Counting the Game: Visualizing Changes in Play by Incorporating Game Events

Jennifer Scianna[1](✉), David Gagnon[1], and Bryan Knowles[2]

[1] Wisconsin Center for Education Research, University of Wisconsin-Madison, Madison, WI, USA
{jscianna,djgagnon}@wisc.edu

[2] Information School, University of Wisconsin-Madison, Madison, WI, USA
baknowles@wisc.edu

Abstract. Lakeland is an educational game developed with the intent of exposing secondary science students to complex systems, namely phosphorous cycling. Data collected anonymously through embedded logging structures was sampled to include sessions where players returned to play more than once during December 2019 consistent with classroom play. Using Epistemic Network Analysis, games from the same player were compared to identify significant differences in how players responded to game events. Consistent with prior research around systems thinking, players' ability to think through temporally distant phenomena, as evidenced by changes in their use of time manipulation and short vs. self-sustaining strategies in Game 1 and Game 2, demonstrate the potential for ENA to uncover and even assess complex student behaviors using log data. Furthermore, this study highlights the importance of including computer-generated data alongside the human-generated reactions being logged.

Keywords: Educational games · Systems thinking · Game-Based assessment

1 Introduction

"You set out to form a new town called Lakeland. Your people love to play in the water. Grow your town without ruining the lakes," [1]. Lakeland's players receive quite the edict upon beginning a new game. A relatively open landscape sets the stage as players build their first house near the beloved lake, but despite the serene music and lighthearted graphics, the tone is set. As a player, you have the power to make or break Lakeland; don't mess up.

The decision space afforded to players is sufficiently wide to see a variety of responses to the problem set out before them. This variety creates an opportune moment for us to gain insight into how players begin to piece together the complex systems that underlie the game's simulation, a challenging proposition given that students often fail to capture the dynamics of complex systems [2]. Yet each time a player's action yields some response from the game, there is a new opportunity presented for the student to assemble a causal relationship that underlies the system. The student and simulation go round and

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round creating a "circle of gameplay" that could be likened to a conversation [3]. We can use log data to "eavesdrop" on the player's conversation with the game to better understand how players progress in their ability to navigate the rules of the game.

While prior games-based, quantitative ethnographic (QE) research has focused primarily on user actions in the analysis of learning [4], collaboration [5], and student quit behavior [6] in games, in this study, we propose the addition of computer-generated events. We utilize Lakeland as the context to explore this while answering the question, "How do player responses to in-game feedback change between first and second games played?" Through this process, we demonstrate that the inclusion of game data allows visualization of the interplay between game and player and is useful in understanding student growth. This work directly contributes to the growing body of work taking a QE approach to analyzing user-generated log data. With this approach, we demonstrate that ENA can effectively visualize differences between first-time play sessions and repeat play sessions by focusing the model on the player-feedback game loop and indicators of systems thinking.

2 Relevant Literature

2.1 Systems Thinking in Science

Student success in Lakeland hinges on the students' ability to understand the varied relationships to seek a solution. They must consider more than just a series of causal events to see the problem posed in a more holistic way, a task that may be considered a "wicked problem" [7]. This framing draws a particular definition of system thinking that highlights the unique nature of problems, interplay between attempts to address the problem and how it is framed, and ambiguity of the causality particularly as it related to the temporal distance between an intervention and any direct effects." [8]. Grohs et al. operationalize the "wicked problem" framing in their attempt to assess systems thinking in students by centering their assessment around student ability to work within three dimensions of understanding the problem, recognizing competing perspectives, and ability to think through different points in time incorporating both historic and present considerations [9].

If this seems like a tall order for students, it's because it is. In problem-based contexts, students often fall short of being able to consider varied aspects of the systems at play to propose solutions [3, 10]. The trouble stems from failing to notice aspects of the system that are either temporally distant, varying in impact, or non-obvious, microscopic as a mechanism [3]. The further away a consequence is from the causal agent, whether enacted by a student or occurring in the environment, the less likely a student is to detect the relationship and incorporate it into their understanding of the system. A student has to notice both the cause and the effect with a short enough time passing to connect the two [3]. Despite systems thinking appearing in a significant portion of the cross-cutting concepts in the Next Generation Science Standards [11], the context in which students encounter these concepts tend to be ill-suited for success. Environmental systems in particular have presented challenges for students in perceiving how toxins accumulate in the environment, understanding the intricacies of stock and flow systems, and reconciling the temporal delays between actions and their effect [10].

The persistent appearance of time as a determining factor for student understanding is something well-suited to exploiting in game contexts. In real-time strategy games, the ability to manipulate time is often afforded to the player easing the demand on players to remember events that occurred long ago and tie them to current consequences. Everything becomes more connected for those who know what to look for. Additionally, rules allow designers to assist students in noticing phenomena by forcing spatial proximity, for example encouraging towns to be in close proximity to the lake in Lakeland. Furthermore, the natural scaffolding that exists in game environments perpetually attunes players to the information available to them through tutorials and visual indicators; thus, as students become more comfortable with the "rules of the game," they will likely progress in their ability to engage in relevant systems thinking.

2.2 Educational Games and Assessment

As noted above, educational games are a particularly good format for circumventing many of the issues that inhibit systems thinking because they put players in a situated learning environment that allows for interactions that might not otherwise be cost or time efficient [12]. These environments also provide a unique opportunity to gain insights into or assess how students think about or approach problems. This can happen by accident through the nature of the task given the student, or they can be intentionally designed and embedded. The latter example, known as stealth assessments are named as such because the assessment is tied to the game mechanic itself and imperceptible to the player [13].

Lakeland was not explicitly developed with stealth assessments in mind. However, we can retroactively compare how an expert system engineer would balance competing problems in Lakeland with how a novice student might approach the same task. Using the idea of an epistemic frame [12] to evaluate student actions, the engineer would be more likely to see the connection between feedback from seemingly disparate areas [9] to find long-term solutions whereas novices (secondary science students) would be more likely to employ short term solutions. Analysis of the solutions players seek may serve as a proxy for a designed assessment.

The student's proposed solutions and decisions are not generated in isolation; they are perpetually influenced by the "circle of gameplay" where the "gamer's input and the game's output reciprocally influence each other," [3]. Players are made aware of hidden mechanisms by the game feedback, and the way a player responds to game challenges and feedback provides evidence of their level of understanding of the underlying content [13]. Therefore, it is essential that we consider the dynamic between game and player as proposed by Owen and Baker [14] who advocate for including game feedback events as essential components of logging systems for behavioral modeling in educational video games.

2.3 Games and Quantitative Ethnography

Prior work has centered on the work of epistemic games or quantitative ethnographic approaches to game data, but there are several gaps that have been identified. Arastoopour Irgens and colleagues began looking at in-game data through ENA modeling, but the observed behaviors of the students largely focused on textual data communicated to teammates or non-player characters in the virtual internship [4]. More recently, log data has been analyzed using ENA to identify trends amongst students who quit challenging levels in Physics Playground, but the analysis was limited to students' actions [11]. Feedback provided by the game did not close the loop of player experience. It is within reason then that by connecting player actions to feedback received, we can build a better understanding of the player's decision space. We seek to extend prior assessment work using Epistemic Network Analysis in games as a method for visualizing the shift in the relationship between in-game feedback and student actions from first play session to subsequent sessions.

3 Methods

3.1 Context

Lakeland was designed to teach students about the complex ways nutrient cycles are manifested in agricultural and environmental contexts, and in doing so encourage systems thinking throughout gameplay. Like many real-time strategy games, players are constantly making decisions that have short-term and long-term impacts in the game space. In Lakeland, the primary player decisions include what they can buy and how they use the resources - corn, milk, and manure - from farms and dairies (Fig. 1). Ultimately, success in the game hinges on understanding how to manage soil nutrition for productivity in order to expand without causing algae blooms.

Fig. 1. Player decisions are limited to decisions around what they buy (left) and how they choose to utilize resources, either before or after production (right).

Players are assisted by a near-constant stream of feedback. As play begins, tutorials are presented by different advisors, a manifestation of the different perspectives inherent to wicked problems [9]: the farm advisor introduces players to the logistics of manure replenishing nutrients in the soil, the mayor focuses on expansion of the town, and the business advisor pushes the player to turn products into profits. Each potential avenue for players to focus on is further elucidated in the achievements available that focus on town growth, number of farms, amount of money, and size of algae bloom (for the destructive player). In the town, farmbits (townspeople) report their satisfaction (Fig. 2a) and needs (Fig. 2b) through emojis. Similarly, farm and lake tiles show visual indicators of production (Fig. 2c) and changing nutrient levels (Fig. 2d). However, learning the rules of a game and its underlying system takes time, and it is not uncommon that players will not be successful at deciphering the help that game is trying to provide on their first try.

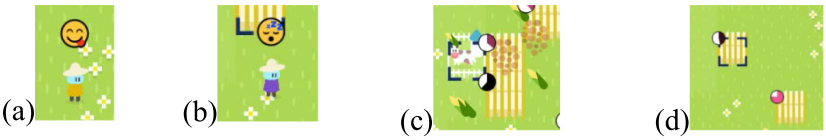

Fig. 2. Positive and negative feedback provided to players from visual cues comes from Farmbits or Farms. (a) A fed Farmbit. (b) A tired Farmbit. (c) A farm that has produced corn. (d) A nutrient depleted farm (upper left) and nutrient rich farm (lower right).

3.2 Data Collection

CSV files containing both processed and raw user data for December 2019 were downloaded from the Open Game Data website [12]. Data is anonymized and contains no additional indication of the context under which it was generated other than the game itself.

The processed data CSV included aggregate features calculated at the scale of a given level as well as an entire session. Session records were filtered to obtain sessions representative of a typical student's classroom play experience: sessions length between 5 and 45 min, active (user generated) event counts greater than 20, and English selected (original language). To subset the data, the processed data was segmented using the "num_play" feature into first ("num_play" = 1) and subsequent ("num_play" >1) games played. From those two segments, a random selection of ten first sessions and ten subsequent sessions was obtained to further down sample. Final selection for included sessions was based on whether a player had both first and subsequent sessions in December as we wanted to eliminate possible interference from long spans of time between plays. This yielded eight session for investigation.

The raw data CSV included a live stream of events for each player organized by session ID. In order to make the event data "human readable" for the purposes of coding, a Python script turned the JSON event data from each line into a textual description of the event using the documentation provided by the developers in the associated ReadMe file. For example, Event 7 is a "Buy" event that is sent with JSON metadata including the item selected to buy, tile data including description, nutrition and position in terms of X, Y coordinates on the map, whether the player can build on that tile, and the information of every tile they hovered over when choosing where to place their item.

3.3 Quantitative Analysis

Filtered data was analyzed to both confirm the effectiveness of the filters and to consider similarity of student experience between first and subsequent game play experiences. A paired, two-tailed t-test was used to compare length of play and number of student actions between games. This was essential to ensure that a student simply did not act in the first game, causing their lone farmbit to die, and necessitating a restart of the game. Additionally, paired, two-tailed t-tests were used to confirm that there were no significant differences in how many of the twenty-six possible tutorials players encountered and how many of the sixteen possible achievements they received. Game tutorials occur as students progress through the game introducing them to concepts as they go. The tutorials range in conceptual complexity from simply explaining the buy mechanism to introducing the idea of fertilizer runoff and algae blooms.

3.4 Qualitative Coding

Codes were developed using a grounded approach based on our own play experiences, prior observations of student game play, and special consideration for feedback and behaviors related to systems thinking. To begin, we played through the game considering the feedback given and our actions before referring to the ReadMe files for the game. We considered game events in isolation to simplify how we looked for a given behavior. For example, in considering the meaning of buying corn, we went through all the possible reasons a player would buy corn. We then looked at the game play log and discussed what was happening in each situation that a player was buying corn. Based on those observations, the code of short-term solution was created to represent the observations that players often bought corn when (1) they had farmbits in crisis with no chance of producing corn or (2) they did not have the resources necessary to invest in a self-sustaining solution. We applied a similar method for game event codes deriving them via a combination of developer intent and our response to the feedback during gameplay.

A final pass on the codes and coordinating definitions sought to incorporate the systems thinking literature. Acknowledging the importance of temporal distance in a student's ability to comprehend complex systems, a code was introduced for Time Manipulation with the thought that students who were trying to understand relationships would use the fast-forward tool to shorten the time between interactions. This aligned with our own verbalized use of the fast-forward and pause features during initial game play and student observations.

With the codes completed, we turned our attention to applying the codes to the log file dataset using the nCoder webtool [16]. Since the event text was generated through a uniform script, our collaborative code-defining process yielded high levels of agreement between coders and the automated coder. Individual codes and agreement measures can be seen in Table 1.

Table 1. Codebook (Kappa agreement reported in order of Rater 1 vs Classifier; Rater 2 vs Classifier, and Rater 1 vs Rater 2.)

Code	Definition	Example	Agreement
Positive farmbit	Farmbit (townsperson) expresses contentment or happiness with emojis	Lucy at 26,26; I've got my floatie on. Swimming emoji	1.00** 1.00** 1.00**
Negative farmbit	Farmbit expresses sadness or distress	Sidney at 20,23… I'm tired. Sleepy face	0.96* 0.96* 1.00**
New resources	When a resource is produced and appears on the map	Farmharvested at 25,25; Items marked for use and sell	1.00** 0.92* 0.92*
Time manipulation	When the player changes game speed	current: fast, previous: play, Player Changed	1.00* 1.00* 1.00*
World feedback	When visual feedback indicates a problem with a world tile	Farmfail; farm at 23,23; Items marked for sell and sell	0.95* 0.92* 0.92*
Short term solutions	Player buys resource that doesn't have lasting impact (food, manure, skimmer)	Tile: Growing, Medium nutrition, land at 19,30; buy: food	0.96* 1.00** 0.96*
Self-sustaining solutions	Players buys a long-term solution such as a farm or dairy	Tile: Growing, Medium nutrition; at 29,24; buy farm	1.00** 1.00** 1.00**
Resource management	When players indicate a resource should be used, sold, or consumed	Itemuseselect; item at 27,23; food for use, Previously Sell	1.00** 1.00** 1.00**

*rho $\leq$ 0.05, **rho $<$ 0.01

3.5 Epistemic Network Analysis

Epistemic Network Analysis [17] was used to explore the data using the ENA Web Tool [18]. Units of analysis were defined as all events associated with a given game (Game 1 or Game 2) subset by Speaker (Player or Game) and Session_id. For example, one unit included all lines associated with player X's first game. The ENA algorithm uses a moving window to judge co-temporality when constructing a network model [19], defined here as 10 events. A window size of 10 was chosen due to the rapid nature of feedback generated from the game and co-occurrence of logging events (i.e. If the game generates new resources, and a farmbit reacts immediately, there may be two more actions before the player has a chance to respond. In order to ensure that we were capturing connections between the game and the player.) The resulting networks are aggregated for the categories of first or second game. Networks for third game or higher were removed due to having too few samples.

The ENA model normalized the networks for all units of analysis before they were subjected to a dimensional reduction using singular value decomposition, which produces orthogonal dimensions that maximize the variance explained by each dimension. A means rotation was performed between the groups to better interpret the axis.

Networks were visualized using network graphs where nodes correspond to the codes, and edges reflect the relative frequency of co-occurrence, or connection, between two codes. These networks were compared using network difference graphs that illustrated differences between first games and second games by subtracting the weight of each connection in the Second Game Played network from the corresponding connections in the First Game Played network. To further test for differences we applied a Mann-Whitney test to the location of points in the projected ENA space for units in each category.

4 Results

4.1 Qualitative Counts

After filtering sessions, eight sessions were identified as having both first and second sessions that occurred in December. The average session durations for Game 1 and Game 2 were 11.6 min and 15.7 min, respectively. Players in Game 1 acted more frequently than those in Game 2 logging one player action for every 3.06 events logged by the game as opposed to a 1 to 3.38 ratio for Game 2. A two-tailed, paired t-test demonstrated no significant differences in the play sessions regarding length of play or number of actions: session duration $p = .30$, session active events $p = .11$, and session events $p = .11$. This indicates that play within each of the selected games was comparable and confirms the effectiveness of the filter in looking for games that fit the typical classroom use. Paired, two-tailed t-tests also compared the number of achievements players received and number of tutorials they encountered in Game 1 and Game 2 and found no significant differences ($p = .06$, $p = .10$).

4.2 Quantitative Models

Epistemic Network Analysis of Game One and Game Two yielded an ENA model that had co-registration correlations of 0.98 (Pearson) and 0.98 (Spearman) for the first dimension and 0.99 (Pearson) and 0.99 (Spearman) for the second indicating a strong goodness of fit between the visualization and the original model. Along the X axis (MR1), a Mann-Whitney test showed that Game 1 (Mdn = 0.05, N = 28) was statistically significantly different at the alpha = 0.05 level from Game 2 (Mdn = −0.44, N = 16 U = 124.00, $p = 0.01$, $r = 0.45$).

Figure 3 shows the relationships most prominent in Game 1. We choose to specifically focus on relationships between player actions with the game and player actions with themselves. Player-Game connections are dominated by frequent connections between *Positive Farmbit Feedback* and *Resource Management* and *Positive Farmbit Feedback* and *Time Manipulation.* Player-Player connections most often occur between *Resource Management* and *Time Manipulation.*

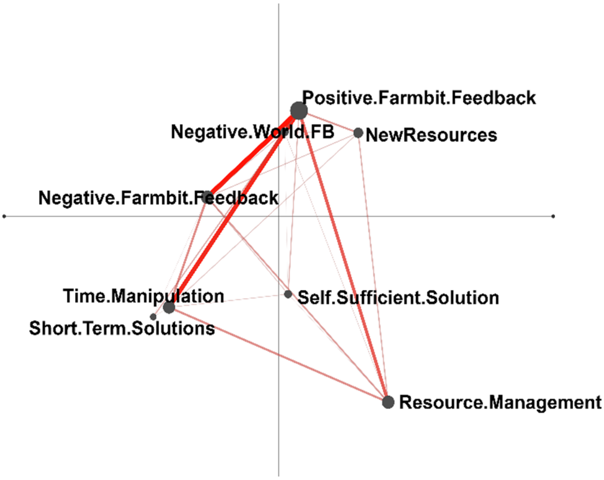

Fig. 3. ENA plot of Game 1 sessions.

In Game 2, shown in Fig. 4, the connection between *Positive Farmbit Feedback* and *Resource Management* dominates the player-game connections with *Time Manipulation* and *Positive Farmbit Feedback* also showing a strong connection. There are not any strong player to player connections.

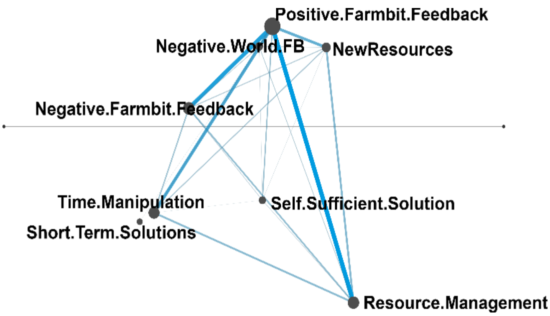

Fig. 4. ENA plot of Game 2 sessions.

In these plots, the Y axis is interpreted as game feedback (positive axis) vs. player events (negative axis). This allows visualization of the connections between player and game as they run vertically through the plot. In the comparison plot, a means rotation of the X axis elucidates the difference between first and second game players (Fig. 5).

Short-term, reactionary actions such as *Time Manipulation* and *Short Term Solutions* fall towards the left on the x axis whereas sustainable, planning actions such as *Resource Management* fall towards the right. First game players tend to manipulate time more in connection to farmbit feedback whereas second game players manipulate time in connection to new resources. Similarly, positive feedback is more often connected to short-term solutions during first games and resource management during second games.

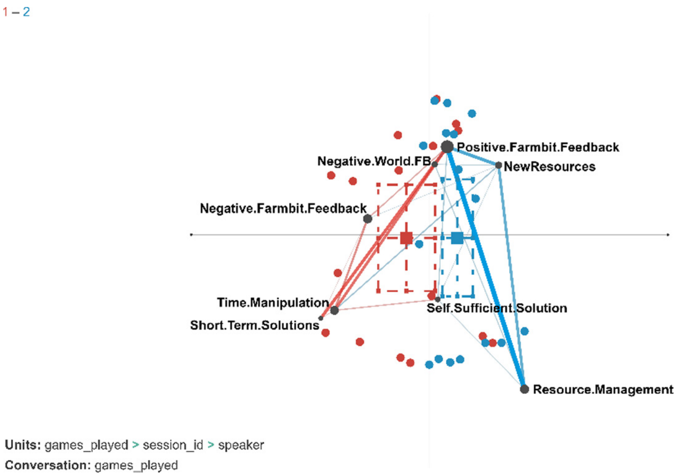

Fig. 5. Comparison ENA plot of Game 1 (red network) and Game 2 (blue network) demonstrate the differences between games. (Color figure online)

4.3 Qualitative Description

To better understand the differences in how players respond to feedback in Game 1 as opposed to Game 2, we can focus on the connections between Time Manipulation in each case. Tables 2 and 3 illustrate narrative differences between how *New Resources* and *Positive Farmbit Feedback* are connected to *Time Manipulation.* The selections chosen include 10 log events to parallel the size of the moving stanza used in the ENA models. Events that were not coded in ways relevant to the model were left in the sequence and marked with "N/A," but they were described in the explanation with possible impact.

The player we observe in the Game 1 event sequence is not showing that they are planning ahead. They have not checked on any of the resources in this section. They have

Table 2. Event sequence of a Game 1 session.

Log event	Coded	Explanation
Farmharvested tile at 24,23, Items marked for use and use	New Resources	The player sees their farm get harvested. Both corn that are produced display on the game board. They are not consumed by a farmbit because they are not hungry. While it was raining, any fertilizer that was placed onto farms by the player moved, but the rain stops. The game slows down the speed of play as another farm produces more food. Sidney goes to the lake to get water to restart the farm. The player pauses the game, likely to take inventory of all the new resources produced after the rain. The rain tutorial ends. The player starts the time back at a normal pace. Noting the abundance of corn, the player selects an item and marks it for sale
Rainstopped	N/A	
Speed: Changed to playfrom fast by game	N/A	
Farmharvested tile at 23,23, Items marked for use and use	New Resources	
Emote Sidney, at 26,26, I've got my floatie on flamingo swim emoji	Positive Farmbit	
Speed: Changed to pause from play by Player	Time Manipulation	
Checkpoint End: Rain	N/A	
Speed to play from pause by Player	Time Manipulation	
Selecti tem item: at 22,22, food for use	N/A	
Itemuseselect item: at 22,22, food for sell, Previously Use	Resource Management	

Table 3. Event Sequence of a Game 2 Session

Log event	Coded	Explanation
Emote Mary, at 21,21, Ive got my floatie on flamingo swim emoji	Positive Farmbit	The player sees their Farmbit enter the water, likely to begin growing another harvest at the farm. The player decides to sell one unit of food, which is not the same resource Mary takes off to sell. The player checks on two other items which lets them see that both are set to be used for food. The player slows time down in preparation for new resources to be produced. Mary continues tending the farm that just produced by getting water with their floatie and taking produce to be sold at the market. The player moves the game back to fast to speed through the production
Itemuseselect item: at 20,24, food for sell, Previously Use	Resource Management	
Emote Mary, at 17,22, Off to market sale	Positive Farmbit	
Selectitem item: at 22,24, food for use	Information Seeking	
Selectitem item: at 23,25, food for use	Information Seeking	
Speed: Changed to fast from play by Player.	Time Manipulation	
Farmharvested: at 22,24, Items marked for use and use	New Resources	
Emote Mary, at 21,21, Ive got my floatie on flamingo swim emoji	Positive Farmbit	
Emote Mary, at 17,24, Off to market sale	Positive Farmbit	
Speed: Changed to play from fast by Player	Time Manipulation	

gotten several pieces of feedback that production is continuing successfully through the farmbit collecting water to restart growth and the new resources now accumulating on the board. It is possible that the player is working towards stockpiling their resources, so they do not need to change their use. However, when the game encourages the player to slow down, calling attention to the changes that have happened after the rain, the player feels it is necessary to slow further and pauses the underlying simulation. It is only in this moment, when the feedback from the game is paused, that the player begins to interact with their resources and plan.

In the selected sequence from Game 2, the player is still changing the speed of the game, but it is not in direct relation to an immediate event. They are responding in order to plan and set up future actions. This is evident through positioning of emotes and actions the player is taking. While the player marks an item for sale at tile 20, 24, the Farmbit takes items to market from tiles 17, 22 and 17, 24 which came from a different farm that previously produced. The player is also checking unrelated items available on the board, likely to confirm their plan.

How players choose to use their ability to manipulate the passage of time in Lakeland differs between Game 1 and Game 2. Through looking at *Time Manipulation* we also are able to see differences in when players manage their resources. The Game 1 player is only able to manage resources in the moment, choosing to pause the game before making decisions, whereas the Game 2 player is able to forecast the needs of their town and manages resources far in advance of when they are needed.

5 Discussion

ENA was an effective tool for capturing the shift in player actions from Game 1 to Game 2. This aligns with prior findings where ENA was used to identify novices and experts in virtual internships [4]. Expert systems-thinkers should be able to predict the causal relationships of the system and be both preemptive in their approach to potential problems as well as know what information is valuable to act on in the moment. By applying a grounded coding approach to the actions that players are taking, we were able to tell a story about how the player's strategy develops between sessions. Grounding the chosen codes in the known challenges of systems thinking (temporal distance in particular), player actions, and game feedback created a sufficient framework for understanding how players are moving through the game in relation to their conceptual understanding of the game and its intended learning objectives.

There are several limitations of this study worthy of further investigation. Primarily, the sample size is small, including only a handful of players; it would be worthwhile to expand the sample for generalizability. The games were also heavily filtered, and it may yield interesting results to include players who experience rapid iteration through quick failed games. Furthermore, the nature of a moving window in ENA creates connections ahead of and behind events. There is no way to determine causality or directionality based on these findings at this time. This provides a potential use case for directional ENA in future iterations.

Moving forward, these exploratory findings indicate the potential application of ENA as a method for assessing students from log data alone. The next steps would include investigating these patterns through both ideographic (comparison of individual to self over time) and nomothetic (comparison of trends within a group) lenses as a test of validity. Here, we have demonstrated the beginnings of this work through the generation of a network based on a group of individuals who share commonalities, in this case being new to Lakeland or a repeat player. Expanding our sample size would allow for nomothetic-like extrapolation to the "general laws that hold across persons" [20].

A next step would include comparing networks that represent an individual's actions over time, such as player 5 at the beginning, middle and end of Game 1, or player 5 over the course of Game 1, Game 2, and Game 3. This would allow an idiographic demonstration should their network shift from session to session demonstrating a change in student behavior and thus understanding.

In this paper, we have focused on the detectable differences between game play sessions, not on their implications. The method demonstrated here could further serve a variety of audiences within the larger educational games community including game designers as a measure of design effectiveness or teachers as a means of assessment. Still, from another angle, the method described serves the larger quantitative ethnography community in furthering the way that we think about data, coding, and models. We have integrated computer-generated actions into our models alongside raw log data in a meaningful way that tells a story of user experience, a contribution that can add to the way we investigate student interactions with digital environments in the future.

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