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I see what you did there! Divergent collaboration and learner transitions from unproductive to productive states in open-ended inquiry

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ABSTRACT

While open-ended and tinkering-based learning environments offer considerable support for developing STEM-based reasoning and collaboration skills, understanding how and when learners are engaged in productive or unproductive exploration is a pressing challenge. This is particularly true in museums where dwell times are short and visitors can enter and exit exhibits at varying times. In response, this work aimed to answer two questions: 1) How can we combine learning analytics and qualitative approaches to understand how learners move from unproductive to productive states during open-ended inquiry? 2) What role do interactions with others play in supporting participants' transitions to productive states? To answer these questions, this study examined how combining a Hidden Markov Model (HMM) and interaction analysis together can reveal important elements of participants' collaboration and exploration that would likely be lost if each method were applied in isolation. The methods were applied to visitors participating at an interactive multi-touch exhibit (named *Oztoc*). The application of HMM successfully captured when participants transitioned from persistent unproductive to productive states, while interaction analysis using the Divergent Collaborative Learning Mechanisms framework (DCLM) showed how specific divergent collaborative interactions supported these transitions. In particular, we reveal the role that visitors engaging in *Boundary Spanning Perception* and *Boundary Spanning Action* played in these transitions. More broadly, this work shows how designs that provide opportunities for these kinds of interactions may help learners effectively transition out of sustained states of unproductive persistence.

1. Introduction

Exploratory and tinkering-focused learning's emphasis on creative and improvisational problem solving (Bevan, Petrich, & Wilkinson, 2014) have shown considerable promise in supporting learners' development of STEM-based (science, technology, engineering, and math) reasoning and collaboration skills (Land, 2000; Resnick & Rosenbaum, 2013). While what exactly falls under tinkering is often ambiguous, it often includes learners' use of physical and digital materials to help them explore possible solutions to their desired goals (Papert & Harel, 1991; Richardson & Rosenblum, 2017). Further, while there may be goals for the learner to achieve, how they go about discovering and achieving those goals are largely left for the learner to decide (Bevan, Gutwill, Petrich, &

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Wilkinson, 2015; Richardson & Rosenblum, 2017).

While there is growing interest in these kinds of learner-centered pedagogies, their assessment and feedback, especially in real time, has been particularly difficult (Berland, 2017; Blikstein, 2013). This is particularly true in informal learning spaces such as museums, where dwell times are short, participants can enter and leave an exhibit at will, and participants and museum facilitators lack a history of shared engagement (Block et al., 2015; Humphrey & Gutwill, 2005; Yoon, Elinich, Wang, Steinmeier, & Tucker, 2012).

Tinkering focuses on promoting iterative, creative, and exploratory processes during learning, and it has demonstrated ability to foster a wide range of STEM literacies (Vossoughi, Escudé, Kong, & Hooper, 2013). However, with tinkering's focus on open exploration and learner-defined goals, understanding when a learner is productively tinkering is a challenging task. Productive tinkering can be conceptualized as making progress towards one's personal goals or the learning goals of an activity (Tissenbaum, Kumar, & Berland, 2016). There is also the issue of unproductive tinkering, which can be conceptualized as unsystematic approaches to exploration and problem solving (Fitzgerald et al., 2010). The problem of not knowing the productivity of tinkerers is compounded by the fact that early struggles and failures are often celebrated, and learners are encouraged to persevere through these obstacles (Martin, 2015). While persistence is important, Kohn (2014) showed that it is not enough for learners to simply persist, but critically, *how and why they persist*. A failure to understand how and why learners persist, risks allowing them to fall into cycles of unproductive perseverance, which can hinder both long term productivity and motivation (Beck & Gong, 2013; McFarlin, Baumeister, & Blascovich, 1984). Further, recent research has shown that in some cases, once learners become unproductive, they struggle to move back to a productive state and instead discontinue/quit (Tissenbaum, Kumar, & Berland, 2016; Maltese, Simpson, & Anderson, 2018).

In technology-mediated learning environments, one approach for providing the information needed to ascertain learners' states while tinkering is through data captured from real-time activities (Krumm, Means, & Bienkowski, 2018). Using data mining and analytics, this data can allow us to develop models for investigating learners' interaction patterns in the hopes of revealing patterns that could be confidently categorized as "productive" or "unproductive" tinkering (McFarlin et al., 1984). Revealing these states can help us better understand what causes learners to fall into unproductive patterns or transition into productive ones. This is turn can help researchers and educational designers develop appropriate interventions or supports.

However, in exploratory learning environments, individual actions cannot be easily classified as being productive or unproductive; as such, they are considered "hidden." One approach to finding hidden states is through the use of Hidden Markov Models (HMM – Rabiner & Juang, 1986), which mine large sets of user data in order to generate probabilistic models of learners' transitions between hidden states (Sutton & Barto, 1998). Through this approach, we can identify patterns in learners' transitions between productive and unproductive states that would be extremely time-consuming to find by qualitative means alone, particularly at a large scale. However, these approaches often only capture what is happening "on the screen". Conversely, qualitative approaches, such as interaction analysis, can provide fine-grained understanding of learners' interactions with each other and the objects/tools/scaffolds in the environment (Jordan & Henderson, 1995). By combining these two approaches, we can highlight potentially fruitful moments in learners' inquiry and exploration and dive in deeper to reveal the fine-grained interactions taking place.

In response, this work aims to combine a learning analytics approach for identifying when participants fall into states of unproductive perseverance (Tissenbaum, Kumar, & Berland, 2016) and a framework for recognizing and classifying divergent collaboration and inquiry (Tissenbaum, Berland, & Lyons, 2017). By combining these two approaches, we highlight how learning analytics can provide important insight into when students are engaged in productive or unproductive exploration, while the qualitative framework can give us fine-grained insight into interactions that precipitate these changes in states. This is particularly helpful for understanding the rare cases in which learners manage to break out of unproductive perseverance, and how and why they are able to do so. The contributions of this work are threefold: 1) showing how a multi-dimensional approach can be effectively employed to reveal when students transition from persistently unproductive to productive states and the factors that caused these changes; 2) understanding the role divergent collaboration plays in these transitions; and 3) broader recommendations for effectively supporting learners' transitions from unproductive to productive states in exploratory learning environments.

2. Background

2.1. Exploration and tinkering as authentic STEM and computational practices

Increasingly, we are seeing research and policy that advocate the need to emphasize the *processes of creating and learning* in addition to (and often instead of) learners' *final products* (Daskolia & Kynigos, 2012; Means, 2018; Whitman & Witherspoon, 2003). Given their focus on playful, iterative and exploratory investigation, environments in which learners can freely tinker and manipulate objects to support their inquiry are particularly well-suited for addressing this need.

In tinkering, learners continually reassess their goals, explore new paths, and, in the process, imagine new possibilities (Resnick & Rosenbaum, 2013). These learning environments also provide greater empowerment for learners, allowing them to more freely explore and have control over tools, content development, production, and sharing (De Freitas & Neumann, 2009). While makerspaces have garnered much attention recently for their support of exploratory, tinkering-focused learning (Bevan et al., 2015; Blikstein, 2018; Silver, Rosenbaum, & Shaw, 2012), they are hardly alone – significant research has shown the potential for robotics (Eteokleous, Nisiforou, & Christodoulou, 2018), programming (Blikstein, 2011), games (Kafai, 2018), and interactive simulations (Zhu et al., 2018) to support exploratory learning.

Tinkering's origins derive from constructionist theories of learning, which focus on hands-on activities in the pursuit of being, doing, knowing, and becoming (Papert & Harel, 1991; Petrich, Wilkinson, & Bevan, 2013). Such approaches have broadly been acknowledged to provide excellent opportunities for learners to engage in disciplinarily authentic engineering, science, and computational practices (Lyons et al., 2015; Berland, Martin, Benton, Smith, & Davis, 2013; (Gutwill, Hido, & Sindorf, 2015); Lamers, Verbeek, & van der Putten, 2013), including encouraging learners to build, test, and iterate on designs (Daskolia & Kynigos, 2012); remix their work and that of others (Ito et al., 2010); creatively explore content/skills/building (Peppler, Halverson, & Kafai, 2016); and "mess around" (Ito et al., 2010). In addition to mirroring the practices of domain experts (Wang & Agogino, 2013), open-exploration and tinkering have been found to develop practices that are useful in their own right (Berland, 2016).

While tinkering's recent popularization is due in a large part to the maker movement and its focus on the design and construction of physical objects, digital environments – and their affordances for immediate feedback, augmenting interactions with additional information, and visualizing users' tinkering the processes – offer additional unique supports for tinkering-based learning (Means, 2018; Resnick & Rosenbaum, 2013). Hybrid systems that combine tangible interactions with augmented digital feedback offer a coherent blend of both approaches (Lyons et al., 2015). Interactive tabletops, in particular, offer considerable potential for supporting tinkering, as they combine physical manipulatives (such as fiducial enabled blocks) with augmented feedback about connections between objects or changes in users' tinkering (Beheshti, Villanosa, & Horn, 2018; Dillenbourg & Evans, 2011; Schneider, Wallace, Blikstein, & Pea, 2013). Interactive tabletops also make participants' thinking and exploration visible, which can support collaboration, group discussion, and sense making (Evans, Wobbrock, & Davis, 2016; Yoon et al., 2012). However, within exploratory settings students can often have goals that diverge from their peers. As such, we need to seek out new approaches for capturing and understanding the collaboration and sense making taking place.

2.2. Understanding divergent collaboration within exploratory learning environments

While collaboration is often touted as an important element in supporting tinkering and exploration (Chan & Blikstein, 2018; Bers, Flannery, Kazakoff, & Sullivan, 2014; Petrich, Wilkinson, & Bevan, 2013), due to their generally open-ended nature, recognizing and classifying successful collaboration requires a careful reframing (Horn et al., 2012). Building on the work of Roschelle & Teasley, (1995), effective collaboration is often characterized as a process of convergent conceptual change (CCC), in which learners' conceptions of the problem space and problem solution evolve (or converge) to be more similar to those of their collaborators. In many exploratory environments, however, learners are encouraged to follow their own pathways and to discover multiple and varied ways of understanding a particular problem and possible solutions (Lyons et al., 2015). In these situations, convergence is not necessarily the only marker of effective collaboration. In contrast, divergence in ideas can actually increase opportunities for learning, as learners are pressed to explain differences in their goals and solutions in juxtaposition with the work of their peers (Chi & Wiley, 2014; Isohätälä, Järvenoja, & Järvelä, 2017; Turkle & Papert, 1990).

Conventional examinations of collaboration require examination at the grain size of the group (Stahl, Koschmann, & Suthers, 2006). However, in drop-in spaces such as museums, individuals can enter and exit groups freely, and define new, differing, and divergent goals (Block et al., 2015). Because of these shifting roles, recognizing and framing effective collaboration in these spaces requires analysis at a more individual level. Within these divergent inquiry spaces, circumstances where participants move *away* from a shared goal via adaptation and differentiation are potentially very fruitful for learning (Tissenbaum, Berland, & Lyons, 2017). Learners can explore the idea space on their own, define their own goals, try out new approaches, while still providing opportunities for effective collaboration. In truth, when learners diverge in their exploration, it provides opportunities for individuals to compare and contrast aspects of their own tinkering to that of their peers towards adapting elements for their own work, or to provide assistance based on their own experiences. However, in order to effectively chart learners' divergent inquiry explorations in exploratory learning environments, we need to develop frameworks and analytical approaches that effectively highlight the nuanced ways this divergence takes place.

2.3. DCLM: recognizing and categorizing effective collaboration in exploratory learning

While divergent inquiry may be fruitful for learning, not all collaboration that takes place in open-ended exploratory environments is inherently divergent – there are many instances where convergence around a shared conceptualization of the problem space or a particular solution may be desirable (or even optimal). However, dynamic changes between convergent and divergent inquiry point to the need for frameworks that recognize and account for both convergent and divergent collaboration. In response, we have developed the Divergent Collaborative Learning Mechanisms (DCLM) framework. DCLM is a response to this challenge and has been found to be effective in categorizing collaboration in open-ended inquiry at both the group and individual levels (Tissenbaum, Berland, & Lyons, 2017). DCLM categorizes interactions in open-ended exploratory inquiry as a means for categorizing forms of effective collaboration that would be missed by collaboration frameworks that focus solely on convergence as a marker of effective collaboration. Below we describe the elements of the DCLM framework, with a particular focus on how DCLM highlights elements of divergent collaboration.

2.4. More than grit: productive versus unproductive perseverance

There is a common refrain from the maker movement, and in tinkering and exploratory learning in general, to "fail fast and fail often" (Dougherty, 2013). The premise of failure as growth is built on Dweck's work on growth mindsets (2006), in which people see their talents as developable through dedication and effort. This notion of perseverance and dedication over the long-term as a predictor of student success has been further popularized by Duckworth et al.'s (2007) research into "grit." Duckworth and colleagues showed that individuals who maintained effort and interest over years despite failure, adversity, and plateaus in progress (i.e., grit) had more "success" than those who did not exhibit these characteristics. The overarching idea is that *how students approach learning* may be as critical *as what they are learning* (Pappano, 2013).

While on the surface the broad notion of promoting perseverance over many years is laudable, a failure to attend to the shorter-term elements of student effort and persistence in the face of failures has a host of potentially negative consequences. When we encourage learners to give themselves permission to fail, there is an implicit assumption that they will have the opportunity to try again or that they will persist in the right way (Ryoo et al., 2015; Ryoo & Kekelis, 2018). McFarlin and his and colleagues (2007) found that participants (especially those with high self-esteem) who spent the majority of their time at the beginning attempting to solve one or two impossible problems became frustrated and stopped working. These findings mirror the work of Janoff-Bulman and Brickman (1982), who found that the ability to discriminate when persistence will or will not lead to success is more valuable than the general tendency to persist. As such, while it is important to allow learners who are engaged in open-ended and exploratory tinkering to persevere through initial struggles and failures, it is equally critical to understand *why they are persisting* and *how they are persisting* (Kohn, 2014). This is especially important given that, when left to their own devices, many learners struggle to make correct strategic decisions (Ahmadzadeh, Elliman, & Higgins, 2005; Alqadi & Maletic, 2017). Therefore, in the short-term, the ability to recognize when learners are engaged in productive versus unproductive perseverance is a critical element in supporting their effective tinkering and to encourage their long-term persistence.

2.5. Revealing unproductive perseverance in exploratory learning environments

There has been considerable work on trying to recognize when learners are stuck in cycles of unproductive perseverance, or floundering, in intelligent tutoring systems (ITS) (Crow, Luxton-Reilly, & Wuensche, 2018; Riofrío-Luzcando, Ramirez, & Berrocal-Lobo, 2017). However, in tinkering environments, with their less structured and open-ended avenues for exploration, recognizing when learners are engaged in productive versus unproductive perseverance is a more challenging endeavor. When examining novice programmers, Perkins, Hancock, Hobbs, Martin, and Simmons (1986) noted that students may engage in tinkering behaviors that superficially appear to be productive, but under the surface, were indicative of either unsystematic thinking or exasperation. The inability to recognize the subtle differences between these practices makes effective facilitation difficult.

This is particularly true in museum settings, where museum facilitators often do not have substantial time to assess the state of participants' explorations and understanding (Humphrey, Gutwill, & Exploratorium APE Team, 2005). This is further exacerbated by the fluidity of participation, as participants may engage and leave exhibits at different times (rather than having well-defined beginning and end points). Also, participants may interact with the exhibit alone, in groups, or simultaneously with strangers (Block et al., 2015). Even if facilitators hover over learners, keeping track of multiple learners' participation during real-time activities is daunting, if not impossible (Dimitriadis, 2012).

Another challenge with understanding and responding to learners' productive and unproductive states is that they are often "hidden" from casual observation. When learners are engaged in exploratory learning, there is rarely a specific input that can be observed as "productive" or "unproductive"; rather, these states are considered to be "hidden" (Jeong et al., 2008). When properly instrumented, technology-supported learning environments can capture learners' tinkering and experimentation in real-time. These interactions can provide rich data streams that can be mined to highlight patterns in learners' behaviors and reveal these hidden states. One approach to finding the hidden states in learners' activities is through the use of Hidden Markov Models (HMM – Rabiner & Juang, 1986). HMMs are similar to Markov Models, which probabilistically describe the likelihood of a future state based on an event's (or user's) current state. A simple version of a Markov Model would be predicting the next day's weather given the current weather (Stengel, 2003, pp. 441–8580). Given a present state (raining or dry), a Markov Model would show the probability that the next day will rain again or will be dry. This can also allow us to predict the probability of a set of sequences (e.g., rain, dry, dry, dry). In HMMs, unlike in Markov Models, the state of the user is not directly observable, only the outcomes of the state are (hence the "hidden" aspect). As such, we need to infer the hidden state based on these observable outcomes.

In education research, HMMs have been used to reveal learners' "hidden" states when engaged in specific learning activities (Martin & Sherin, 2013). For instance, HMMs have been used to successfully categorize student behaviors in computer-based inquiry environments (Jeong & Biswas, 2008); classify users through their navigation in learning systems (Fok, Wong, & Chen, 2005); and model the processes of collaborative learning (Soller & Lesgold, 2007).

2.6. Combining qualitative frameworks and learning analytics to understand when and how learners transition out of persistent unproductive states

While learning analytics can reveal patterns in large data sets that would be prohibitively time consuming (if at all possible) by humans alone, qualitative approaches can provide a richer understanding of the nuanced interactions taking place (Jordan & Henderson, 1995). Qualitative approaches provide the "thick description" needed to understand the nuances of inquiry, collaboration, and learning in open-ended exploratory environments (Geertz, 1994). Despite the complementary affordances of these approaches, especially in regards to the granularity for different data set sizes, there has been relatively little work that has combined them to help inform research around technology-supported collaborative learning (Romero & Ventura, 2010; Wise, Hausknecht, & Zhao, 2014). In response, building off our earlier research into the use of learning analytics for identifying productive and unproductive states in open-ended inquiry (Tissenbaum, Kumar, & Berland, 2016) and recognizing and categorizing divergent collaboration within open-ended exploratory setting (Tissenbaum, Berland, & Lyons, 2017), this study aims to combine these two approaches together to recognize when learners transition from unproductive states of tinkering into productive states and what elements of the environment supported these transitions. To this end, we were interested in two questions about learner transitions from *persistent* unproductive tinkering (i.e., unproductive perseverance) to productive tinkering:

1) How can we combine learning analytics and qualitative approaches to understand how learners move from unproductive to productive states during open-ended inquiry?
2) What role do interactions with others play in supporting participants' transitions to productive states?

In answering these questions, we combine approaches for recognizing how and when learners engage in sustained unproductive persistence and for qualitatively coding their collaborative interactions when they successfully transition out of these states. We anticipate that these findings will add an important methodological exemplar to the growing interest among researchers (Munshi et al., 2018; Spikol, Ruffaldi, Dabisias, & Cukurova, 2018) who wish to recognize productive and unproductive states in their own learning designs. More broadly, this work provides a valuable example to educational designers and researchers on the importance of making the explorations and tinkering of others observable to their peers as a way to support divergent forms of collaboration.

3. Methods

3.1. Participants and research setting

In this study, we analyzed the actions of 3546 participants ($N = 47{,}630$). Visitors to the museum generally come from a wide range of cultural and SES backgrounds, and are multi-generational. Visitors entered the exhibit alone, as families, and in large groups.

This study was conducted in a multi-touch tabletop exhibit named *Oztoc*. *Oztoc's* narrative situates participants as electrical engineers helping fictional scientists in an uncharted aquatic cave teeming with never-before-documented species of bioluminescent fish (see Fig. 1). Participants design and build glowing fishing lures to attract fish for the scientists to study. To do this, participants place wooden blocks on the interactive table surface to create simple circuits that illuminate an LED (Fig. 2). To catch all the different fish, participants must experiment with creating circuits with different colors (red, blue, or green) and numbers (one, two, or three) of LEDs.

Oztoc was designed to promote participants' agency in choosing and achieving their own goals (e.g., choosing which fish to target), rather than imposing pre-defined ones, while still providing a common set of resources (e.g., circuit blocks) and processes (e.g., connecting two blocks by "bumping" them together). Further, participants' explorations in *Oztoc* are not directly coupled to others' explorations at the table; the actions of one participant do not necessarily affect the actions of others. In this way, participants can move between working with others on shared goals and pursuing their own divergent goals. By supporting participants in inquiry activities in which they are free to pursue divergent goals within a shared domain, we open up new ways for participants to investigate phenomena, engage in discourse, and collaborate with peers (Tissenbaum, Berland, & Lyons, 2017).

Oztoc is installed in its own room, connected to the main exhibit space. A 'lollipop' sign just outside the room indicated when videotaping took place, letting participants decide to enter and consent to recording or return when data collection was not active. Video data was collected via three cameras unobtrusively placed across the room, and audio was captured using a boundary microphone near the table. Visitor interactions with the table were logged using the ADAGE system (Owen & Halverson, 2013). We manually synchronized log and video data to ensure alignment between events captured by the table and by audiovisual recordings.

3.2. Identifying productive states using analytics

With millions of logged user events captured during Oztoc's operation (about 14 days in total), we needed an approach for identifying patterns in the data that gave us a lens into participants' states, especially when participants moved from unproductive to productive states. For us, a productive state was one that would be indicative of the visitor progressing in their understanding of the system and their achieving their goals. However, understanding whether a particular action a visitor made was productive or unproductive was a challenging task. For example, a visitor creating a non-working circuit could be representative of them trying out new ideas (productive), getting stuck without understanding why (unproductive), or repeating a non-working circuit to try and debug what is going on (productive). In *Oztoc*, each of these would initially be logged the same, as a non-working circuit, but the underlying state (i.

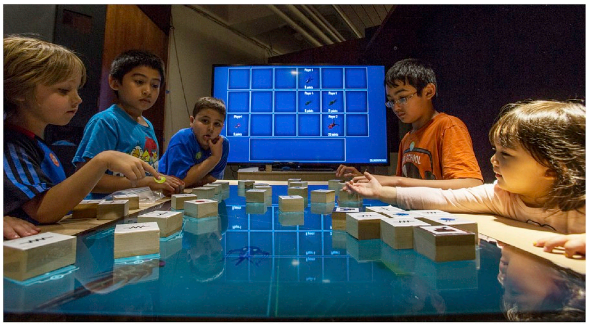

Fig. 1. Children gathered around the *Oztoc* exhibit. The large scoreboard can be seen behind the children.

Fig. 2. Participants assemble virtual circuits using wooden blocks that represent resistors (1), batteries (2), timers (3), and different colored LEDs (4). Participants make circuit connections (5, depicted as lines on the tabletop) by bringing the positive and negative terminals of the blocks (augmentations displayed on the table) in contact with one another. Creating a successful circuit (i.e., one that has the correct ratio of resistors, batteries, and LEDs) causes the LEDs to glow and lure the fish attracted to that light out for cataloging.

e., productive or unproductive) would be hidden. It was for this reason that we decided a Hidden Markov Model (HMM) would be an effective approach for examining visitors' exploration. As shown, in the example above, HMMs are particularly useful in these kinds exploratory and inquiry-based learning, as learners' states at any moment in the activity are fluid and hard to capture naturalistically.

In order to develop our HMM, we needed a unit of analysis that was at a sufficient level of granularity. Based on our previous research (Lyons et al., 2015), we selected the "MakeCircuitCreate" event in the data as the marker for examining participants' tinkering and exploration. The MakeCircuitCreate indicated when a participant made a complete, although not necessary working, circuit. This event gave us detailed data about participants' tinkering, including components used and state of the circuit. Using the "MakeCircuitCreate" logs, we developed a coding scheme that we could apply to each user's circuit (Table 2; Tissenbaum, Kumar, & Berland, 2016).

When applying the coding scheme, we kept track of all the circuits that a visitor made (as well as all the circuits made by others) from the time they arrived at the exhibit. The coding scheme could then provide us with a detailed picture of each visitor's explorations at the table. For instance, if a visitor came up to the table and their very first circuit had 6 components, but did not work and no one had made a similar circuit since they had arrived, the circuit would be coded as a CNUO (complex, not-working, unique for them, and original to the table). On the other hand, if a visitor made a 3-component circuit that worked and it was the first time they had made it and it was the same configuration as a circuit that someone else at the table had made since they arrived, the circuit would be coded as a SWUE (simple, working, unique, and an *echo* of someone else's circuit). For this second circuit, it may be that the visitor saw the circuit that the other visitor made and this influenced their own exploration (however, the analytics alone would not be able to show this).

Using this coding scheme, we developed an HMM (Fig. 3) that accurately predicted the productive or unproductive state of a participant based on their most recently constructed circuit. The model's ROC/AUC score was 0.79, which is considered satisfactory to consider the HMM's as reliable; for a detailed description of the HMM's construction, see Tissenbaum, Kumar, & Berland, 2016.

Initial examinations of the model (Fig. 3) were encouraging. We noted that visitors tended to stay in a productive state 69% of the time (as shown by the arrow looping back to the "productive" state) or leave the exhibit 16% of the time (as shown by the arrow pointing to "new" which indicates a new visitor at that location at the table). However, we also noted that once a visitor became unproductive (the arrows from "productive" or "new" to "unproductive", they rarely transitioned back to being productive. Only 3% of the time did a visitor transition back to a productive state (as shown by the arrow going from "unproductive" to "productive"), tending instead to stay unproductive (89%) or leave the exhibit entirely (8%). This was particularly concerning as it meant once a student fell into an unproductive they were unable to transition out. Instead they tended to remain unproductive until leaving the exhibit.

Given that participants were unlikely to leave an unproductive state upon entering it, we wanted to understand what was happening in those rare cases in which participants did move from unproductive to productive, especially after prolonged unproductive exploration. In response, we used a Markov Model (Baum & Petrie, 1966) to develop a list of all the times there was a sequence of three or more unproductive circuits followed by a productive circuit (Tissenbaum, Kumar, & Berland, 2016). We chose three consecutive events as a benchmark because we surmised that two or fewer unproductive circuits did not constitute enough events to consider participants' struggles as "sustained". Across all 3546 participants, only 204 (5.7%) of participants made this transition from a persistent unproductive state to a productive one.

While our approach was able to identify these 204 participants and their transitions from sustained unproductivity to productive states, it did not explain to us why these transitions occurred. In order to understand what caused these transitions, we needed to apply methods that incorporated visitors' interactions off the table. Below, we describe the qualitative approach we used to give us this finer-grained understanding of visitors' interactions and sensemaking.

Table 1
The DCLM framework. The categories "Making and Accepting Suggestions," "Negotiation," "Joint Attention and Awareness," and "Narration" were adapted from Fleck and colleagues' (2009) Collaborative Learning Mechanisms Framework.

Mechanisms of Collaborative Discussion	Description
Making and Accepting Suggestions (MA or MS)	**Making** and **accepting suggestions** are important aspects of collaboration as children who talk constructively together, introduce knowledge to peers and accept information from peers, showed improved performance. Within divergent inquiry activities, **making** or **accepting suggestions** provides opportunities for participants to relate their own understanding of the problem space to the tinkering and exploration of others.
Clarification (CL)	**Clarification** focuses on explicit discussion between participants to disambiguate actions by the system or by users. Clarification may include a participant asking a peer how a part of the system works, or what caused a particular system response. In shared-goal activities, participants may require clarification in order to understand how the actions of their peers help in addressing the groups' overall goals. During divergent tasks, **clarification** can be particularly important, as participants may be trying to do different things (i.e., achieving different goals). In such cases, clarification can help participants better understand peers' goals to provide suggestions or support. Participants can also use clarification to better understand the work of their peers towards advancing their own explorations.
Negotiation (NG)	**Negotiation** focuses discourse in which participants engage in critical and constructive discussion with the ideas of their peers. When participants are engaged in a shared goal this may include discussion around the best course of action to achieve a desired outcome. Similarly, when participants are engaged in divergent goals, **negotiation** might involve discussion on the sharing of resources or debate on each participant's individual course of action.
Seeking Help (SH)	Because open-ended constructionist spaces often allow participants to freely come and go, it is important to provide entrants the means to learn from the expertise of more knowledgeable members. Within exploratory activities, the ability to seek help is a critical means for participants to make sense of and progress their own inquiry. **Seeking help** can highlight moments in participants' exploration where they need to draw on the expertise of others *even if they have divergent goals*. Understanding when and how participants seek help and how others provide help can provide added insight into how participants relate their own learning and exploration to the problem states of others. As such, **seeking help** (and the resulting exchanges) provide us an important lens into the ways common ground can be established between participants with divergent conceptualizations of the problem space and goals.
Mechanisms for Enacting Divergent Collaboration	**Description**
Joint Attention and Awareness (JA)	**Joint attention** and **awareness** are used to orient other participants to a feature of the activity for further consideration and discussion. In shared goal activities, participants need to be aware of the actions of others in order to ensure their actions are properly coordinated towards achieving the stated goal. In divergent inquiry activities, **joint awareness** can be used to orient peers to phenomena that may be of interest to the larger group or as a means for asking for help or clarification.
Goal Adaptation (GA)	Because open-ended, exploratory activities can allow participants to more freely define their goals (both individually and collectively), it is important that such environments enable participants to understand the larger "learning ecology", what others are doing, and to define and refine their own goals in relation. While in some cases this may involve all the participants orienting towards a shared goal, it is not a requisite. **Goal Adaptations** (moments in the activity when participants expressly change or adapt their goals) serve as important markers of when participants diverge, or converge, in their goals.
Boundary Spanning Actions (BSA)	Open-ended tabletop environments offer unique opportunities for participants to directly interact and manipulate the tinkering spaces of others. Actively engaging with other's spaces is unique to parallel tinkering and offers opportunities to tangibly show others your own tinkering practices and/or work out mutual challenges. **Boundary Spanning Action (BSA)** serve as markers of the voluntary input coupling that occurs as learners shift from a more solo/parallel mode of work to a more mutual mode of work. Tabletop activities that employ tangible artifacts are particularly fruitful for supporting cross boundary interactions among participants, as tangibles have been shown to provide easier and faster manipulation of objects across the surface than direct touch alone (Lucchi, Jermann, Zufferey, & Dillenbourg, 2010) and a clearer spatial relationship to the object between participants (Scott, Grant, & Mandryk, 2003).
Boundary Spanning Perceptions (BSP)	Having multiple participants working synchronously on similar challenges allows users to simply watch and learn from the tinkering of others, which can serve as a form of "passive collaboration" and as a means for sparking discussion between participants. Well-designed tabletop environments can support this kind of collaboration by allowing participants to clearly see the tinkering of others, relate it to their own tinkering, and refer to it in follow-up discussions. **Boundary spanning perception (BSP)** moves mark instances where users actively observe the work in others' spaces. BSP in an important marker because its awareness is not about establishing mutual grounding (i.e., one participant can be engaged in surveilling the workspace of another participant without the second participant's attention being simultaneously engaged).
Narrations (NA)	**Narrations** are discursive moves in which participants say out loud what they are doing in order to think through their actions or to enable the monitoring of each others' activities. **Narrations** do not necessarily need to have an intended audience, but others may pick up on and act on them.
Modeling (MD)	**Modeling** extends Fleck et al.'s concept of narration. With narration, learners are verbally describing their actions or intentions as they execute a task, with the purpose of keeping companions abreast of their current state of activity so as to facilitate group coordination. When modeling, an "expert" explains what they are thinking and doing to others while simultaneously exhibiting it through physical actions (such as manipulating objects on the tabletop) so that novices (or others engaging in BSP) can replicate the actions in their own workspace, without the explainer explicitly engaging with the space or work of their audience.

Table 2
The coding system for each participant's MakeCircuitCreate event.

Marker	Code	Description & Motivation
Is the circuit complex?	**S/C** – S for Simple; C for Complex	Simple circuits are circuits with three or fewer components. This number was chosen because three is the minimum number of components required to make a "working" circuit (a circuit that lights up) – typically a power source, resistor, and LED. Using a greater number of components is an indicator of participants trying out more complex configurations.
Does the circuit work?	**N/W** – N for Not working; W for Working	When a circuit has the correct ratio of resistors, batteries, and LEDs, the LED will glow and attract a fish for cataloging. Participants' understanding of the relationship between individual components and making a working circuit is a key factor in determining the success of their exploration. Circuits that had the correct ratio of components (i.e., circuits that lit up) were coded with a **W**; those that did not have the correct ratio (i.e., circuits that did not light up) were coded with an **N**.
Is the circuit unique for self?	**R/U** – R for Repeat; U for Unique	To shed light on the exploratory aspects of tinkering, we wanted to know if the circuits participants made were unique (i.e., circuits they had not previously made). Circuits that were unique to the participant were coded with a **U**; circuits that the participant had created previously were coded with an **R**. This allowed us to get a fine-grained understanding of both working (**W**) and non-working (**N**) circuits. If a participant made working (**W**) circuits, but continually made the same circuit, it is unlikely that they progressed in their tinkering or expanded the problem space. Conversely, a participant may make non-working (**N**) circuits that are unique, indicating that they expanded their thinking about the problem.
Is the circuit unique at the table?	**E/O** – E for Echo; O for Original	*Oztoc* is designed to support participants in collaborating and building off of the ideas of peers to advance their individual and collective explorations. This use of others' constructed artifacts as a basis for one's own work has been termed "echoing" and has been shown to be an important part of open-ended and exploratory tinkering (Wielgus, 2015). We considered a circuit to be an echo if it had the same number of batteries, resistors, and LEDs as circuits made since a participant's arrival at the table (note: the LED color is not a factor when determining echoes, as echoes are characterized as reference points and not exact copies. Circuits that echo other participants' circuits were coded with an **E**; circuits that were unique to the table were coded with a **U**.

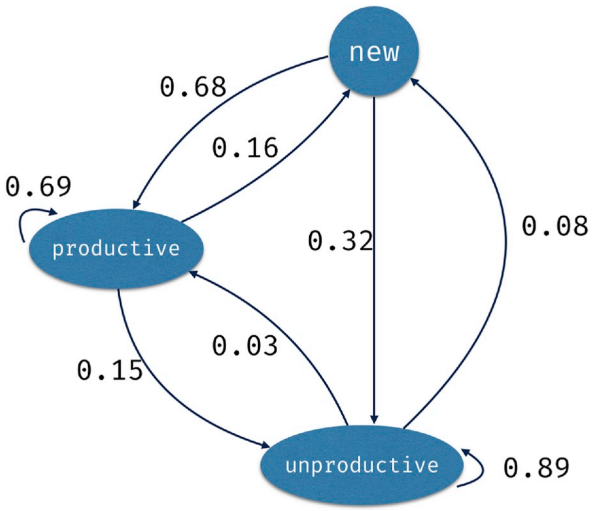

Fig. 3. A Markov chain depiction of the Hidden Markov Model of participants' circuit creations in *Oztoc*. This figure shows the likelihood of transitioning from the initial state (new) to the two hidden states (productive or unproductive) and also between different hidden states. The model shows that once a participant moves into an unproductive state, they are likely to stay there (89% of actions). Further, they are unlikely to transition to productive exploration (3%). Similarly, once a participant reaches a productive state, they are unlikely to transition to an unproductive state (15%) but instead remain productive (69%)(Tissenbaum, Kumar, & Berland, 2016).

3.3. Interaction analysis of transitions to productive states

Categorizing participant events in open-ended exploratory learning environments can be challenging, as participants often shift between individual and collective goals and fluidly switch between collaborative and divergent inquiry (Lyons et al., 2015). In response, we developed the Divergent Collaborative Learning Mechanisms (DCLM) framework (Tissenbaum, Berland, & Lyons, 2017) as a means for categorizing these interactions (see Table 1). DCLM has been shown to be effective in highlighting productive patterns among participants in open-ended inquiry environments (Tissenbaum, Berland, & Lyons, 2017).

Using the DCLM framework, we conducted interaction analyses (Jordan & Henderson, 1995) on 22 of 284 instances (across the 204 participants) identified by the Markov model of participants moving from persistently unproductive to productive states. This subset consists of all the transitions out of unproductive states that occurred during one day of visitors' interactions with *Oztoc*. This day was chosen because it was representative of an average day at the exhibit and all the data (log, video, and audio data) could be definitively synchronized (not all days had complete qualitative data). Two researchers familiar with DCLM and *Oztoc* worked together to synchronously code all 22 episodes. All disagreements were resolved during coding.

Interaction analysis is particularly well suited for this data because it focuses on the interactions of human beings with each other and the objects in their environment (Jordan & Henderson, 1995). Below, we describe how our interaction analysis, using the DCLM framework, revealed the role that divergent collaboration and boundary spanning play in supporting participants' transitions to productive tinkering.

4. Findings

Human-conducted coding of 22 events identified by the Markov model showed that our model correctly identified 20 out of 22 (91%) events (when compared to our qualitative coding) when participants transitioned from consistent unproductive to productive tinkering. Visitors' states were coded as productive if visitors transitioned to focusing on achieving new goals, including figuring out new elements of the exhibit or moving towards building new, previously undiscovered, working circuits. Because the Markov model identified unproductive-to-productive transitions at a high success rate (91%), we considered the model to be successful (RQ1).

When we used the DCLM framework for interaction analysis of the 22 events, we found that 19 of 22 unproductive-productive transitions (86%) involved one or more DCLM interactions (Table 3). Of the three participants who did not engage in DCLM interactions, two (Player IDs 12 & 21) were inaccurately identified as productive by the HMM, and the third (Player ID 10) was able to transition to a productive state on their own.

Examining the types of DCLM interactions that took place revealed that the most common event was *Boundary Spanning Perception (BSP)*, which occurred in 15 of the 20 (75%) instances when participants who transitioned from unproductive to productive states. *Boundary Spanning Actions (BSA)* were the second most common action, with 8 of 15 (53.3%) instances. These were followed closely by *Seeking Help (SH)* and *Making Suggestions (MS)*, each with 7 instances, and *Clarification (CL)* with 6 instances. Many DCLM interactions were coupled together, with 5 of the 7 *Seeking Help* events occurring along with *Boundary Spanning Perceptions*. Similarly, 4 of the 6 *Clarification* occurred along with *Boundary Spanning Perceptions*. 3 of the 7 *Seeking Help* events were connected with *Boundary Spanning Perceptions* events and 2 of the 7 were connected to *Boundary Spanning Action* events. The high frequency of *Boundary Spanning Perception* and *Boundary Spanning Actions* indicate that interactions between visitors were key to supporting transitions from unproductive to productive states.

An illustrative example of how the different DCLM interactions can come together to support participants moving from unproductive to productive states can be see through a detailed breakdown of Player 5. In Table 4, we show the coded interactions of Player 5, and how her interactions with others supported her effective tinkering and transition towards productivity. It is important to note that Player 5 had already been at the table for a few minutes before these interactions, but the analysis begins with the first of the three unproductive codes indicated by the Hidden Markov Model (HMM). In this episode, we see that shortly after Player 5 makes their unproductive circuit, she looks at PX's playspace and compares it to their own (BSP). This results in Player 5 making a circuit that more closely mirrors that of PX. After discussing their circuit with PX, Player 5 makes three quick circuits, coded unproductive,

Table 3
Coded examples of participants' use of DCLM categories when transitioning from a sustained unproductive state to a productive state (as per the above Markov model – Figure 4). Legend and explanation of short codes is shown in DCLM framework description (Table 2, above).

Player ID	MS	AS	CL	NG	SH	JA	GA	BSA	BSP	NA	MO	Correctly Identified?
1			✓	✓					✓			✓
2									✓			✓
3									✓			✓
4								✓	✓			✓
5	✓				✓	✓		✓	✓	✓		✓
6					✓				✓			✓
7	✓		✓		✓	✓	✓	✓	✓	✓		✓
8	✓					✓		✓	✓			✓
9	✓		✓		✓			✓				✓
10												✓
11	✓		✓		✓					✓		✓
12												
13			✓		✓		✓	✓	✓	✓		✓
14									✓			✓
15			✓		✓				✓	✓		✓
16									✓			✓
17	✓	✓						✓				✓
18								✓	✓			✓
19									✓			✓
20									✓			✓
21												
22	✓	✓										✓

Table 4
A coded set of interactions by Player 5 at the exhibit. A second participant they interact with during this episode is named PX (as they are not one of the participants identified in Table 3).

Time	Event Description	DCLM Codes
10:49:45	Player 5 makes a SNRO circuit (Coded Unproductive by HMM)	
10:49:54	After tinkering in their space, Player 5 looks at PX's circuit and compares it to their own.	BSP
10:50:19	Player 5 watches PX build their circuit	BSP
10:50:36	Player 5 continues making a larger circuit, with similar components to PX's	
10:50:44	Player 5 discusses their circuit in relation to PX's.	NA
10:50:49	Player 5 makes a CNUO circuit (Coded Unproductive by HMM)	
10:51:06	Player 5 makes a CNRO circuit (Coded Unproductive by HMM)	
10:51:23	Player 5 makes a CNUO circuit (Coded Productive by HMM)	
10:51:34	Player 5 compares their current circuit to that of PX	BSP, NA, JA
10:51:38	Player 5 shows exasperation about PX's circuit working and hers not	NA
10:51:40	PX points at Player 5's circuit and shows them a difference in their blocks	BSA, NA, JA
10:51:50	Player 5 changes their circuit configuration based on discussion with PX	
10:52:30	Player 5 makes several combinations of CNUO and CNRO circuits experimenting with combinations of blocks	
10:53:06	Player 5 looks at PX's space	BSP
10:53:56	Player 5 points to the scoreboard to note differences in the fish caught between her and PX	JA, NA
10:54:27	Player 5 looks at PX's space and points at their circuit and talks about differences between them	BSA, JA, NA, SH
10:54:43	Player 5 Makes a CWUO circuit	

unproductive, and productive by the HMM. While none of these circuits worked, the circuit codes do show that Player 5 moved from building simple circuits to a more complex one that she had not tried before. These new circuits prompted a discussion between Player 5 and PX about the differences in their designs, with several instances of Narration (NA), Joint Attention (JA), Boundary Spanning Action (BSA), and Boundary Spanning Perception (BSP). Finally, after several different exploratory circuits and exchanges between Player 5 and PX about their respective circuits, Player 5 finally makes a Complex Working Unique Original circuit (a particularly challenging task). This exchange highlights how the DCLM interactions between Player 5 and PX were instrumental in helping Player 5 make sense of her own tinkering and progress towards more productive exploration, and eventually, a new working circuit that was completely original.

5. Discussion

This paper aimed to understand two key issues around participants open-ended tinkering. The first, concerns the role interactions with others play in supporting participants' transitions to productive states. As shown above, the presence of others and the ability to see their work and interact with them, played a key role in participants' transitions out of unproductive states. Overwhelmingly, participants who transitioned from unproductive to productive states engaged in some form of DCLM interactions (95%). This highlights the different ways visitors can effectively collaborate *even when they have divergent goals*. The fact that only 4 of the 20 of successful transitions did not involve either *Boundary Spanning Perception (BSP)* either *Boundary Spanning Actions (BSA)* reveals the importance of making the tinkering of others visible and referenceable as a means for reflection on ones' own practices. Below, we take a closer at these interactions to give us better insight into how each of these interactions promoted participants' sense making and exploration.

The instances of *Boundary Spanning Perception* primarily consisted of a visitor looking at the work of the others at the table and relating it back to their own explorations. In many cases (6 of the 15 cases coded with *BSP* – Table 3), no additional collaboration or assistance was needed. In other cases, the awareness of others' work prompted additional and more direct forms of interaction, such as *Seeking Help* or *Clarification* (5 and 4 times respectively). This reinforces the importance of visitors being able to compare and contrast their own work to that of their co-located peers as a way to help them break out of unproductive loops and to try out new approaches in their tinkering.

Instances of *Boundary Spanning Actions* primarily consisted of two distinct types. The first were instances where a visitor would see what another participant was doing, and take a block from them to try and build a similar circuit in their own playspace (as shown by the large overlap between *BSP* and *BSA* in Table 3). In these cases, the visitor tried to replicate the circuits made by others by directly incorporating the peers blocks into their own work. A similar, but more direct form of appropriation than was observed in with *Boundary Spanning Perception*. The other observed type of *Boundary Spanning Action* observed were instances where a participant would reach into the unproductive visitor's space and either place a new block into their space or directly manipulate existing blocks. As shown by the fact that 5 of the 8 instances of *BSA* also coded with *Making Suggestions*, and 3 of those instances also coded with *Joint Attention* (Table 3), these cases were often combined with the assisting participant directly explaining what to do.

This work drives home the importance of making the work of others visible, even if participants do not share the same convergent goal. Very rarely in *Oztoc* are participants aiming to do the same thing, or build the same circuits (Tissenbaum, Berland, & Lyons, 2017); and yet, the ability to see the work of others allowed individuals to reflect on what they were doing and ask new questions of themselves (or others). In some cases, this was all the visitor needed to get unstuck. In other cases, this was the launching off point for more detailed inquiry or collaboration between participants. In most of these instances, the visitors went back to their own explorations and goal seeking, reinforcing the notion that convergence on a shared goal is not always necessary to provide productive moments of collaboration.

Our other research question aimed to reveal how combining learning analytics and qualitative approaches could help us understand how learners move from unproductive to productive states during open-ended inquiry. The nuanced collaborative and sense-making that occurred as visitors transitioned between productive and unproductive states shows the importance of a multi-dimensional lens for understanding learning. While the Hidden Markov developed in our earlier work (Lyons et al., 2015) was able to reveal critical moments for learners, it lacked the ability to explain *why these transitioned occurred*. Similarly, if we had only employed a qualitative approach to coding learners' interaction in *Oztoc* we could still have coded their DCLM interactions (as in Tissenbaum, Berland, & Lyons, 2017). However, we would likely have either not recognized the subtle transitions between the hidden states revealed by the HMM, or we would have had to manually code literally millions of events across thousands of visitors – a daunting task to say the least! Only through the combination of the two approaches were we able to reveal the fine grain learning and collaboration that occurred across this coarse grain of visitors interacting with *Oztoc*.

One limitation to the study is that the events analyzed came from a single day of the exhibit. Different days at the exhibit may have resulted in different groups attending the museum (e.g., a higher proportion of families on the weekends compared to weekdays), and therefore different interactions between visitors. The decision to focus on the single day stemmed from both technical considerations (having all the necessary sources of qualitative and analytics data) and our perception that randomly sampling visitors could have resulted in us missing important interactions and knowledge that moved across fluid group formations as visitors entered and exited the exhibit (Block et al., 2015).

Another limitation of the current study is our focus on only one kind of visitor condition, the transition from a persistently unproductive state to a productive state. There are many different conditions that could be analyzed, such as persistently productive states or rapid transitions between states, that may provide additional insights into how and why students explore and engage with their peers at the exhibit. There may also be other hidden states that are not captured in by our Hidden Markov Model and would be fruitful for understanding how visitors converge and diverge during their exploration and tinkering. Each of these issues raises valuable questions that we would look forward to answering in future studies and with new analytical approaches.

While the context of an exhibit in a museum may initially be considered a limitation for the broader applications of this work, particularly in terms of the role *Boundary Spanning Actions* and *Perceptions* played in supporting productive transitions and divergent collaborations, we feel the examples shown in this paper highlight their potential for use in other research contexts. The ability of participants to see the work of others during their exploration has applications across many different settings, including makerspaces and other design-based learning environments. Makerspaces, provide opportunities for participants to see the work of others (Farrar, 2018), and yet the opportunities this could play in supporting learning and collaboration has not been extensively researched. Given the push for encouraging students to embrace "failure" and the inherent problems that this can produce (see Beck & Gong, 2013), designing makerspaces spaces to expressly support the kinds of collaborative mechanisms shown here could reduce participants' unproductive cycles and unresolved failures by increasing opportunities for collaboration and mentorship. We also believe there are similar opportunities to consider the observability of others' tinkering in other (even formal) learning environments that embrace design-based learning.

6. Conclusion

This study aimed to understand two key research questions: 1) how learning analytics could identify transitions from persistent unproductive states to productive states in open-ended inquiry; and 2) the role interactions with others play in participants' transitions. In terms of the first question, we showed how our hidden Markov Model (HMM), was effective in highlighting learners' transitions from unproductive to productive states (with 91% accuracy). Our findings see parallels with the work of Holstein et al. and their work on detecting episodes of unproductive persistence in intelligent tutoring systems (2018). The key difference being that intelligent tutoring systems tend to have a more linear progression. As such, our work here provides a valuable compliment to their work, providing a broader scope of approaches for other researchers to draw from depending on their learning context. Baker and Koedinger (2018) and Munshi et al. (2018) also applied learning analytics to understand learners' states, focusing more on affective states, such as excitement and boredom, as a means for understanding long-term student success. Munshi et al. (2018) is particularly relevant, as their work looked at open-ended learning environments. We can see a natural synergy between the work here and Munshi et al.'s work, with the potential to understand the relationships between learners' productive and unproductive states and their affective states.

It is critical to note that in order to effectively conduct our analytics (and similarly in the other examples above) we needed to have the necessary data logging features built into our system. The careful understanding of what we needed to capture and then building in the necessary data "hooks" into *Oztoc* was essential. A failure to think deeply about the data logging in the design of one's digital learning environment can cause serious problems down the line. While the field is increasingly pushing for the storing of a wide range of learners' data beyond simply their final products (Recker, Krumm, Feng, Grover, & Koedinger, 2018), the uptake has been slow. To advance this work further and support the work of the of the wider learning sciences community, there is a growing call for standardizations of the data logging formats (Baker & Siemens, in press). The system described herein, ADAGE (Owen & Halverson, 2013), is one attempt at this standardization and has been used across a range of educational designs (Anderson, Dalsen, Kumar, Berland, & Steinkuehler, 2018; Gutierrez et al., 2014). As we see an increase in standardizations of data formats, we will also see an increase in applications of methods across contexts. To this end, there is the potential for more easily adapting models such as the one used in this work in new learning designs.

In terms of the second research question (the role interactions with others play in participants' transitions), we showed how making the explorations and tinkering of others visible can be an important means for supporting collaboration, even when learners may have divergent goals. Many researchers note the value of making learners' tinkering and exploration visible to others (Fields, Kafai, & Giang, 2017; Litts et al., 2016). However, most of this research focuses on learners' final or in-progress work, rather than the value of learners being able to observe the work of others *as it is happening*. The research presented here is an early attempt at exploring these how making this work visible opens up new avenues for collaboration, particularly by supporting *Boundary Spanning Perception* and *Action*. We feel this offers up a new challenge to a broad range of educational designers and researchers to think deeply about how the value of making learners tinkering and exploration available to their peers in real-time (in addition to asynchronously).

Being able to accurately understand how and when learners are struggling is a persistent challenge in the learning sciences (STELLAR, 2011) and is particularly critical in exploratory and tinkering-focused inquiry designs. The ability of the approaches described here to reveal learners' hidden states and the nuanced ways that they transitioned between them is a major step towards understanding and supporting learners' productive states in these kinds of environments.

If we are serious about giving students agency over their exploration and inquiry (Engel & Conant, 2002), we need to establish means for recognizing the unique forms of collaboration that exist in such environments, and how they support productive student interactions. Through successive studies (Tissenbaum, Berland, & Lyons, 2017; Wielgus, 2015), DCLM has shown progress in making inroads into revealing productive interactions and collaborations that would otherwise be hidden.

Even if we have the means for recognizing how to categorize these events, understanding *which events* we should examine, especially across days or weeks of interactions, is a significant challenge to the field. This study shows the potential for a multi-lens approach to analyzing learning data. Using data mining and learning analytics together, we accurately identified instances of unexplained learner interactions over a large subset of data, which may be difficult to do with qualitative analysis alone (Wise & Schwarz, 2017). However, to gain a richer description of participants' interactions, qualitative interaction analysis provided us with a fine-grained understanding of how events involving transitions between productive and unproductive states occurred. This differs from traditional mixed-method approaches that apply simultaneous qualitative and quantitative analyses to pre-selected events. Rather, we argue for cycles of analytics and qualitative methods that highlight novel unanticipated events and patterns in the data for further analysis and study. We see our approach as contributing to a nascent body of research that is attempting to leverage multi-dimensional approaches to reveal and support learning in tinkering and exploratory learning (Fields, Quirke, Amely, & Maughan, 2016).

Similarly, there is complementary research on interactive tabletops that combines multi-modal learning analytics (MMLA) with data logs to understand student learning. For instance, Schnieder and Blikstein combined data collected from a Microsoft Kinect and from an interactive tabletop to reveal which students gestures and behaviours resulted in higher learning gains. We believe there is considerable potential for combining these types of approaches towards understanding how students interact, collaborate, and overcome obstacles in their learning and exploration. Where Schneider and Blikstein's approach helped understand which actions were predictive of high learning gains, our work examined the specific actions that were associated with overcoming unproductive explorations. Moving forward, we can envision research trajectories that combine these approaches. By revealing the types of actions that are broadly associated with learning gains and those that help learners overcome obstacles, we can more effectively support them in their learning.

Further, by identifying and understanding how learners naturally transition between unproductive and productive states when tinkering, we can begin to investigate new ways to scaffold learners who are unable to make this transition on their own. Given the growth of data collection capabilities in technology-enhanced learning environments, we have new opportunities to capture these states in real-time. Similar to the work of Holstein et al. with intelligent tutoring systems (2018), our work presents a starting point for a new way of approaching real-time learner support by leveraging the transition models and learning patterns they reveal in exploratory learning spaces. For instance, a facilitator at *Oztoc* could be alerted that a visitor is stuck in a persistently unproductive state. Knowing this, the facilitator could encourage the students to compare what they are doing to others at the table (i.e., engage in *Boundary Spanning*). This could help them effectively transition to a productive state while retaining their own sense of agency (Engle & Conant, 2002). This could also increase opportunities for others at the table to engage in peer mentorship, increasing possibilities for them develop their identities as mentors and engage in tutor/tutee learning (Roscoe & Chi, 2007). To this end, we are have begun pilot-testing a tablet application that leverages modelled outputs to provide museum facilitators with information about the current state of participants' exploration at the *Oztoc* exhibit, along with facilitation strategies based on the productive interactions highlighted by DCLM to help participants who are struggling or about to give up Tissenbaum, Kumar, & Berland, (2016).

By showing one approach for capturing learner transitions and the role that making tinkering visible plays in these transitions, we believe this work is important to the broader community of educational researchers and practitioners. As stated above, we acknowledge the educational value of seeing the asynchronous work of peers, both as a feedback tool and as a means for meta reflection; however, the ability to see the tinkering of one's peers *as it happens* is also a potentially powerful means of supporting learning and collaboration. We hope this research stands as both an example of the potential for visible tinkering and as a call for an increase in educational designs to deeply consider learning space designs that allow learners to actively see the work of their peers in real-time, even when their respective goals may diverge.

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