FOOD FOR THOUGHT: HOW INTERFACE DESIGN FOSTERS COLLABORATIVE DATA DISCUSSIONS

BY

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THESIS

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ABSTRACT

Data literacy is an important component in math and science, and an essential skill for participation in society, but research shows it is difficult for students to make sense of data in meaningful ways. Thus, there is a need to understand whether technology, and specific design choices, can affect students' discussions when using multiples sets of data. This paper presents the first two phases of a design-based research project that focused on data-based discussions during a collaborative activity using the *Food for Thought* software. In this paper, I aim to examine if changes to the visual design of the software impact data discussions in two samples of students, draw comparisons between the two, and address the importance of creating intentional visual designs for learning.

Keywords: *design; interface design; collaboration; data literacy; data representations; design-based research*

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

This paper discusses the design and implementation of software called *Food for Thought*. This software was built to help middle school students understand climate change and their impact on the environment through the food they eat, by working with multiple sets of data. Research indicates that it is challenging to teach children to work with data (Kastens, Krumhansl, & Baker, 2015; Manduca & Mogk, 2002) and it is deemed an advanced skill to make sense of and see patterns across multiple sets of data at once (Friel, Curcio, & Bright, 2001). This study addresses this problem using two strategies: collaborative learning and multiple representations. Collaborative learning has been shown to improve learning outcomes for students (e.g., Barron & Darling-Hammond, 2008; Hmelo-Silver & Chinn, 2016; O'Donnell & Hmelo-Silver, 2013) and engage students in productive group practices such as co-constructing their understanding of information (Roschelle, 1992).

The ability to represent data has changed immensely the last hundred years, driven in part by the innovations of technology and data collection techniques (Friendly, 2008). As the form that these representations take changes, there persists a needs to more concretely understand how students build on their ideas with each other and with the scientist producing the data (Gordin & Pea, 1995). Research shows that representations can help students' comprehension of science phenomenon (Cook, 2006) and suggests that multiple representations can foster deep learning when created intentionally for the learners (Ainsworth, 2014). However, it is challenging for teachers to facilitate learning using multiple representations (Kastens et al., 2015; Manduca & Mogk, 2002). Eye tracking analysis shows that student struggle integrating text and representations and that the task and visual layout can influence students strategies when integrating content (Michal, Uttal, Shah, & Franconeri, 2016). Results on student's ability to integrate content indicates that students that make connections between representations achieve deeper learning than those that could not, however, few students could achieve this level of understanding (Wilkerson & Laina, 2017). This research shows that using data in the classroom is challenging and introduces copious variables for the teacher to consider, some to which they do not have control over. The *Food for Thought* software was designed to address these issues by creating an experience to support students' discussions around data using collaboration and multiple representations, therein also supporting the teacher and their ability to use data in the classroom. This paper presents the design and implementation of two iterations of the software that were built with the goal to help students collaborate and work with multiple sets of data.

In this paper, I present two studies that look at discussions of groups of middle school students using the *Food for Thought* software. As a design based research project (Baumgartner et al., 2013; Brown, 1992), this paper discusses two iterations of the software, tested to assess if modifications made to the design of the software changed the amount of data discussion had among the groups and what preceded these discussions. I begin by introducing collaboration and the framework used to design the tool and then discuss the use of multiple perspectives to create this software. I then present two studies, both of which explore the same research questions to analyze if and how the modifications to the software changed data discussions. I compare the two iterations and close by discussing how working with an intentional design process that integrates learning and multiple perspectives can affect group discussions.

CHAPTER 2: LITERATURE REVIEW

Introduction

In my review of the literature on collaborative learning, I found that documentation and explanation of decisions on the visual design of technology are not explicit. One critical aspect of research is the documentation and dissemination of findings to others; researchers should not exclude design from this process. How is it expected of others to learn how to create collaborative experiences without explaining the decisions behind a design? Disciplines such as human-computer interaction (HCI) and design include in-depth descriptions of their design process; this thesis is grounded in the idea that educational researchers need to be explicit about the decisions they make regarding the design of collaborative experiences.

A collaborative experience is described by all the variables that converge when a group is working together; this includes the technology and design of that technology. Collaborative experiences are not easy to frame, and the rise of technology to support collaboration calls to understand how the design of interfaces effect group processes to create more supportive technologies.

In some educational research projects, visual and experience designers are seen as problem solvers after researchers have made the core decisions about the study. Design goes beyond problem-solving when something doesn't function as expected or doesn't look engaging for learners. Designers introduce a process that can improve an experience through iterative creation and reflection, working to accomplish goals at all stages of a project (Chandra Kruse & Seidel, 2017), and is most beneficial to the project when introduced in the initial stages. The role of a designer is to consider all the variables of the project and question what the tradeoffs are for each (Collins, 1993). Addressing these tradeoffs become increasingly important when designing for collaboration. Designers must consider the costs and benefits of all factors when making design decisions about a collaborative learning experience. The *Food for Thought* software, being presented in this paper, was developed using findings and principles from research in multiple disciplines to make these decisions.

In order to understand how to make these design decisions, this section discusses the complexities of collaborative learning, a framework to design collaborative experiences, and the research on representations from multiple disciplines used to design the software. I conclude with reasons why design plays a prominent role in designing collaborative experiences.

Collaboration

Research on collaborative learning has shown that groups of students can achieve a higher understanding through social interactions where group members are construction knowledge iteratively (Roschelle, 1992). Collaboration is a process which engages students in joint meaning making, through interactions between a group (Stahl, Koschmann, & Suthers, 2014). Interactions are typically the unit of analysis when analyzing the quality of collaboration processes within a group, although the quality of the interaction is highly dependent on the group itself (Barron, 2003). However, to engage in collaborative processes students must have an understanding of what a good interaction is. To engage in good collaborative interactions, teachers need to prepare students to do so; it cannot be achieved by simply asking them to do so.

When working on collaborative activities, students need two kinds of skills to work together, social skills to address the collaborative component and cognitive skills to address the problem-solving component (Hesse, Care, Buder, Sassenberg, & Griffin, 2012). Cognitive skills, such as hypothesizing, setting goals, and collecting information, are significant in the classroom as they are often closely aligned with what teachers are assessing. While social skills, such as social regulation, negotiations, and interactions, are more challenging to monitor and formally assess. In order to incorporate collaborative learning in the classroom effectively, students need to have adequate social skills; therefore, there needs to be a formal way to assess them. By not assessing these skills they are not deemed as important to students. Students and teachers should value outcomes that focus on social and collaborative skills, in addition to learning.

Computer supported collaborative learning (CSCL) is one area of this literature that uses technology to facilitate social interactions. CSCL involves the integration of collaborative learning and computerized devices such as multi-touch tables, mobile devices, and interactive environments (Stahl et al., 2014). Dillenbourg, Baker, Blaye, & O'Malley, (1996) proposed three ways to use computers in collaborative learning: at least two students interacting with a computer, a group of students interacting through multiple computers, and collaboration between a human and a computer. Dillenbourg and colleagues go on to explain that the interfaces of these tools can act as a form of scaffolding, or supports for the learner(s), and the decisions about the features and design of the interface have a significant effect on students' interactions and learning (1996). Technology for CSCL and the interfaces within them have the capabilities to scaffold conceptual understanding around complex issues (Linn & Slotta, 2000; Shimoda, White, Borge, & Frederiksen, 2013), to learn from these findings, educational researchers successively need to analyze how these scaffolds affect collaboration.

Collaborative Framework. Context is highly influential when implementing collaborative learning; many factors come into play when designing for a collaborative environment. Mercier & Higgins (2015) identify four main factors when implementing collaborative learning as the teacher, teams (student groups), tasks, and technology (figure 1) and explain that the overlap of these factors is essential when studying CSCL. They use examples to illustrate that research on collaborative learning often considers two or three factors when designing and implementing a study, but rather, research should consider all four to account for more fine-grained details (Mercier & Higgins, 2015). By clarifying how these factors influence collaborative learning in the classroom, researchers and designers should explain what is and isn't happening, in order to design scaffolding that improves the enactment of collaborative learning.

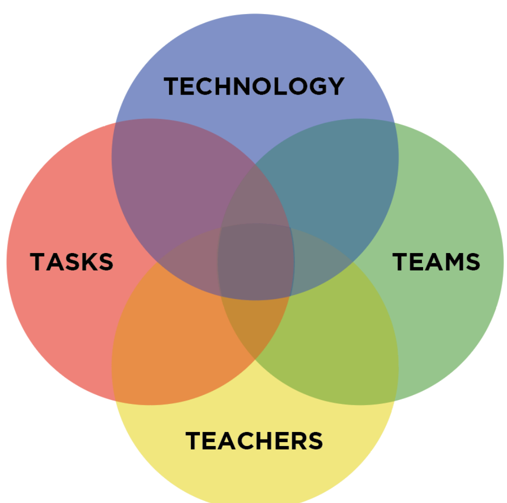

Figure 1. The 4Ts Framework.

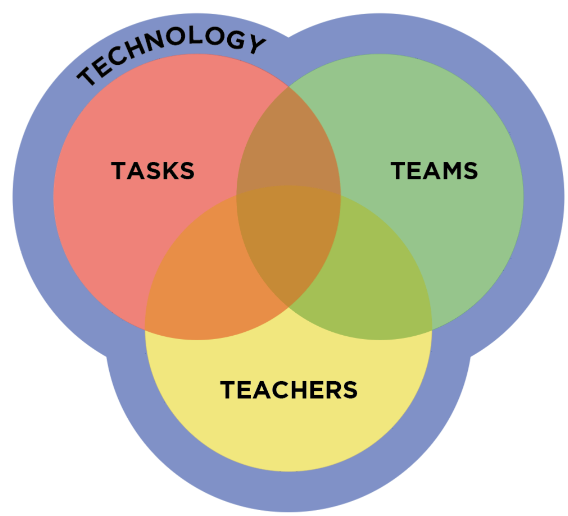

Figure 2. Adapted 4Ts Framework.

One valuable characteristic of technology in this framework is its flexibility to be built or adapted to achieve a specific collaborative goal. Rather than focusing on Mercier and Higgins' four factors as equals, I suggest that teams, tasks, and teachers be placed at the forefront when designing collaborative experiences, and include technology as support (figure 2). The overlap of these elements is necessary to create meaningful technology to support collaboration, and by framing technology as a form of support, researchers can appropriately scaffold the preceding three factors.

The elements that go into creating good teams and tasks and training teachers to implement collaboration are very complex and the most important factors when creating a collaborative experience. Classrooms are complicated and in a constant state of flux depending on these factors. Technology, on the other hand, can be designed with the specific goals to support these factors and comparatively can be more stable. Although technology can be dependable, it is not without its limitations. While the software can remain unchanged during the lesson, there are still weaknesses such as unstable software or internet access, distractions, and inequality of access among students. Additionally, technology should never replace the role of the teacher or the interactions between students, but technology can appropriately *support* collaboration when the other factors are fluctuating.

Collaborative research studies often only consider a few factors when designing a tool, rather than all four. If researchers do consider all four in the initial stages of the project, these decisions are often not discussed explicitly. For example, Martinez-Maldonado, Clayphan, & Kay, (2015) built a tool that supports the teacher when implementing a collaborative activity in an undergraduate level HCI course. Their findings show that providing a teacher with the appropriate supports can have a positive impact on the teacher's ability to run a course using collaborative learning. The technology was not just used to support the teacher; multi-touch tables were used in the classroom to support the teams while solving a task embedded in software on the tables. The authors use technology to support all three factors of this framework, and by designing them intentionally have created a classroom experience that was successful for collaboration among groups.

Another study that considered all three factors used technology to support the teacher through a tablet and projection tool, the teams through multi-touch tables, and the task through software designed with students interactions in mind (Mercier, 2016). The author discussed the goals and learning opportunities and the intended purpose for each. A tool created from the same project, allowed teachers to monitor the progress of the task and teams through technology (Joyce-Gibbons, 2017). While the teams don't directly engage with the technology, it allowed the teacher to better monitor groups and their progress on the task, therefore affecting the students' interactions.

These examples illustrate how technology can support more than one of these factors, and when being designed intentionally to do so can have positive effects on collaborative learning. I believe this adaptive version of the software emphasizes that technology should not be the focus of the learning, but a form of scaffolding for the teams, teacher, and task. However, just because researchers use technology does not mean it will have a positive effect on collaboration. As described above, researchers should place importance on the teams, teacher, and task, and develop technology that will be supportive of these factors, not just for the sake of using technology.

Documentation and Assessment. While the CSCL community emphasizes how technology affects learning, interactions, and group processes, one gap in this literature is the documentation and assessment of these tools. By being explicit about the decisions of the design, function, and features of these technologies, and evaluating how these decisions influence collaboration, researchers and designers can ascertain how technology effects collaborative learning. It is possible to build technology that negatively effects collaboration. These failures are significant when building tools, and by documenting the process that leads to these failures, as well as successes, allows other researchers to learn from them.

This paper is not the first call to action for researchers to place value on the design and documentation of collaborative technology. Borge & Shimoda, (in press) discuss the importance of using principles from design and HCI to develop technology, in conjunction with learning theory. Their paper calls out the process of designing a tool that allows students to reflect on their collaborative processes online; the authors discuss the steps taken to build and evaluate the tool and the limitations of design principles that were used (Borge & Shimoda, in press).

Martinez-Maldonado and colleagues created a tool and evaluated it by comparing what the teacher extracted with the number of interactions with each group (2012). In order to understand how the tool supported collaborative science learning, the authors documented the process and evaluated the tool, thus were better able to understand how and why their tool was helpful for students and identify issues to improve future iterations. In a later iteration of the same tool, the authors explicitly described their process and expressed the limitations of the design (Martinez-Maldonado et al., 2015). They state even after an iteration that further exploration needs to be done to evaluate the design and explain how teachers can translate and discuss student-generated content in real time. Their work allows other researchers to understand how they went about making decisions, and identify what changes could be made to the design of the tool to assist teachers better.

Yuill & Rogers, (2012) developed a framework explicitly to evaluate collaborative multi-touch interfaces through the awareness of others' actions and the control and availability of the interface. Evaluating the interactions of the interface allowed the authors to dive into the physical and social actions the technology afforded. Another assessment conducted on a web-based tool, set out to determine if the design of the technology supported student interactions around science concepts (Shimoda et al., 2013). They evaluated the students and teachers' interactions with the technology and were able to address weaknesses in their software and point out four possible areas to improve students' experiences.

These examples show an array of methods for documenting and evaluating collaborative technologies. While there is no one right way to evaluate technology, by attempting different strategies and identifying strengths and weaknesses researchers and designers can build stronger software to support collaboration. While this is an important component of research, it is not one that is often happening in education. Most documentation and assessment work reported on above is from HCI researchers. To continue moving forward in the field, education researchers and designers need to document these processes with an education specific lens so that others can learn from decisions and in turn create more effective technology for collaborative learning.

Design Principles + Research

I believe that by accounting for design principles and theories, in conjunction with research about collaborative learning, designers can create more cohesive tools to foster group discussions. As explained in the examples above, the process of making intentional decisions about the design of technology, considering the task, teams, and teacher, can have a positive impact on collaboration. In this section, I will discuss the principles and theories used to make design decisions about representations in the *Food for Thought* software.

The literature on the design of technology spans many disciplines. However, no one perspective has all the answers when it comes to making decisions about the design of technology. While multiple disciplines report on features and uses of tools for learning, the *Food* *for Thought* software drew from research on design, multimedia learning, and data literacy to inform decisions about the software.

Design Principles. The visual design of an interface has a substantial influence on how a user interacts with the technology. When an interface is aesthetically pleasing and appears to be easy to use, it is more likely to be seen as welcoming and simple to understand, than something that does not seem well designed, also known as the aesthetic-usability effect (Lidwell, Holden, & Butler, 2010). To account for this, interface designers use visual metaphors as cognitive support to address the expectation of a user. These representations can be used to leverage the knowledge of the user so that they can effectively interact with something (Norman, 1990). Some researchers, such as Nardi & Zarmer (1993) argue that the use of simple metaphors are unnecessary and call for designers to represent information more complexly. Decisions about what kind of representation to employ are ones that designers grapple with, and even after making a choice based on the variables available to them can still be implemented poorly.

Design principles used to make decisions are often framed as the right or wrong way to make decisions about design. Chandra, Kruse, & Seidel, (2017) argue, after collecting data to compare how designers use different design principles, there are tensions and contradictions between the creation and use of these principles. Design principles should be used as a baseline to build upon to guide designers through a process of making decisions about a final outcome, rather than a single approach to create something.

Borge and Shimoda's (in press) paper, discussed previously, emphasized an education perspective on design principles, explaining that even when considered in conjunction with theory, design principles alone could not make all the decisions about the features and interactions of technology. Design principles should be used as a framework to create and ideate, but in the end, designers should consider decisions about the learner(s) and their individual differences in order to be successful in supporting teams, teachers, and tasks during collaborative activities. While there is a range of research on design principles and guidelines that explain what each principle is and how they should be applied in interface design or similar contexts (Lowe & Schnotz, 2014; Mayer & Fiorella, 2014; Najjar, 1998; Norman, 1983), there are contradictions among these design principles. Researchers build design principles from the context of specific frameworks and audiences, therefore can be used to frame a design but should not be the only factor that goes in to design decisions.

Representations and Individual Differences. Representations can be helpful to build deep learning about abstract science phenomena, however, while a representation is helpful to one student does not mean it will be for another (Cook, 2006). Representations are created to symbolize meaning and can be interpreted differently depending on the viewer and how they define meaning (Hall, 1997). When designed intentionally for an audience, representations can promote interactions among users; by considering the representations regarding learning it, they can act as a form of scaffolding for students to understand the content (Cook, 2006). The Universal Design for Learning framework stresses the importance of using representations as a method for students to communicate and increase problem-solving ability when discussing complex topics (Parette & Blum, 2015). Representations are challenging to use when designing for collaboration because the design needs to account for each students' perceptions and differences within a group. When implemented together, representations and collaboration can foster contextualized learning for students that may not have otherwise been feasible without

(Sun & Looi, 2013). While representations alone have multiple benefits to learners, the use of multiple representations is also used to promote learning for students.

Multiple representations are ones that reiterate an idea through multiple channels, sometimes text and image but can also be auditory or other visuals forms, and are often used to drive interest and additional comprehension for learners (Ainsworth, 1999). As elaborated on in multimedia learning theories, multiple representations can be beneficial for learning but can be interpreted differently based upon individual differences of the learners (Mayer, 2014; Schnotz, 2013; Sweller, 2010). These theories build on the multimedia effect that explains that students learn better from the combination of text and image rather than text alone (Butcher, 2016). While these theories build on this knowledge, Schnotz (2013) explains that just because representations and additional mediums can be included does not mean that they will be effective and that they should be included every time. The ability to comprehend multiple representations is dependent on the students' individual differences. These differences such as prior knowledge (Moreno & Durán, 2004), working memory (Gyselinck, Ehrlich, Cornoldi, De Beni, & Dubois, 2000; Lowe & Sweller, 2005), and spatial ability (Lee, 2007; Rick et al., 2009) have an effect on what students interpret from a representations and what inferences they can attain. Multiple representations that are most clear to a variety of learners are ones that are created to relate to one another, or reiterate a fundamental concept, and should be designed in conjunction with pedagogical models to foster deep learning (Ainsworth, 2014). Design is complex, and making decisions about representations and multiple representations are not easy. These decisions have implications for learners, therefore reiterating the fact that design should call on additional disciplines to understand how different designs are interpreted based on the teams of students using it.

Data Literacy. Another beneficial use of representations is the ability to engage students in collaborative discussions around data. Data literacy has become an important component of the Framework for 21st Century Learning skills (Dede, 2010). K-12 classroom curriculum (NGSS Lead States, 2013) indicates that students need to able to synthesize and distribute data in order to be successful employees, consumers, voters, and citizens in general (Manduca & Mogk, 2002). Research indicates there is a need for students to be able to decipher and generate data considering the increase in access to data via technology (Trautmann & McLinn, 2012). However, while there is a need to foster more data literacy in our future generations, it is a challenging topic to teach (Kastens et al., 2015; Manduca & Mogk, 2002). This calls for researchers to understand how representations affect student's ability to learn with multiple data sets. One way to foster this understanding is through the use of graphical representations.

Research on graphs as representations tell us that the interpretative process to understand a graph is challenging for students (Shah, Mayer, & Hegarty, 1999) and it is considered a high-level skill to make sense of and see patterns across multiple sets of data at once (Friel et al., 2001). For students to synthesize data and draw inferences from multiple data sets, educational scaffolding needs to be introduced effectively (Kanari & Millar, 2004). Research by Hogan (2002), found that students struggle to reason around more than one piece of information, and often focus on one section of the data when making collaborative decisions. Cook (2006) explains that to be able to interpret more than one data set, students need to have prior knowledge that is relevant and aligns with the new information. By adding to existing mental models and working with well-designed visual representations, students can be afforded more successful experiences when working with complex, science data (Cook, 2006). This work supports the issue that students find it difficult to synthesize data and explain their process of making these decisions and reiterates the call to understand how the design of representations can aid in this kind of learning.

Explained above, to prepare students to work collaboratively with multiple sets of data, researchers need to design technology in a way that is scaffolding the teams, teacher, and task. One element that may be important to consider is the process by which students interpret data. Carpenter & Shah (1998) propose that to interpret data students need to go through an iterative process to address patterns in quantitative and qualitative ways. The findings from their two studies indicate that the more complex a graph is, the more challenging it is to extract information and that graphs displayed with more visual elements allow students to identify patterns more quickly (Carpenter & Shah, 1998). A meta-analysis on signaling, highlighting relevant information to make it more accessible for students, concluded that design elements to emphasize content were helpful to low prior knowledge learners (Richter, Scheiter, & Eitel, 2016), therefore visual signals may be beneficial when designing graphs when the learning goal is for students to recognize patterns within them. By using signaling as a form of representation, researchers can subtly or obviously guide the learner's attention to relevant materials that will support the learning goals (van Gog, 2014), again legitimizing the use of technology to support tasks in collaborative learning.

The research on collaboration, representations, and data is very diverse and stems from multiple disciplines. The *Food for Thought* software drew from differing perspectives to build a tool that supports collaboration in a more effective way.

Importance of Design in Collaborative Technology

Principles and guidelines for creating learning experiences are extensive, but as indicated throughout this section they are scattered among a variety of disciplines and contexts.

While design principles can be used as guidelines to help facilitate the decisions making process, they are often interpreted differently depending on who is using them (Chandra Kruse & Seidel, 2017). The issue with design principles is that they are often created or researched for specific learners in a specific content area, making it difficult, but not impossible, for designers to interpret and use them in a different context. This paper attempts to bridge the gap between these disciplines and design the *Food for Thought* software with these perspectives in mind. Indicated by the variety of literature presented here, making decisions about a design are not easy, and research completed in a variety of disciplines can influence the design of a tool.

The process of making these decisions as well as implementing and evaluating the use of the tools needs to be put at the forefront of future research. By explaining the reasoning behind the design of a tool, researchers can make their findings more valuable for those developing similar studies down the road. The *Food for Thought* software was built to consider these topics, but as in all design based research, has room for improvement. The experience discussed in this paper includes the teacher's role in facilitating the students learning, the teams of students that were interacting with the application, the tasks presented to the teacher, and finally the technology that supported these three factors. This paper specifically focuses on the latter. In completing more iterations with this tool, these factors will change and be documented and evaluated to continue improving and learning from the experience.

CHAPTER 3: STUDY ONE

Introduction

The first iteration of the *Food for Thought* software was implemented in a lab classroom with middle school students. The purpose of this study was to investigate how the visual design of the *Food for Thought* software impacted students' discussions. In this section, I discuss the design of the software, examine the data collected from study 1, and address the following research questions:

1.1 Do students discuss data when using the *Food for Thought* software?

1.2 What precedes discussions of data?

1.3 What do discussions of data look like?

Methods

Study Design. This study was the first phase of a design based research project (Baumgartner et al., 2013; Brown, 1992). Members of the research team provided eight class days of instruction across a ten-day period, one day of instruction occurred within the lab classroom, which is the focus of this chapter. Groups were recorded in a lab classroom, and video analysis was conducted in order to understand what data discussions looked like in groups.

Context. The study took place in a lab classroom in a midsized, Midwestern town. The classroom was set up to record audio and video from all groups while students completed the *Food for Thought* activity (see figure 3). The students completed the activity on either one 80" and four 55" multi-touch tables. The multi-touch tables allowed each group member to interact with the software simultaneously. Student groups were recorded using an overhead camera and microphone, either hanging or table mic, to capture their interactions. Groups of four or five students worked on the tables in the lab, and their discussions and interactions were captured via recordings. The member of the research team that was facilitating the 50-minute class in the lab wore a linked lapel microphone to capture her discussions with the whole class and individual groups.

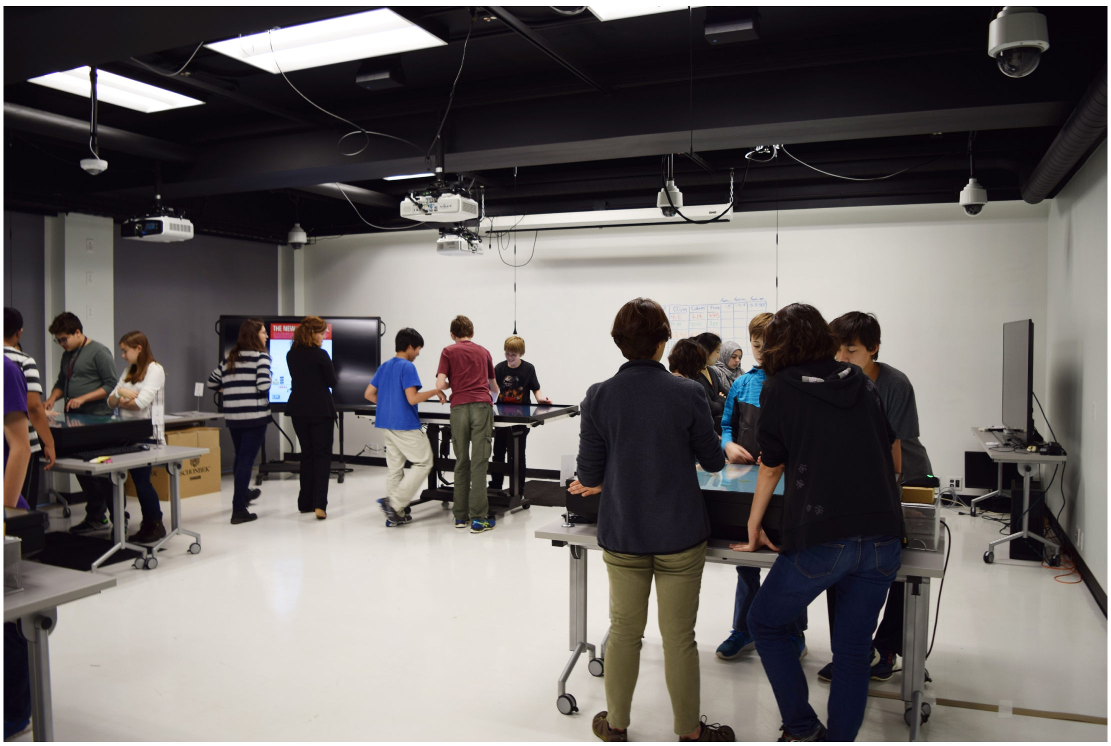

Figure 3. Lab classroom.

Participants. Sixty-three students from three combined 7th and 8th-grade classes, attending a public, selective admission school, came to the lab classroom to participate in the study. Data were collected from 45 students (10 groups) who had both parental consent and student assent to participate in the research. Consent rates were higher, but only groups where every student consented were recorded. All students in the class participated in all tasks as part of their typical classroom activities regardless of their consent.

Each class had five groups of four or five students (see figure 4); each group worked on one multi-touch table. The membership of the groups was approved by the class' regular teacher before the study began. From the three classes, 11 groups were recorded; one was excluded from analysis due to poor audio quality; ten videos were transcribed for analysis.

Figure 4: A group of 5 students working on one multi-touch table.

The Food for Thought Software. The *Food for Thought* software was designed to encourage collaboration. Due to the affordances of the multi-touch table, the software was designed to allow all students to work with the foods and data simultaneously with the intent to promote collaboration. The software and the lesson were an ill structure design problem with many possible solutions to encourage discussion among groups. The interface was designed to represent a kitchen table with a plate, 24 foods, and four data sources (see figure 5). The interface was created to be a photo-realistic representation of the foods students eat at home so that they could map their experience directly.

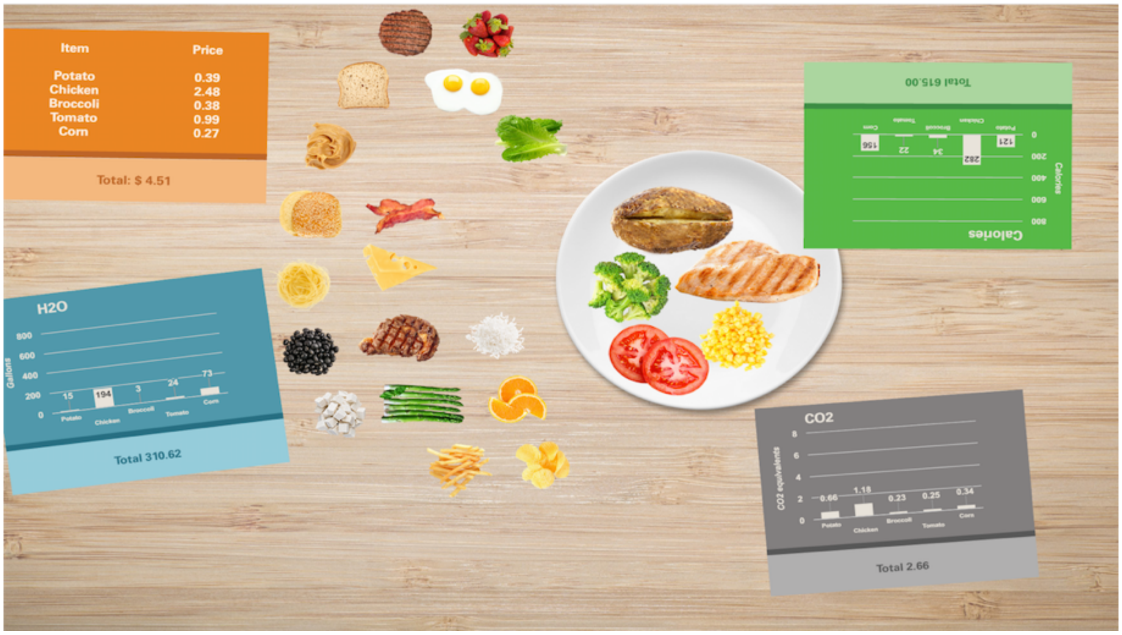

Figure 5. Top down screenshot of the *Food for Thought* software.

Students could move the food freely around the table, but they initially began oriented around the plate. The software allowed students to place food on the plate to create different meals, with a limit of 8 foods on the plate at once. This limit was chosen so that all the foods on the plate could be on the graphs at once without overextending the x-axis. To interact with the software, students could drag different foods onto the plate, and the four data sources would populate with data simultaneously. Each data set was displayed in a box and represented as either a bar graph or list. The graphs were initially positioned at each corner of the screen but could to be scaled, rotated, and moved freely around the screen. The intention was to foster flexibility to allow students to share and compare data sets as a group or draw emphasis to one at a time. Students moved the food on the plate and each graph displayed a value for that food. Two of the graphs represented the main topics from the classroom intervention which were the carbon and water footprint associated with the production of the food; a third graph represented the calories contained in the food; a list presented the local price. All values were calculated by the serving size for each food established by the United States Department of Agriculture (USDA).

The carbon footprint was measured by the amount of carbon dioxide equivalence that goes into the production of the food. Carbon dioxide equivalence (CO_2-eq) is a standardized unit to measure all the greenhouse gases involved in the process to produce each food and was covered in the content during the preceding days before the class in the lab classroom. The water footprint was measured in gallons per serving and shows the water that goes into the production of each food per serving. The calories were determined using the USDA serving size recommendations. Food costs were compiled from the United States Department of Labor Bureau of Labor Statistics and compared to the median price for the same item at a local grocery store. If the cost differed between the two, the local price was used.

Design Justification. The design decisions of this software were made intentionally to foster collaborative interactions around multiple sets of data. The key components of the software include the overall style, the bar graphs, and the food representations. Each of these will be discussed briefly and explain why and how the decisions were made.

The style of the software went through multiple iterations before landing on a realistic table environment. After I made an initial design (see figure 6), the research team discussed style options for the software. Discussion compared a more open and clean setting versus a realistic table setting. The team settled on situating the environment on a table to make a more engaging and aesthetically pleasing experience for the groups.

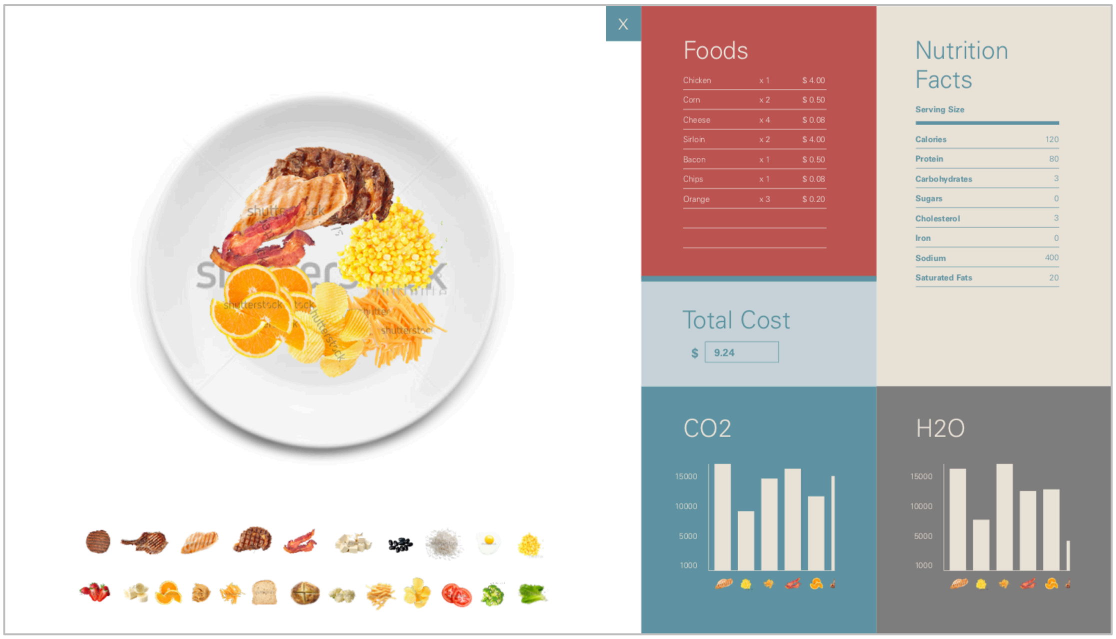

Figure 6: First iteration of the design of the *Food for Thought* software.

A design decision that influenced how the students worked with the data was the choice to use bar charts to display the data. This choice was based on an understanding of middle school students' likely level of comprehension of different types of graphs. From a representation perspective, bar graphs afford quick, perceptual comparisons of data due to the simple arrangement of the bars (Norman, 1991). However, it has been found that middle schoolers struggle to understand graphs in science but that using different instructional techniques could support them in achieving comprehension (Lai et al., 2016). The decision to make the graphs flexible to be scaled and rotated around the interface was to build a shared space for the students' understanding. By building the functionality around a collaborative perspective, the intent was to give groups more flexibility, therefore leading to collaborative discussions. Another factor that affected this decision was the static and directional issues of the graphs. In the iteration shown in figure 6, the graphs are static and due to the directionality of multi-touch tables poses challenges for students working on either side of the table. By implementing the flexible graphs, students can share the data with students on any side of the multi-touch table.

The decision to use realistic food representations was made by the research team to ensure that students could quickly identify the foods without hesitation. A set of representations were selected and approved by the research team and tested with middle school students to see if they could identify the foods. Students were presented with 24 foods and asked to identify each. Students consistently identified six foods incorrectly (potato, egg, cheese, peanut butter, bun, asparagus), so new representations were chosen for each food. The final set of foods were tested with a new class; they were again asked to identify the foods (see test sheet in Appendix A). Students made few errors, therefore, the foods were approved and used in the software.

Procedure. Students participated in an eight-day intervention over a ten-day period, seven of which were in their normal classroom. All students in all classes completed the same activities across the eight days and worked within their assigned group in all activities. One member of the research team (henceforth the teacher) facilitated the instruction and acted as the classroom teacher to teach the eight days of instruction about climate change in relation to food. On the seventh day, students came to the university lab classroom to work with the *Food for Thought* software. The teacher, who taught the preceding six days, taught the lesson in the lab classroom. The three remaining members of the research team stayed in the lab classroom during the lesson to address technical problems or other issues as they arose. Students began the 50-minute class period seated in the lab classroom and were given a short lecture to reiterate the relationship between food and climate change. Students then stood around the tables organized by group number and were given an introduction to the features and functions of the software. Up until this point students had not previously interacted with the *Food for Thought* software.

The teacher taught the class by presenting a series of tasks to engage the students with the content. The teacher presented the class with the first of three tasks, make your favorite meal. This task was intended to familiarize students with the information, and allow them to adjust to the lab classroom space and interactions with the table and data. As the class continued the tasks became more complex. The second task prompted students to make a meal using a meat and students were later asked to replace meat with different foods and make comparisons with the data. The final task asked the students to make the most environmentally friendly meal using the constraints of the data. This task was created to be open-ended with many answers so that students could make comparisons with the data and discuss the tradeoffs of each data set. During one class, there was extra time at the end due to the transition between classes; therefore, an additional task, make a meal that has the highest carbon and water footprint, was given to the groups. The other class did not receive this task because they did not have extra time. The overall progression of complexity of the tasks gave the students time to continue familiarizing themselves with the data and build more advanced solutions as the class time went on.

After presenting each task, the teacher circled the classroom and interacted with groups individually. When interacting with the groups, she would ask questions to spur discussion about the data and their findings. At the end of each task, the researcher asked each group to list the foods on their plate and the data for the meal and concluded with a summary of the class' findings.

Analysis. The analysis focused on the data discussions of the group and what proceeded them. To analyze these discussions, the video data was transcribed in playscript form. After viewing the videos, emergent coding schemes were created to account for student's data discussion and what preceded them from a grounded theory approach (Corbin & Strauss, 1990). The video and transcripts were coded together using multiple coding schemes, discussed below.

Data discussion coding. The first coding scheme was created to identify evidence of times students were talking about the data. Each turn was coded as data talk or other talk. Table 1 shows definitions and examples of the categories of data talk. All other forms of talk not included in the data definitions were coded as other talk. Two researchers coded 10% of transcripts (1 full transcript) to assess reliability, with a Cohen's Kappa of .92. The two researchers discussed disagreements until they reached a consensus.

Table 1: *Data-talk definitions (criteria for inclusion).*

Definitions	*Examples*
Explicit data values.	*"We have only 1020 calories, that's good."*
Using descriptors to define data talk.	*"Beans are pretty low." "Calories are ok."*
Moving food to test for changes.	*"Let's try taking out rice. Is it better or worse?"*
Drawing inferences from the data.	*"We don't have enough calories for the day guys."*
Simple data talk response.	*"It doesn't matter, it's healthier." "No"*
Complex data talk response.	*"385 calories is not enough for a meal."*
Abandoned data turn.	*"Beans turned out to be really like…"*
Unresponsive questions.	*"Which one did you say was better than tomatoes?"*

Data episodes. In the second stage of coding, the data turns were organized into episodes in order to identify what preceded each episode. An episode of data talk was defined as a discrete discussion about the data that was defined by the breaks of discussion that were not about the data. An episode could be one turn of the transcript, for example, an abandoned data turn or can be many turns of talk in discussion with multiple topics. Episodes were determined by analyzing the data turns coded in the transcripts while viewing the video.

Preceded data talk. In order to answer the question 1.2 (what preceded data talk), turns before each episode were coded. The second emergent coding scheme (table 2) was created and applied to up to three turns preceding each episode identified as data talk. Three turns preceding the episodes were used because it captured the transition from other talk to data talk. With four to five students in each group, there were often multiple conversations happening simultaneously. To account for this, separate conversations and off topic interjections were not coded. The extracts below illustrate examples of the coding schemes. To establish inter-rater reliability, two researchers coded 10% of the data set; Cohen's Kappa was .93.

Table 2: *Coding scheme for preceding talk*

Code	Definition	*Example*
Whole class instruction	Instructor speaking to the entire class.	
Instruction to a group	Instructor speaking to table individually.	
Prior knowledge	Data discussed that was not in the software or the lesson; students learned elsewhere or looked something up.	*"Beans are a good source of protein."*
Procedural	Deciding what to do next in relation to the task.	*"What are we supposed to be doing?"*
Table Food	Discussion centered around the food on the table without data.	*"Use the burger, I like burgers."*
Table Data	Data talk is used to initiate the discussion.	*"The sandwich has a lot of water."*

Six classifications were identified as types of turns that preceded data episodes: whole class instruction, instruction to a group, prior knowledge, procedural, table food, and table data. Whole class instruction and instruction to a group were interactions where the teacher was speaking to students. Whole class instruction included anytime the teacher was speaking to the class; this included presenting tasks, asking the class questions, and introductions and wrap-ups. Instruction to a group was coded any time a member of the research team talked to a group that led to data discussion. This included any member of the research team, not limited to the member teaching the course. Table data and table food include turns where students reference information being presented on the multi-touch table. Table data was coded when a student referenced information presented on the interface; this must be from one of the four graphs, carbon footprint, water footprint, cost, or calories. Table food indicates turns about the food represented on the table. Turns coded as prior knowledge included instances when a student discussed information or data that was not included in the table. All external data discussed was coded as prior knowledge even if the information discussed was incorrect. Food discussions not represented on the table (i.e., pizza or a specific restaurant) were coded as prior knowledge rather than food talk. Procedure codes were those that students used to ask about what they were supposed to be doing and lead to discussions about the data.

Results

Data Discussions. In order to understand the number of data turns (research question 1.1), student turns were coded as being data or not and divided into episodes. The mean number of data episodes across all groups was 27.5 (*SD* = 7.2). Groups had a mean total of 420.80 turns during the class period (*SD* = 120.66), this ranged from 177 turns to 589 turns. Data turns made up 22.9% of all student turns across all groups (*SD* = 8.2%). The mean number of turns coded as data across groups were 90.30 (*SD* = 25.01), ranging from 56 data turns to 140 data turns.

To determine what preceded the data episodes, three turns before each episode were coded using the coding scheme in table 3. Results show that the majority of data episodes were prompted by the teacher during whole class instruction. Of the mean 27.5 episodes each group, the teacher prompted the data discussions a mean total of 13.8 times (*SD* = 4.2) per group. See table 4 for the means for each code.

<u>Table 3</u>: *Mean for each code that preceded data episodes*.

Code	*M*	*SD*
Whole class instruction	13.8	4.2
Instruction to a group	2.6	3.1
Prior knowledge	2.2	1.9
Procedural	1.9	1.4
Food Talk	3.8	2.0
Data Talk	3.2	2.4
Total	*27.5*	*7.2*

Examples of how different codes that preceded data talk.

To answer research question 1.3, what do data discussions look like, examples are drawn from the data. These examples provide insight into the coding used and represent the range of interactions seen in the dataset. Extracts will be introduced in tables and list out codes that were applied to the turns if applicable. All names are pseudonyms.

Extract 1: Prior knowledge prompts data discussion. In the first extract in table 4, a group of four students was working to create a meal with the most amount of carbon equivalence and water (an extra task given to one class). One student (Josh) draws on his outside knowledge about nutrition, coded as prior knowledge (PK) which lead the group to engage in a data discussion, coded as data.

Table 4: *Extract 1*

Transcript	Code
Josh: "*Can we add peanut butter?*" [asks whether the group should consider adding peanut butter to their plate.]	
Sarah: "*It's, it's more of a filler.*"	PK
Josh: "*Peanut butter's not much for protein.*" [uses prior knowledge about peanut butter to note the amount of protein is low compared to the other foods that are available.]	PK
Sarah: "*Oh, can we see how much peanut butter…* [drags peanut butter to the plate and looks at graphs] *well it's low in carbon.*" [asks to check peanut butter by dragging it on the plate which will populate the graph. She then comments on the data.]	Data

This extract illustrates an example of how students used prior knowledge (e.g., that peanut butter is a protein) to help guide their decisions to discuss the data. Since the table did not contain data about protein, this was coded as prior knowledge, and two turns were used to code the discussion. Accuracy of turns were not considered, even if incorrect information was discussed it was still coded according to the coding scheme.

Extract 2: Discussion about the food leads to data discussion. The second example in table 5, illustrates how students began talking about data while working to create the most environmentally friendly meal. Two students, working in a group of four, are deciding what to put on the plate based on their food preferences, coded as food talk, which lead to curiosity about the data, coded as data talk.

Table 5: *Extract 2*

Transcript	Code
Qing: "*I love fries.*" [begins the conversation by making a claim about what she likes.]	Food

Table 5 Continued

Joe: "*Take off fries.*" [asks to take off fries, presumably to see what the data says without the fries on the plate.]	**Data**
Qing: "*Why take off fries?*"	Data
Joe: "*Ahh it's off.* [takes the fries off and checks the water level] *The water is ok.*"	Data
Qing: "*Yeah but the CO_2…*" [noting the carbon levels are still not good, even without the fries.]	Data

In this example, Qing was generally speaking about her food preferences, and Joe decided the food should be moved to compare water and CO_2 amounts, this is an example of a food discussion preceded data talk. Only one turn preceding the episode was coded, as the previous turns were unrelated to this discussion.

Extract 3: Teacher to the whole class. Teacher interventions are different than the discussion among students because there are no transitions between topics. In table 6, the teacher is speaking to the whole class about their prompt, make the most environmentally friendly meal, and asks a question. Two students from a group respond while analyzing the data.

Table 6: *Extract 3*

Transcript	Code
Teacher: "*What do you notice on your graphs when you add asparagus?*" [asks a question to the whole class.]	Teacher
Curtis: "*A lot more CO_2.*" [looks at the carbon graph and reports the amount has increased.]	Data
Ryan: "*Everything is higher.*" [scans around the table and notices all bars on all graphs have increased.]	Data

Discussions like these were direct and asked with the intention of getting the students to reference and discuss the data. The longest segments of data discussion seen across the video occurred during the last task where students were asked to create the most environmentally friendly meal and immediately followed the teacher presenting the prompt.

Extract 4: Graph ownership. Extract 4, shown in table 7, demonstrates how students interacted with the graphs due to their arrangement on the multi-touch table. During the first prompt, make your favorite meal, a group of four students set a precedent that each student had their own graph to analyze and report on. Carrie is standing in front of the water graph, and Collier is standing across the table from her with the carbon graph in front of him.

Table 7: *Extract 4*

Transcript	Code
Carrie: "*No, I want to read. Give it back*" [trying to look at the carbon graph positioned across from her.]	
Collier: "*No, you already have one [graph]. You have the water one ok?*" [taking ownership over the carbon graph and explaining the water graph intended for her.]	
Carrie: "*You need to chill.*" [responding to Collier and goes back to observing the water graph in front of her.]	

In this example and other similar discussions, students took ownership of the graphs closest to them. This caused problems in some groups as it limited their ability to view and discuss the different types of data simultaneously.

Extract 5: Affordances of the software on the multi-touch table. In this extract, illustrated in table 8, a group of four students is organizing the foods based on categories they created. They organized the foods during the entirety of the lesson, but this extract happens while another group is presenting their most environmentally friendly meal to the whole class.

Table 8: *Extract 5*

Transcript	Code
Tia: "*There we go… this doesn't match.*" [reorganizing foods that weren't used to make the most environmentally friendly meal.]	
Alex: "*What is this?*" [pointing at corn.]	
Tia: "*Corn.*" [responding to Alex.]	
Alex: "*No, no! The vegetables go far away from the bread. Wait, the bread is part of the starches.*" [discussing the location of the vegetables and starch categories on the table.]	
Sam: "*Alex, please.*" [reacting to Alex's excitement.]	
Alex: "*But it's green. But where should it go?*" [asking what category, a vegetable falls into.]	
Sam: "*Protein?*" [responding to Alex.]	

This example demonstrates how the students used the flexibility of layout of the food to categorize and discuss their prior knowledge about food nutrition (protein and starch), helping them create an external representation of their knowledge to structure their solution process. However, while they organized the food the entirety of the lesson, it did become a distraction, as in this example they were discussing their categories while another group was presenting to the class.

Conclusions

The goal in the design of this software was that students would engage in collaborative discussion about the data presented in the software. Results show that the mean number of data turns made up less than a quarter of discussions across all groups, indicating that it was only a small part of their discussion. The results also indicated that more than half of data discussions were preceded by teacher intervention, demonstrating that most of data discussions were not precede by direct interaction with the software. The longest section of data talk came from the last prompt of the class. There could be a number of reasons to explain this finding. First, the final task, make the most environmentally friendly meal, was designed for the students to draw from more than one dataset, which in turn may have engaged them in a more in-depth discussion about the content. Another factor was that being the last prompt, students had time to familiarize themselves with the system and the data. It is possible that more students addressed the data, the more comfortable they became. The intent was that students would engage with the data with the software acting as a form of scaffolding, but due to the structure and organization of the system that was not always the case. It can be inferred that the two representations in the software, bar graphs and food icons, both supported and prevented these kinds of discussions.

As seen in figure 5, the four graphs are positioned at each of the four corners of the multi-touch table. One of the research interests of this project was to understand how students make sense of multiple data sets. The graphs were designed to allow flexibility so that students could change the size and position to draw comparisons between the data sets. The intention was that groups could make one graph large in the middle of the table to discuss, or line two or more up to compare across graphs. The position of the graphs was problematic as some students took ownership over the graphs positioned in front of them and felt it was their responsibility to report on its data, replicating Rick et al.'s (2009) findings that students take ownership of the content nearest to them on a multi-touch screen. In extract 4, one group explicitly called out that they each had one graph to report on, although this was not recognized in all groups – with some groups sharing and comparing graphs as intended. The spatial arrangement of the graphs led to the disconnect of the data and lack of discussion around it. While the approach that the students used the graphs lends toward more of a cooperative, jigsaw task, where students become an expert in one area and share out their findings (Cohen, 1994), our goal was to engage students in collaborative discourse where they are jointly constructing knowledge (Barron, 2003). Future iterations will examine organizing the graphs in a way that allows students to understand them as a set rather than individually in order to engage groups in more collaborative discourse.

The second form of representation used in the software was the food visualizations. The foods were represented as images to display realism and make it easier for students to recognize them. The food may have had similar complication as the arrangement of the graphs, possibly limiting students to use the foods closest to them and not allow them to interact with foods located farther than arms reach. However, it did allow a level of flexibility for students to use the food how they see fit. For example, in extract 5 students made categories for the foods and used them to organize the foods throughout the class. This led to discussions about the food in relation to their prior knowledge and shows how the flexible design allowed some groups to create external representations of their process and use it to support more complex decisions about the foods they chose. Thus, in future designs, there will need to be a balance between flexibility of the interface with access in order to permit students to adapt the software to support their collaborative interactions.

Design Suggestions from Study 1

The findings explained above are summarized from the coding and also observations from viewing the video of students' interactions. By evaluating and discussing some of the successful and detrimental features and functions of the software, inferences can be draw for changes and additions to help make the software more successful in future iterations. There are two main goals moving forward with this software: (1) engage students in more data based discussions and (2) change to software to act as more of a scaffold to facilitate data discussion rather than relying so heavily on the teacher. After completing this analysis and developing these goals, I suggest several possible changes to enhance the design of the software.

1. *Addition of multiple representations*. Successful multiple representations are clear, reiterate key concepts, and should be built on pedagogical knowledge (Ainsworth, 2014). The addition of simple representations to reiterate the key concepts of the class (water and carbon footprint) could give groups an additional way to access the information, and lead to more data discussions.
2. *Reorganize the graphs*. As seen in extract three, and evident in other groups in the data set, individuals often took ownership over the graphs in front of them rather than sharing the graphs among the group. While this could afford a cooperative task structure, one of the goals of this project is to engage students in collaborative discourse around multiple sets of data. To make up for these findings, I suggest removing the graphs flexible nature and make them static on the software. To account for the directionality of the text, the graphs should be displayed twice so that regardless of placement all students have access to the information.

CHAPTER 4: STUDY TWO

Introduction

Design changes were made to the software between the first and second study. The second iteration of the *Food for Thought* software was implemented in a lab classroom with middle school students. The purpose of this study was to investigate how the changes to the visual design of the *Food for Thought* software from study one, affects students' discussions around data. In this section, I discuss the design of the software, examine the data collected from study two, and address the same research questions as study one:

2.1 Do students discuss data when using the *Food for Thought* software?

2.2 What precedes discussions of data?

2.3 What do discussions of data look like?

Methods

Study Design. This study presents the second phase of a design based research project. Conclusions made in study one were used to make changes to the *Food for Thought* software and implemented in study two with a different sample of students. Members of the research team provided three days of instruction, one of which occurred in the lab classroom, which is the focus of this study.

Context. The study took place in a lab classroom in a midsized, Midwestern town. The setup was the same as study one, see chapter 3. The same member of the research team that facilitated the class in the first study also facilitated the 50-minute class in the lab in study two (henceforth the teacher). She wore a lapel microphone to capture her conversations with the whole class and individual groups.

Participants. Thirty 8^{th} grade students from two classes, with two different teachers, consented to participate in the study. Two different sessions were conducted, one class per session. All students in the class participated in all activities, regardless of consent; only groups where all members had consent, and who assented to participate, were recorded. Each class had five groups of three or four students each; each group worked at their own multi-touch table. The membership of the groups was approved by the class' regular teacher before the study began. Of the eight groups that were recorded, two were excluded from analysis due to poor audio quality; therefore, six were transcribed for analysis.

Food for Thought App. Similar to the first study, the software presents the students with a plate, four graphs (now displayed twice), and 24 foods, with an addition of two representations of water and smoke (carbon) (see figure 7 for the new design). The foods were arranged around the plate at the beginning of the activity and students moved them on and off to populate the graphs with data and update the two representations to reflect the impact of the food on the data.

Figure 7: Top down screenshot of the *Food for Thought* software used in study two.

The data presented in study two was identical to the data presented in study one, carbon and water footprint, cost and calories, with the addition of two representations of the carbon and water footprint. As students placed foods on the plate, the water and smoke representations would expand or shrink in size based on the food's carbon and water footprint values.

Design Justification. In the first phase of the project, findings indicated that teacher interventions drove data discussions to the whole class and student took ownership over the graphs that were in front of them. Due to those findings, changes were made to the software. After implementation in study one, I suggested two changes, reorganize the orientation of the graphs and add representations of the two main concepts of the curriculum (carbon footprint and water footprint).

In study one, a graph was located at each corner of the multi-touch table and had the flexibility to be scaled and rotated around the screen. While the graphs were flexible, it did not allow all students access to the same information, replicating Rick et al.'s (2009) findings. Access to the graphs posed a challenge when prompting the students to draw conclusions across all four graphs, one of the goals of the project. To give all students the same access to the information, the graphs were reorganized so that all four were visible and mirrored on both sides of the table. The goal of this change was to allow all students the same access to the information and engage them in more data-based discussions.

As recommended at the end of the first study, representations of carbon equivalence (smoke) and water footprint (water puddle) were also added with the intention that students would use them as an entry point to talk about the data. When the teacher is not instructing the whole class, groups should still be able to continue solving the prompt and discussing the data. Since this was not evident in study one, the goal of adding the representations is to give students another way to discuss the data rather than relying solely on the graphs. Similar to the food representations in study one, smoke and water representations were tested with the research team to determine if the representations were identifiable. The research team unanimously decided upon the smoke representation, the water, however, took two rounds of revisions to find an image that was identifiable (see Appendix B for water and smoke representations). The purpose of adding representations to the software was to give groups an additional entry point to the data and engage them in more discussions around the data sets.

Procedure. Students participated in a three-day intervention, two of which were in their normal classroom. All students in both classes participated in all activities across the three days.

The teacher facilitated lessons on climate change in relation to food on the first two days. On the third day, the students came into the lab classroom and worked with the *Food for Thought* multi-touch app. The three remaining members of the research team stayed in the lab classroom during the lesson to address technical problems or other issues as they arose. Both of the class' normal classroom teachers were also present in the lab and worked with different groups throughout the lesson. Students began the 50-minute class period seated in the lab classroom and given a short lecture to reiterate the relationship between food and climate change. Students then stood around the tables organized by group number and were given an introduction to the features and functions of the app. Up until this point students had not previously interacted with the *Food for Thought* app.

The same tasks were used in both studies, although, during the final task groups were asked to describe their meal and explain the justifications for their environmental meal by presenting their claim, evidence, and reasoning. The research team added this because the class was currently learning about and using claim, evidence, and reasoning in their classroom.

After presenting each task, the teacher circled the classroom and interacted with groups individually. When interacting with the groups, she would ask questions to spur discussion about the data and their findings and answer questions as they arose. At the end of each task, the researcher asked each group to list the foods on their plate and the data for the meal and concluded with a summary of the class' findings.

Data sources and analysis. The data sources, coding, and analysis protocol were identical as those used in study 1; please see chapter three for details.

Results

Data Talk. In order to answer research question 2.1, do students discuss data when using the *Food for Thought* app, the transcripts were coded for the number of data turns. The mean number of data talk episodes across all groups was 29.2 (*SD* = 9.9). Across all groups, the total mean number of turns during a class period was 327.80 (*SD* =107.61), this ranged from 234 turns to 487 turns. Data turns made up 45.39% of all student turns across all groups (*SD* = 19.21%). The mean number of data turns per group were 136.00 (*SD* = 36.82), ranging from 97 data turns to 189 data turns.

To determine what preceded data discussions, the turns were divided into episodes, and preceding turns were coded according to the coding scheme in table 2. Results are shown in table 9.

Table 9: *Mean for each code that preceded data episodes.*

Code	*M*	*SD*
Whole class instruction	8.2	5.2
Instruction to a group	5.2	5.0
Prior knowledge	1.2	1.6
Procedural	2.2	0.8
Food Talk	5.4	1.8
Data Talk	7.0	1.9
Total	*29.2*	*9.9*

Examples of different codes that preceded data talk.

In order to answer research question 2.3, what do discussions of data look like, extracts have been pulled from the data to represent the range of data talk seen in the data set. Extracts will be introduced in tables and list out codes that were applied to the turns if applicable. Names are pseudonyms.

Extract 1: Data talk with the smoke representation. Since representations were added to the software, the example in table 10 illustrates turns that were coded as data discussion that incorporated the smoke representation. The group is observing the changes of the representation when the plate has chicken, steak, or both chicken and steak on it.

Table 10: *Extract 1*

Transcript	Code
Sarah: "*Chicken has less water, less carbon, less calories*" [observing the values of the chicken compared to the steak, which was just on the plate.]	Data
Thomas: "*And look at this, yeah*" [as he drags the steak back onto the plate.]	Data
Jennifer: "*Look at the smoke!*" [points at the representation on the table.]	Data
Sarah: "*Let's put them both on at the same time. Let's see…!*" [suggesting that the group put both steak and chicken on to see what happens to the representation.]	Data
Jennifer: "*Oh!*" [gasping at the drastic change of the representation.]	Data
Thomas: "*That ain't good.*" [commenting on the added carbon with both types of meat on the plate.]	Data

In this example, the group begins by discussing the values of the foods. The representation of the carbon leads them to make additional investigations with more than one meat, building on their discussions.

Extract 2: Claim, evidence, and reasoning for most environmentally friendly meal. One change made from the first study to the second was that the teacher asked students in the second study to justify their environmentally friendly meal by explaining their claim, evidence, and reasoning. Groups were asked to share their result with the class. This example, in table 11, illustrates one group's answer to the task.

Table 11: *Extract 2*

Transcript	Code
Gabriel: "Okay, so, we said we used oranges, lettuce, bread, spaghetti, broccoli, tomatoes, and strawberries, I guess?" [reads the group's meal that is written on a whiteboard.]	Data
Toby: "Yeah" [prompting him to continue.]	Data
Gabriel: "And we said these foods are healthy because, um, there's little water footprint and carbon footprint and if you eat this meal three times a day you would have enough calories to live. And it costs a little and there's lots of vegetables." [continues reading the evidence and reasoning.]	Data

This group uses vocabulary presented in the graphs to discuss their decisions. The group presents all four of the data sets in their evidence to the class, indicating that they were drawing from all the graphs available to them, but not the representations. Other groups, however, did not respond in the same way, another example is displayed in extract 3.

Extract 3: Claim, evidence, and reasoning for the most environmentally friendly meal. This example, in table 12, shows how another group justified their meal choice by presenting their claim, evidence, and reasoning. This group was in the same class as the previous extract and was also working on the last task, make the most environmentally friendly meal.

Table 12: *Extract 3*

Transcript	Code
Alison: "Alright. The most environment, the most environmentally friendly meal we found was chicken, broccoli, and eggs. We think this because when we added the meal on, on. Correct?" [she takes the whiteboard from the member of the group that was writing and reads from it.]	Data
Ava: [nods in response to Alison's question.]	Data

Table 12 Continued

Alison: “On the plate because there was barely any smoke and water. So yeah, that is our answer.” [finishes reading the content of the whiteboard.]	**Data**

In this example, the group’s answer references the representations instead of the contents of the graph. Rather than drawing from the content on the graphs like the group in extract 2 did, this group only referenced the representation.

Conclusion

The goals of the second study were to engage groups in more data discussions and alleviate some of that responsibility from the teacher by making changes to the software so that it functions more so as a form of scaffolding for groups. Results show that 45.39% of turns were coded as data talk while using the new version of the software, whereas data talk made up 25.4% of discussions in study one. Some of these changes can be accounted by the alterations of the design, however, because this is a design based research project multiple factors should be taken into consideration. For instance, a different class from a different local middle school used the software in study two, and additional changes were made to the class instruction where students were asked to present their claim, evidence, and reasoning for their answers to the final task.

In addition to the changes found in the data talk itself, the codes that preceded data talk were found to be more evenly distributed between whole class instruction and data presented on the app, while in study one, whole class instruction precedes the majority of data episodes. This finding indicates that the modifications made to the orientation of the graphs and the addition of the multiple representations changed what preceded data episodes.

An important finding from this study was that the types of data discussions that students engaged in varied group to group. As indicated in extracts two and three, there was a difference in the way students discussed the data in the final task, make the most environmentally friendly and justify your claim, evidence, and reasoning for it. Some groups used the representations as their justification, while some groups used the graphs or a combination of the two. While it seems some students weren't synthesizing the data because they were just using the representation and not the numerical data, research shows that visual representations can act as data and assist in sensemaking and comprehension (Baker, 2009). Visual representations are a form of data and can engage students with the content in ways that may not have otherwise been possible with only numerical data. Further analysis needs to be completed to understand fully how the representations affected group discussions and their comprehension of the content.

Design Suggestions from Study 2

The findings explained above are summarized from the coding and also observations from viewing the video of students' interactions. By evaluating and discussing the features and functions of the software, inferences can be drawn that inform changes and additions to help make the software more successful in future iterations. After completing this analysis and developing these goals, I suggest several possible changes to enhance the design of the software.

1. *Addition of multiple representations.* Knowing the representations have been beneficial for scaffolding students' data discussions, representations may be considered for the remaining two data sets in the software. The cost and calories, while not the focus of the lessons taught in this study, may be beneficial representational supports for students

drawing conclusions across all four sets of data. Further testing would need to be done to ensure that additional representations do not overload the students.

2. *Save plates to allow student to offloading information.* During the second task, make a meal with a meat, students were asked to exchange the meat with different replacement options (e.g., other meats, tofu, or beans). The goal of this interaction was to get students to compare food with high and low carbon footprints. To facilitate these tasks, the software could save plates so that students can see distinct differences between meal choices, as it becomes hard to remember what past values were after exchanging out multiple foods.
3. *Create flexible options for teachers to adapt the software for their class and domain.* One valuable aspect of the *Food for Thought* software is its ability to address a complex issue like climate change from multiple perspectives (e.g., science, social studies, health, etc.). One way to capitalize on this is to create the flexibility for teachers to customize the representations or functions of the software to fit into their curriculum or domain they are addressing. This change could make the software more useful to teachers, as they could adapt it into their classroom as they see fit rather than how the research team used it in the studies.

CHAPTER 5: STUDY COMPARISON

Introduction

In order to understand how the changes to the software influenced data discussions, comparisons were drawn between study one and study two. In this section, I investigate the research questions:

3.1 Were there differences in how groups discussed data between study 1 and study 2?

3.2 Were there differences in what preceded data discussions between study 1 and 2?

Results

Mann-Whitney Tests were run to compare turns in study one and study two in order to examine differences (see Table 13 for results). Results indicate there was no significant difference between the total number of turns from study one to study two. However, groups in study two had a significantly higher number of turns coded as data.

Table 13: *Differences in turns between study one and study two*.

Turns	*U*	*P*	Study 1 (*Mdn*)	Study 2 (*Mdn*)
Total turns per group	14.0	.18	409	298
Data turns per group*	6.0	.02	87	123

* $p < .05$

Tests were also run to compare the codes that preceded data episodes between study one and study two (see Table 14). There was no significant difference between the total number of episodes between study one (*Mdn* = 28) and study two (*Mdn* = 28), $U = 21.5$, $p = .665$, indicating that groups had the same number of episodes in both studies. The only two codes that preceded data episodes were significantly different between the two studies were whole class instruction and data talk. Whole class instruction preceded data episodes more in the first iteration of the software, while data talk preceded data episodes more in the second iteration of the software.

Table 14: *Differences in codes that preceded data talk between study one and study two.*

Codes preceding data talk	*U*	*P*	Study 1 (*Mdn*)	Study 2 (*Mdn*)
Whole class instruction*	8.5	.04	13	8
Instruction to individual groups	16.5	.29	2	5
Prior knowledge	17.0	.31	2	0
Procedural	21.0	.62	2	2
Food talk	13.0	.14	4	6
Data talk*	6.0	.02	2	7

* $p < .05$

Conclusion

To answer research question 3.1 (were there differences in how groups discussed data between study 1 and study 2) Mann Whitney Tests were run to identify differences between the number of turns in the two studies. Results indicate that there was no difference between the number of turns between study one and study two. All classes in both studies worked in the lab classroom for 50 minutes, explaining why there was no difference between the number of turns in the studies. There was, however, a difference in the number of turns coded as data. There was a significantly higher number of data turns in study two than study one, indicating that the changes made between the two studies (e.g., software design, students, task) may have affected the amount of data discussion in the groups. One similarity between the two studies was the number of data episodes. Groups in both studies averaged about the same number of data episodes. Since there was overall more data turns, this shows that while there was the same number of episodes in the two studies the episodes were longer. This finding means that the duration of data episodes was longer for groups in study two, which may indicate more collaborative discourse and data synthesis. However, more analysis needs to be completed to ascertain how students were leveraging the data to build a joint construction of knowledge and enacting collaborative interactions.

In order to answer research question 3.2 (were there differences in what preceded data discussions between study 1 and 2), the codes that preceded data talk were compared between study one and study two. There was no significant difference between instruction to individual groups, prior knowledge, procedural, or food talk; however, there was a significant difference between the number of times data episodes were preceded by whole class instruction and data talk. Study one indicated that teacher intervention preceded the majority of data episodes; this difference between the two studies suggests that changes made between the two studies lowered the number of times the teacher had to discuss with the class to facilitate data discussions. Data talk that preceded data episodes increased from study one to study two, implying that the changes to the software both the reorganization of the graphs and the addition of multiple representations may have engaged students in more data episodes.

In conclusion, the changes made between the two studies did change how groups discussed the data and the changes to the software altered what preceded data episodes by scaffolding their discussions more so through the software. This suggests that the design of software can have an effect on collaborative data discussions for students, and that documentation and assessment of software made in study one can help foster changes in how students interact with the software as well as each other.

CHAPTER 6: DISCUSSION

Implications

The goal of this study was to understand if students discuss data while using the *Food for Thought* software and if the visual changes of the software influenced their discussions. Our findings indicate that changes made between the two studies engaged students in more data discussions. The changes could attribute to some of the findings. For example, the classes and students were different from one study to the other, the last task, make the most environmentally friendly meal, was altered for the class during the second study to accommodate what they were learning in their science classes, as well as the software modifications. All of these changes could have affected the students' discussions; further analysis may be needed to understand the differences between these changes.

Issues found in study one, students taking ownership of the graphs in front of them and teachers preceded the majority of data episodes, were addressed in the next iteration of the software. Findings from study two show that the changes to the software, among other changes discussed above, affected these issues. There was no issue of ownership among group members, for example, there was no discussion of ownership of graphs in study two as seen in extract four (see table 7). Discussion about the data also preceded more data episodes rather than teacher instruction as found in study one. I attribute some of them to the ease of access to content and additional representations on the software.

As our findings suggest, design has the capabilities to change how students use and discuss data, and planning the design with learning theory in mind can help create more effective technology for students. To design multi-touch software effectively, I recommend using representations purposefully with the intention to promote interactions that may support learning rather than focusing specifically on adding style to a design. While style and aesthetics are important to the use of learning experiences, by incorporating learning theories and principles into the design process, experiences can be catered specifically to learning and hopefully have a positive effect on comprehension and collaboration.

Limitations

This paper presents two-phases of a design based research project, and there continues to be room for improvement to move this tool forward. One limitation to be accounted for in future iterations is the small sample sizes. For the next implementation of the software, collecting data from a larger sample will allow for more in-depth insight into how the visual design is impacting data discussions for a broader population. Another limitation due to the small classes presented here is that it is difficult to make general claims about designing software from our findings. Therefore, designers and developers of educational software can learn from the decisions and assessments documented in this paper, but should always take into consideration the specific learner characteristics and goals of the learning for their specific project, and choose guidelines that can be used as a base to build upon.

While the sample size is an issue, one aspect to take into consideration before implementing this software with a larger sample is to do more thorough user testing as we make changes to develop a detailed understanding of how students are using the software. Due to the timeline of this project, older students tested the software, which may account for some of the findings in study one. User testing may afford additional insight into the different design components and reveal higher quality design features for middle school students explicitly.

Overall conclusion

The contributions of this paper are three-fold. First, the paper emphasizes the importance of designing technology intentionally for learning, uniting learning theory with perspectives from other disciplines to create technology that acts as a form of scaffolding for students as they interact with a learning experience. This study used an adapted version of the four Ts framework (see figure 2) and perspectives from design, multimedia learning, and teaching data literacy to make decisions about the software. Through the process of integrating these perspectives with findings and observations from watching students interact with the software, additions and changes were made to the software that altered how the groups discussed data. This suggests that the process of designing software with learning in mind as well as style and aesthetic decisions can influence how the software scaffolds groups in learning experiences. Discussed in chapter 2, designers can do more than address problems with style or organization after a project has been started. By including designers in the process of building a tool upfront, they can help to account for all the factors of the project rather than cope with decisions researchers make initially.

The second contribution is that documenting and assessing the design decisions can help others to create similar experiences. Also discussed in chapter 2, designers should use design principles to frame or build a design, but they should not be the only factors going into the decisions. Some of these factors should include learning from the success and mistakes of other researchers and designers that are working with similar contexts, domains, or tools. While papers focused on the design on tools are valuable, I'm not suggesting all papers need to go into such detail, rather that researchers highlight the key decisions of their design to help ground their work and make it clear to the readers why and how they made decisions. In this paper, I added a design justifications section to the methods. In doing so, allowing the reader to understand the rational and work that went into creating the software. Sharing these ideas and processes is valuable and something that all research projects should consider, document, and assess, therein helping others further build upon the literature and develop more successful learning experiences for students.

The final major contribution was the significant findings from the study. While additional research will need to be conducted to understand how the design affected data discussion fully, the results of these studies show that design had some influence on the data discussion among groups. As I have reiterated across this paper, design plays an important role in learning. By making intentional design decisions regarding learning, researchers and designers can build better tools that support students and their collaborative processes.

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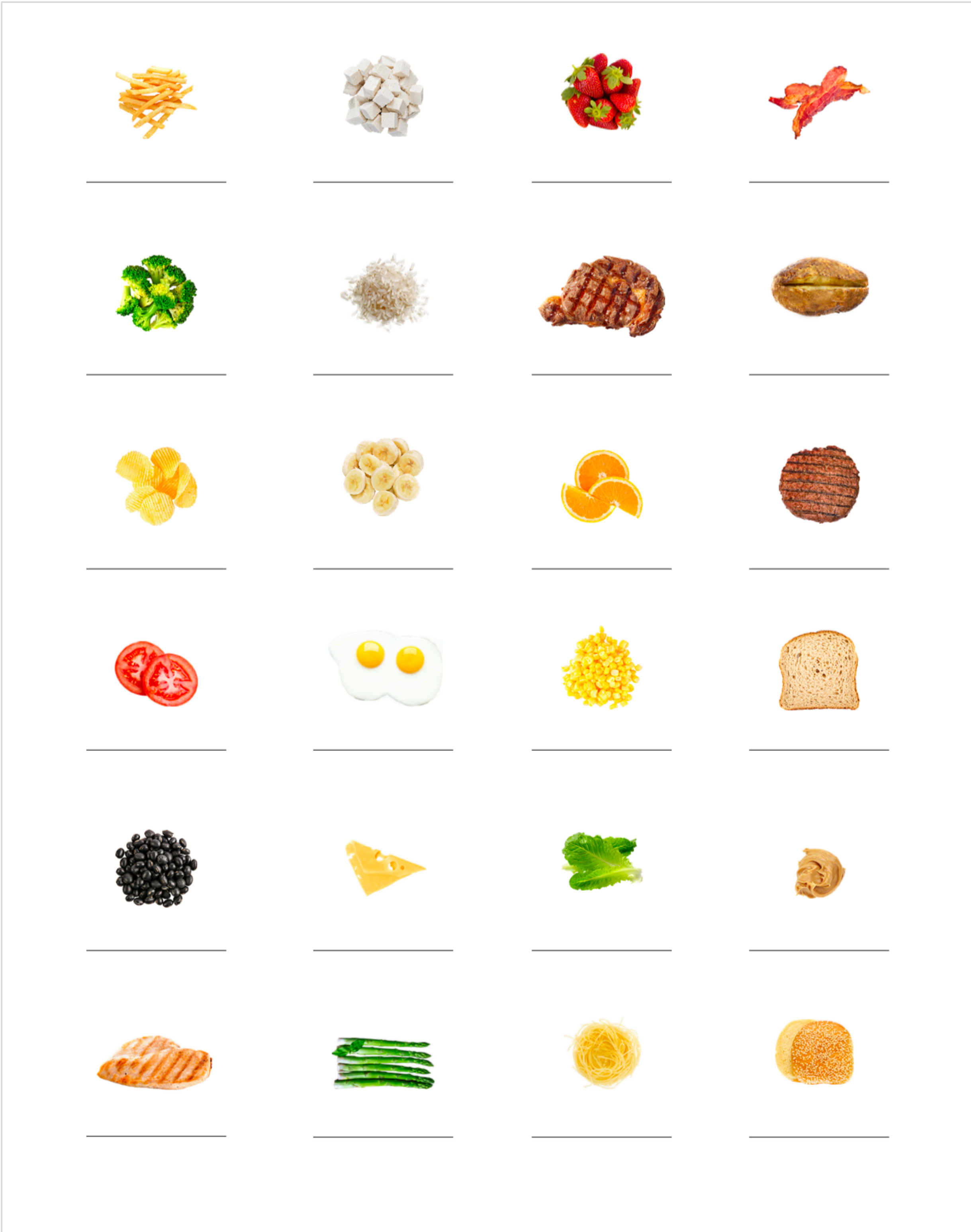
APPENDIX A: FOOD QUIZ



APPENDIX B: SMOKE AND WATER REPRESENTATIONS