in this study, visual analysis helped to differentiate students based on types of co-occurring behavior. For example, in U1L4 student A01 was very static in regards to general orientation and movement, the most nonverbal of all students across all three cohorts. In addition, A01 was not peer-oriented. In contrast, student C10 was overly active, moving his avatar back and forth without discernible purpose and displaying “jittery movements” with a high amount of verbal behavior.

While the purposive sampling in chapter 5 focused on selecting students based on maximum variation for drill-downs and descriptions, we could also see students that performed similar to each other even when they differed between their cohorts. For example, in U4L4, in addition to many students performing similarly to each other overall, B07 and C10 were also very similar to each others’ behaviors across all three PCs in their scores, meaning that their behavior patterns were very similar. As long as there is fidelity of implementation across cohort deliveries, this ability to see similarities and differences across students, no matter their group, enables us to see patterns across students, not based on simple frequencies, but on complex behavior patterns that resonate with the complexity of behavior found within a 3D CVLE.

For example, in the U5L5 NP activity, simple frequencies would show how student A01 had the greatest frequency of behaviors in: facing the online guide while she was speaking, facing the online guide while she was not speaking, and

facing the mediaboard learning object. Student A01 also had the behaviors to much less degree in: facing peers who were speaking, facing peers who were not speaking, verbal responses, and verbalizations greater than or equal to 5 words in length. However, co-occurrence analysis reveals a much more rich description fitting of embodied interaction within a 3D CVLE. With co-occurrence analysis, we can see that A01 faced the mediaboard learning object while facing the online guide while she was speaking, as well as while she was not speaking. When A01 did verbally respond, his responses were primarily greater than or equal to 5 words in length. In addition, while he was verbally responding with greater than 5 words, he was also facing the online guide. However, A01 did not face his peers while verbalizing. When he was facing his peers, it was while he was not speaking, and turned towards the mediaboard learning object while also facing the online guide. The co-occurrence analysis provides details in a way that makes for insights about how behaviors play out in a context of objects, peers and online guide rather than simply seeing behaviors in the more limited context of objects, peers or online guide.

It is important to note that while we were able to differentiate between students, this study was observational in nature; we were not able to compare students to an “ideal” performance pattern within the activities. All students who were participants within this study were deficient in social competency, and this was the reason for participating in the iSocial 3D CVLE. However, because we demonstrated that we can compare and see differences in performance within a 3D CVLE using ENA techniques, which looks at co-occurrences of qualitative codes, it is further evidence that we could also compare students to more ideal, or “expert”

performance. An expert performance could be represented by someone who has mastered the competency and can display that competency within the 3D CVLE. In this case, it would be a person with high social competency skills that can demonstrate those skills successfully according to the objectives defined within the iSocial 3D CVLE.

This technique of comparing novice to experts, and growth from novice to expert performance over time is done in many of the ENA studies. The purpose of ENA techniques, which looks at qualitative co-occurrence of codes, is not only to characterize performance, but to compare a student's change over time in relation to how an expert would perform. ENA studies have done this by including the expert data when constructing the principal components, thus the variance of the PCs no longer represents solely student variation, but student *and* expert variation. For example, if this study were to also include expert data along with our student data, representing experts that perform socially appropriate behavior within a 3D CVLE environment, we could then classify students as overly active or overly static, overly verbal or overly non-verbal. We could then use that information as a basis for providing formative and summative feedback regarding how that student was performing in relation to the ideal, or expert, performance. This would, however, require much more data than was used in this study as well as well-understood expert models for all activities or environments used. This could allow for formative feedback to be given, either in the form of reports that a teacher receives or intelligent agents which use the data to provide student with feedback based on his/her performance. It should be noted that while this comparison topic is

interesting, comparisons are likely more complicated than simple novice to expert. For example, there may be multiple expert models and levels of expertise. However, this discussion section was used as an example to explicate ENA's power for comparison and developing trajectories over time compared to an ideal.

(3) Performance and learning assessment triangulation

The use of close-level data can be used to assist in performance assessment and learning outcomes triangulation. As Ketelhut et al. (2010) found, one type and level of performance and assessment data can lead to mis-categorization of student learning or leading teachers or researchers astray if distal data is not triangulated with another level such as proximal or distal data. By using multiple types of data, not only can additional data provide a more well-rounded picture of a student, but the data can be used to more fully inform the reasons for certain proximal and distal outcomes. For example, if certain learning outcomes were low for one cohort, we could look at the behavior patterns to further inform and provide context to the outcome measurements. In another example, if certain segments of distal learning outcomes are low or not as optimal, triangulating that data with close-level performance data could provide information as to why the distal outcomes in that part of the assessment are low.

(4) Identifying echoes across units of analysis

Echoes appeared across student performances throughout the nine activities, meaning that particular students showed tendencies to perform with certain co-

occurrence patterns across the activities. For example, Student A01, no matter the activity, was often more static, less verbal, but tended to be more peer-oriented than his peers. This pattern is echoed often throughout A01's activity performances relative to his peers. Students B06 and A02, however, were often more active than A01 in regards to general orientation and movement, spoke more (and could possibly be termed verbal dominators), but B06 was often less peer oriented than his peers while A02 was often moderately peer-oriented. Figure 58 summarizes these echoes, and is a useful tool for looking at overall performance over all activities. We can see that cohort B students are shown to primarily have little peer orientation; however it could also be an artifact of having fewer students in the environment. In addition, the echoes can either be seen by (a) looking at a unit of analysis representing the unit of interest as in Figure 58, or (b) connecting lines between the units to establish the trajectories in performance scores across the repeated measurements or time.

Given enough student data, it could be possible to look at *types* of student performances and be able to classify the students, similar to Thawonmas et al. (2008). This could serve to make modifications in world or formative feedback based on the types of student, to study classifications of students and how they interact with types of students in world or with specific design environments, and also potentially to help explain some of the additional student individual variation as was identified in research question 2.

(5) Methods for understanding complex performance within 3D CVLEs

The results indicate that we can gain useful insight in order to characterize complex performance within 3D CVLEs using co-occurrences of behavior. However, our analysis was limited to using 10-second segments, keeping the unit of analysis as student-with-activity, studying naturalistic practice activities (similarly-structured activities), and using all behavioral data collected. The 10-second segment was chosen for multiple factors, some of which were based on the technical constraints of the 3D CVLE software; for example, the students could only use the arrow keys to orient or move, but could never orient and move at the same time. As such, exact co-occurrences were not used and thus a partial-interval approach was taken. This affects the interpretations of the co-occurrences as being more about time spent than number of co-occurrences. Thus segmentation is still being explored and recommendations continued to be refined based on aspects of type of coding (telemetry, qualitative, or both), software capabilities, and purpose of the research.

Whereas this study focused solely on one activity structure type, the naturalistic practice activity, there could also be comparisons regarding different activities and characterizing performances of students between differently structured activities. For example, a comparison of structured practice activities compared to naturalistic practice activities should show a subtle change in student performance. This could inform if there is an overall difference between the structured practices and the naturalistic practices in terms of student performance.

Additionally, this study used all behavioral data coded, but the data could also be split as to analyze only behaviors while individuals are speaking, and the analysis re-run in order to understand how, in what ways, and to what extent students vary according to the types of verbalizations they make and what they are doing with their bodies while they are speaking. This would allow further analysis of a subset of behaviors. Data could also be organized and grouped by different meta-data codes; in this study it was student and activity. However, other studies could further analyze performances by looking at age, gender, activity elements, cohort, or other meaningful lenses for understanding and characterizing performance.

Summary of research question 1

Our study revealed that we can richly characterize performance based on behavior co-occurrences to gain insight into student behavior patterns that would not otherwise be present with frequency alone. While our findings are limited in regards to generalization to other 3D CVLEs, there are potential implications for further and continued study to understand characterizing performance in 3D CVLEs.

It was stated earlier that co-occurrence analysis is useful for revealing performance competency due to the nature of characterizing not just how many behaviors a student is using, but how they are using the behaviors together in a performance. Findings for research question 1 supported this. However designs in which the performances must occur may have the potential to constrain or invite certain behaviors. If that is the case, designers may be unintentionally constraining performances. On the other hand, designers may have the ability to invite certain

performances by designing with intention if the relationship between design attributes and performance are more fully understood. This leads to research questions 2 and 3.

Research Questions 2 and 3: Associating design attributes with patterns of behavior

Research questions 2 and 3 asked if co-occurrences of behavior differed significantly across activities, and if so, if there were design attributes that were associated with patterns of behavior. The purpose of research questions 2 and 3 were to determine (1) if there was a significant difference between levels of environment on behavior scores, and (2) how design attributes might be associated with patterns of behavior by (a) looking for key attributes in designs and (b) associating those attributes with behavior patterns. The purpose of this question is to understand more fully how design attributes may facilitate certain performance patterns and co-occurrences of behavior. In doing so, designers may be better able to design with intention as well as iterate future designs based on these methods.

(1) Significant behavior differences between environments

Descriptive statistics revealed increasing and decreasing changes over time rather than a smooth linear trend over time across the principal components. An interesting observation for the PC 3 graph shown in Figure 62 was suppression in

Cohort B for peer orientedness. Cohort B only had 3 students, and as such, this suppression of peer orientation scores could reflect on the opportunity to orient to peers. The fewer the peers there are in the environment, the more “work” it takes to orient to them, and thus the likelihood of doing so may be less. This could be one of several “opportunities” that is constrained by student number in the environment.

Linear mixed modeling was then performed using a random-intercept model, equivalent to repeated measures ANOVA (West et al., 2012). This approach benefits smaller studies with higher numbers of repeats and missing data, in that no data is thrown out due to a missing time point. In addition, the linear mixed model is flexible enough to also add in additional random effects, such as time, if it is a covariate that is not of interest to the study but needs to be controlled.

In this study, *time* did not have a significant linear effect across any of the three PC scores. However, *environment* was significant across all three PC scores. It would be naturally expected that as students became more comfortable and skilled over time, that they may perform more movement and orientation, verbalizations, and peer-oriented behaviors. However, the lack of significant linear effect and the significant effect of activity environment on behavior demonstrated that it may be the environmental design, rather than time spent in the environment, that is the influences patterns of behavior.

The post-hoc Sidak multiple comparison tests revealed there were significant differences in behavior scores between activities, with the most differences found across PC 1 (general orientation and movement), followed by PC 3 (peer orientation), with the fewest differences found across PC 2 (verbal behavior). The

differences on PC 1 and PC 3 tended to coincide with environment attribute patterns.

This means that environment design matters, and design is likely to invite and constrain behaviors, whether desirable or undesirable. The analyses also demonstrate that environmental design played an important role in students' non-verbal behavior such as active and static orientation and movement. Environmental design played *less* of a role in the type and extent of student verbalization patterns. This could indicate that verbalizations may need more direct prompting; however design attributes can play a significant role in avatar behavior, both in inviting and constraining not just numbers but patterns of behavior.

Given the nature of the behavior score fluctuations across time, the significance of the LMM and the post-hoc results support the validity of looking at design attributes and how they are associated with behavior patterns. By finding associations, this can then inform what is potentially inviting and constraining overall behavior in environments.

(2a) Types of environments based on key attributes

Key attributes of environmental and activity design emerged through qualitative memos. The attributes were rated as high, moderate, low, or not present within each of the nine naturalistic practice activities. Two general types of activities were labeled, "Type I" and "Type II". These types were not made to generalize across all 3D CVLEs, but were specific in regards to the salient attributes present within the nine iSocial NP activity designs and environments. Type I and Type II environments

tended to differ from each other across general orientation and movement (PC 1), and peer orientation (PC 3) with much less differentiation between the groups in regards to verbalization (PC 2).

Some of the key attributes of Type I had: restrictive tool use, no circular positioning regarding worldbuilding design, and high levels of wall positioning. Type I environments were associated with less orientation and movement (more static avatar behavior), less peer orientation, and slightly greater verbal, with the exception of U4L5 and U4L6, which fell high on peer-orientation. These two activities were different from the rest of the Type I activities in that rather than focusing on learning objects of interest (items in world), the students were told to focus on each other and perform role plays. In a sense, they used each other as the learning objects rather than told to converse about objects in world. For the remaining Type I activities, the strong use of wall positioning may have made it more difficult for students to find a position where they could see each other as well as the learning object of discussion. This would be especially true if that learning object is restrictive in nature and locks their avatar in place when they are actively using it. It is important to note that all except for one (U1L4) of the tools that were restrictive in nature were also writing tools. The slightly greater verbal behavior that is seen in these activities could be more related to the fact that students are writing and less about the tool use, but that is unknown and is an area for further investigation.

Some of the key attributes of Type II environments were: no restrictive tool use, use of large group activities, and containing all three types of world positioning

for worldbuilding design (circular, wall, and open). Type II environments were associated with greater general orientation and movement, greater peer orientation, and slightly less verbal behavior patterns, with the exception of U3L5, which fell amongst the Type I activities regarding orientation and movement. It is of interest to note that while U3L5 had moderate use of circular positioning in regards to worldbuilding design, many of the students did not take advantage of this because the environment was not as spacious as in the other activities. For example, the accuracy one needed in order to navigate around the learning objects (meaning the space between the objects and restaurant buffets were tight) were much greater in U3L5 than in any of the other activities in which circular positions were used. This could have resulted in fewer students navigating around some of the buffets, although that was done in one of the cohorts by one student (C10). This would be an ideal area where merging playtrace data with co-occurrence could be useful.

Additionally, the use of circular and open positioning in many of the Type II environments allowed students to easily surround a learning object or group together for discussion, increasing movement and peer orientation. In one sense, it could be seen that the student is acting the same way in the following situations: (a) a student looks at a learning object in the wall position, and (b) a student looks at a learning object in a circular position but someone walks around the other side and stands in front of him/her. In scenario b, the student is not behaving differently than scenario a. However, the key here is that the learning object and environment was designed in such a way as to facilitate, and not restrict, opportunities for interaction and learning. Open and circular positioning and designs tended to promote

opportunities for peer orientation, general orientation, and movement over environments with wall position designs and other restrictive tool use attributes.

Another interesting example is that of U5L6, which has the highest amount of orientation and movement of all the activities, as well as very low peer orientation. It is possible that due to the heavy amount of required movement throughout the environment that this decreased the amount of time they could be facing each other, as the students were running from location to location. In essence, the design of the activity and environment might have removed opportunities for peer orientation in favor of running from one location to another.

(2b) Findings for iSocial based on patterns of attributes associated with patterns of behavior

Network graphs were used to visually describe the relationship of Type I and Type II designs (yellow and blue nodes) with significant differences according to the post-hoc multiple comparison tests. This served to visually display the relationship between and among those elements.

For PC 1, Type I and Type II designs differed, with all Type I plus U3L5 somewhat grouping together to form the more static orientation and movement, whereas the Type II environments (minus U3L5) grouped together to form the more active orientation and movement. U4L4 was the most dissimilar from all other lessons in orientation and movement (the most static), having only a non-significant difference from U1L4. Here the Type I / Type II dichotomy in designs is somewhat confirmed in regards to Type II generally promoting more active orientation and

movement and Type I generally constraining active orientation and movement. However, U4L5 and U4L6, the role playing activities, do have some more similarity to U2L4 than U2L5 and U5L6. It is also important to note that U4L5 and U4L6 are the only Type I designs that have some level of open positioning attribute.

This could indicate, for example, that iSocial designers may want to redesign U4L4 and U1L4 to have more Type II properties such as unrestrictive tool use and open or circular positioning so that students may have more opportunities to orient towards peers.

For PC 2, The Type I and Type II designs still have somewhat of a behavior association, but it is not as clear as PC 1 or in PC 3. What stands out here is that there is much less difference in verbal performance behavior relationships between Type I and Type II designs than in PC 1 or PC 3. In general, the Types are not significantly different from each other in regards to performance, but U1L4 and U4L6 stand out as extremely high verbalizing activities. Activity U4L6 was the role playing with mediaboard planning, and U1L4 was the mediaboard facial expressions activity. In addition, they were all small group activities. It is possible that small group activities may promote more opportunities for verbalization.

For PC 3, we see a very distinct association between activities and behavior performance, but they are not perfectly across Type I and Type II design attribute lines. One Type II activity, U5L6 quest activity, is extremely low in peer orientation and is paired with the other Type I environments which used restrictive tools such as mediaboards and sticky notes for their main interactions. Again the two role playing activities, U4L5 and U4L6 are over with the other two Type II activities for

peer orientation. As mentioned earlier, that students are to role play with each other helps them to use each other as learning objects in a sense, and may facilitate the peer orientation. Since orienting to peers is a desired behavior across all activities for our students, we might consider having more open and circular areas, as well as redefining the lessons to include each other in ways other than simply verbal in order to interact, as was done in the role playing activities.

Implications

Results from research questions 2 and 3 provide us with interesting insight and implications. We can see that as a whole, we confirmed that the way environments are designed can invite and constrain patterns of behavior, and that this power to do so, in this study with these students, was more “powerful” than the influence of time spent learning in the environment. In addition, *specific attributes* and combinations of attributes separated the types of behavior, especially nonverbal behavior, that was performed in the environment.

Additionally, there is currently no literature that the researcher found that discusses the type of positioning (e.g. wall, circular, open) and the impact it may have on user performance, other than research that looks for navigational issues. It may likely be due to the fact that most 3D VLEs are not highly collaborative like iSocial, nor are they open-ended in the numerous ways users can enact performances. However, as designers make learning areas for 3D CVLEs and wish for users to participate with the object as well as with each other, the results of this

study show that lowering the height and making less wall-type positions may support greater peer orientation.

It was mentioned earlier that we can look at data based on units of analysis of varying types based on the meta data. An interesting implication of this method is that we could also label segments with certain meta-data labels according to activity types or specific attributes, such as wall or circular positioning. For example, we could label all segments according to the positioning that the student was in. We could then filter all segments for only those that contained positioning information. Then, we could graph 3D Points of each positioning type onto graph representing the principal components, and drill down into the common co-occurrences for each positioning type. This could server to inform designers on the differences between certain styles of worldbuilding, or other types of attributes they would like to explore.

While this study was a case study and the results are not meant to generalize to a broader population, the methods may have broader application and implications regarding studying performance within a 3D CVLE. Further studies on attributes of design which are associated with patterns of behavior finds promise within this study, and thus further study is recommended. By understanding how attributes of design can relate to behavior patterns and opportunities for facilitating behavior patterns, best practices for design as well as developing design theory for 3D CVLEs and VLEs can be developed.

Future Directions

This study was an exploratory, retrospective case study of student performance within the iSocial 3D CVLE. The findings provide insights about behavior and performance within a 3D CVLE, but point to future directions of study. Additional studies would serve to extend our understanding of how understand, gain insights about performance, and create generalizations and inferences beyond the context of this study.

While the purpose of this study was to explore behavior co-occurrences, it would be beneficial to explore methodological affordances of multiple approaches in understanding and describing performances within 3D CVLEs. For example, what can be gained from using the same method, but instead using behaviors rather than behavior co-occurrences? What if both methods are employed? Since behavior co-occurrences have the potential to lose data when there are no co-occurrences, what might be ideal environments in which co-occurrences are better than simply frequencies? How might multiple methods inform each other?

The inclusion of expert data and trajectories over time would also be of key importance. While the ENA literature has performed novice-to-expert comparisons and analyzed these trajectories over time, it has yet to be performed within a 3D CVLE, as this was a beginning application of that technique into this type of environment. Additional ways to explore and compare performances to ideal performances should also be explored and techniques refined.

Additional future directions could be in relating performance data and how that rich in-world behavioral data can inform proximal and distal outcome measurements. How and in what way might this in-world data be related to student outcomes? If that can be understood to a greater degree, that would then be related to our design question of promoting behavior patterns in world through design.

As mentioned in the previous section, additional studies would also be to extend the current methods to analyze design attributes and behavior patterns that are associated with those attributes. This study was not conclusive and as such, provides an insight that there is a relationship, and further studies should be conducted. This would provide insight into needed design theory for 3D CVLEs and VLEs.

Additionally, it should be noted that the methods used in this study can be generalized, and applying these methods or iterations thereof to different domains within 3D CVLEs would be an additional future direction. Figure 77 illustrates the methods process used in this study to answer (a) How to characterize performance via behavior co-occurrences in a 3D CVLE, (b) how this then informs how to detect differences in performance across design environments, and (c) how then to associate patterns of performance with patterns of design attributes. This process represents identifying the desired codes a priori by identifying the objectives or behaviors within that domain. If those are not yet identified, they would be identified during the coding process using grounded theory techniques (as indicated by the asterisks). It is in this customization of the codes that this process can be

adapted for domains in which behavior co-occurrences are important to measure rather than just frequencies alone.

Overall, understanding how behaviors and behavior patterns can be promoted and opportunities created through activity and environmental design attributes, an important aspect in human computer interaction and virtual world design, is going to continue to be a key future direction for research.

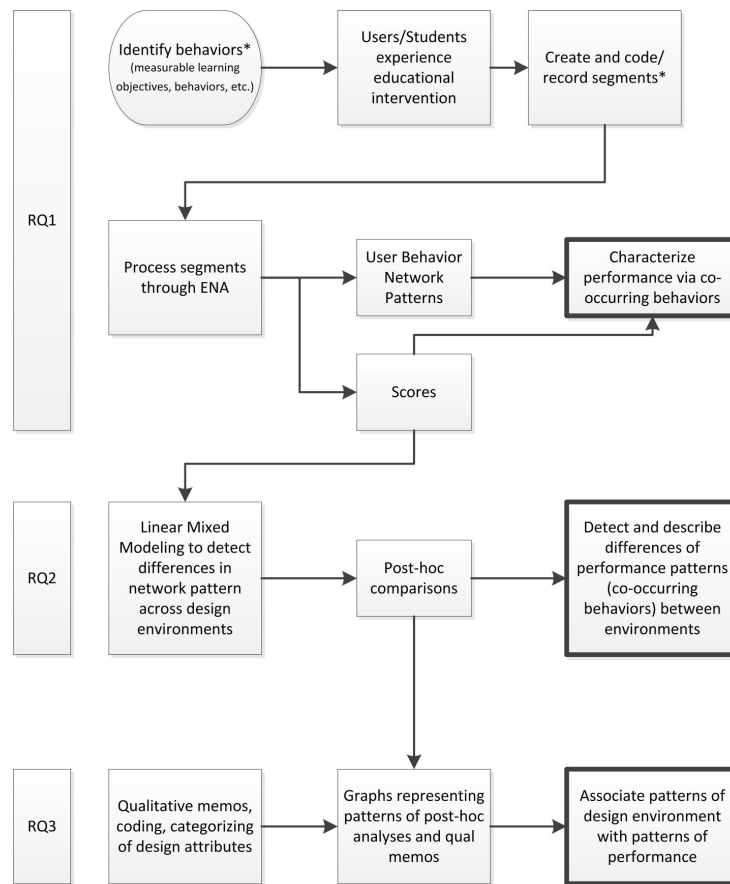


Figure 77. Methods to study performance via co-occurrences of behaviors in 3D CVLEs.
 * If codes are not identified a priori, one can use grounded theory techniques as found in the ENA literature during the coding process

Limitations

This study design was an exploratory, retrospective case study, which means the findings are used to enlighten and understand the unique aspects of performance within this special and unique context. In other words, the findings in this study cannot be generalized to other studies with different contextual attributes. iSocial is an innovative design for addressing special needs at a distance that require social and active learning. Because of this, the results should be interpreted with caution outside of different contexts. However, the results may provide insight and prove to be a model for like-forms of 3D CVLEs in the future.

The statistical analyses used to quantify the qualitative codes (PCA using SVD) were a form of intra-sample statistical analysis (Shaffer & Serlin, 2004), and are “elements of quantification and generalization within [the] qualitative research design” (Ercikan & Roth, 2006 p. 15), rather than to make inferences to a broader population. The statistical analyses used in the co-occurrence data were meant to highlight features within the samples used. In addition, the linear mixed model was also employed, though the analysis was used in the qualitative sense of highlighting patterns within a case study in order to reveal and highlight those differences. Because of this, the statistical analyses should not be used to make inferences beyond this case study, but could be used to inform future study designs that would be able to make broader inferences about 3D CVLE design.

The study used participants with a diagnosis of ASD who were all males, Caucasian, and adolescents; as such the resulting performances should not be

considered typical, although we do not have “typical” data to compare in order to determine to what level or degree their performance might have differed from typical 3D CVLE behavior. In addition, only 11 participants were studied, and thus the resulting principal components and ways in which students varied could change as additional data would be added to the dataset.

The design attributes, which emerged from the data, were the most salient ones, however they are related to iSocial 3D CVLE design. It is likely that as other designs are analyzed and attributes categorized, different and more specific attributes may emerge. As such, the attributes identified in this study should be seen within the context of this case study and used to inform other methods of future studies rather than to make broader inferences about 3D CVLE design.

Conclusion

In conclusion, this study showed that behavior co-occurrences can provide insight into multiple levels of rich characterizations of student within 3D CVLEs. We found that student performance did differ across design environments, and that patterns of behavior were associated with patterns of design attributes. This study built knowledge about an additional way to understand performance within 3D CVLEs through the case study of iSocial 3D CVLE, and established promising future directions for building design theory for 3D CVLEs.

REFERENCES

- About OpenWonderland. (n.d.). About Open Wonderland. [Web page]. Retrieved from <http://openwonderland.org/about>.
- American Psychiatric Association. (1994). *Diagnostic and statistical manual of mental disorders (Fourth ed.)*. Washington, D.C.: American Psychiatric Association.
- Amory, A. (2007). Game object model version II: A theoretical framework for educational game development. *Educational Technology Research and Development, 55*(1), 51-77. doi:10.1007/s11423-006-9001-x
- Arici, A. D. (2009). *Meeting kids at their own game: A comparison of learning and engagement in traditional and 3D MUVE educational-gaming contexts*. Retrieved from ProQuest Digital Dissertations. (UMI No. 3342204)
- Bagley, E. A. S. (2011). *Stop talking and type: Mentoring in a virtual and face-to-face environmental education environment*. (Doctoral Dissertation, University of Wisconsin). Retrieved from <http://edgaps.com>.
- Barab, S., Gresalfi, M., Ingram-Noble, A., Jameson, E., Hickey, D., Akram, S., & Kizer, S. (2009). Transformational play and virtual worlds: Worked examples from the Quest Atlantis project. *International Journal of Learning and Media, 1*(2). doi:10.1162/ijlm.2009.0023
- Barab, S. A., & Plucker, J. A. (2002). Smart people or smart contexts? Cognition, ability, and talent development in an age of situated approaches to knowing and learning. *Educational Psychologist, 37*(3), 165–182. doi:10.1207/S15326985EP3703_3
- Barab, S., Thomas, M., Dodge, T., Carteaux, R., & Tuzun, H. (2005). Making learning fun: Quest atlantis, a game without guns. *Educational Technology Research and Development, 53*(1), 86-107. doi:10.1007/BF02504859
- Baron-Cohen, S., Leslie, A. M., & Frith, U. (1985). Does the autistic child have a 'theory of mind'? *Cognition, 21*, 37-46. doi:10.1016/0010-0277(85)90022-8

- Baron-Cohen, S., Wheelwright, S., Spong, A., Scahill, V., & Lawson, J. (2001). Are intuitive physics and intuitive psychology independent? A test with children with asperger syndrome. *Journal of Developmental and Learning Disorders, 5*, 47-78.
- Bartholomew, D., Steele, F., Galbraith, J., & Moustaki, I. (2008). Analysis of multivariate social science data (2nd ed.). Boca Raton, FL: CRC Press.
- Benson, A. D. (2003). Assessing participant learning in online environments. *New Directions for Adult and Continuing Education, 2003*(100), 69-78. doi:10.1002/ace.120
- Bowers, L., Huisingh, R., & LoGiudice, C. (2007). *Test of problem solving 2: Adolescent*. LinguiSystems East Moline, IL.
- Börner, K., Penumarthy, S., DeVarco, B., & Kerney, C. (2005). Visualizing social patterns in virtual environments on a local and global scale. Lecture Notes from Digital Cities III: Information Technologies for Social Capital: Cross-cultural Perspectives in Springer, Berlin. (pp. 325-340).
- Brown, J. S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher, 18*(1), 32-42. doi:10.3102/0013189X018001032
- Bryant, F. B., & Yarnold, P. R. (1998). Principal-components analysis and confirmatory factor analysis. In L. G. Grimm & P. R. Yarnold (Eds.), *Reading and understanding multivariate statistics*. Washington, DC: American Psychological Association.
- Carroll, C., Patterson, M., Wood, S., Booth, A., Rich, J. & Balain, S. (2007). A conceptual framework for implementation fidelity. *Implementation Science, 2*(40). doi:10.1186/1748-5908-2-40. Retrieved from <http://www.implementationscience.com/content/2/1/40>.
- Chen, C., & Börner, K. (2005). From spatial proximity to semantic coherence: A quantitative approach to the study of group dynamics in collaborative virtual environments. *Presence: Teleoperators & Virtual Environments, 14*(1), 81-103. doi:10.1162/1054746053890260
- Cheng, Y., & Ye, J. (2010). Exploring the social competence of students with autism spectrum conditions in a collaborative virtual learning environment – the

- pilot study. *Computers & Education*, 54(4), 1068 - 1077.
doi:10.1016/j.compedu.2009.10.011
- Cheng, Y., Chiang, H. -C., Ye, J., & Cheng, L. -H. (2010). Enhancing empathy instruction using a collaborative virtual learning environment for children with autistic spectrum conditions. *Computers & Education*, 55(4), 1449 - 1458.
doi:10.1016/j.compedu.2010.06.008
- Chittaro, L., Ranon, R., & Ieronutti, L. (2006). VU-Flow: A visualization tool for analyzing navigation in virtual environments. *Visualization and Computer Graphics, IEEE Transactions*. 12(6), 1475-1485. doi: 10.1109/TVCG.2006.109
- Chodos, D., Stroulia, E., Boechler, P., King, S., Kuras, P., Carbonaro, M., & de Jong, E. (2010). Healthcare education with virtual-world simulations. In L. Clarke & J. Weberjahnke (Eds.), *Proceedings of the 2010 ICSE workshop on software engineering in health care* (pp. 89-99). New York: ACM. (pp. 89-99).
doi:10.1145/1809085.1809097
- Choi, B., & Baek, Y. (2011). Exploring factors of media characteristic influencing flow in learning through virtual worlds. *Computers & Education*, 57(4), 2382-2394. doi:10.1016/j.compedu.2011.06.019
- Cicchetti, D. V. (1994). Guidelines, criteria, and rules of thumb for evaluating normed and standardized assessment instruments in psychology. *Psychological Assessment*, 6(4), 284. doi:10.1037/1040-3590.6.4.284
- Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, 20(1), 37-46.
doi:10.1177/001316446002000104
- Constantino, J. N., & Gruber, C. P. (2005). *Social responsiveness scale (SRS)*. Los Angeles, CA, USA: Western Psychological Services.
- Dede, C. (2005). Planning for neomillennial learning styles. *Educause Quarterly*, 28(1), 7-12. Retrieved from www.educause.edu.
- Dede, C. (2012). Interweaving assessments into immersive authentic simulations: Design strategies for diagnostic and instructional insights. *Presented at the Invitational Research Symposium on Technology Enhanced Assessments, K-12 Center at ETS*, May 7-8, 2012.

- Dede, C., Clarke, J., Ketelhut, D. J., Nelson, B., & Bowman, C. (2005). *Students' motivation and learning of science in a multi-user virtual environment*. Paper presented at the annual meeting of the American Educational Research Association Conference, Montreal, Canada.
- Dede, C., Nelson, B., Ketelhut, D. J., Clarke, J., & Bowman, C. (2004). Design-based research strategies for studying situated learning in a multi-user virtual environment. In *Proceedings of the 6th international conference on learning sciences* (pp. 158-165). Mahwah, NJ: Lawrence Erlbaum.
- Design Based Research Collective. (2003). Design-Based research: An emerging paradigm for educational inquiry. *Educational Researcher*, 32(1), 5-8. Retrieved from <http://www.jstor.org/stable/3699927>.
- Dickey, M. D. (2005a). 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(3), 439-451. doi:10.1111/j.1467-8535.2005.00477.x
- Dickey, M. D. (2005). Engaging by design: How engagement strategies in popular computer and video games can inform instructional design. *Educational Technology Research and Development*, 53(2), 67-83. doi:10.1007/BF02504866
- Dickey, M. (2007). Game design and learning: A conjectural analysis of how massively multiple online role-playing games (MMORPGs) foster intrinsic motivation. *Educational Technology Research & Development*, 55(3), 253-273. doi:10.1007/s11423-006-9004-7
- Dickey, M. D. (2011). Murder on Grimm Isle: The impact of game narrative design in an educational game-based learning environment. *British Journal of Educational Technology*, 42(3), 456-469. doi:10.1111/j.1467-8535.2009.01032.x
- Dixit, P. N., & Youngblood, G. M. (2008). Understanding playtest data through visual data mining in interactive 3d environments. In *12th international conference on computer games: AI, animation, mobile, interactive multimedia and serious games (CGAMES)* (pp. 34-42).
- Drachen, A., & Canossa, A. (2009). Analyzing spatial user behavior in computer games using geographic information systems. In *Proceedings of the 13th*

international mindtrek conference: Everyday life in the ubiquitous era (pp. 182-189).

Ducheneaut, N., & Moore, R. J. (2004). The social side of gaming: A study of interaction patterns in a massively multiplayer online game. In *Proceedings of the 2004 ACM conference on computer supported cooperative work* (pp. 360-369).

Ducheneaut, N., & Moore, R. J. (2005). More than just XP: Learning social skills in massively multiplayer online games. *Interactive Technology and Smart Education*, 2(2), 89-100. doi:10.1108/17415650580000035

Ducheneaut, N., Moore, R. J., & Nickell, E. (2007). Virtual third places: A case study of sociability in massively multiplayer games. *Computer Supported Cooperative Work (CSCW)*, 16(1), 129-166. doi:10/1007/s10606-007-9041-8

Eaves, L. C., & Ho, H. H. (1997). School placement and academic achievement in children with autistic spectrum disorders. *Journal of Developmental and Physical Disabilities*, 9(4), 277-291. doi:10.1023/A:1024944226971

Elliott, R. (2003). Executive functions and their disorders imaging in clinical neuroscience. *British Medical Bulletin*, 65(1), 49-59. doi:10.1093/bmb/65.1.49

Ercikan, K., & Roth, W. M. (2006). What good is polarizing research into qualitative and quantitative? *Educational Researcher*, 35(5), 14-23. doi:10.3102/0013189X035005014

Fleiss, J. L. (1971). Measuring nominal scale agreement among many raters. *Psychological Bulletin*, 76(5), 378.

Gagné, A., El-Nasr, M., & Shaw, C. (2011). A deeper look at the use of telemetry for analysis of player behavior in RTS games. *Entertainment Computing--ICEC 2011*, 247-257. doi:10.1007/978-3-642-24500-8_26

Galyen, K. (2012). *Analyzing Behavior Co-occurrences in the iSocial 3D CVLE: A Pilot Study*. Unpublished work.

GAPS. (n.d.). Web page of the Epistemic Games Group. [Web page.] Retrieved from edgaps.org: <http://edgaps.org/gaps>.

- Gee, J. P. (2007). *What video games have to teach us about learning and literacy* (2, revised ed., p. 256). New York: Macmillan.
- Gioia, G. A., Isquith, P. K., Guy, S. C., & Kenworthy, L. (2000). *Behavior rating inventory of executive function: Professional manual*. Lutz, FL: Psychological Assessment Resources, Incorporated.
- Goggins, S., Schmidt, M., Guajardo, J., & Moore, J. L. (2011). 3D virtual worlds: Assessing the experience and informing design. *International Journal of Social and Organizational Dynamics in IT*, 1(1), 30-48.
doi:10.4018/ijsoedit.2011010103
- Goggins, S. P., Schmidt, M., Guajardo, J., & Moore, J. (2010). Assessing multiple perspectives in three dimensional virtual worlds: Eye tracking and all views qualitative analysis (AVQA). In *System sciences (HICSS), 2010 43rd Hawaii International Conference* (pp. 1-10). doi:10.1109/HICSS.2010.71
- Halperin, M., Lan, K. K. G., & Hamdy, M. I. (1988). Some implications of an alternative definition of the multiple comparison problem. *Biometrika*, 75(4), 773-778.
doi:10.2307/2336318
- Hatfield, D. (2011). *The right kind of telling: An analysis of feedback and learning in a journalism epistemic game*. (Doctoral Dissertation, University of Wisconsin). Retrieved from <http://edgaps.com>.
- Hew, K. F., & Cheung, W. S. (2010). Use of three-dimensional (3-D) immersive virtual worlds in K-12 and higher education settings: A review of the research. *British Journal of Educational Technology*, 41(1), 33-55. doi:10.1111/j.1467-8535.2008.00900.x
- Hickey, D., Ingram-Goble, A., & Jameson, E. (2009). Designing assessments and assessing designs in virtual educational environments. *Journal of Science Education and Technology*, 18(2), 187-208. doi:10.1007/s10956-008-9143-1
- Hou, H. T. (2012). Exploring the behavioral patterns of learners in an educational massively multiple online role-playing game (MMORPG). *Computers & Education*, 58, 1225-1233. doi:10.1016/j.compedu.2011.11.015
- Howlin, P. (2000). Outcome in adult life for more able individuals with autism or asperger syndrome. *Autism*, 4(1), 63-83.
doi:10/1177/1362361300004001005

- Howlin, P., Baron-Cohen, S., & Hadwin, J. (2000). Teaching children with autism to mind-read: A practical guide. *European Journal of Special Needs Education, 15*(1), 99-103. doi:10.1080/008562500361745
- Howlin, P., Mawhood, L., & Rutter, M. (2000). Autism and developmental receptive language disorder: A follow-up comparison in early adult life. II: Social, behavioural, and psychiatric outcomes. *Journal of Child Psychology and Psychiatry, 41*(5), 561-578. doi:10.1111/1469-7610.00643
- Jeanie, T., Jack, S., Vicki, T., Linyan, M., & Eric, F. (2007). Social skills training for adolescents with asperger syndrome and high-function autism. *Journal of Autism and Developmental Disorders, 37*, 1960-1968.
- Kafai, Y. B., & Giang, M. T. (2007). Virtual playgrounds: Childrens multi-user virtual environments for playing and learning with science. In *Children's Learning in a Digital World*. Blackwell Publishing, Oxford, UK.
- Kelley, K. (2005). The effects of non-normal distributions on confidence intervals around the standardized mean difference: Bootstrap and parametric confidence intervals. *Educational and Psychological Measurement, 65*(1), 51-69. doi:10.1177/0013164404264850
- Ketelhut, D. J., & Schifter, C. C. (2011). Teachers and game-based learning: Improving understanding of how to increase efficacy of adoption. *Computers & Education, 56*(2), 539 - 546. doi:10.1016/j.compedu.2010.10.002
- Ketelhut, D. J., Dede, C., & Clarke, J. (2008). Studying situated learning in a multiuser virtual environment. In *Assessment of Problem Solving Using Simulations, 37*.
- Ketelhut, D. J., Nelson, B. C., Clarke, J., & Dede, C. (2010). A multi-user virtual environment for building and assessing higher order inquiry skills in science. *British Journal of Educational Technology, 41*(1), 56-68. doi:10.1111/j
- Krueger, C. & Tian, L. (2004). A comparison of the general linear mixed model and repeated measures ANOVA using a dataset with multiple missing data points. *Biological Research for Nursing, 6*, 151-157. doi:10/1177/1099800404267682
- 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

- Laffey, J., Schmidt, M., Stichter, J., Schmidt, C., & Goggins, S. (2009). iSocial: A 3D VLE for youth with autism. In *Proceedings of the 9th international conference on computer supported collaborative learning-volume 2* (pp. 112-114).
- Laffey, J., Schmidt, M., Wang, X., Henry, H., & Stichter, J. (2009). Examining interaction in 3D VLE: A case study of an analytic approach. Paper presented at the 2009 American Educational Research Association.
- Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159-174. Retrieved from <http://www.jstor.org/stable/2529310>.
- Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge Univ Press.
- Leonard, A., Mitchell, P., & Parsons, S. (2002). Finding a place to sit: A preliminary investigation into the effectiveness of virtual environments for social skills training for people with autistic spectrum disorders. In *Proceedings of international conference on disabilities, virtual reality and associated technology*. (pp. 249-258). University of Reading: Veszprem, Hungary.
- Leont'ev, A. N. (1981). The problem of activity in psychology. *The Concept of Activity in Soviet Psychology*, *13*(2), 37-71. doi:10.2753/RPO1061-040513024
- Lin, L. J. (2008). The action research of children's empathy by the using of the picture books. Master Dissertation, National Taitung University.
- Lord, C., Risi, S., Lambrecht, L., Cook, E. H., Leventhal, B. L., DiLavore, P. C., . . . Rutter, M. (2000). The autism diagnostic observation schedule generic: A standard measure of social and communication deficits associated with the spectrum of autism. *Journal of Autism and Developmental Disorders*, *30*(3), 205-223. doi:10.1023/A:1005592401947
- Lord, C., Rutter, M., & Couteur, A. (1994). Autism diagnostic interview-revised: A revised version of a diagnostic interview for caregivers of individuals with possible pervasive developmental disorders. *Journal of Autism and Developmental Disorders*, *24*(5), 659-685. doi:10.1007/BF02172145
- McEvoy, M. A., Nordquist, V. M., Twardosz, S., Heckaman, K. A., Wehby, J. H., & Denny, R. K. (1988). Promoting autistic children's peer interaction in an integrated early childhood setting using affection activities. *Journal of Applied Behavior Analysis*, *21*(2), 193. doi:10.1901/jaba.1988.21-193

- Metcalf, S., Kamarainen, A., Tutwiler, M. S., Grotzer, T., & Dede, C. (2011). Ecosystem science learning via multi-user virtual environments. *International Journal of Gaming and Computer-Mediated Simulations (IJGCMS)*, 3(1), 86-90.
- Metcalf, S. J., Clarke, J., & Dede, C. (2009). Virtual worlds for education: River city and ecomuve. In *MiT6 International Conference* (pp. 1-6).
- Mikropoulos, T. A., & Natsis, A. (2011). Educational virtual environments: A ten-year review of empirical research (1999--2009). *Computers & Education*, 56(3), 769-780. doi:10.1016/j.compedu.2010.10.020
- Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook*. SAGE publications, Inc.
- Mineo, B., Ziegler, W., Gill, S., & Salkin, D. (2009). Engagement with electronic screen media among students with autism spectrum disorders. *Journal of Autism and Developmental Disorders*, 39(1), 172-187. doi:10.1007/s10803-008-0616-0
- Moore, D., Yufang Cheng, McGrath, P., & Powell, N. J. (2005). Collaborative virtual environment technology for people with autism. *Focus on Autism and Other Developmental Disabilities*, 20(4), 231-243. doi:10.1177/10883576050200040501
- Moura, D., el-Nasr, M. S., & Shaw, C. D. (2011). Visualizing and understanding players' behavior in video games: Discovering patterns and supporting aggregation and comparison. In *ACM SIGGRAPH 2011 game papers* (p. 2). doi:10.1145/2037692.2037695
- Myles, B. S., & Simpson, R. L. (2002). Asperger syndrome an overview of characteristics. *Focus on Autism and Other Developmental Disabilities*, 17(3), 132-137. doi:10.1177/10883576020170030201
- Nardi, B. A. (1996). Activity theory and human-computer interaction. In B. Nardi (Ed.), *Context and Consciousness: Activity Theory and Human-computer Interaction*. Boston: MIT Press.
- Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education*, 31(2), 199-218. doi:10.1080/03075070600572090

- Nowicki, S., & Carton, J. (1993). The measurement of emotional intensity from facial expressions. *Journal of Social Psychology, 133*(5), 749-750. doi:10.1080/00224545.1993.9713934
- Octavia, J., Beznosyk, A., Coninx, K., Quax, P., & Luyten, K. (2011). User modeling approaches towards adaptation of users roles to improve group interaction in collaborative 3d games. *Lecture Notes in Computer Science: Users and Applications, 6764*, 668-677. doi:10.1007/978-3-642-21619-0_79
- Orrill, C. H., & Shaffer, D. W. (2012). Exploring connectedness: Applying ENA to teacher knowledge. In J. van Aalst, K. Thompson, M. J. Jacobson, & P. Reimann (Eds.), Sydney, NSW, Australia: International Society of the Learning Sciences.
- Parsons, S. (2005). Use, understanding and learning in virtual environments by adolescents with autistic spectrum disorders. *Annual Review of CyberTherapy and Telemedicine, 3*, 207-215.
- Parsons, S., & Mitchell, P. (2002). The potential of virtual reality in social skills training for people with autistic spectrum disorders. *Journal of Intellectual Disability Research, 46*(5), 430-443. doi:10.1046/j.1365-2788.2002.00425.x
- Parsons, S., Beardon, L., Neale, H. R., Reynard, G., Eastgate, R., Wilson, J. R., . . . Hopkins, E. (2000). *Development of social skills amongst adults with aspergers syndrome using virtual environments: The AS interactive project*. Paper presented at the 3rd ICDVRAT, Sardinia Italy, 163-170.
- Parsons, S., Leonard, A., & Mitchell, P. (2006). Virtual environments for social skills training: Comments from two adolescents with autistic spectrum disorder. *Computers & Education, 47*(2), 186-206. doi:10.1016/j.compedu.2004.10.003
- Parsons, S., Mitchell, P., & Leonard, A. (2005). Do adolescents with autistic spectrum disorders adhere to social conventions in virtual environments? *Autism, 9*(1), 95-117. doi:10.1177/1362361305049032
- Penumarthy, S., & Borner, K. (2004). The Activeworld toolkit: Analyzing and visualizing social diffusion patterns in 3D virtual worlds. In *Workshop seven virtual worlds: Design and research directions* (p. 39).
- Penumarthy, S., & Börner, K. (2006). Analysis and visualization of social diffusion patterns in three-dimensional virtual worlds. in *Avatars at Work and Play*, 39-61.

- Perner, J., Frith, U., Leslie, A. M., & Leekam, S. R. (1989). Exploration of the autistic child's theory of mind: Knowledge, belief, and communication. *Child Development, 60*, 689-700. Retrieved from <http://www.jstor.org/stable/1130734>.
- Peterson, M. (2007). Learner interaction management in an avatar and chat-based virtual world. *Computer Assisted Language Learning, 19*(1), 79-103. doi:10.1080/09588220600804087
- Powell, J., Martindale, B., Kulp, S., Martindale, A., & Bauman, R. (1977). Taking a closer look: Time sampling and measurement error. *Journal of Applied Behavior Analysis, 10*(2), 325-32. doi:10.1901/jaba.1977.10-325
- Quellmalz, E. S., & Pellegrino, J. W. (2009, January). Technology and testing. *Science, 323*(5910), 75-79. doi:10.1126/science.1168046
- Quellmalz, E. S., Timms, M. J., & Schneider, S. A. (2009). *Assessment of student learning in science simulations and games*. Washington, D.C.: National Research Council.
- R Core Team. (2012). R: A language and environment for statistical computing [Computer Software]. Vienna, Austria.
- Rupp, A. A., Choi, Y., Gushta, M., Mislavy, R. J., Bagley, E., Nash, P., . . . Shaffer, D. (2009). Modeling learning progressions in epistemic games with epistemic network analysis: Principles for data analysis and generation. In *Proceedings from the learning progressions in science conference* (pp. 24-26).
- Rupp, A. A., Gushta, M., Mislavy, R. J., & Shaffer, D. W. (2010). Evidence-centered design of epistemic games: Measurement principles for complex learning environments. *The Journal of Technology, Learning and Assessment, 8*(4), 4-47.
- Rutten, A., Cobb, S., Neale, H., Kerr, S., Leonard, A., Parsons, S., & Mitchell, P. (2003). The AS interactive project: Single-user and collaborative virtual environments for people with high-functioning autistic spectrum disorders. *The Journal of Visualization and Computer Animation, 14*(5), 233-241. doi:10.1002/vis.320
- Scheucher, T., Bailey, P. H., Gütl, C., & Harward, V. J. (2009). Collaborative virtual 3d environment for internet-accessible physics experiments. In *Proceedings of*

the international conference of remote engineering and virtual instrumentation (pp. 65-71).

- Schmidt, C., Stichter, J. P., Lierheimer, K., McGhee, S., & O'Connor, K. V. (2011). An initial investigation of the generalization of a school-based social competence intervention for youth with high-functioning autism. *Autism Research and Treatment, 2011*, 1-11. doi:10.1155/2011/58953
- Schmidt, M., & Laffey, J. (2012). Visualizing behavioral data from a 3D virtual learning environment: A preliminary study. In *2012 45th Hawaii International Conference on System Sciences* (pp. 3387-3394). doi:10.1109/HICSS.2012.639
- Schmidt, M., Laffey, J. M., Schmidt, C. T., Wang, X., & Stichter, J. (2012). Developing methods for understanding social behavior in a 3D virtual learning environment. *Computers in Human Behavior, 28*(2), 405 - 413. doi:10.1016/j.chb.2011.10.011
- Schmidt, M. M. (2010). *Social influence in a 3D virtual learning environment for individuals with autism spectrum disorders*. (Doctoral Dissertation). Retrieved from <http://laurel.iso.missouri.edu/record=b8183270~S8>
- Schroeder, R., Heldal, I., & Tromp, J. (2006). The usability of collaborative virtual environments and methods for the analysis of interaction. *Presence: Teleoperators and Virtual Environments, 15*(6), 655-667. doi:10.1162/pres.15.6.655
- Shaffer, D. W., & Gee, J. P. (2011). The right kind of GATE: Computer games and the future of assessment. In M. Mayrath, J. Clarke-Midura, H. Robinson, & G. Schraw (Eds.), *Technology-based assessments for 21st century skills: Theoretical and practical implications from modern research*. Charlotte, NC: Information Age.
- Shaffer, D. W., Hatfield, D., Svarovsky, G. N., Nash, P., Nulty, A., Bagley, E., . . . Mislevy, R. (2009). Epistemic network analysis: A prototype for 21st-century assessment of learning. *International Journal of Learning and Media, 1*(2), 1-22. doi:10.1162/ijlm.2009.0013
- Shaffer, D. W., & Serlin, R. C. (2004). What good are statistics that don't generalize? *Educational Researcher, 33*(9), 14-25. doi:10.3102/0013189X033009014

- Shute, V. J. (2009). Simply assessment. *International Journal of Learning and Media*, 1(2), 1-11. doi:10.1162/ijlm.2009.0014
- Shute, V. J. (2011). Stealth assessment in computer-based games to support learning. In S. Tobias & J. D. Fletcher (Eds.), *Computer Games and Instruction*. Charlotte, NC: Information Age Publishers.
- Shute, V. J., & Ke, F. (2012). Games, learning, and assessment. In D. Ifenthaler, D. Eseryel, & X. Ge (Eds.), *Assessment in Game-based Learning: Foundations, Innovations, and Perspectives*. New York, NY: Springer. doi:10.1007/978-1-4614-3546-4_4
- Solomon, MS., Goodlin-Jones, B. L., & Anders, T. F. (2004). A social adjustment enhancement intervention for high functioning autism, asperger's syndrome, and pervasive developmental disorder NOS. *Journal of Autism and Developmental Disorders*, 34(6), 649-668. doi:10.1007/s10803-004-5286-y
- Squire, K., Barnett, M., Grant, J. M., & Higginbotham, T. (2004). Electromagnetism supercharged!: Learning physics with digital simulation games. In *Proceedings of the 6th international conference on learning sciences* (pp. 513-520).
- Squire, K. D., & Barab, S. A. (2004). *Replaying history: Learning world history through playing civilization III*. (Doctoral Dissertation, Indiana University).
- van Staaldouin, J. P., & de Freitas, S. (2011). A game-based learning framework: Linking game design and learning outcomes. In M. S. Khyne (Ed.), *Learning to play: Exploring the future of education with video games*. Springer.
- Stichter, J., Herzog, M., Visovsky, K., Schmidt, C., Randolph, J., Schultz, T., & Gage, N. (2010). Social competence intervention for youth with asperger syndrome and high-functioning autism: An initial investigation. *Journal of Autism and Developmental Disorders*, 40(9), 1067-1079. doi:10.1007/s10803-010-0959-1
- Stichter, J. P., Herzog, M. J., O'Connor, K. V., & Schmidt, C. (2012). A preliminary examination of a general social outcome measure. *Assessment for Effective Intervention*. doi:10.1177/1534508412455213
- Stichter, J. P., Herzog, M. J., Visovsky, K., Schmidt, C., Randolph, J., Schultz, T., & Gage, N. (2010). Social competence intervention for youth with asperger syndrome and high-functioning autism: An initial investigation. *Journal of Autism and*

Developmental Disorders, 40(9), 1067-1079. doi:10.1007/s10803-010-0959-1

Stichter, J.P., Laffey, J., Galyen, K., Herzog, M. (in press). iSocial: Delivering the Social Competence Intervention for Adolescents (SCI-A) in a 3D Virtual Learning Environment for Youth with High Functioning Autism. *Journal of Autism and Developmental Disorders*.

Stichter, J. P., O'Connor, K. V., Herzog, M. J., Lierheimer, K., & McGhee, S. D. (2012). Social competence intervention for elementary students with aspergers syndrome and high functioning autism. *Journal of Autism and Developmental Disorders*, 42(3), 354-366. doi:10.1007/s10803-011-1249-2

Stichter, J. P., Randolph, J., Gage, N., & Schmidt, C. (2007). A review of recommended social competency programs for students with autism spectrum disorders. *Exceptionality*, 15(4), 219-232. doi:10.1080/09362830701655758

Thawonmas, R., & Iizuka, K. (2008). Visualization of online-game players based on their action behaviors. *International Journal of Computer Games Technology*, 2008, 1-9. doi:10.1155/2008/906931

Thawonmas, R., Kurashige, M., & Chen, K. T. (2007). Detection of landmarks for clustering of online-game players. *International Journal of Virtual Reality*, 6(3), 11-16.

Tromp, J. G., Steed, A., & Wilson, J. R. (2003). Systematic usability evaluation and design issues for collaborative virtual environments. *Presence: Teleoperators and Virtual Environments*, 12(3), 241-267. doi:10.1162/105474603765879512

De Vries, H., Elliott, M. N., Kanouse, D. E., & Teleki, S. S. (2008). Using pooled kappa to summarize interrater agreement across many items. *Field Methods*, 20(3), 272-282. doi:10.1177/1525822X08317166

Vygotsky, L. S. (1978). *Mind in society*. In Cambridge, MA: Harvard University Press.

Wallner, G., & Kriglstein, S. (2012). A spatiotemporal visualization approach for the analysis of gameplay data. In *Proceedings of the 2012 ACM annual conference on human factors in computing systems* (pp. 1115-1124). doi:10.1145/2207676.2208558

- Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*, Cambridge: Cambridge Univ Press.
- West, B. T., Welch, K. B., & Galecki, A. T. (2007). *Linear mixed models: practical guide using statistical software*. Boca Raton: Chapman & Hall/CRC.
- West; Brady T., Welch, K.B., Galecki, A.T. (2012). *Linear Mixed Models: A Practical Guide Using Statistical Software*. Chapman & Hall, Kindle Edition.
- Wilson, B. A., Alderman, Burgess, Emslie, H. C., & Evans, J. J. (1986). *Behavioural assessment of the dysexecutive syndrome: Manual*. Bury St Edmunds, Thames: Valley Test Company.
- Wilson, K. A., Bedwell, W. L., Lazzara, E. H., Salas, E., Burke, C. S., Estock, J. L., . . . Conkey, C. (2009). Relationships between game attributes and learning outcomes. *Simulation & Gaming, 40*(2), 217-266.
doi:10.1177/1046878108321866
- Yee, N., Bailenson, J. N., Urbanek, M., Chang, F., & Merget, D. (2007). The unbearable likeness of being digital: The persistence of nonverbal social norms in online virtual environments. *CyberPsychology & Behavior, 10*(1), 115-121.
Doi:10.1089/cpb.2006.9984

APPENDIX A: FIDELITY DATA

Fidelity of FT2 Data

Fidelity refers to the extent to which the OG adhered to the curricular intent of the lesson, including content, process, behavior, specific verbal feedback, and timing. The data below refers to the entire unit, not just naturalistic practice activities. Data reveals high fidelity of delivery across cohorts (see Stichter et al., in press).

Table 32. Cohort A Fidelity

	Unit 1		Unit 2		Unit 3		Unit 4		Unit 5		Avg. Complete Units	
	Fidelity	IOA %	Fidelity	IOA%	Fidelity	IOA %	Fidelity	IOA %	Fidelity	IOA%	Fidelity	IOA%
C	2	100	1.96	97.44	2	100	2	100	1.99	100	1.98	98.15
P	2	100	2	100	2	100	1.83	100	2	100	1.89	98
Bx	2	100	2	100	2	100	2	100	2	100	1.98	100
SVF	2	90	2	100	1.94	100	1.94	100	2	100	1.96	98.28
Time	1.5	100	1.83	100	2	90	1.88	100	1.82	90.91	1.66	91.80

C=compliance to content delivery; P = compliance to process of delivery; Bx=Behavior system used appropriately; SVF = Specific verbal feedback given to all students appropriately; Time = on time for delivery +/-2 minutes

Table 33. Cohort B Fidelity

	Unit 1		Unit 2		Unit 3		Unit 4		Unit 5		Avg Complete Units	
	Fidelity	IOA%	Fidelity	IOA %	Fidelity	IOA %	Fidelity	IOA %	Fidelity	IOA %	Fidelity	IOA%
C	2	100	2	100	2	100	1.98	98.21	1.96	100	1.99	99.63
P	2	100	2	100	2	100	2	100	1.98	100	1.99	100
Bx	1.93	100	2	100	2	100	2	100	2	100	1.99	96.55
SVF	2	100	2	100	2	100	2	100	2	100	2	100
Time	1.75	100	1.94	100	1.88	100	2	100	1.83	100	1.81	100

C=compliance to content delivery; P = compliance to process of delivery; Bx=Behavior system used appropriately; SVF = Specific verbal feedback given to all students appropriately; Time = on time for delivery +/-2 minutes

Table 34. Cohort C Fidelity

	Unit 1		Unit 2		Unit 3		Unit 4		Unit 5		Avg Complete Units	
	Fidelity	IOA%	Fidelity	IOA %	Fidelity	IOA %	Fidelity	IOA %	Fidelity	IOA %	Fidelity	IOA%
C	1.91	98.3	2	100	1.92	98.1	1.99	100	1.99	100	1.962	99.28
P	2	100	2	100	1.6	100	2	100	2	100	1.92	100
Bx	2	100	2	100	1.75	100	2	100	2	100	1.95	100
SVF	1.93	100	1.94	100	2	100	2	100	2	100	1.974	100
Time	1.83	100	1.75	100	1.91	100	1.96	100	1.92	100	1.874	100

C=compliance to content delivery; P = compliance to process of delivery; Bx=Behavior system used appropriately; SVF = Specific verbal feedback given to all students appropriately; Time = on time for delivery +/-2 minutes

APPENDIX B: CODES FOR CHARACTERIZING PERFORMANCE (BEHAVIOR CODES)

Definition of terms used within initial codebook

- **Learning Objects:** Learning objects are environmental elements in the virtual world that the OG directs them to pay attention to, use, or discuss in the activity. Examples from pilot study: Images with scenarios, sticky notes, PDF, restaurant models. Non-examples from pilot study: restaurant models that are not a part of the current activity (e.g. chairs when they are to be looking in the opposite direction towards the buffets), or a prior object that they just transitioned away from and is no longer the target learning object
- **Inappropriate:** Behavior that is undesirable according to iSocial expectations for student
- **OG:** Online guide, or teacher.
- **Peers:** Students from their cohort in the environment
- **Camera view:** Students are to be in 3rd person camera view and sometimes use 1st person camera view. If a student can see another 's avatars face but it is not due to the avatar moving in an appropriately social manner but due to camera view changes, it is not counted as facing the avatar's face. It should be coded how the avatar is orienting and behaving.

Codes for Characterizing Performance

Category 1: Static Orientation (“Facing”)

Definition: Static orientation is defined as staying in one spot without orientation or movement for 3 or more seconds.

- **F-LO** (Facing Learning Objects): Avatar's face direction is approximately a 45-degree angle or less facing the learning object, and the object is clearly in view.
- **F-OG-ns** (Facing the Online Guide who is not speaking): The user can see half or all of the OG's face using 1st or 3rd person camera view. The OG is not speaking for three seconds to qualify as "not speaking."
- **F-OG-sp** (Facing the Online Guide who is speaking): The user can see half or all of the OG's face using 1st or 3rd person camera view. The OG is speaking when the user is facing the OG's direction.
- **F-P-ns** (Facing one or more peers, none are speaking that user is facing): The user can see half or all of one or more of a peer's face using 1st or 3rd person camera view. None of the peers that the student is facing is not speaking for 3 or more seconds.
- **F-P-sp** (Facing one or more peers, one or more are speaking that the user is facing): The user can see half or all of one or more of a peer's face using 1st or 3rd person camera view. At least one of the peers that the student is facing is speaking.

- **FI** (Facing inappropriate): The student is facing in a direction that is not towards peers, teacher, or the target learning object direction. This is an "undesirable" code.
 - Example: The group moves but Joe stays in place. The rest of the group has transitioned but Joe is standing there facing the previous LO (not the current LO) and is not moving for 5 seconds.

Category 2: Active Orientation

Definition: Active orientation is defined as using the left or right keys to orient the virtual body in space. It is equivalent to moving the head left and right in the real world and a substitute for practicing eye contact in the virtual world.

Orienting "towards" can be determined by where the user stops pressing key (lifts off of left or right key) to determine who/what user was orienting towards.

- **O-LO** (Orienting towards learning objects): Orienting towards the learning object(s).
 - Example: During the restaurant activity, the students are to be looking at the main menu buffet. Joe's avatar orients to the main menu buffet.
- **O-OG-ns** (Orienting towards the OG who is not speaking): Student orients towards the OG who is not speaking at the start of the orienting. Student can see at least half of the OG face.
 - Joe orients his avatar towards the online guide. He stops using the arrow key to turn when he gets to the OG, who is not speaking.

- Joe begins to orient his avatar to the OG who is not speaking, and before he stops the OG begins to speak.
- **O-OG-sp** (Orienting towards the OG who is speaking): Student orients towards the OG who is speaking at the start of the orienting. Student can see at least half of the OG face.
 - The OG is speaking, and then Joe orients his avatar towards the online guide. He stops using the arrow key to turn when he gets to the OG.
- **O-P-ns** (Orienting towards one or more peers who are not speaking): Student orients towards one or more peers, none of which are speaking at the start of the orienting move. Student can see at least half of a peer's face in order to qualify as orienting towards the peer(s).
 - Joe orients his avatar towards a peer. He stops using the arrow key to turn when he gets to the students, none of whom are speaking.
- **O-P-sp** (Orienting towards one or more peers who are speaking): Student orients towards one or more peers, at least one of whom are speaking at start of the orienting movement. Student can see at least half of a peer's face in order to qualify as orienting towards the peer(s).
 - Joe orients his avatar towards a peer. He stops using the arrow key to turn when he gets to the students, one of whom is speaking
- **O-I** (Orienting inappropriate): The student is orienting in a direction that is not towards peers, teacher, or the target learning object direction. This is an "undesirable" code.

- Example: Joe orients his avatar away from the group and away from the learning objects.

Category 3: Movement

Definition: Movement is defined as using the up or down keys to move the avatar forward or backward in virtual space. It is equivalent to walking in the real world.

- **M-LO** (Movement to or around learning objects): Movement to or around learning objects. Includes within-activity transitions when users are following directions to move to another area with another set of learning objects.
 - Example: Joe moves toward and around the learning objects “Desserts” using his up and down arrow keys.
- **M-G** (Movement to or with the group): Movement towards or with the group. Includes within-activity transitions when users are following directions to move with the group, or when returning from an inappropriate movement back to the group.
 - Example: The group is moving from discussing main dishes in the restaurant over to desserts. They move as a group together.
- **M-I** (Movement inappropriate): Movement that is not towards peers, teacher, or the target learning object direction. This is an “undesirable” code.

Category 4: Verbalization

Definition: Verbal utterance that uses words, separate from laughing, humming, breathing, coughing, moaning, or other non-word-oriented vocalizations (see Schmidt, 2010, p. 178).

- **V-I** (Verbal initiation): An initiation is starting a conversation, or getting a conversation going. An interaction is when there is not another verbalization by another peer(s) or instructor(s) to whom the initiation was directed within 3 seconds. (see Schmidt , 2010, p. 175).
 - It is a vocal behavior clearly directed to a peer/online guide that attempts to occasion a response, including greeting, asking and answering questions, commenting, sharing materials, helping behavior, or saying someone's name
 - Example: "Ok, let's get started with this buffet. What do people think?"
- **V-I-I** (Verbal initiation, inappropriate): Inappropriate initiation is a verbal initiation that is classified as appropriate due to the following reasons such as (see Schmidt, 2010 p. 176):
 - off-topic (not related to the topic of conversation),
 - Uses an inappropriate tone (e.g., yelling, mocking),
 - Is rude, unkind or insensitive (e.g., calling names, making rude comments),
 - Is socially unacceptable (e.g., student telling teacher that s/he looks good),

- Does not follow directions (e.g., student is directed to speak to a specific person but speaks with someone else),
- Is otherwise deemed by the coder to be inappropriate.
- It is a vocal behavior directed to a peer/online guide that does not meet the definition of an appropriate initiation (for reasons such as: topic being contextually irrelevant, perseverative, socially inappropriate, or an inappropriate interruption)

This is an “undesirable” code.

- **V-R (Verbal response):** Verbal acknowledgement that is executed within 3 seconds by the student, instructor, or physical facilitator from whom the response was solicited by the initiator (see Schmidt, 2010, p. 175)
 - It is a vocal behavior that acknowledges an initiation within 3second (e.g. answering when name was called, responding to a comment, answering a question)
 - Example: [Responds to initiation] “I think it’s OK.”

- **V-R-I (Verbal response, inappropriate):** A verbal response that is deemed inappropriate (see “Verbal initiation, inappropriate” for reasons a verbalization may be considered inappropriate). This is an “undesirable” code.
 - It is a vocal behavior that inappropriately acknowledges an initiation within 3 seconds (e.g. providing a response that is off topic, using inappropriate tone of voice or voice volume)

- **V-NR** (Verbal non-response): A verbal response is expected but “the participant fails to acknowledge the interaction in any way within three seconds” (see Schmidt et al., 2012, p. 408). This is an “undesirable” code.
- **V-UT*** (Verbal Undirected-talk): Student verbalizations do not seem directed at anyone (not socially interactive in nature), do not sound like conversation, but are not inappropriate. (Example: muttering while writing)
 - A vocal behavior that is not clearly directed to a peer/online guide, is not clearly attempting to occasion a response as part of a conversation, and is not classified as a response.
 - Example: “[mumbling while writing]
So.....they.....are.....going.....hm.....to.....”
- **V-5ge*** (Verbal length: greater than 5 words): A descriptor code that describes the type of verbalization length within a student utterance; this utterance can cut across segments. A 5ge verbal utterance is greater than 5 words in length (6 or more words). Humming, mmmmm, uhhh, or stuttering (words that are repeated due to speech issue such as verbal pausing or speech impediment) do not count in the word count.
 - Example: “I like brick because it goes with our theme of a sports restaurant.”
- **V-5l*** (Verbal length: less than 5 words): A descriptor code that describes the type of verbalization length. A verbal utterance that is 5 words or less; this utterance can cut across segments. Humming, mmmm, uhhh, or stuttering

(words that are repeated due to speech issue such as verbal pausing or speech impediment) do not count in the word count.

- Examples: “Yes.” “Brick.” “I agree.” “I like it.”

**Not a part of original Schmidt 3D CVLE interaction model coding (2010, 2012), but rose out of the pilot study as interesting aspects of verbalization to capture.*

Category 5: Gestures

Definition: Using a gesture by clicking on the gesture button in the gestures panel. (All gesture codes were merged into one Gesture code).

Appendix C: ENA Analysis Visuals

Step 1: Split raw data into meta-data and data files

After coding segments with presence or absence of behavior, process the raw segment data by splitting it into two files: meta data and corresponding adjacency vectors.

Raw Data

	A	B	C	M	N	O	P	Q	R	S
1	St_ID	Activity_ID	Excerpt_	F.Los	F.List	F.Spkr	F.OG	F.Stud	F.Othr	O.LOs
2	A.S01	3.6	00:02:20	0	0	0	0	0	0	1
3	A.S01	3.6	00:02:30	1	0	1	1	0	0	0
4	A.S01	3.6	00:02:40	0	0	1	1	0	0	1
5	A.S01	3.6	00:02:50	1	0	1	1	0	0	0
6	A.S01	3.6	00:03:00	1	0	1	0	0	0	0
7	A.S01	3.6	00:03:10	1	0	0	1	0	0	0
8	A.S01	3.6	00:03:20	1	0	0	1	0	0	0
9	A.S01	3.6	00:03:30	1	0	0	1	0	0	0
10	A.S01	3.6	00:03:40	1	0	0	1	0	0	0

portion of segment presence or absence data
(single co-occurrence vector for Cohort A, Student 1, U3L6, at time 03:00)



After splitting data into co-occurrence and meta data files

	A	B	C	D	E
1	St_ID	Activity_ID	Excerpt_	Doc_Title	Sex
2	A.S01	3.6	00:02:20	U3L6_NP_BuffetRestaurant_Cit	Male
3	A.S01	3.6	00:02:30	U3L6_NP_BuffetRestaurant_Cit	Male
4	A.S01	3.6	00:02:40	U3L6_NP_BuffetRestaurant_Cit	Male
5	A.S01	3.6	00:02:50	U3L6_NP_BuffetRestaurant_Cit	Male
6	A.S01	3.6	00:03:00	U3L6_NP_BuffetRestaurant_Cit	Male
7	A.S01	3.6	00:03:10	U3L6_NP_BuffetRestaurant_Cit	Male
8	A.S01	3.6	00:03:20	U3L6_NP_BuffetRestaurant_Cit	Male
9	A.S01	3.6	00:03:30	U3L6_NP_BuffetRestaurant_Cit	Male
10	A.S01	3.6	00:03:40	U3L6_NP_BuffetRestaurant_Cit	Male

meta data

	A	B	C	D	E	F	G	H
1	F.Los	F.List	F.Spkr	F.OG	F.Stud	F.Othr	O.LOs	O.Spkr
2	0	0	0	0	0	0	1	0
3	1	0	1	1	0	0	0	0
4	0	0	1	1	0	0	1	0
5	1	0	1	1	0	0	0	0
6	1	0	1	0	0	0	0	0
7	1	0	0	1	0	0	0	0
8	1	0	0	1	0	0	0	0
9	1	0	0	1	0	0	0	0
10	1	0	0	1	0	0	0	0

corresponding adjacency vectors

Figure 78. Processing Raw Data into meta data and adjacency vectors

Step 2. Each segment is formed into an adjacency matrix

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	
1																															
2	F-Los	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	F-List	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	F-Spkr	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	F-OG	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	F-Std	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	F-Othr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	O-Los	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	O-Spkr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	O-Lstnr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	O-OG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	O-Std	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	O-Othr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	M-Los	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	M-TGr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	M-Othr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	V-I	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	V-R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	V-Cb	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	V-Cc	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	V-ST	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	V-RLos	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	V-Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	V-Com	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	V-Com	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	V-RA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	V-I	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	V-Tone	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	T-R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	T-U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 79. Sample adjacency matrix representing one adjacency vector for time t

Step 3. Each activity (or unit of analysis) is then summed into the cumulative adjacency matrix

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	
1																															
2	F-Los	0	19	21	0	0	2	0	0	0	0	0	1	1	0	2	4	4	1	0	0	0	0	0	0	0	0	0	0	0	
3	F-List	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	F-Spkr	19	0	20	0	0	2	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	
5	F-OG	21	0	20	0	0	2	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	
6	F-Std	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
7	F-Othr	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
8	O-Los	2	0	2	2	0	1	1	0	1	0	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
9	O-Spkr	0	0	0	0	0	1	0	2	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
10	O-Lstnr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	
11	O-OG	0	0	0	0	0	1	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
12	O-Std	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
13	O-Othr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
14	M-Los	1	0	1	1	0	1	2	1	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
15	M-TGr	1	0	1	1	0	1	3	2	0	1	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
16	M-Othr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
17	V-I	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
18	V-R	4	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
19	V-Cb	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
20	V-Cc	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
21	V-ST	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
22	V-RLos	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
23	V-Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
24	V-Com	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
25	V-Com	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
26	V-RA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
27	V-I	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
28	V-Tone	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
29	T-R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
30	T-U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

Figure 80. Cumulative adjacency matrix for Student 1, Cohort A, U4L4 NP Activity using the pilot study coding scheme

Step 4. Cumulative adjacency vectors before norming

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Code1	F-Los	F-Los	F-Los	F-Los	F-Los	F-Los	F-Los	F-Los	F-Los	F-Los	F-Los	F-Los
2	Code2	F-List	F-Spkr	F-OG	F-Std	F-Oth	O-Los	O-Spk	O-Lstr	O-OG	O-Std	O-Oth	M-Los
3	Frequency	0	26	41	0	0	1	0	0	0	0	0	0

Figure 81. Portion of the cumulative adjacency vector from Student 1, Cohort A, U3L6 NP Pilot study

Step 5. Norm the cumulative adjacency vectors , then multiply to rotation matrix to establish positioning

	B	C	F	G	H	I	J	K	L	M
1	St_ID	Activi	Variable ->	V1	V2	V3	V4	V5	V6	V7
2			Code 1 Name->	F.List	F.Spkr	F.Spkr	F.OG	F.OG	F.OG	F.Stud
3			Code 2 Name->	F.Los	F.Los	F.List	F.Los	F.List	F.Spkr	F.Los
6	A.S01	3.6	->	0	0.402	0	0.633	0	0.392	0
7	A.S02	3.6	->	0	0.21	0	0.485	0	0.203	0
8	A.S03	3.6	->	0.013	0.18	0.006	0.45	0.015	0.21	0.039
9	A.S04	3.6	->	0	0.359	0	0.685	0	0.377	0
10	B.S05	3.6	->	0	0.224	0	0.757	0	0.224	0.084
11	B.S06	3.6	->	0	0.095	0	0.165	0	0.129	0
12	B.S07	3.6	->	0.021	0.236	0.009	0.559	0.022	0.246	0.021

Figure 82. Portion of normed cumulative adjacency vector across 8 students in U3L6 NP pilot study

APPENDIX D: BEHAVIORS, BEHAVIOR PATTERNS, AND CHARACTERIZATIONS OF PERFORMANCE

Below is a visual which helps to explain the differences in the usage of “behaviors”, “behavior patterns” and “characterization of performance.”

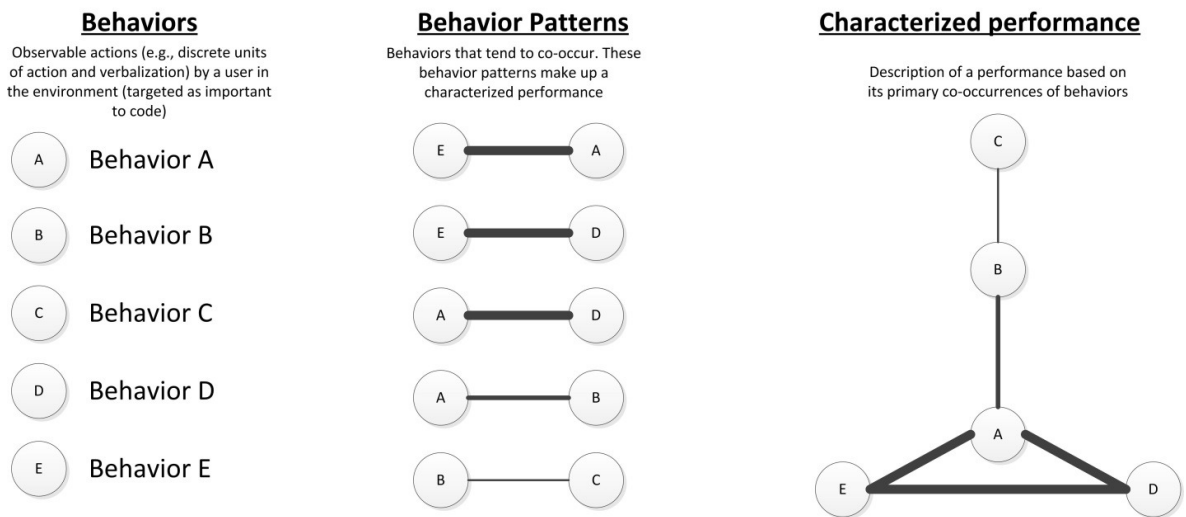


Figure 83. Depiction of differences between behaviors, behavior patterns, and a performance

There are indeed many types of behavior patterns, such as groups of 2 or 3 behaviors that are used together, as in the above diagram it is also a pattern that behaviors D, A, and E are often used together. In essence, behavior patterns are a subset of the characterized performance.

VITA

Krista Galyen was born in Oregon to the parents of Gary and Mary Galyen, and has two older brothers, Robert and Steven Galyen. She attended Western Oregon University and received a B.S. in Elementary Education with supporting areas in mathematics and earth sciences. Afterwards she received her M.S. in Deaf and Hard of Hearing Education, also from Western Oregon University in Monmouth, Oregon, having done internships at Oregon School for the Deaf and Willamette Education Service District. After working for Willamette Education Service District as a Deaf and Hard of Hearing Education Specialist in Salem, Oregon, she moved to Craig, Alaska. It was here on this island that she taught elementary and special education, grades 3, 4 and 5. After teaching in Craig, Alaska for three years, she moved to Anchorage, Alaska to work as a Deaf and Hard of Hearing Education Specialist for students ages 3-21 around the state of Alaska for the Special Education Service Agency (SESA). She was also Program Coordinator for the birth to three statewide consultation grant, Consultation and Education for Early Hearing Impairment (CEEHI). If there was a child with a hearing loss born in the state, she would fly to their location whether it be in the city or their local village, work with families, schools, clinics, and community in supporting language development. While she was always interested in integrating technology, it was with this travel and remote educational consultancy work that she started to strongly integrate technology with education.

While working for SESA, she obtained an MS in Educational Technology from the University of Missouri. In doing so, she became interested in becoming a leader in the field in order to support greater access to online learning. In 2007, she was accepted into the PhD program at the University of Missouri for Information Sciences and Learning Technologies and moved to Missouri in 2008. She worked under the guidance of Dr. James Laffey and was a

research assistant for the Context-aware Activity Notification System (FIPSE-CANS) as well as the iSocial 3D virtual learning environment project. She also worked as a Zone Mentor under the guidance of Dr. Joi Moore in the Digital Media Zone, the completely online design and development courses for the School of Information Sciences and Learning Technologies at the University of Missouri.

In 2010 she became a full-time employee at the University of Missouri, becoming Project Manager of the iSocial 3D VLE research and development grant. She worked with a team of developers, curriculum designers, and researchers to implement multiple field tests of the iSocial 3D VLE and its curriculum in schools across the state of Missouri. One of the field tests became the context of her dissertation work.

She continues her past work of language development and teaching others by teaching American Sign Language at Columbia College Online, and is currently working on publishing her research work from her dissertation.