LEARNING ANALYTICS IN ONLINE PHYSICAL EDUCATION: STUDENT ATTRIBUTIONS TOWARD HEART RATE MONITORING

by

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(Under the Direction of Lloyd P. Rieber)

ABSTRACT

This dissertation is presented in multiple article format with an introduction, a literature review, a design case, a mixed methods study, and a conclusion. The literature review outlines important concepts and theories that appear in subsequent manuscripts. The design case describes the seven-year design process that resulted in the online physical education app, a tool used in online physical education classes to monitor student progress toward heart rate goals. The mixed methods study investigates student attribution of outcomes observed in the physical education app. These manuscripts present both a long-term iterative design process and an empirical research study to better understand how students use their own data to inform and shape their learning.

INDEX WORDS: Learning analytics, Physical education, Wearable technology, Attribution theory, Design case, Online physical education

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DEDICATION

I dedicate this dissertation to Kimberly and Anna, who have been with me each step of the way and to the memory of my grandmother, Opal Allen, who desperately wanted me to get an education so I would never know poverty as personally as she had.

Additionally, I dedicate this dissertation to the memory of Dr. Keith Bailey, who encouraged me to pursue this degree and without whom this project might have never happened. Your spirit lives on through those your work elevated.

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CHAPTER 1

INTRODUCTION

Data have revolutionized many aspects of our lives. Predictive analytics allow Amazon to ship your next order to your area before you've even ordered it (Spiegel, McKenna, Lakshman, & Nordstrom, 2013). Ride sharing service Uber uses GPS signals from individual customers' cell phones to figure out how long a ride will take and how much it should cost based on real-time demand and traffic flow. In education, the emerging field of learning analytics makes it possible to monitor a student's progress in real-time, increasing the chance of an intervention before failure (Daniel, 2017).

Learning Analytics and Data-Driven Decision Making

It is important to understand how data is used to make decisions about student learning. Learning analytics is defined as the measurement, collection, analysis, and reporting of data about learners and their contexts for the purposes of understanding and optimizing learning and the environments in which it occurs (Siemens, 2013). Over the past decade, learning analytics has emerged as a major concept in the field of education. Technology tools used for learning capture thousands of data points that are relevant to students' learning outcomes (Picciano, 2012; Siemens, 2013). These data points might reflect behavioral patterns, such as course navigation and logins, or they might reflect the attainment of learning outcomes, such as assessment responses and discussion posts. Learning analytics is also a manifestation of the concept of big data in education (Picciano, 2012). That is, with the increased availability of data for learning,

learning analytics provides a framework by which educators can make sense of data to inform educational decision making (Siemens, 2013; Daniel, 2017).

Another concept that is important in the application of learning analytics is educational data-driven decision making (DDDM). DDDM is a process of turning data into information and information into evidence (Jimerson, 2014). This process leads from raw data (i.e., numbers in a spreadsheet) to a contextualized, rational basis for decisions. There are many sources of data that can be used for DDDM, such as interaction data from digital content and performance data form formative assessments. Learning analytics should be thought of as one way that data can become information upon which a decision can be made. However, while learning analytics can be used as a basis for DDDM, not all learning analytics efforts are directed solely toward providing information upon which a person can base a decision. In a review of the use of big data and analytics in higher education, Daniel (2015) categorized learning analytics models as descriptive, predictive, and prescriptive. Descriptive learning analytics provides teachers, students, and administrators an opportunity to examine data related to current and past behavior and make decisions based on the information provided. Predictive learning analytics goes a step further, seeking to identify risks or opportunities from patterns in the data. Prescriptive learning analytics attempts to combine outcomes from descriptive and predictive models to design an appropriate curriculum or learning experience (Daniel, 2015). Of these three types of analytics, descriptive analytics alone aligns with the DDDM model of education. That is, descriptive analytics are most conducive to being used by an individual to inform a decision rather than imposing a decision.

Much of the research on DDDM and learning analytics has focused on implementation of these constructs at the institutional or individual teacher level. Fewer studies have investigated how students might engage with a DDDM process informed by learning analytics. One study found that teachers at the middle school level used data in potentially demotivating, performance-oriented contexts (Marsh, Farrel, & Bertrand, 2016). However, that study only used interviews with teachers to understand their interpretations of data use with students. The researchers did not collect any data directly from students. Another study investigated the implementation of a student-facing dashboard for displaying assessment performance data for students to consult while they accessed instructional materials (Broos, Verbert, Langie, Van Soom, & De Laet, 2017). The study examined student use of the dashboard, finding that 47% of the 1,905 students given access to the learning analytics tool actually accessed it. Additionally, the researchers studied the students' perceived usefulness of the dashboard, the clarity of the information presented, and the influence of the information on student satisfaction. The study found that students generally rated the learning analytics dashboard positively, but that students who performed better in the class were more likely to use the dashboard. This raises the question of how best to use learning analytics to improve outcomes for all students. There is a notable lack of research on student DDDM related to the implementation of learning analytics in the learning environment.

Technology-Enabled Physical Education

Obesity and sedentary lifestyle are two of the most well-documented health crises of the 21st century (Cawley & Meyerhofer, 2011; Freedman, 2011). The U.S. Department of Health and Human Services (HHS) recommends that people over 17 do, at a minimum, 150 minutes of moderate-intensity or 75 minutes of vigorous-intensity aerobic physical activity per week (U.S. Department of Health and Human Services, 2018). However, only 22.4% of U.S. adults report sufficient activity to meet these goals (Blackwell & Clarke, 2018). Consequently, average weight, waist circumference, and body mass index have all increased among US adults over the past 15 years (Fryar, Kruszon-Moran, Gu, & Ogden, 2018).

One area where technology and data have made strides in the past ten years is wearable technology (Reddy et al., 2018). Devices now exist that can monitor heart rates, steps, and overall physical activity. The data provided by these devices make it possible for people to monitor progress towards meeting HHS physical activity heart rate goals in ways that were either not possible or not practical 15 years ago. Heart rate data can be seen in summary or broken out by exercise event for defined time periods. Technology enables people to document improvements in performance of physical activity in detailed and meaningful ways, such as documenting the aggregate moderate and vigorous activities undertaken to produce an accurate profile of a person's physical activity.

Technology-enabled physical education is flourishing in the online physical education classes at the University of Georgia (UGA). Students participate in the courses from many different states and countries while completing internships or study abroad opportunities. To date, two online physical education courses have been developed, one for walking and one for jogging. In order to participate in the courses, students must obtain a Fitbit (a brand of wrist-worn technology that records physical activity data) device that is capable of capturing heart rate data during intentionally recorded exercise events. As students participate in the course, the data from their Fitbit are processed by a custom application that is connected to the Fitbit application programming interface (API). This custom application presents contextualized data to the student about his or her performance on the homepage of the online course so students can monitor their individual progress towards their heart rate goal for each module. The custom application built for the online physical education classes is a student-facing implementation of learning analytics, designed to help students improve the attainment of the learning outcomes for the online physical education courses at UGA. The data presented to students via the application are contextualized to the course in the sense that the data from the Fitbit are transformed so as to inform the student's performance toward class goals. The purpose of this research project is to: (a) describe the design process that resulted in the current version of the custom application used in the online physical education courses; and (b) investigate student attributions of the results shown in the contextualized data to better understand the effects of the learning analytics tool on student motivation.

Introduction to Attribution Theory

It is important to investigate the students' underlying responses to data presented in learning analytics tools. Attribution theory is one theoretical lens that can provide some insight into this process. Attribution theory proposes that there are four main perceived causes of achievement outcomes: ability, effort, luck, and task difficulty (Weiner, 1972; Weiner, 2010). An individual's perception of how these four causes contribute to an outcome informs the expectancy of future positive outcomes and pride in the accomplishment. For example, someone who attributes a negative outcome on a math test to lack of ability is not likely to be motivated to work toward a positive outcome on future math tests. However, someone who attributes a poor grade on a math test to lack of effort is more likely to be motivated to achieve on future math tests. This causal relationship is explained by the stability of the two attributes in question—ability is seen as a stable internal attribute while effort is seen as an unstable internal attribute. This means that effort can be increased or decreased in future endeavors while perceived ability will stay static. See Table 1.1 for a basic overview of the elements of attribution theory.

Table 1.1.

Overview of Four Main Causes of Outcomes According to Attribution Theory

Cause	Locus	Stability	Controllability
Effort	Internal	Unstable	Controllable
Ability	Internal	Stable	Uncontrollable
Task Difficulty	External	Stable	Uncontrollable
Luck	External	Unstable	Uncontrollable

Research on DDDM using attribution theory has looked at the attribution on educators using data to make decisions (Marsh et al., 2016). A key finding from this study was that uses of data that fostered a mastery orientation (e.g., individual improvement, rewarding effort) were more beneficial than uses that fostered a performance orientation (e.g., rewarding achievement relative to others, diverting attention from learning to achievement). Another study on physical activity of senior citizens used attribution theory to reshape participants attributions away from stable, uncontrollable attributions regarding decreasing physical activity and aging (Sarkisian, Prohaska, Davis, & Weiner, 2007). The study found that fostering unstable, controllable attributions caused participants to attribute physical activity to an internal locus, resulting in increased physical activity as measured in steps per day.

Attribution is also related to achievement pride (Weiner, 2010). Individuals who exhibit an internal causal locus (e.g., effort) for achievement are more likely to exhibit pride in the achievement than those with an external causal locus. This means that people who perceive themselves as being in control of the outcomes of their activity are more likely to have pride upon a positive outcome of that activity. Figure 1.1 illustrates the relationship between the action, data, the representation of the data, and the attribution of the outcome seen in data.

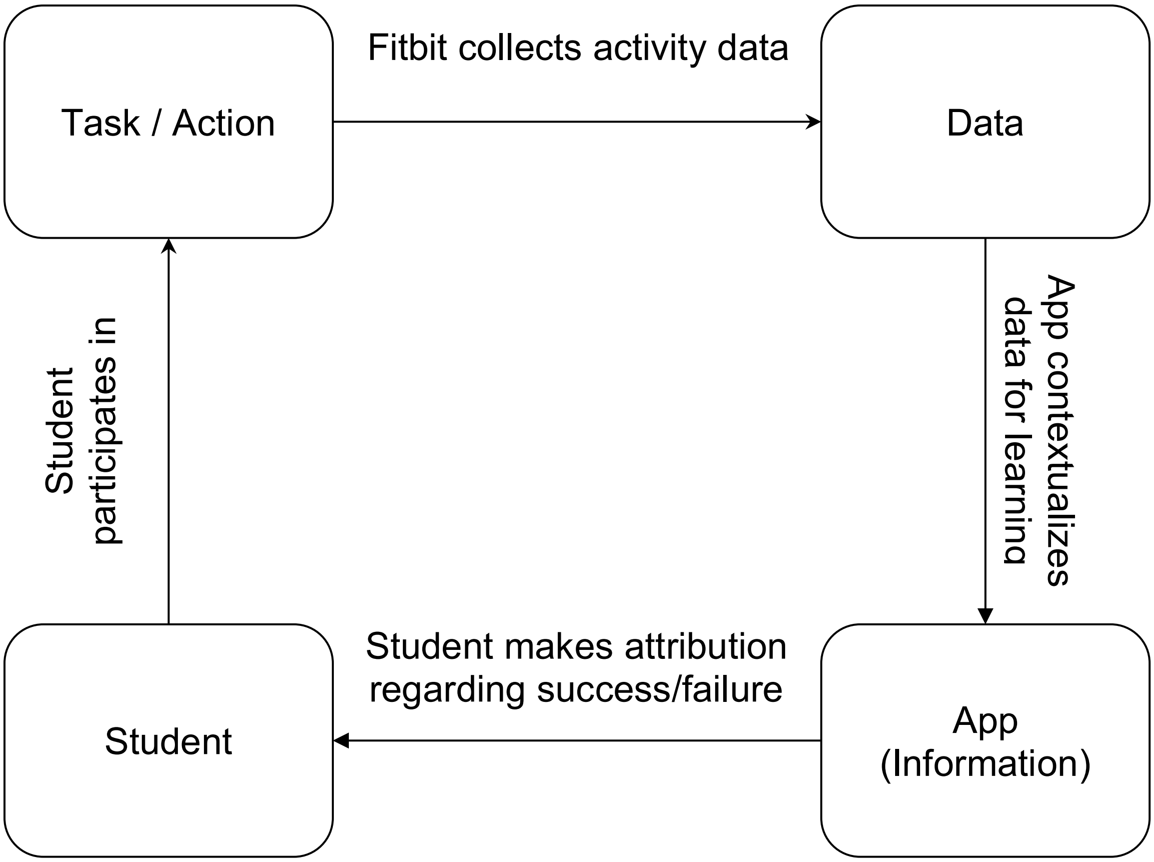

Figure 1.1. Relationship between action, data, information, and attribution in the online physical education classes.

Multiple Article Format

This dissertation has two goals: (a) to document the design process that has resulted in the online physical education app in use in online physical education courses and (b) to study how students attribute results from learning analytics (i.e., the online physical education app) in an activity-based online physical education class. In pursuit of these goals, this dissertation is presented in a multiple article format, with each chapter contributing to one or both of these goals. Table 1.2 lists the title and purpose of each of the three articles.

Table 1.2.

Multiple Article Dissertation Overview

Article	Chapter	Title	Purpose
1	2	Literature Review & Conceptual Framework	Identify major themes and concepts for both the design case and the mixed-methods study.
2	3	Design Case	Describe the design and development of each of the four versions of the online physical education app.
3	4	Mixed Methods Study	Investigate student attributions related to learning analytics in an online physical education class.

The literature review addresses learning analytics, wearable technology, online physical education, and the confluence of these three concepts. It also examines attribution theory and transactional distance theory as related to educational achievement generally and learning analytics specifically.

The documentation of the design process is presented in a design case. This case uses design artifacts to describe the evolution of the online physical education app.

The mixed methods study of student attributions is phenomenological in nature with the purpose to understand students' experiences in the class. Students completed the achievement scale of the Multidimensional-Multiattributional Causality Scale to indicate their general attributions toward academic outcomes (Lefcourt et al., 1979). They also participated in interviews designed to uncover their individual experience using the online physical education app in order to better understand their specific attribution of their achievement in the online physical education course. The study investigates differences between general and specific attributions, particularly in students who make external general attributions and internal specific attributions.

Design Case Introduction

In the physical education classes offered online at the University of Georgia, students must practice intentional exercise with the goal of recording a set amount of time in elevated heart rate zones in each module of the class. This intentional progress toward heart rate goals is an important pedagogical element of the class, and it is facilitated by a custom online physical education app that displays individualized, contextual progress for each student on the homepage of the online course. The design of this app, which is integrated with both Fitbit and UGA's learning management system, has been evolving over the past seven years in collaboration between myself and Dr. Ilse Mason, the undergraduate physical education coordinator in the Kinesiology department in the College of Education at UGA. It is important to document the design context, process, and decisions in a design case, such as those found in the *International Journal of Designs for Learning* (IJDL). This design case documents the evolution of our design to help other instructional designers and faculty who are looking to solve difficult or non-traditional pedagogical design challenges for learning (i.e., how do we build a fully online physical education class with rigor?).

As indicated by the summaries of the purposes of design cases in Table 1.3, articles published in IJDL over the past nine years have served largely to present design processes, decisions, and challenges in order to share design knowledge. This documenting and sharing of design knowledge is valuable to the field of instructional design, where approaches to design challenges vary widely (Boling, 2010). The chief purpose of a design case about the online physical education project is to contribute to the body of design knowledge in the field of instructional design.

Table 1.3.

Summaries of Purpose for Design Cases

Article	Purpose
Lara et al., 2010	Describe design process for a new version of an online learning game to overcome limitations of a previous version. Participate in design conversations and contribute to a "bank of precedent" for other designers to draw from.
Ionas et al., 2012	Present a design and development process with issues encountered, solutions developed, and decisions made to best support learning.
Modell, 2013	Details effort to design a method to grade group work and develop a tool to implement a substantial portion of that method. Present the path leading to the designed artifact to enable the reader to "reach the destination with me."
Bell, Sawaya, & Cain, 2014	Reports ongoing efforts to design learning models in which online and face-to-face students share rich learning experiences at the Tells how models of "synchromodal learning" have come to be.
Luo & Creswell, 2016	Overview of the design and development process for a mixed methods research app, along with key design decisions, failures, and refinements.
Yamagata-Lynch & Paulus, 2016	Introduce how collective design intentions were identified and shared amongst a team of three faculty designing an online course. Discuss lessons learned for future designers who might be in similar situations.
Cherrez & Nadolny, 2017	Demonstrate approach to creating learning-experiences; Describe design decisions and present accomplishments and challenges implementing experiential learning with gaming elements.
Stansberry & Haselwood, 2017	Present challenges, considerations, and decisions associated with the design, development, and delivery of a master's level educational technology course.
	"This paper aims to reveal benefits in two key areas: (a) helping a population of primarily non-gamer educational technology graduate students see games and simulations as viable resources

	for improving learning and (b) modeling gamification as a means to help instructors use gamification as their own instructional strategy.”
Bellah, Chen, & Zimmer, 2018	Details development of project management software. Includes “empirical evidence” that students find the software easy to use and that it improves their understanding of project management.

One alternative to presenting a design case is completing an evaluative case study of the online physical education app. This approach is commonly used in a design-based research (DBR) or educational design research (EDR) context to evaluate the effectiveness of a particular design. While these articles provide an overview of the designs they evaluate, they do not serve the primary purpose of sharing design processes and knowledge that resulted in a particular design. Table 1.4 presents a summary of purposes for a sampling of evaluative case studies from the past few years. It is worth noting that some articles in IJDL have also begun to include some evaluation of the design in addition to a presentation of design processes (Bellah, Chen, & Zimmer, 2018; Stansberry & Haselwood, 2017). While this is not a requirement of a design case, it provides evidence to support the usefulness of the design presented in the design case.

Table 1.4.

Summaries of Purpose for Evaluative Case Studies.

Article	Purpose
Howard et al., 2017	Evaluate the effectiveness of synchronous online activities for allowing participation in study abroad activities from home or on campus.
Kopcha et al., 2017	Evaluation of 5th grade teachers and students use of an integrative curriculum to support student problem solving and effective teacher practices.
Stockdale et al., 2019	Evaluating use of the ARCS model to motivate midwifery students through the use of technology for enquiry learning.

Thomas et al., 2019	Evaluate the EDR process as a means of developing a collectible card game for teaching cybersecurity to middle school students.

This comparison of approaches provides a strong justification to present a design case of the collaborative and iterative process that has resulted in the current version of the online physical education class. Table 1.5 gives a brief description of each version of the online physical education app. A full description of the process, context, and evolution of the design of each version of the app provides a valuable contribution to a larger body of design knowledge for instructional designers.

Table 1.5.

Project Phase Descriptions

Phase (Year)	Description	Milestones
Garmin CSV (2013)	Students have to download specific CSV from Garmin site to upload to system.	Heart rate data was programmatically processed in the context of the course.
Fitbit Instructor Email (2017)	Instructor requested data report via a web form. CSV report delivered via email.	Instructor access to student heart rate data made seamless.
Fitbit External App (2018)	Students and instructors can access basic performance data via an external LTI app.	Students are able to see data regarding performance in specific modules.
Fitbit Embedded App (2019)	Students and instructors access detailed performance data from within the course.	Students can see more information about their own performance. Instructors have access to detailed data regarding all student activities.

Design Principles for Physical Education App

In designing the custom app for the online physical education courses, we have worked to improve students' access to the contextualized data representing their activity in the course. The evolution of the app has served to foster mastery orientation toward physical activity and develop an internal, controllable, unstable causal locus for the outcomes seen in the data. Table 1.6 outlines several design features built into the online physical education app intended to promote a mastery orientation as aligned with attribution theory in the use of the app for learning.

Table 1.6

Online Physical Education App Design Principles

Design Feature	Use in App	Supporting Research
Focus on individual improvement	Track progress for each module. Provide access to see growth from module to module.	Marsh et al., 2016
Evaluate students privately	Students are only able to see their own data. They are not compared to others.	Marsh et al., 2016
Short-term goals	Students success is evaluated for each module in the course.	Marsh et al., 2016
Foster sense of responsibility	Students log activity at any time during module window.	Marsh et al., 2016
Access to learning analytics data	App appears on the homepage of the course and loads data from active module.	Broos et al., 2017

Scaffolded goals	The app allows instructors to set individual goals for each module, allowing them to ease students into the more difficult goals. Also, heart rate goals are based on maximum heart rate, which is dependent on an individual's age.	Hunter & Barker, 1987

Introduction to the Research Study

Research is needed to study technology-enabled physical education involving activity-based fully online for-credit physical education courses. The study contributes to the literature on using learning data with students through by combining learning analytics and DDDM through the lens of attribution theory. Here are the research questions guiding this study:

1. How do students attribute their personal learning outcomes to information provided by the wearable technology (e.g., Fitbit)?
    a. Do students make internal (effort, ability) or external (luck, context) causal locus attributions for observed outcomes?
    b. Do students make unstable (effort) or stable (ability, luck, context) causal stability attributions for observed outcomes?
2. How do student attributions of their personal learning outcomes to information provided by the wearable technology (e.g., Fitbit) differ from self-reported attributions of general academic achievement?
    a. How does causal locus differ for students between general academic attributions and specific attributions of their personal learning outcomes to information provided by the wearable technology (e.g., Fitbit)?

b. How does causal stability differ for students between general academic attributions and specific attributions of their personal learning outcomes to information provided by the wearable technology (e.g., Fitbit)?

3. How do students describe the experience of using the physical education app?

These questions guided an explanatory sequential mixed methods study with students participating in the fully online physical education classes at UGA. Quantitative data were collected first using the Multidimensional-Multiattributional Causality Scale (MMCS) (Lefcourt, Von Baeyer, Ware, & Cox, 1979). The MMCS provides information about the participants' beliefs about the causes of their own success or failure. Following the administration of this survey, I interviewed participants with diverse attributional profiles in order to identify themes across participants (Maxwell, 2013; Merriam & Tisdell, 2016).

I created transcripts of all interviews and coded each interview using Atlas.ti to determine statements relevant to causal locus and causal stability. I also looked for connections between student action, learning analytics displayed in the app, and attribution of the student outcomes (Maxwell, 2013). Data analysis began concurrently with data collection to allow for the emergence of themes and categories throughout the data collection process (Merriam & Tisdell, 2016). After the initial category creation, I identified patterns in the data to refine the categories into a set of exhaustive, mutually exclusive, and conceptually congruent categories upon which my data analysis was based (Bogdan & Biklen, 2007; Merriam & Tisdell, 2016). I contextualized the interview data into these categories in order to understand how the students perceived the causal locus and causal stability of the outcomes they see in the online physical education app.

Contributions to the Field

This study makes several contributions to the field of instructional design. First, I documented the six-year design process of the online physical education application in a design case. This documented my design knowledge and experience in order to help other instructional designers facing similar challenges. The design case analyzed seven years' worth of design artifacts and documentation regarding the design of this application. The pedagogical journey of improving the contextualization of data in the learning process is a theme present throughout the design case. The profile of the technologies used in the evolution of the app include Google Drive, Google Apps Script, VueJS, and several Amazon Web Services tools. Setting the rich context of UGA's course development processes and explaining the journey of answering the challenge of activity-based fully online physical education makes a contribution to the field of instructional design.

Context of the Project

This project has grown out of work I have conducted as an instructional designer in the Office of Online Learning at the University of Georgia. As mentioned previously, the project has evolved over seven years, transitioning through four major versions — each version building upon the success of the last. In 2013, as I began to collaborate with Dr. Mason to create a rigorous online physical education class that included both active and conceptual components, I was unsure of how we would make the project successful. The foundation of the course design has always been enabling students to learn how to affect their own physical health through exercise through a personalized, yet challenging and unambiguous, online course experience. The decision to monitor and measure heart rate activity as it relates to intentional physical activity in the course stems from this foundational goal.

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CHAPTER 2

A REVIEW OF LEARNING ANALYTICS AND TECHNOLOGY-ENABLED PHYSICAL EDUCATION[1]

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Abstract

This literature review covers several areas relevant to student use of learning analytics. In addition to general learning analytics concepts, it covers student use of learning analytics tools in educational contexts. An overview of digital physical education technology and wearable technology are included in the conceptual framework for investigating the use of learning analytics in online physical education courses. Additionally, attribution theory is introduced and explained. Several recent studies that used attribution theory are reviewed, as well as one study that examined physical education in adults using attribution theory.

Learning Analytics and Data-Driven Decision Making

The fusion of behavioral and contextual data to inform learning is referred to as learning analytics. Commonly, learning analytics is defined as the measurement, collection, analysis, and reporting of data about learners and their contexts for the purposes of understanding and optimizing learning and the environments in which it occurs (Siemens, 2013). Learning analytics data can come from any system or tool a student or teacher uses, such as learning management systems. For example, behavioral data, such as the time and duration of student access to assignments, can be paired with contextual data, such as the due date of the assignment, to glean a better understanding of how students function within the learning environment.

The use of data to inform instructional practices in education is referred to as data-driven decision making (DDDM) (Mandinach, 2012). DDDM has been at the forefront of education since the implementation of the No Child Left Behind (NCLB) act in 2001(Jennings, 2012; Mandinach, Rivas, Light, Heinze, & Honey, 2006). While NCLB initially influenced educators to incorporate the use of assessment data into their decision making, DDDM models have grown to include more types of data, such as behavior and engagement data, into an inquiry process of DDDM (Ikemoto & Marsh, 2007).

Commonly, learning analytics are thought of as being related to “big data” (Picciano, 2012). Big data is a somewhat loose classification of data sources that refers to the “volume, velocity, and variety” of a data source and the ability to work with that data at a given point in time (De Mauro, Greco, & Grimaldi, 2016, p. 125). This indicates that data generated very quickly or in such large quantities as to not be processed via conventional means can be considered big data. In an overview of the applications of big data in higher education, Daniel (2015) outlined three applications of big data that are relevant to learning analytics efforts. These types of applications are descriptive, predictive, and prescriptive (Daniel, 2015). Descriptive learning analytics offer the opportunity to investigate data trends, while predictive and prescriptive analytics attempt to draw conclusions as to the probable outcomes indicated by data or the interventions most likely to be effective in light of those data. In her analysis of the mental models for data use among educators, Jimerson (2014) described a continuum of data, information, and evidence. In this continuum, data are codified representations of behavior, information is data that has been "imbued with meaning" (p. 7), and evidence is the accrued information that informs a decision. Daniel's learning analytics categories and Jimerson's data use models form an alignment between learning analytics and DDDM: descriptive analytics are similar to data that has yet to be imbued with meaning, predictive analytics are data upon which context and meaning have been placed, and prescriptive analytics are the representation of evidence to make a decision (Daniel, 2015; Jimerson, 2014). An important question in the implementation of learning analytics systems is how much meaning the learning analytics tool should inject into the data. Where do we place the line of autonomy in having humans consider the data upon which we are acting? Likewise, how do we monitor the algorithmic "black box" powering many predictive and prescriptive analytics systems (Williamson, 2015)?

Research on Student Use of Learning Analytics

Most research on learning analytics and DDDM in education has focused on how educators and institutions use data to inform decisions (Jimerson, 2014; Ikemoto & Marsh, 2007; Gummer & Mandinach, 2015; Bertrand & Marsh, 2015; Coburn, Toure, & Yamashita, 2009; Faber, Glas, & Visscher, 2018). Fewer studies have focused on how students use data and learning analytics to inform their own learning (Broos, Verbert, Langie, Van Soom, & De Laet, 2017; Hamilton, Halverson, Jackson, Mandinach, Supovitz, & Wayman, 2009; Marsh, Farrell, &

Bertrand, 2016). Learning analytics and DDDM research usually cast students as sources of data, not participants in the decision-making process (Marsh et al., 2016).

Student participation in data use is not a new idea. Kennedy and Datnow (2011) advocated for a new typology of data use to incorporate student perspectives, articulating three tiers of data use that schools should consider for students. The tiers are: engaging students in data use, using data to assess student engagement, and student involvement in planning DDDM efforts. In their study of ten schools, they found that engaging students in data use to inform their own learning was the most commonly employed type of student participation in DDDM.

Wise (2014) articulated design elements conducive to the pedagogical application of learning analytics with students. Learning analytics should be grounded in the desired outcome of the learning activity, learners should know the goals they are working toward and have the ability to monitor progress, and learners should receive feedback sufficient to provide a catalyst for reflection on and adjustment to the learning process (Wise, 2014). The processes should be integrated into the learning experience, allowing the student to feel a sense of agency in the use of learning analytics as a tool for learning. Two other important aspects of designing learning analytics are providing a reference frame (i.e., to what should the student compare his/her data), and allowing for dialogue between the instructor and student about the interpretation of learning analytics (Wise, 2014).

The motivational value of data use to shape student behavior has been investigated in a middle school context (Marsh et al., 2016). Specifically, the study investigated how teachers engaged students in data use and whether the engagement supported a performance or mastery-oriented mindset (Dweck & Leggett, 1984; Fishman & Husman, 2017). The study found that while teachers espoused data as a motivational tool, they engaged students in performance-oriented activities around data. For example, they shared data publicly among students in the class, made comparisons among students, and focused on status rather than providing the support and resources needed for growth.

An important question, particularly in higher education, is whether students will use a learning analytics dashboard if one is offered to them and what conditions will encourage student use of learning analytics. A learning analytics dashboard is an interface that offers visualization and reporting of data relevant to a given learning context. Schumacher and Ifenthaler (2018) found that students expect learning analytics dashboards to support planning and organization of learning processes, provide self-assessments, adapt to learner performance, and display individual analyses of learning activities. A study of 1,905 first-year higher education students found that 47% of the students used a learning analytics dashboard offered to them via an email invitation (Broos et al., 2017). Student feedback on the dashboard was positive, but the results of this study indicated that weaker students were less likely to use the dashboard, raising a question of how to effectively reach struggling students with meaningful data.

While student use of data for learning only constitutes a small portion of the learning analytics and DDDM literature base, there have been calls for increased research in this area. Hamilton (2011) called for research-based guidance on student participation in learning analytics in order to engage students as partners in data use. Clow (2013) noted that “Students typically know and care more about their own learning situation than even the most dedicated teacher… Using learning analytics, they can be encouraged to take personal responsibility for their own situation making use of the feedback available about what they are doing and making appropriate decisions about support” (p. 692).

The Technology of Physical Education

Obesity is a major cause of non-communicable diseases in the United States. The rise of obesity over the past five decades in the US has led to over 160,000 excess deaths and added over $209 billion to national medical care costs (Cawley & Meyerhofer, 2011; Freedman, 2011). Another study found that during the period from 2000-2018, the mean weight, waist circumference, and BMI for adults in the US increased significantly (Fryar, Kruszon-Moran, Gu, & Ogden, 2018). More recently, the COVID-19 pandemic has worsened the obesity crises, as socio-economic depression and social lockdowns have resulted in an increase in reliance on processed foods (Chua, 2021; Clemmensen, Peterson, & Sorensen, 2020).

In an effort to address the growing national obesity, several organizations have published guidelines for recommended physical activity. The Centers for Disease Control (CDC) recommends 60 minutes of moderate to vigorous physical activity (MVPA) for children daily (Centers for Disease Control, 2014). The guidelines recommend types of activities that might fall into the moderate (e.g., walking, biking) or vigorous (e.g., playing tag), but they do not provide specific criteria (i.e., heart rate ranges) for what constitutes MVPA (Van Camp & Hayes, 2017). The U.S Department of Health and Human Services (2018) recommends that children participate in 60 minutes of MVPA daily, with muscle strengthening and bone strengthening activity on at least three of those days. For adults HHS (2018) recommends 150-300 minutes of moderate intensity or 75-150 minutes of vigorous intensity aerobic physical activity per week. HHS defines moderate and vigorous activity in terms of metabolic equivalent of task (MET), with moderate intensity activity falling between 40 percent to 59 percent of aerobic capacity reserve and vigorous activity falling between 60 percent to 84 percent of aerobic capacity reserve (HHS, 2018). The guidelines state that monitoring intensity in children is more flexible, as indicators such as "change in breathing" can indicate vigorous activity in children (HHS, 2018, p. 110).

However, an inactive lifestyle is a contributing factor to the rise in obesity. From 2010-2015, 22.9% of adults in the US met minimum guidelines for aerobic and muscle-strengthening activities (Blackwell & Clarke, 2018). About 50% of children do not engage in sufficient physical activity to achieve health benefits (Kerner & Goodyear, 2017). Logically, it stands to reason that sedentary children will grow into sedentary adults, with individuals becoming more sedentary as they age.

One goal of physical education is to overcome the tendency toward sedentary behavior by facilitating healthy physical activity. However, this goal is not without controversy. Gard (2014) warns against physical education picking up the mantle of solving the obesity crisis because: (1) he does not believe it can be effective at changing the complex social behaviors that led to the obesity epidemic; and (2) he believes physical education should have a broader, wellness-based focus. However the development of wearable technology is a mechanism by which physical education can have a greater impact on health, if the algorithms and their uses are carefully considered (Williamson, 2015).

Digital technology has emerged as a mechanism for helping students be more active in physical education contexts. Dedicated heart rate monitors have been studied as a mechanism for evaluating physical activity (Freedson & Miller, 2000; Healy, 2000; Nicholls, Davis, McCord, Schmidt, & Slezak, 2009). Pedometers have been investigated as a means for measuring activity in physical education contexts (Sarkisian, Prohaska, Davis, & Weiner, 2007; Van Camp & Hayes, 2017). These uses of digital technology in physical education allow for an external representation of the effort expended during exercise. The external representation (i.e., heart rate, total steps) provides both the participant and the facilitator a means for judging actual effort and expended energy, as well as a basis for achieving desired intensity in future exercise sessions.

Wearable Technology

Wearable technology has become ubiquitous in recent years. Smart watches and fitness trackers are two of the most commonly worn forms of wearable technology. However, the earliest wearable technology, eyeglasses, dates back to the 13th century (Gies & Gies, 1994). A handful of other wearables were developed over the next several centuries, but the first wearable computer, a device that helped cheat at roulette, was developed in the 1960s. The user of the device would wear it around their waist and control it with their shoe in order to predict the outcome of the roulette games (Thorp, 1998). In the 1970s, portable heart rate monitoring became possible (Janz, 2002). In that same decade, calculator wristwatches made it to market. A few years later, Sony released the Walkman, a portable music player, and digital hearing aids became available for the first time.

The advancement of computing technologies, such as solid state storage and Bluetooth connectivity, has fostered rapid development in wearable technology over the past ten years, with companies such as Apple and Google entering the wearable market. Fitbit is another popular company that makes wearable devices aimed at the health and fitness markets. The earliest Fitbit model, revealed in 2008 and known as the Fitbit Tracker was a clip-on pedometer that measured movement (Greene, 2008). Fitbit is now more known for its wrist-based fitness trackers, such as the Fitbit Charge line of products. The most recent model, the Fitbit Charge 3, is worn like a wristwatch and provides a host of functionality, such as continuous heart rate monitoring.

Wearable Technology Research

Research investigating the affordances and usage of wearable technology has increased dramatically over the past decade. Dehghani and Kim (2019) found that the number of published studies related to wearable technologies grew from 134 in 2007 to 3,170 in 2016. The majority of the publications were in the form of conference presentations (*n*=4,391), with journal articles being the second most common publication type (*n*=2,293). The United States was the single largest contributor to the research pool, participating in 19% of the studies, and the Georgia Institute of Technology was the most prominent source of publications (*n* = 113) on the topic over the past ten years (Dehghani & Kim, 2019).

Increased interest in wearable technology is unsurprising, given the development of products over the past 20 years. In a study involving the use of wearable technology for measuring physical fitness activity, Freedson and Miller (2000) found contemporary pedometers to have limited usefulness because they could not provide temporal activity data or measure physical exertion during activities not involving movement (i.e., isometric exercise). They cited heart rate monitors as an attractive tool for measuring physical activity during exercise, noting that research participants could wear a chest strap heart rate monitor and a receiver wristwatch (Freedson & Miller, 2000). However, while this technology was suitable for contained research studies, it was not yet considered as a viable tool for everyday consumer usage.

In a paper considering the future of electronic activity monitoring, Healey (2000) noted that while a range of wearable devices were available for a variety of activities, including physiological monitoring, they were still "cumbersome for some activities and may restrict movement" (Healey, 2000, p. 138). The article displays an optimism for the future of wearable technology's ability to provide long-term profiles of a person's physical activity, specifically as a tool for informing exercise or other health treatment programs.

As heart rate monitors became more feasible for use in physical education programs, researchers began evaluating their efficacy as teaching tools to help supplement physical education curricula and assess student progress toward fitness goals. By 2009, wearable technology that could track minute-by-minute heart rate data in a physical education context was available and in use in some schools (Nicholls et al., 2009). One interesting finding from studies that looked at the use of heart rate monitoring in physical education contexts was that the students heart rate did not always match the educator's perception of student effort (Nicholls et al., 2009; Partridge, King, & Bian, 2011). Researchers found that before the use of heart rate monitors, educators would often push students of lesser physical capacity (i.e., "out-of-shape" students) to work harder without knowing the student's heart rate response to the work being done. Similarly, students with greater physical capacity (i.e. "in-shape" students) would receive little feedback, as they appeared to be working harder. However, after the implementation of heart rate monitors, the researchers found that the "out-of-shape" students were operating at a significantly higher percentage of their maximum heart rate than the "in-shape" students, even though the "out-of-shape" students moved slower or with less intensity (Nicholls et al., 2009). This created a situation where "in-shape" students felt that they were punished for having more physical capacity, as they had to work even harder to attain heart rate goals set for the class. One student noted that "some people just walk up and down stairs. And they, you know, just don't have to do hardly any activity and it's [heart rate] up, and other people have to sprint to keep it up high enough to get points" (Partridge et al., 2011, p. 7). These investigations of wearable technology in physical education could also be considered applications of learning analytics.

They focused on the use of data collected by wearable technology to inform the educators' judgement and decision making. Additionally, they uncovered areas where the analytics tool at hand created dissonance between the educators' and students' perceived reality and the reality of the data from the wearable device (e.g., more fit students not achieving general heart rate goals).

More recent publications about wearable technology have raised concerns regarding how wearable technology and surveillance of physical activity might shape the future of physical education (Gard, 2014; Lupton 2015; Williamson, 2015). Chief among these concerns is that the role of the physical educator will be transformed into overseeing student use of technology, which will de-professionalize the role of the physical education teacher (Gard, 2014). Another concern is that the business interests behind wearable technology will exert an undue influence over physical education curricula, in essence redefining physical education away from a holistic, wellness-based field to a more narrowly defined "healthist" field by cutting educators out of the loop (Gard, 2014; Lupton 2015). One example of this is the arbitrary 10,000 step goal hardcoded into Fitbit's devices and apps. Such non-personalized, predetermined goals have been found to be unhelpful for developing competence among physical education students (Kerner & Goodyear, 2017).

Research on the cognitive effects of using wearable technologies has focused largely on the effects of self-surveillance and competition among peers. Students who are able to monitor their own heart rate during exercise have been found to keep their heart rate in target zones significantly longer during exercise sessions (Marzano, 2017). Likewise, Fitbit pedometers have been found to be useful for identifying types of activities that involve more sustained moderate-to-vigorous physical activity in school contexts (Van Camp & Hayes, 2017). These results indicate that when students know how their body reacts to physical activity, they are more able to regulate intensity to meet heart rate goals.

In a study on the use of Fitbit devices in a middle grades physical education class, Kerner and Goodyear (2017) found that students showed motivational declines after wearing the Fitbit as part of their educational experience. This result was attributed to Fitbit's predetermined 10,000 step goal and the competitive elements incorporated into the Fitbit app. While some students found the competition motivating, others found it demotivating to fall short of the goal or get less steps than their friends. Other students reported feelings of guilt if they hadn't reached their goal before bedtime, reporting that before they could sleep they "used to just walk up and down the corridor because I couldn't let someone else beat me" (Kerner & Goodyear, 2017, p. 293). In the same study, the Fitbit was also found to have a novelty effect, whereby students' activity declined after about 4 weeks as students became bored with the device (Kerner & Goodyear, 2017).

In a subsequent study, students reported via focus groups that the Fitbit promoted negative feelings because of the decontextualized step goals and their perception that the Fitbit did not accurately measure their physical activity (Goodyear, Kerner, & Quennerstedt, 2019). Students reported resisting surveillance by simply not wearing the Fitbit or by manipulating the step count by shaking their arms sufficiently to alter the step count. Other students reported a desire to have a more personalized measure of success, acknowledging that each student is different in terms of their physical fitness (Goodyear et al., 2019). This brings into question the sustained impact of analytics provided by wearable technologies and their potential to positively shape behavior in the long term. It also underscores the importance of tying the learning analytics to the learner's individual context rather than simply relying on a generic measure provided by a wearable manufacturer (e.g., Fitbit's step count).

Attribution Theory

To understand students' use of wearable technology in physical education, it is important to investigate the technology's underlying impact on motivation. Attribution theory is concerned with perceived causality and personal judgements outcomes (Weiner, 1972). Attribution theory is one of the prominent theories of motivation in educational psychology, alongside self-efficacy theory, self-worth theory, and achievement goal theory (Seifert, 2004). Attribution theory holds that success and failure are perceived to be caused by four factors: effort, ability, luck, and task difficulty (Weiner, 1972). Each of these factors can be placed on three continuums of causality: locus, stability, and controllability (Hunter & Barker, 1987; Weiner, 1972; Weiner, 2010). The factors and causality attributed to an outcome affect the expectancy of future success at similar tasks, and, therefore, inform motivation on future performance in light of success or failure.

Attributional Factors

Attribution theory holds that outcomes are attributed to effort, ability, luck, and task difficulty/context. These factors are mutually exclusive (Weiner, 1972). For example, effort is how hard one tries to be successful at a task, while ability is an innate characteristic. The application of these labels is important to attribution theory. For example, if a student believes they failed a math test due to not studying hard enough, they have attributed his outcome to effort. However, if they simply believe they are not good at math, they have attributed the outcome to ability. This distinction between ability and effort is a theoretical sticking point at times (Greene, 2015), but in the context of attribution theory ability should be thought of as something a person believes could not be overcome by effort. Luck is defined as an attribution to chance (Weiner, 2010), and context refers to the perceived complexity or demand presented by a task or challenge. While these factors are mutually exclusive, it is possible to attribute a single outcome to multiple factors (e.g., attributing success to trying really hard and being a little lucky).

Attributional Causality

The four attributional factors can each be placed along three continuums of causality: locus, stability, and controllability. Locus refers to the origination of the factor in relation to the person making the attribution (i.e., did the cause of the outcome originate with me or someone else?). Effort and ability are described as being internal, while luck and context are external (Hunter & Barker, 1987). Stability refers to a person's belief in a factor's ability to change. Effort and luck are described as unstable, while ability and context are seen as stable (Weiner, 1972). Controllability is a person's belief that they are able to change an attributional factor. Effort is often seen as the only controllable attributional factor (Hunter & Barker, 1987; Seifert, 2004; Weiner, 1972; Weiner, 2010). As stated above, this is a theoretical point of argument, which other theorists arguing that "virtually any factor can be viewed as controllable or uncontrollable" (Dweck & Leggett, 1988, p. 269).

Attribution Theory in Educational Research

Many aspects of learning and the educational experience have been studied through the lens of attribution theory. Recent studies by attribution theorists have studied a wide range of educational topics, such as classroom dynamics (LeBelle & Martin, 2014; Samson & Wehnby, 2018), student achievement in language learning (Bouchaib, Ahmadou, & Abdelkader, 2018; Liu & Zhang, 2018), and physical education with adult learners (Sarkisian et al., 2007). These studies commonly examine the relationship of attributional factors and causality with learning behaviors and achievement.

LeBelle and Martin (2014) examined the attributional aspects of instructional dissent in higher education classrooms. Specifically, they examined student attributions of instructor behavior as related to disagreements in the classroom. They found that all types of disagreements or dissent, whether procedural or philosophical in nature, were correlated with a belief that the disagreement was internally motivated by the instructor (LaBelle & Martin, 2014). In a similar study of conflict in elementary classrooms, Samson and Wehnby (2019) found that fourth grade boys who engaged in conflict with their teachers were more likely to attribute hostile motives to their teachers.

Student success is often attributed to some combination of the factors outlined above, each of which have different elements of causality. Three common factors to which students attribute success are ability (internal, stable, uncontrollable), effort (internal, unstable, controllable), and teacher behavior (external, unstable, uncontrollable). Several studies have examined the domain-specificity of these attributions—whether students attribute success with specificity as related to subject area or generally for all academic domains (Boekarts, Otten, & Voeten, 2003; Bong, 2004; Vispoel & Austin, 1995; Vuletich, Kurtz-Costes, Bollen, & Rowley, 2019). These studies concluded that European, White American, and Asian students make domain-specific attributions (Boekarts et al., 2003; Bong, 2004; Vispoel & Austin, 1995) while African-American students attribute academic success more generally (Vuletich et al., 2019). This difference in attribution for African-American students is hypothesized to exist because of the students' perception that success in academics represents overcoming system-level bias rather than mastering specific academic subjects (Vuletich et al., 2019). These studies highlight the importance of considering how the person making the causal attribution defines success.

In a longitudinal study of the relationship between self-concept of ability and causal attributions in upper level (age 13-16) Finnish schools, students with higher self-concepts of ability in math were more likely to attribute outcomes in math to internal causes while students with lower self-concept of ability more often to externalized outcomes (Clem, Aunola, Hirvonen, Maatta, Nurmi, & Kiuru, 2018). These findings are in line with the perspective that people tend to explain success with internal factors and blame failure on external factors, but it also suggests that positive self-concept of ability can lead to more productive attributions. These findings are in line with Greene (1985) who found that elementary school students achievement was best predicted by their self-concept of ability and attributions to ability.

Two studies of student success in English language learning both found attributional consequences for student success (Bouchaib et al., 2018; Liu & Zhang, 2018). In one study, all students, both successful and unsuccessful, were found to attribute some of their success to external factors, such as the teacher's influence and class atmosphere (Bouchiab et al., 2018). However, successful students also viewed internal factors, such as ability, interest, and effort as important to their success in language learning. Similarly, Liu and Zhang (2018) found that internal factors were most important for student success in language learning, but they also related those internal factors to the design of the instruction, encouraging for classroom and activity design most likely to bring about beneficial causal attributions.

In a study of the attributions made by adolescents regarding obesity, Klaczynski and Felmban (2019) compared culture and obesity stereotypes in the United States and China. The results of the study indicated that American adolescents more strongly believed that obesity arises from character flaws (i.e., internal, unstable, controllable factors) while Chinese adolescents were more likely to attribute obesity to both the context and the individual (i.e., a mix of internal and external factors). Attribution retraining has been used as a tool to improve the physical activity in sedentary older adults (Sarkisian et al., 2007). Participants took part in four weekly 1-hour group sessions consisting of a facilitated discussion designed to shift attributions related to physical activity and health. Each participant set verbal and written goals for the number of steps to be taken per day as measured by a digital pedometer, and the discussion session was followed by a one-hour exercise session. After seven weeks, participants reported an increase in both physical activity and quality of life, including improved energy levels, mood, and sleep quality (Sarkisian et al., 2007). This study indicates that attributional factors should be considered in physical education instruction and intervention design and research.

Transactional Distance Theory

Transactional distance theory is a broad theory that articulates three important variables for distance learning: course structure, instructor-student dialogue, and learner autonomy (Moore, 2019). *Transactional distance* can be thought of as the gap between the desired outcome of the course and the current understanding of the student. This theory has its roots in distance education efforts of the 1970s and 1980s, such as correspondence education and educational broadcast programs. In the context of these programs, distance education was seen as “the family of instructional methods in which the teaching behaviors are executed apart from the learning behaviors” (Moore, 1972, p. 76). With roots in the work of John Dewey, transactional distance theory was an attempt to articulate the critical factors in distance education to serve as an overarching framework under which research and development could flourish.

The inclusion of course structure as a critical variable in transactional distance theory reflects the underlying belief that education is a deliberate and planned process (Moore, 2019). However, the rigidity of a course's structure affects the overall educational process. In some courses, the entire curriculum is pre-planned for the student. In those cases, students must progress through the curriculum as planned by the designer or teacher. In other cases, students have more of a role in building some aspect of the course structure, such as helping to articulate learning outcomes or giving input on how they will be evaluated. More rigid course structures are thought to increase transactional distance because courses with more structure are less able to "accommodate or be responsive to each learner's individual needs and preferences" (Moore, 2019, p.35).

The second critical variable in transactional distance theory is dialogue, which is specifically defined as a constructive exchange between two or more people directed toward discovery and new understanding (Burbules, 1993). Distance education courses can involve varying amounts of dialogue, with some courses having frequent dialogue and others having none. Courses with more dialogue are thought to have lower transactional distance, meaning that we should consider not only the frequency of interaction in a course, but also the nature of the interaction. Courses with frequent interactions that are not geared toward constructive discovery and new understanding (e.g., dealing with administrative or technical issues) could still be considered to have a lower than desired amount of dialogue.

Learner autonomy, the last critical variable in transactional distance theory, refers to the degree to which the student can influence what to learn, how to learn, and how to evaluate success in learning (Moore, 2019). While different levels of autonomy are appropriate in different contexts, a student's ownership of learning (i.e., self-efficacy) is a key factor in success in distance courses (Leasure et al., 2020; Tsai et al., 2020; Yu & Richardson, 2015). Therefore, it is important to consider the degree to which a student is able to influence their own learning experience and how particular designs foster or limit learner autonomy. One recent trend that supports learner autonomy is the use of technology for the personalization of learning. Personalized learning has been defined by the New Media Consortium as a range of instructional interventions designed to address a specific student's learning needs (Johnson, Adams Becker, Estrada, & Freeman, 2015). This vision for personalized learning meshes well with the concept of "optimizing learning" found in the learning analytics literature (Siemens, 2013). The concept of personalized learning could be thought of as operationalizing learning analytics to empower students in their own learning process. For example, in a 2017 report, the U.S. Department of Education's Office of Educational Technology (OET) cited technology-enabled personalized learning as enhancing learner autonomy and preparing students to "organize and direct their learning for the rest of their lives" (OET, 2017, p.7).

Summary

Learning analytics offer powerful insight into student performance. While most research on learning analytics has looked at instructor use, student use of learning analytic tools to inform their own performance offers great potential to improve student achievement. Obesity is a major problem facing the United States, and regular exercise is a key component to shape a healthier country. One goal of physical education classes is to help students learn to better care for their bodies through physical activity that achieves an increased heart rate. Wearable technology has evolved over the past decade to make heart rate monitoring simple and affordable, but people should know how to achieve a proper heart rate stimulus. Using wearable technology as a learning analytics tool in physical education classes is a means to educate students about exercising with the appropriate intensity and duration. However, little is known about the use of learning analytics tools with students in physical education classes, especially as related to individual heart rate monitoring. It is not known if the use of relevant learning analytics might help students with a generally external causal locus to attribute their outcomes internally, specifically to their own effort. Student attributions of general academic outcomes have been studied extensively, but more research is needed on student attributions through the lens of learning analytics and as related to physical education.

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CHAPTER 3

DESIGNING A TOOL TO SUPPORT ONLINE PHYSICAL EDUCATION[1]

[1] Castle, J. To be submitted to *International Journal of Designs for Learning*.

Abstract

This design case details a seven-year iterative design process to create an app for use in online physical education classes. Each iteration addresses the shortcomings of the previous version. The most recent iteration of the app allows students to use Fitbit devices to record heart rate data, which each student sees as progress toward course goals on the homepage of the course. The current version of the app has evolved to provide a seamless student experience using a web application programming interface (API) and data standards such as learning tools interoperability (LTI) The student experience of using the app is thoroughly documented, as are design processes and principles for engaging in similar design processes.

Introduction

The very concept of online physical education seems paradoxical at first glance. However, advances in both consumer and web technology over the past decade have made it possible for students to participate in meaningful physical education courses while at a distance. Wearable technology, such as Fitbit or Apple Watch, make it possible for people to collect physical activity data with the press of a button. These devices are typically wrist-worn and gather a range of biometric data like heart rate, steps, or sleep quality. Among the data these devices can collect, heart rate data during exercise are the most valuable for applied physical education. The activity data can then be shared in the context of a course to provide the basis for an authentic physical education experience to compliment the conceptual components of the course. Cultivating this applied physical education experience has been challenging in a formal education context. An online physical education web application, called simply hereafter as the app, was created for a fully online physical education course to begin to address this challenge. This design case presents the design iterations of this app developed over a seven-year period.

Design Cases

Design cases are meant to capture a design artifact and the process that led to it so that the lived experience of creating the design can be shared (Boling, 2010). The field of instructional design has historically done a poor job of collecting and sharing design knowledge, making design cases an important means for setting precedence in design (Howard, 2012). Design cases have several important qualities that make them effective in sharing design knowledge and experience. A fundamental quality of design cases is that the outcome of the case is the design itself and the process that led to it (Howard, 2011). While it is important to describe the experience of interacting with the final design, design cases are not a venue for reporting performance measures as "results." Other important aspects of successful design cases outlined by Howard (2011) include: (a) situating the design in a particular context, (b) adequately describing the design team, (c) using appropriate modalities to describe the design (e.g., text, images), (d) documenting design failures, and (e) acknowledging the complexity of design decisions.

Design Context

The design case presented here began as an online course development project between an instructional designer (the author) from the institution's Office of Online Learning and a faculty member from the kinesiology department in the institution's College of Education in 2013. At the institution where this project took place, all undergraduate students are required to complete at least one physical education course in order to graduate. The faculty member had a vision for an online physical education class (i.e., *Online Walking)* that students could complete while participating in internships away from campus or study abroad programs, thus enabling them to complete a graduation requirement while away from campus. A fundamental part of this vision was that students would track their heart rate while completing exercise to make progress toward course goals of accumulating time in elevated heart rate zones. The core design challenge for this aspect of the course was to transform data collected by a heart rate monitoring device into data that were meaningful in the context of the course. This challenge is more complex than it appears on its face, and it is the central narrative of this design case.

The physical education app described in this design case has been in use in online physical education classes since the summer of 2013, and those classes have been the main venue for design feedback for the app. I was given the opportunity to talk with students, particularly in the early offerings of the course, to identify key areas where students struggled with using the app. These conversations and experiences were critical in identifying the weaknesses that were addressed in each successive design iteration. The four design iterations detailed in this design case are outlined in Table 3.1.

Table 3.1.

Physical Education App Iterations

Iteration Name (Year)	Description
Students Tracking Down Data (2013)	Students submit specific CSV from Garmin's website for processing
Seamless Data Delivery (2017)	Data is accessed via Fitbit API. Data reports are delivered to instructors via email. No student access to data within app.
Surfacing General Data (2018)	Students and instructors access basic performance data from Fitbit via an external LTI app.
Ubiquitous Access and Detailed Data (2019)	Students and instructors access detailed performance data using a widget on the course homepage.

It is also worth noting that the opportunity to collaborate with a faculty member on a design project such as this one over the course of seven years is somewhat unusual. Instructional designers from our institution's Office of Online Learning typically move from one development project to the next, helping to launch several online courses each year. However, in the case of the online physical education course (to which I was initially assigned by sheer luck), I have been given the time and resources to complete several revisions of the project. We have also launched an additional online physical education class (*Online Jogging*) and scaled up our physical fitness app in response to remote learning necessitated by the COVID-19 pandemic. Over the seven years that this project has evolved I have been promoted twice (first to *Lead Instructional Designer* then to *Assistant Director for Instructional Design*), but I am still afforded the opportunity to maintain my relationship with the people using the physical education app. This is, by far, the longest running project our office has undertaken, and we could not have completed the design iterations described here without the time and resources allocated to it.

Iterative Design

Iteration One: Students Tracking Down Data

Development of the first iteration of the physical education app began in spring of 2013. The major challenge we faced was how to take data from a heart rate monitoring device and transform it into data that were meaningful in the context of the course's goals and timeline. During this iteration of the app students were required to wear Garmin chest strap heart rate monitors. After completing an exercise, the students would synchronize data from their chest strap with their Garmin account via the Garmin Connect App. This presented a challenge, as there was not a seamless way for students to share their activity data from Garmin Connect with their instructor to demonstrate the completion of course goals.

To address this challenge, the first version of the physical education app required students to download a specific report from Garmin Connect, formatted as a CSV, and upload it to a Google Drive folder that was shared with the student individually. We then used a Google Apps Script to monitor each student's upload folder for new files, and once a new file was detected it could be processed to deliver the student's activity results to the instructor of the course. This system allowed us to take general activity data from Garmin Connect and transform it into contextualized data for the online physical education class. However, this system introduced several usability challenges. After reviewing a tutorial video we created in 2013 for the course that used this version of the tool, I noted that students had to follow a very specific set of steps to successfully submit their activity data. Students had to:

1. Configure their Garmin profile to set their week to start on Monday.
2. Navigate to the reporting interface in Garmin Connect.
3. Navigate to the Progress Summary area of the Garmin Reporting site.
4. Set the Progress Summary to Group By Week.
5. Set the Report Dates to correspond with the course Module Dates.
6. Export the report to a Comma Separated Values (CSV) format.
7. Navigate to their individual Google Drive Upload folder.
8. Upload the CSV that was exported from Garmin Connect to their Google Drive folder.

Every student was required to complete this process every week in order for their activity data to be submitted for the course. If a student made a mistake on any of these steps, their data would not be submitted properly. In practice, students would often not configure their progress summary report correctly or upload the incorrect file type for the system to process (e.g., uploading a PDF instead of a CSV). When this happened, students would inevitably need to reach out to the instructor to figure out which step they had missed. While this iteration of the app provided a conceptual basis to build upon (i.e., connecting activity data with physical education course goals), the design of the system: (a) left too much room for error in submission processes; and (b) led to more effort and focus on data submission than on the learning outcomes of the course. After using this system for several semesters, we decided to undertake a major overhaul of the app to simplify the data submission process for students.

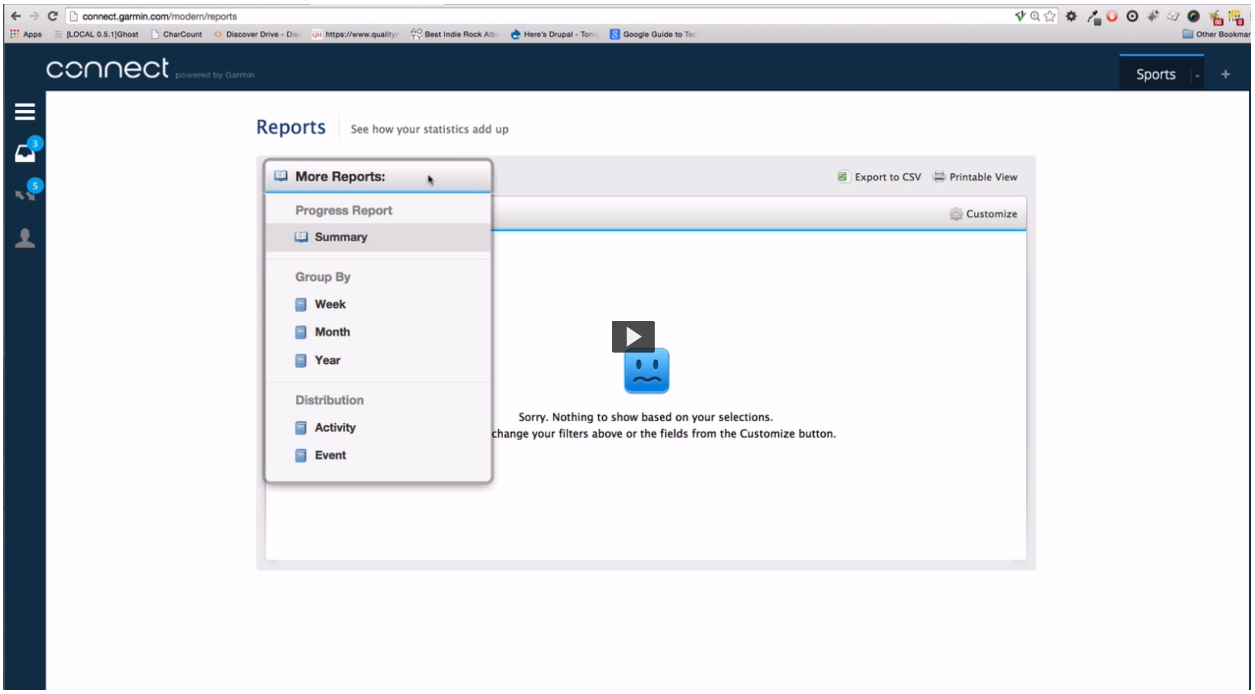

Figure 3.1. A screenshot of the Garmin Connect web interface at the point when the student generates a CSV formatted report.

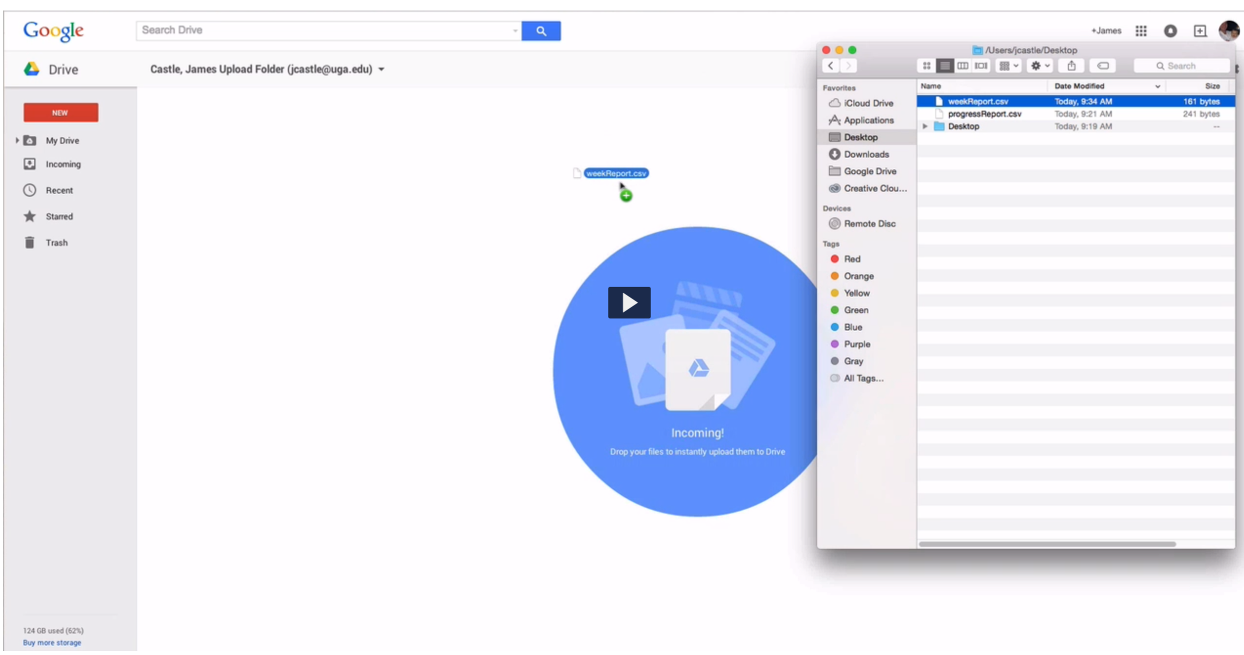

Figure 3.2. The interface for uploading a CSV into Google Drive for processing.

Iteration Two: Seamless Data Delivery

Development of the second iteration of the online physical education app began in the fall of 2016. We started by re-examining wearable devices that were available for use by students in the online physical education classes. In 2013 we had chosen the Garmin chest straps because wrist-based devices were not yet accurate enough at monitoring heart rate. However, by 2016 products developed by Fitbit had improved their heart rate monitoring technology to the point that they were accurate enough for our needs. This was a key decision in the design process, as Fitbit also provided a public application programming interface (API) that could be used to allow students to seamlessly share their activity data for use in the course. The API provides a mechanism to retrieve data from Fitbit's servers programmatically, which allowed us to build automatic heart rate data retrieval into our app. This allowed the data to be used in our application, which was developed specifically for the online physical education courses. This gave us the opportunity to replace the tedious process from the first iteration with a single link that students could click one time at the beginning of the course to share their data. By clicking the link, the students' data would become available for retrieval via the Fitbit API as needed for course assessment. While we have continued to improve this app since making the change to using an API to retrieve student data, this was the most impactful design decision we have made over the course of the development of this app. Changing from a manual data reporting process to an automated API-driven process facilitated every design improvement we have made since.

To use the Fitbit API, we first needed to request access from Fitbit. This involves requesting API keys, which are values that identify our app to Fitbit when we make requests for data. Once our access to the API was in place, we had to set up a workflow for allowing students to grant access to their data. We ended up doing this with a link from our learning management system in the introduction to the course. We also had to determine what data we needed to access via the API to demonstrate each students' performance toward course outcomes. In order to access one of the needed data sets (activity data with heart rate), Fitbit first had to approve the request. After some negotiation with Fitbit's support staff, Fitbit granted the request.

Our next big design decision was where we would build the application. Up to this point, the app had been processed using Google Drive and Google Apps Script, but those were not great tools for redesigning the app to work with Fitbit's API. After a bit of consultation with engineers from Amazon Web Services (AWS), we settled on AWS Lambda[2] as the primary technology that would power this iteration of the app. AWS Lambda provides access to computing power on demand without the need to manage server infrastructure. This allowed us to build the logic and data flows of our app without worrying about the more technical details of server deployment.

Once completed, this version of the app enabled course instructors to request a summary of their students' course activity at any time via a simple web form. Each time an instructor made a request, our Lambda script (which was written in Python) would query the Fitbit API for the necessary student data, put the data into a format meaningful for the context of the course, and deliver the CSV to a predetermined list of email addresses that included the course instructor and the designer of the app.

While this iteration of the app improved upon the previous version by greatly simplifying access to student activity data, a new set of challenges emerged. First, as the course rosters grew longer, the amount of time needed to gather all of the students' data grew as well. Once

[2] There is much more technical infrastructure underlying this part of the app's development, an explanation of which would be out of place in this conversation of design decisions. It is mentioned here only to acknowledge that as our design has evolved, our technical tools and skills have had to evolve along with it.

enrollment in the online walking classes reached close to 60 students the Lambda script had to gather data for all of those students each time the CSV was requested. Gathering activity data on that many students can take 3-4 minutes, which meant that after clicking the "request" button on the web form the requestor would need to wait until all the data were retrieved before closing their browser window.

For students, this version of the app presented a simplified activity loop. They simply had to walk and sync their data. However, a challenge for students was that they could not see any of their data in the context of the course. The CSV reports only went to instructors, and students only knew if they had missed their goal once their grade had been entered into the course gradebook. They could see their activity data via the Fitbit app or website, but those data were decontextualized — it didn't factor in how heart rate activity contributed to the overall grade or the date cutoff for the course modules. This resulted sometimes in students failing to meet a course goal that they thought they had met.

While the second version of the app was clearly an improvement over the first version, we knew soon after launching the second version that we needed to address these two major challenges. In fall of 2017 we continued working on the app with the goal of (a) making it more performant and (b) allowing students better access to their data.

Iteration Three: Surfacing General Data

The third iteration of the app was first used in classes during summer 2018. The most noticeable revision to the app in the third iteration was adding a user interface that was accessible by both instructors and students. We designed the app to use the learning tools interoperability

(LTI) standard[3] to securely pass data between the Learning Management System (LMS) and the app. Adding LTI to the app allowed us to detect the identity of the person accessing the app. It also allowed us to detect the specific course section in which the student was enrolled. These enhancements were key for providing more individualized, contextual access to data within the app.

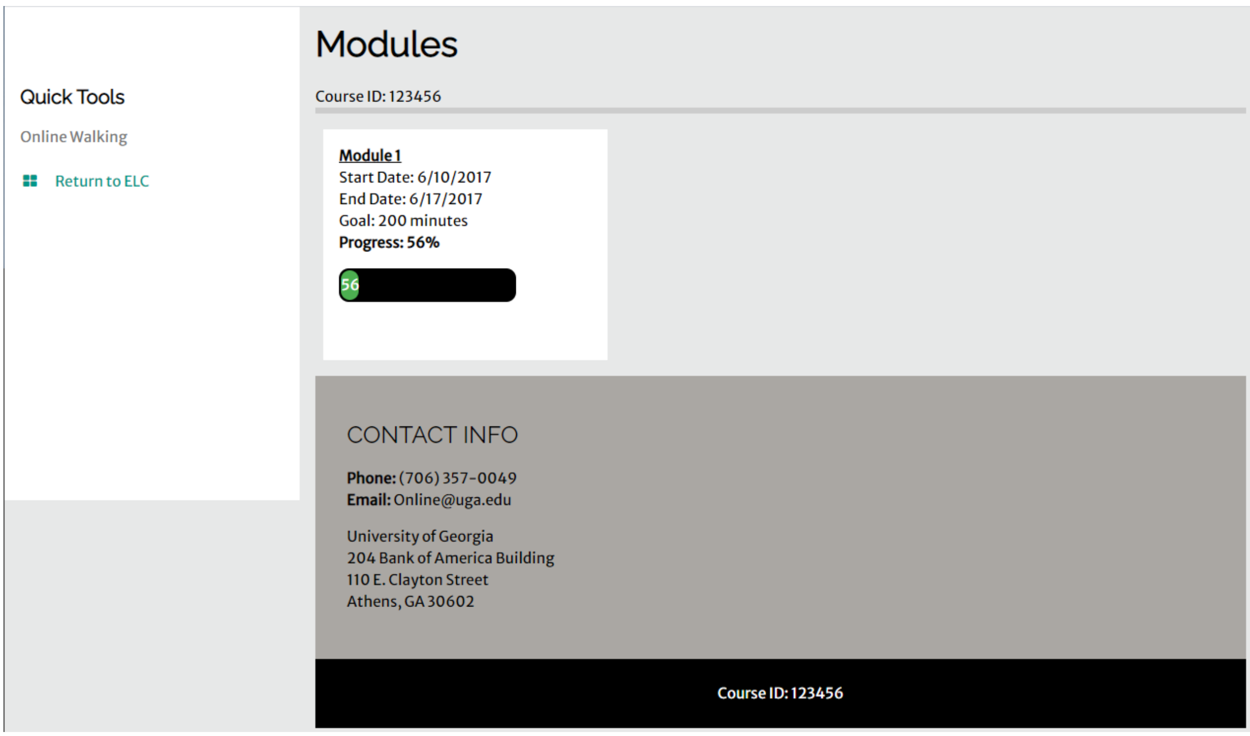

Figure 3.3. Screenshot of the student view of progress in iteration three of the app.

[3] This is a standard for sharing data between systems. For more information see: http://www.imsglobal.org/activity/learning-tools-interoperability

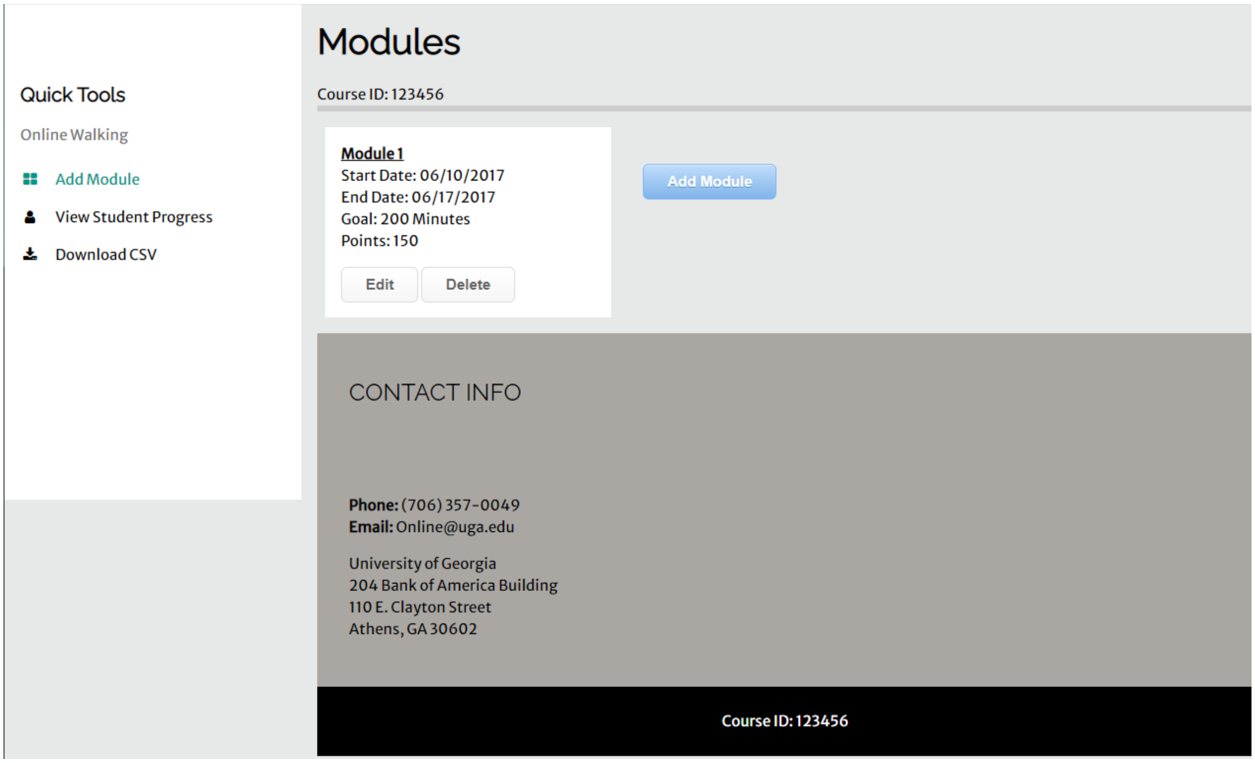

Figure 3.4. Screenshot of the instructor view for managing modules.

Another benefit of LTI was that we could detect the course role of the person using the app. Therefore, when someone clicked the link to launch the app, we could differentiate between students and instructors. This allowed us to present different data to people in each role. When students visited the app, they would see an overview of each module in the course as well as their progress toward the goal for each module. The ability to access their data allowed more transparency for students to monitor their own progress in the context of the course. Each student was now able to view their activity data as it pertained to their progress toward class goals, an ability that was not available in either of the two previous versions of the app. This was another major milestone in the development of the app, as it helped to bring the physical fitness activity portion of the class into focus for students. Previously, students had to rely on the instructor to translate their activity data into a grade. Now, students could now keep track of their own progress in real time.

The design of this third version of the app dealt with the challenge of performance. As described earlier, the second version of the app became inefficient once full enrollment in the online physical education classes was reached. This was because the app had to fetch and process data from the Fitbit API every time a request was made to the app. While this resulted in the app always using up-to-date data, it also made the app inefficient, often taking several minutes to load. To address this challenge, we developed a system where the app would fetch data for each course on set intervals and store the data in CSV files that were readily accessible to our app. These CSV files could be loaded in a fraction of a second resulting in improving the app's performance tremendously. The drawback to this approach was that the data shown in the app was not always up-to-date. We experimented with different intervals for refreshing data, from once a day to once every four hours, but this time lag in data availability presented a problem with the third version of the app. We quickly identified this as a challenge we would address if we were able to undertake another design iteration.

There were other challenges we wanted to address as well. First, the user interface for our application ran on a fairly complicated technical infrastructure that came with a monthly cost of around $35 to run the entire system. While this is not a huge sum of money, we also did not have a revenue stream tied to the project. Initially, the user interface was set up with performance as the priority, but since we had solved the performance challenge, we wanted to re-evaluate the user interface to see if we could simplify it from a technical standpoint and eliminate the monthly cost to run it. Another challenge with the user interface was that the student had to click a link to access it. We wanted to try to get the user interface of the app embedded on the homepage of the course so that it was a ubiquitous part of the course. Finally, we needed the user interface to provide more contextual data than the original design allowed for. For example, we wanted to display the date that the data in the app was last updated so that students would know if there was a time lag on their activity data loading. We also wanted to provide students with more granular activity data so they would know how their activities contributed to their progress in the course. Finally, we wanted to address challenges with students in other time zones missing deadlines because all of the course deadlines were shown in US Eastern time.

Iteration Four: Ubiquitous Access and Detailed Data

For the fourth iteration of the app, we completely redesigned the user interface. Our motivation for the redesign was to move away from the technologies we were using that were: (a) difficult to maintain; and (b) had a monthly cost. While we had abandoned Google Drive as part of the app's infrastructure after iteration one, we reconsidered it for use in the fourth version, albeit in a very different way.

A lesser known feature of Google Drive is that it can be used to host web apps via Google Apps Script. Setting up web apps using Google Apps Script is relatively easy, and there is no cost to build or host apps on Google Drive. These factors made Google Drive web app hosting an attractive option to host the user interface of the fourth iteration of the physical education app. Unlike our previous use of Google Drive, this iteration of the app did not require students to upload anything to Google Drive. Because of the way the web app was set up using Google Apps Script, students did not need a Google Drive account to use the app, nor did they even know that the finished product was running in Google Drive.

The new user interface running in Google Drive still used LTI so that the LMS could pass identity, role, and course offering details to the physical fitness app. However, with the new version of the app we were able to embed the app in a widget on the homepage of each course in the LMS rather than requiring a link to launch the app in a new browser window. Situated in the homepage widget, the app is an ever-present part of the course. Students see it the first time they log into the course, and anytime they want to check their progress they can just go to their course homepage.

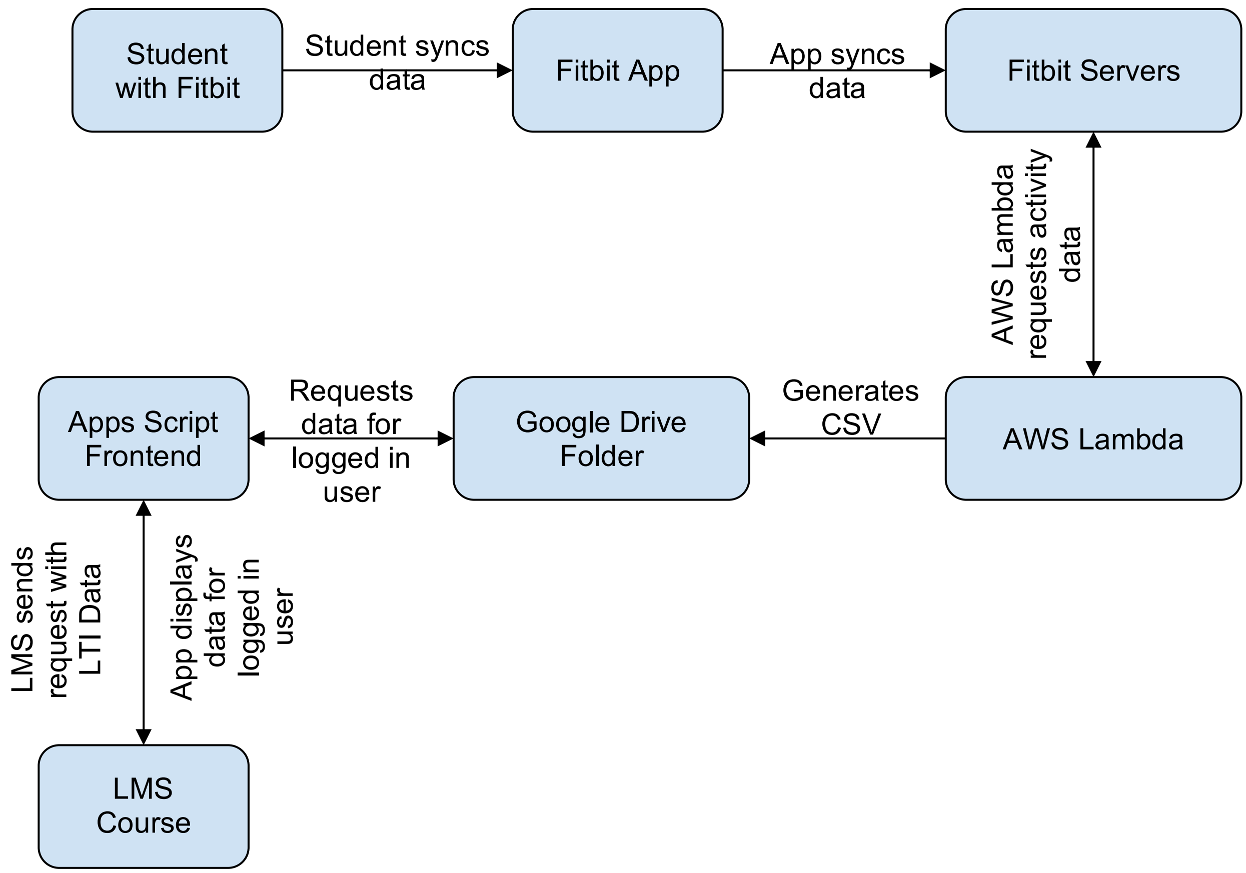

Figure 3.5. Illustration of the data flow in the current version of the physical education app.

The new widget provided a dropdown menu with the name of each module in the course. When a student chooses a module from the dropdown, the widget shows data for that module. In addition to showing the student their progress and requirements for the selected module, the widget showed the date that data was last updated, which helped set student expectations for when specific activities would show up. Additionally, the widget showed a summary of all activities completed in the selected module, along with the time spent in each heart rate range during each activity. This activity breakdown made it clearer for students how the time they spent on their activities was contributing to their course progress as compared with earlier versions of the app. The widget would also show students activities that did not count toward their module progress and gave them the reason the activity did not count (e.g., the activity was auto-detected or the activity had no associated heart rate data). Last, we added a time zone interpreter that could detect the student's time zone and translate the module due date to their local time zone. These changes decreased student questions regarding their activity progress. This version of the app (shown in Figure 3.7), which is currently in use in online physical education classes, provides students with all of the information they need to succeed in meeting their activity goals in their physical education course.

Minor Iteration: Scaling the App for COVID-19

In March 2020 the COVID-19 pandemic forced all courses at our university to operate at a distance. For traditional physical education courses, this presented a challenge. However, the Fitbit app that was developed specifically for use in online physical education challenges was able to help fill the void created by social distancing with only a few minor "under-the-hood" changes. This is a minor iteration because from the student and instructor viewpoints nothing changed. The app still functions for end users as it did before the pandemic. However, scaling the app from 60-100 students using it concurrently to potentially several thousand students using it concurrently did require some design changes.

Having the app serve potentially an unlimited number of students required changes with how the app pulls data from the Fitbit API. When we changed the app to fetch data at intervals and store the data in CSVs, we still had the app fetch data for every student in the system every time it ran. With around 60-100 students in the system, this is not a problem. It might take the data retrieval script five minutes to run, but it's running in the background (i.e., no one is waiting on it to finish for the app to load). However, as the number of students in the system increases, we run the risk of the data retrieval script timing out before it is able to finish. This poses a serious risk for the data integrity of the system, as if the data retrieval script constantly times out, then the data in the system never updates, rendering the app useless.

To mitigate the effects of the system being flooded with new students, we re-wrote the data retrieval script to pull data course-by-course rather than for all students in the system. This allowed us to specify a certain number of courses to pull data for each time the retrieval script ran, ensuring that we would not try to pull data for too many students at a time. After a bit of testing, we settled on pulling data for six classes every fifteen minutes on a rolling basis. So, every fifteen minutes our data retrieval script gathers data for six courses in the system, and once it reaches the end of the course list it simply starts back at the top of the list. This ensures that every course in the system is updated multiple times per day, but it also keeps the load of each data retrieval low enough that we are confident the script will finish.

I added this section to not only highlight how we adapted the app to function at scale for the COVID-19 pandemic, but also to draw attention to the value of this sort of design project when such a situation arises. We did not set out to design the online physical education app to prepare for a pandemic. However, because we had put in years of work to execute a vision of quality online physical education, we had an infrastructure in place that could be adapted to serve the entire university community. This is a benefit of innovative learning design that should be highlighted and celebrated.

Review of Current Student Experience

With the current version of the app, students must grant the app access to their Fitbit data. They do this by clicking a link that directs them to login to their Fitbit account. They are then given a description of the data the app will access, and they must affirm the app's access to the data by clicking a confirmation button. This authorization flow is illustrated in Figure 3.6.

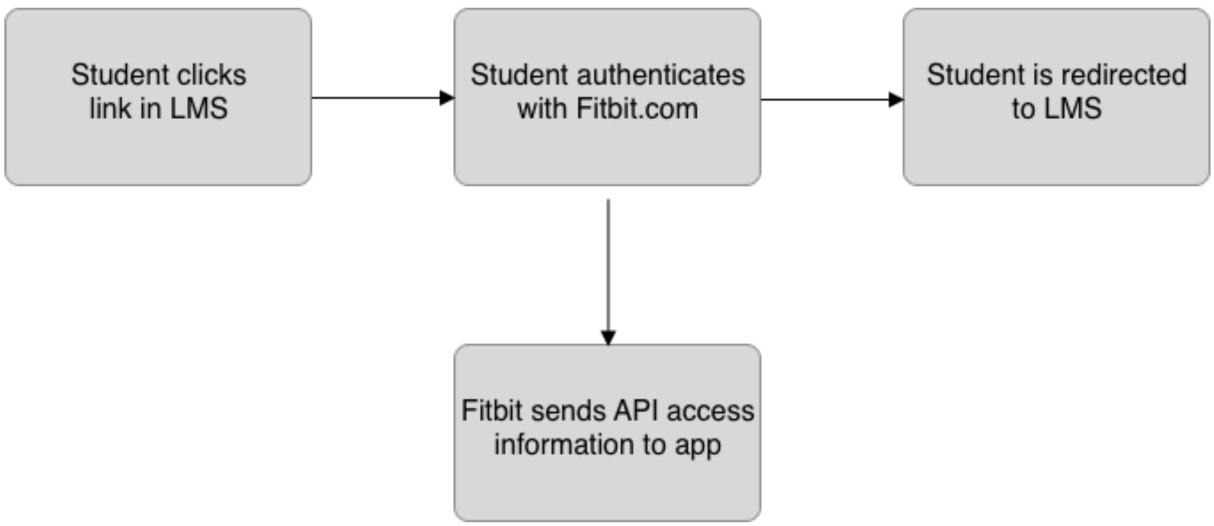

Figure 3.6. Student authorization flow for physical fitness app

Students then complete exercise activities while wearing the Fitbit device. They sync the device like any other Fitbit user would (typically, but not exclusively, via a smartphone), and the data they synchronize then becomes available to the online fitness app via Fitbit's API. Once students begin completing exercise activities, they see their progress reflected in the online fitness app, which is embedded on the homepage of their course. When students visit their course in the LMS, the module loads the data for the currently active module and display the student's performance data. Specifically, the online fitness app gives students the following information regarding their progress toward course requirements:

- Overall progress toward the goal for the chosen module;

- Minutes required and points available in the currently selected module;
- Date that the data were last updated from Fitbit’s servers;
- Start and end date of the module;
- Local time zone we believe the student is in, along with the due date of the selected module in that time zone;
- List of activities counted for the selected module, along with a breakdown of time spent in each of four heart rate zones;
- List of activities that did not count for the selected module, along with the reason the activity did not count.

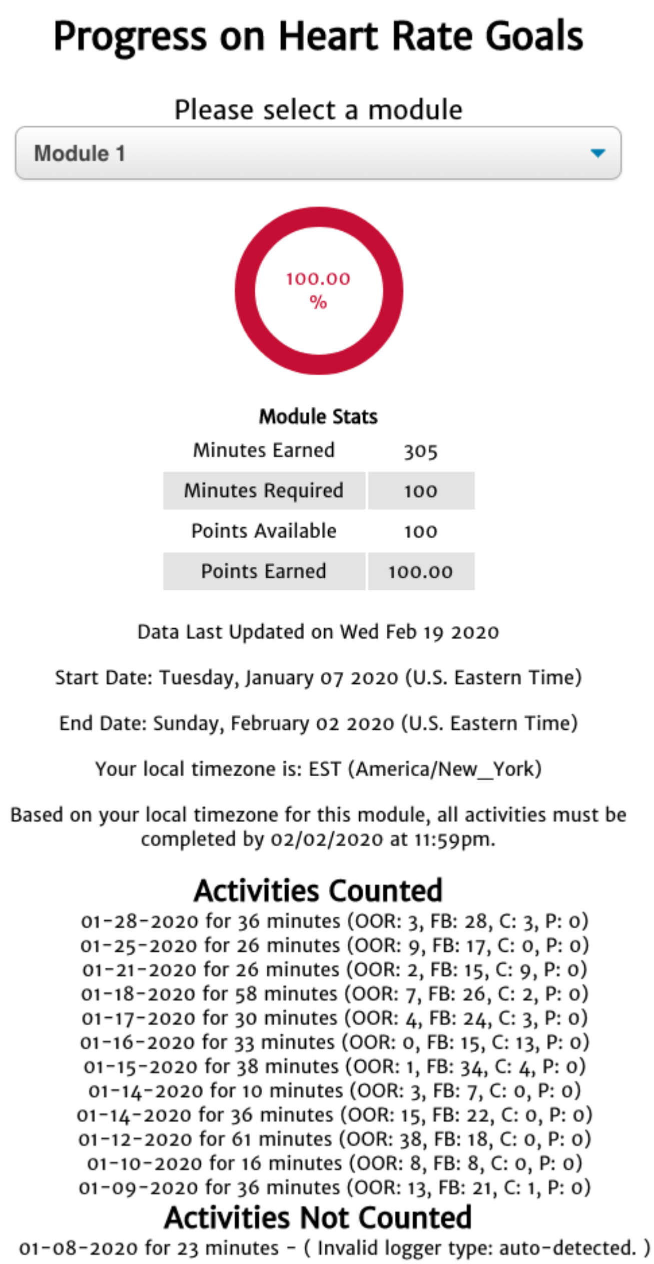

Figure 3.7. Screenshot of the student view of the current iteration of the app.

Students are able to use data presented by the app to monitor their progress in the course and improve their performance over the duration of the class. Figure 3.7 provides a screen snapshot from the LMS of a students' activity on the first module of the course. The widget shows that the student's first attempted activity was logged on January 8, 2020, but it did not count because it was auto-detected rather than intentionally recorded. The student then completed 12 more activities over the course of the module, each of which is shown along with the time in three different heart rate zone for each activity. The heart rate zones are listed as *OOR* (out of range), *FB* (fat burn), *C* (cardio), and *P* (peak). At the end of the course, students are instructed to revoke the app's access to their Fitbit data. Once access is removed, the app can no longer retrieve data from Fitbit's servers for the student.

Review of Current Instructor Experience

The physical education app also loads on the homepage of the course for instructors. However, instructors are provided with additional data, such as allowing instructors to select any module in the course from a dropdown menu to see an overview of class data for that module. Upon selecting a module, they see a list of students who have accrued minutes for that module, along with their total minutes and current score for that module, as shown in Figure 3.8. Additionally, they are given links to either (a) make changes to the modules for the class (i.e., editing dates or goals) or (b) download a csv file with all of the detailed activity data for their course. The csv download can be useful in cases where an instructor needs to closely examine each activity for a student in the course to provide clear feedback on activity for a module.

Figure 3.8. Screenshot of the current instructor view of the app showing all students' progress along with contextual course data and access to full activity data.

Design Reflections

The design of the physical education app started with a novel idea (heart rate based online physical education) that has remained consistent in its vision and orientation. The design iterations were informed first and foremost by reflections of student and instructor usage of the app. Each of the iterations outlined in this design case takes steps to remedy a shortcoming of the previous version. However, another important factor in the evolution of this design was the availability of technology to meet the instructional vision. In 2013, there was no reliable heart rate monitoring device that had a well-documented, publicly available API. The closing of the gap between the course vision and technical possibilities enabled our design to close the gap between the user experiences in the early iterations and the current user experience.

While design cases do not exist to test theory, a reflection on the iterations of this design process brings to mind the critical variables identified by transactional distance theory (Moore, 2019). Although the first iteration of the app did take substantial steps toward contextualizing heart rate data for the online physical education courses, it did not provide a good contribution to the design in terms of the course structure (sharing information with students), dialogue (encouraging constructive interaction), or learner autonomy (empowering students to make decisions about their learning).

Each successive iteration of the design improved the app in these aspects while responding to the shortcomings of the user experience. For example, providing students with an interface to view their data in the context of the course helped to improve the course structure so that students more readily knew what was expected of them. Providing more transparency and clarity to students by showing them their data helped to transform the interactions in the course from technical exchanges (e.g., “Why didn’t my minutes count?”) to constructive dialogue (e.g., “How can I maintain elevated heart rate during exercise?”). Finally, by showing students their own course progress in terms of their exercise activities, the app empowers students to make decisions about how they will approach meeting their course goals. This fosters learner autonomy. While this design case does not test the app based on transactional distance theory, it does illustrate how a naturalistic design process can unfold along established theoretical lines.

Summary

With wearable technology becoming more commonplace, possibilities for technology-enhanced online physical education should increase. However, in order to facilitate meaningful learning, it is important to consider how we design those devices (and the data they generate) into the learning experience. This design case presents the evolution of one such design, along with the most important decisions and iterations that have taken place over seven years of design and development work. The transformation of the app from the first iteration to the fourth iteration has informed other instructional design projects of mine over the past several years. Of all the ways this project has helped me improve as a designer, I think the most profound is that it has made me consider how best to expose students to data that reflects their own performance so as to encourage learner success.

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CHAPTER 4

STUDENT ATTRIBUTIONS OF LEARNING ANALYTICS DATA[1]

[1] Castle J. To be submitted to *Educational Technology Research & Development*.

Abstract

This study examines student use of a custom-built learning analytics tool in an online physical education class. Attribution theory is used to investigate how students view the outcomes observed in the learning analytics tool. A mixed-methods design is used to investigate students' general academic outcome attributions as compared to their specific attributions in the online physical education class. Results indicate that students make attributions to effort while using the learning analytics tool. For the students interviewed, the tool provided mediating support for academic success in the form of time management and clarity of expectations. Other outcomes are also explored.

Introduction

The potential of learning analytics to improve teaching and learning has been well documented (Clow, 2013; Daniel, 2015; Siemens, 2013). However, the evidence for improved learning has not kept pace with this potential (Viberg, Hatakka, Balter, & Mavroudi, 2018). As a result, more studies are needed that examine how student use of learning analytics shapes fundamental experiences as a learner.

Attribution Theory

It is important to understand the underlying reasons for the decisions students make when presented with data about their performance. One theoretical perspective that provides some insights into this issue is attribution theory. Attribution theory is concerned with an individual's perceived causes of an academic outcome. It states that when a student observes success or failure in their own actions, they attribute it to ability, effort, luck, or task difficulty (Weiner, 1972). These four perceived causes can each be characterized as to their locus (internal/external), stability (changeable/immutable), and controllability (controllable/uncontrollable) (Weiner, 2010). The perceived cause of an outcome has an impact on future expectancy of success. For example, if the perceived cause of a failure is internal, controllable, and unstable, then there is greater potential to change the antecedent behavior, which may lead to future success. According to attribution theory, effort is the only perceived cause that is internal, controllable, and unstable (Hunter & Barker, 1987; Weiner, 2010).

Attribution theory has been used in recent educational research to examine instructional dissent in higher education classrooms (LeBelle & Martin, 2014), student achievement in language learning (Bouchaib, Ahmadou, & Abdelkader, 2018), and adult physical education (Sarkisian, Prohaska, Davis, & Weiner, 2007). One longitudinal study in upper level Finnish schools found that students with higher self-concepts of ability in math made more internal attributions than students with lower self-concepts (Clem, Aunola, Hirvonen, Maatta, Nurmi, & Kiuru, 2018).

Sarkisian et al. (2007) used attribution theory to examine physical activity level in older adults. In that study, attribution theory was used because of the common notion that aging necessarily leads to less physical activity (i.e., a stable, uncontrollable attribution). The intervention in this study was to conduct four weekly one hour group discussions focused on attributions toward physical activity where participants made "promises" (i.e., goals) for their physical activity, including their daily step count. In this case, physical activity was measured using steps rather than heart rate, likely because portable pedometers were more readily available at the time than accurate, portable heart rate monitors. Interestingly, these researchers obscured step counts from the research participants by putting tape over the pedometer displays until after the study was complete in order to mitigate the motivational effects of pedometer usage. However, in doing so they also removed the ability for participants to monitor their own progress toward meeting their stated goals. While the study did not indicate if participants met the individual goals they set during the group meetings, they did find that focusing on attributional attitudes toward physical activity led to an increase in physical activity. Specifically, they found that helping people cultivate internal, controllable attributions led to an approximate increase of 6,000 steps per week in older adults.

Student attributions toward learning outcomes displayed in learning analytics are an important indicator for how learning analytics contribute to the student experience. Understanding whether students experience learning analytics as representing controllable outcomes in their academic experiences will help us understand how learning analytics can be best applied to help students achieve successful outcomes. The literature indicates that attribution theory is commonly used and supported in educational research generally, and that attributions are important in physical education specifically.

Designing a Learning Analytics Tool

The tool used in this study is the product of seven years of iterative design. While the design process is laid out fully in the previous chapter, it is important to review how the theories guiding this study are reflected in the design of the app. Our understanding of student use of the app has been guided primarily by attribution theory because it is important to examine how students experience agency over their actions while using the app to inform their performance. In order to foster a sense of control of their outcomes, students should attribute their observed outcomes to effort (Weiner, 2010). One way the design of the app supports this is through fostering a mastery-oriented approach rather than a performance-oriented approach (Marsh, Farrell, & Bertrand, 2016). Students are shown their module goal along with their own data in order to help them gauge their progress toward their course goals. They do not see their data compared to any other students. There is no “leaderboard” or any other similar display of class data. The data are not used to promote competition or to shame students who struggle to meet goals, as this can have a demotivating effect (Kerner & Goodyear, 2017).

Another theory important to the design of the app is transactional distance theory (Weiner, 1972). Transactional distance theory, which can be applied to any distance learning scenario, seeks to explain the gap that exists between student understanding and desired outcomes. To aid with this examination, transactional distance theory outlines three critical learning design aspects: structure, dialogue, and autonomy (see chapter 2 for a more complete overview of transactional distance theory). The app interacts with each of these critical design aspects. First, the presentation of course goals provides a structure around which much of the course is built. The clear communication of these goals is meant to give students sufficient information to meet the goals for each module. The app supports beneficial dialogue in the class by making the presentation of relevant performance details clear for students. Rather than students asking an instructor how to access data to submit for credit, the student's data appears automatically. This helps foster more productive conversations around topics like how to reach and sustain elevated heart rate zones during exercise. Finally, the app is meant to support learner autonomy by presenting student progress toward course goals so that students can plan their exercise accordingly. Students are not given autonomy over the amount of time spent in elevated heart rate zones, but they have complete autonomy over how they go about meeting the goals. In theory, this autonomy should foster a sense of agency, encouraging internal, controllable attributions of the data seen in the app.

Learning Analytics

Learning analytics is most commonly defined as the measurement, collection, analysis, and reporting of data about learners and their contexts for the purposes of understanding and optimizing learning and the environments in which it occurs (Siemens, 2013). Any data related to student participation or performance could be used for learning analytics. Often, data for learning analytics comes from a learning management system (LMS) or other technology used to facilitate teaching and learning.

While most research on learning analytics has cast students as sources of data rather than actors using learning analytics in the learning process (Marsh et al., 2016), it is important to consider how students might use learning analytics to shape their own experiences. Clow (2013) supposed that students would be the most appropriate consumers of learning analytics data, as they have the most to gain or lose as a result of their academic performance. However, little research has focused on how learning analytics alter students' normal decision making processes.

Student Use of Learning Analytics

A recent literature review of studies published in the area of learning analytics between 2012-2018 found that 9% of the published work showed evidence that learning analytics improved student learning outcomes. Another 16% of the articles espoused the potential for learning analytics to improve learning, but did not provide any evidence for their claims (Viberg et al., 2019). While many more studies found evidence of the efficacy of learning analytics to improve teaching (35%), the application of learning analytics to the process of learning remains an understudied area with as yet unrealized potential.

Studies that have focused on the student use of learning data for decision making have varied in their approaches. One study in higher education found that 47% of first-year students would access a learning analytics dashboard if it were available to them, with weaker students being less likely to use the data (Broos, Verbert, Langie, Van Soom, & De Laet, 2017). In the P-12 context, one study investigated how different types of data use with students might lead to performance or mastery-oriented mindsets.

Viberg et al. (2019) developed three areas of focus in studies that involved learning analytics and improved learning outcomes: (a) knowledge acquisition; (b) skill development; and (c) cognitive gains. The studies that evaluated knowledge acquisition typically evaluated student outcomes after being exposed to a learning analytics tool as compared with students who did not use learning analytics (Guarcello, Levine, Beemer, Frazee, Laumakis, & Schellenberg, 2017; Whitelock, Twiner, Richardson, Field, & Pulman, 2015). Skill development studies looked at things like students' time management (Tabuenca, Kalz, Drachsler, & Specht, 2015) and problem solving skills (Worsley, 2018). Studies that focused on cognitive gains looked at knowledge creation processes (Chiu & Fujita, 2014) and metacognition (Sonnerberg & Bannert, 2015).

Wise, Vytasek, Hausknecht, and Zhao (2016) outlined challenges in students' use of learning analytics from the perspective of both the interpretation of data and the action taken as a result of the data. The four challenges to interpretation are context, trust, priorities, and individuality. Each of these challenges represents a different aspect in the process of making meaning from learning analytics data. For example, how do students generalize data regarding past activity as it relates to their desired or expected classroom performance? Or, put differently, how does the learning analytics tool support a beneficial student interpretation of data? The study presents four principles that support student use of analytics: (a) integration with learning activities; (b) student agency in the learning process; (c) providing a reference frame to which analytics can be compared; and (d) dialogue about learning analytics use (Wise et al., 2016).

Wearable Technology in Physical Education

The U.S Department of Health and Human Services (HHS) recommends adults participate in 150-300 minutes of moderate or 75-150 minutes of vigorous activity each week. Heart rate is one way to monitor moderate and vigorous activity, with elevated heart rate indicating higher levels of activity. Dedicated heart rate monitors have been researched as mechanisms for evaluating physical activity (Freedson & Miller, 2000; Healey, 2000; Nicholls, Davis, McCord, Schmidt, & Slezak, 2009). However, advancements in wearable technology have made heart rate monitoring more ubiquitous than ever before.

Over the past decade, as brands of wearable, physical activity tracking technology, such as Fitbit, have grown in popularity, research on wearable technology has increased dramatically.

A subset of research on wearable technology has focused on its use in physical education contexts. Two studies that investigated the use of dedicated heart rate monitors in physical education contexts found that the monitors caused dissonance in the instruction provided in the physical education classes (Nicholls et al., 2009; Partridge, King, & Bian, 2011). Researchers found that students of lesser physical capacity (i.e., "out-of-shape" students) would reach an elevated heart rate while appearing to work much less vigorously than students of greater physical capacity (i.e., "in-shape" students). However, while the "in-shape" students appeared to be working harder, their heart rates did not reach levels required to satisfy the standards of the class. This led to teachers needing to adjust their student feedback, as before heart rate monitoring they had been instructing the "out-of-shape" students to work harder, even though they were (unbeknownst to the instructor) already working at an elevated heart rate. This also caused "in-shape" students to feel as though they were being punished, as they felt they were working harder than other students to receive course credit.

Causation and Qualitative Research

The need to demonstrate evidence of causation between an intervention and learning outcomes is a controversial issue among educational researchers. The positivist view holds that causation lies firmly in the domain of quantitative, experimental research designs and has been touted as the gold standard (i.e., randomized trials) for educational research (National Research Council, 2002, p. 125). In this paradigm, qualitative research is relegated to providing data to support controlled randomized studies. The assertion that qualitative research has no role to play in establishing causal explanation assumes one particular definition for "causality" and ignores the strengths of qualitative research (Maxwell, 2004a; Maxwell, in press).

The traditional view of causation in research is establishing *that* one thing causes another. This concept of causation, sometimes called the *regularity view*, has been traced back to the 18th century work of David Hume by several methodologists (for more information see Johnson, Russo, & Schoonenboom, 2019; Maxwell, 2004a). This positivist view on causality is inherently general rather than local, leading proponents of this view toward research methods they believe are more readily generalizable as well. However, other concepts of causality are more apt to be addressed by qualitative or mixed-methods studies.

One alternate concept is the *realist* approach to causality, which focuses on causal mechanisms and processes rather than on regularities (Maxwell, 2004b). This view of causation is more local than global, and it fits with the qualitative research concept of transferability rather than the traditional concept of generalizability (Kaplan & Maxwell, 2005; Maxwell, 2019). Shifting the emphasis to mechanism and process leads to the possibility of explaining causality through qualitative research. This view of causality is concerned with providing evidence of *how* interventions lead to particular outcomes given the complexities of a given context rather than proving *that* an intervention caused an outcome. In this study, attribution theory provides a framework for examining causal relationships, and the qualitative portion of the mixed-methods design investigates local causal relationships by using interviews to establish how antecedent conditions are linked to outcomes in line with the *realist* view of causation.

Purpose of Study

The purpose of this study was to investigate student attributions related to learning analytics in an online physical education class. More specifically, the study was designed to determine if students who used learning analytics as part of a learning experience make internal, unstable attributions for their performance, particularly in cases where the student generally attributed academic achievement to external or stable factors. Students participated in an online physical education course using a learning analytics app situated in a widget on the course homepage. The widget was populated with data that reflected the performance of the student logged in to the course (i.e., each student only sees his or her own data). Here are the questions that guided this study:

1. How do students attribute their personal learning outcomes to information provided by the wearable technology (e.g., Fitbit)?
    a. Do students make internal (effort, ability) or external (luck, context) causal locus attributions for observed outcomes?
    b. Do students make unstable (effort) or stable (ability, luck, context) causal stability attributions for observed outcomes?
2. How do student attributions of their personal learning outcomes to information provided by the wearable technology (e.g., Fitbit) differ from self-reported attributions of general academic achievement?
    a. How does causal locus differ for students between general academic attributions and specific attributions of their personal learning outcomes to information provided by the wearable technology (e.g., Fitbit)?
    b. How does causal stability differ for students between general academic attributions and specific attributions of their personal learning outcomes to information provided by the wearable technology (e.g., Fitbit)?
3. How do students describe the experience of using the physical education app?

Material and Methods

Participants

The study was conducted at a large research university in the southeast United States. The institution where the study took place requires every undergraduate student to complete at least one physical education class for graduation. The study participants were undergraduate students engaged in an online physical education class using the online physical education learning analytics app embedded in a widget, an area that presents information for students, on the course homepage within the institution's learning management system (LMS). Participants were entered into a drawing for a gift card as an incentive for participating in the study. The participants were distributed geographically, as the study was conducted during the COVID-19 pandemic.

Online Physical Education Instruction

The online physical education courses focus on helping students understand the benefits of physical activity on health and well-being. Through the physical education curriculum, students learn skills to help improve and maintain physical health for the rest of their lives. One major component of this instruction is the importance of time spent in elevated heart rate zones during exercise. Class activities are completed asynchronously, and each student is responsible for managing their activity schedule. Students have increasingly difficult heart rate intensity goals to meet during each module of the course. Students wear Fitbit devices capable of monitoring heart rate during walking or jogging exercises.

As part of its heart rate monitoring functionality, Fitbit calculates each individual's maximum heart rate (MHR) using the commonly accepted formula of 220 minus the student's age, which is calculated using the birthday the student enters in their Fitbit profile. During exercise, the Fitbit records the student's heart rate and calculates intensity as a percentage of MHR. The intensity levels recorded by Fitbit are fat burn (50 to 69 percent of MHR), cardio (70 to 84 percent of MHR), and peak (85 to 100 percent of MHR). For the online physical education classes, students earn one active minute for each minute recorded in the fat burn zone and two active minutes for each minute recorded in the cardio or peak zones. This scoring mechanism aligns the course with the moderate and vigorous-intensity goals set by the U.S. Department of Health and Human Services (2018).

The online physical education courses were arranged in modules, with each module lasting one week. Students participating in a course recorded exercise events using their Fitbit devices then synchronized the Fitbit device with their Fitbit profile, thus sending their heart rate data to Fitbit's servers. The online physical education learning analytics widget retrieved data from Fitbit's servers every four hours, and displayed the student's progress toward the current module's goal on the homepage of the online course. Students' heart rates goals increased in duration as the course progressed, ranging from 150 to 300 active minutes per module.

Rationale for Mixed Methods

Mixed methods research is understood as a combination of qualitative and quantitative approaches to research, employed with the intent to provide a more complete inquiry than either approach alone (Maxwell, 2013). This design can be reflected in a study's techniques, viewpoints, data collection, and analysis (Johnson & Onwuegbuzie, 2004; Johnson, Onwuegbuzie, & Turner, 2007). Combining the strengths and weaknesses of qualitative and quantitative approaches to improve overall research methods is known as *integration*, or how each source of data combines to allow the researcher to draw conclusions (Onwuegbuzie & Johnson, 2006). Mixed methods research can be aligned to a pragmatist approach (e.g., John

Dewey), combining the practicalities of quantitative research approaches with the reality of the social and contextual nature of experience and truth asserted in qualitative traditions (Johnson & Onwuegbuzie, 2004).

The mixed method design for this study allowed the qualitative results to be built upon the quantitative findings, improving the meaningfulness and validity of the results. The use of quantitative measures to establish baseline characteristics for the participants followed by qualitative measures to understand their context and lived experiences helps provide warranted assertibility for the findings of the study (Boyles, 2006; Dewey, 1941). This approach places the context-bound nature of the participants experiences against a more concrete situated backdrop informed by theory.

Data Collection

As a mixed methods study, both quantitative and qualitative data were collected. This study used an explanatory sequential mixed methods design, with the quantitative data being collected first to establish the characteristics of the individuals being interviewed (Creswell, 2014). The quantitative results were then used in the interview phase to ensure that the individuals participating in the interviews did not differ significantly in their general academic attributions from all survey respondents. The independent analysis allowed for the generation of descriptive statistics from the quantitative MMCS data and the coding and theme analysis of the qualitative interview data.

Multidimensional-Multiattributional Causality Scale. The multidimensional-multiattributional causality scale (MMCS) is an instrument used to measure students' attributional locus for academic success or failure (Lefcourt, Von Baeyer, Ware, & Cox, 1979). The MMCS consists of two 24-item Likert scale surveys, one concerning achievement and one concerning affiliation. Participants were asked to complete only the achievement scale of the MMCS, as the affiliation scale is irrelevant for the present study (Gordon & Debus, 2002; Nauta, Epperson, & Waggoner, 1999). This provides a measurement for students' causal attributions in alignment with Weiner's attribution theory (1972). Each scale presents students with 12 items concerning success and 12 items concerning failure. Of those groups of 12 items, there are three questions each concerning the four attributional factors of ability, effort, task difficulty (i.e., context), and luck. This instrument allows for students' internal and external causal attributions to be examined for both success and failure events.

Interviews. Semi-structured interviews were completed with all participants who agreed to the study. All interviews were conducted via video conference. At the beginning of each interview I received permission to record the interview and I verified the participant's consent to participate in the survey. The interviews were conducted near the end of the semester during which students used the online fitness app. This ensured that students had ample experience with the app to provide useful information regarding its use. Interviews were used rather than observations because: (a) the distributed, asynchronous nature of the class made observations impossible; and (b) interviewing allowed access to the lived experience of the participants via their episodic memory of using the learning analytics app (Maxwell, 2013). The interview questions were designed to be open-ended to allow participants the opportunity to explain how the learning analytics app helped to shape their experience in the online physical education class. However, the questions were also specific enough to ensure that the responses were relevant to the study. For example, students were asked about the general experience of tracking their heart rate for their online physical education course. For a full list of questions, see appendix A.

While I interviewed all students who volunteered in order to get as much student perspective on the use of the app as possible, I was particularly interested in students who generally attributed less of their success in academic achievement to their own effort (i.e., unstable attribution). These cases help answer research question two regarding the difference between general and specific attributions, with the hypothesis that students who make stable/external general attributions will reflect more unstable/internal attributions regarding their use of the learning analytics tool.

Data Analysis

Data from the MMCS were used to establish the general academic attributions of the survey respondents, which helped ensure that the interview participants were representative of the overall sample and had representation from students who scored lower of the internal, unstable attribute scores. The interviews were then analyzed to identify outcomes, antecedent conditions, and mediating variables. The alignment of research questions, data sources, and data analysis can be found in Table 4.1.

Table 4.1

Alignment of Research Questions, Data Sources, and Data Analysis

Research Question	Data Source	Data Analysis
Question 1a & 1b	Interview	Causality Coding & Theme Analysis (Saldaña, 2016)
Question 2a & 2b	MMCS & Interview	Achievement Attribution Score & Sample Comparison (Lefcourt et al., 1979; Weiner, 2010)
Question 3	Interview	Causality Coding & Theme Analysis (Saldaña, 2016)

MMCS. Descriptive statistics were produced from the MMCS responses to generate attributional scores for each student. The attributional scores indicated the extent to which the students attributed general academic outcomes to effort, ability, luck, and task difficulty. The scores were also combined into locus and stability scores as indicated in Table 4.2.

Table 4.2

Alignment of Locus and Stability Scores with Research Questions

Research Question	Area	Attributional Factors
Question 2a	Internal Locus	Effort, Ability
Question 2a	External Locus	Luck, Task Difficult
Question 2b	Unstable Attribute	Effort
Question 2b	Stable Attribute	Ability, Luck, Task Difficulty

Interviews. All interviews began by obtaining informed consent of the participant. Interviews took place via video conferencing and were recorded and transcribed for data analysis. Interview transcripts were coded to identify categories of information that were important to answering the research questions (Maxwell, 2013; Merriam & Tisdell, 2016). Data analysis began after the first interview was completed and continued concurrently with the remainder of data collection in order to keep the study focused and identify themes early (Merriam & Tisdell, 2016).

Interview transcripts were loaded into the Atlas.ti qualitative data analysis software and pre-coded to identify participant quotes that stood out as particularly important (Saldaña, 2016). The first-cycle coding method of causation coding was applied to the data in order to establish the participants' perceived outcomes, the causes of the outcomes, and the links between them

(Saldaña, 2016). Causation coding is an adaptation of the premises of the Leeds Attributional Coding System (LACS) (Munton et al., 1999). The goal of causation coding is to "locate, extract, and/or infer causal beliefs from qualitative data such as interview transcripts, participant observation field notes, and written survey responses" (Saldaña, 2016, p. 187). Causation coding maps a three-part process as code 1 > code 2 > code 3 (where ">" means "leads to") to show the relationship between the antecedent condition (code 1), the mediating variable (code 2), and the outcome (code 3). Causation coding is most appropriate as a first cycle coding method, as it aligns with attribution theory and structures the data for the application of attributional causes (i.e., effort, ability, luck, task difficulty/context). Saldaña (2016) states that causation coding is appropriate for "discerning motives (by or toward something or someone), belief systems, worldviews, recent histories, interrelationships, and the complexity of influences and affects on human actions and phenomena" (p. 188). Therefore, it is an attractive data analysis technique to determine if the use of a learning analytics tool could influence students to make internal, unstable attributions where they otherwise might not.

After the initial coding of antecedent conditions, mediating variables, and outcomes, the code combinations were categorized into an array with the initial categories. Following this initial categorization, similar codes were categorized further to produce major categories. Each category is described in the results section.

Results

This section is organized as follows: quantitative results (MMCS) then qualitative results (interviews).

MMCS Results

In total, 18 students completed the MMCS survey. Each response was evaluated on a scale from 0 (strongly disagree) to 4 (strongly agree). The students generally attributed their academic outcomes to effort ($M = 2.75$, $SD = .69$) more than any other factor. The group mean and standard deviation for each area can be found in Table 4.3.

Table 4.3

Mean and Standard Deviation for Each Attributional Area

Attribution	Mean	Standard Deviation
Effort	2.75	.69
Ability	2.42	.60
Context	2.37	.70
Luck	1.95	.80

In addition to group statistics, each individual respondent's attributional scores were also calculated to determine each students' general academic attributions. These scores were used to try to identify students who scored lower on the internal, unstable attributes. The individual scores can be found in Table 4.4.

Table 4.4

General Attribution Scores for Each Participant

Participant	Effort	Ability	Context	Luck
Respondent 1	1.00	1.33	3.84	3.67
Respondent 2	3.17	1.33	1.34	1.00
Respondent 3	2.67	3.00	2.83	2.00
Respondent 4	3.33	3.00	3.00	2.83
Respondent 5	2.84	2.50	1.50	1.17
Respondent 6	3.50	2.00	2.67	2.33
Respondent 7	3.17	2.34	1.83	1.00
Respondent 8	2.50	2.84	3.00	2.84

Respondent 9	2.17	3.00	2.17	1.00
Respondent 10	2.50	2.50	1.50	1.67
Respondent 11	3.17	3.00	1.67	1.17
Respondent 12	3.50	3.17	2.67	1.84
Respondent 13	3.34	2.83	2.84	2.34
Respondent 14	2.67	2.50	2.83	2.00
Respondent 15	3.34	2.33	1.67	1.67
Respondent 16	1.67	1.34	3.00	2.50
Respondent 17	3.00	2.00	1.84	1.17
Respondent 18	2.00	2.50	2.50	3.00

The attributional scores indicated the extent to which the students attributed general academic outcomes to effort, ability, luck, and context. Additionally, the grouped locus and stability scores indicate that overall the respondents made more internal ($M = 2.58$, $SD = .54$) than external ($M = 2.16$, $SD = .72$) attributions, and their attributions were more unstable ($M = 2.75$, $SD = .69$) than stable ($M = 2.25$, $SD = .50$). This is an important point, as it indicated that more of the participants were likely to make internal, unstable attributions generally. It also underscored the importance of including interviews with students who cut against the group norm in these areas to answer the research questions regarding the effect of the learning analytics widget on students' causal locus and stability.

Interview Results

Of the 18 survey respondents, nine responded to a request to participate in a thirty minute interview. Participants who completed the interview were entered into a drawing to receive one of six fifty dollar gift cards as an incentive for participation. In order to answer research question two regarding the differences between specific and general attributions, it was important for the survey group to reflect the overall respondent group, particularly as related to internal locus and unstable attribute scores. Table 4.5 gives an overview of those scores for both all survey respondents and the subset of respondents who completed the interview. Comparison between respondents who participated in the survey and those who did not participate in the survey showed no significant difference in their internal locus scores, $t(16) = .211$, $p = .8355$, or their unstable attribute scores, $t(16) = .1666$, $p = .8698$.

Table 4.5

Internal Locus and Unstable Attribute Mean Scores for All Survey Respondents and Interview Participants

Group	Internal Locus Score	Unstable Attribute Score
All Respondents	2.58	2.75
Interview Participants	2.61	2.72

Causation coding and analysis of the interview data indicated two main categories of outcomes stemming from the use of the physical education widget: academic-oriented outcomes and personal fulfillment outcomes. Each of these outcome categories had multiple specific outcomes, each with their own antecedent conditions and mediating variables. Table 4.6 outlines examples of student quotes along with the corresponding codes.

Table 4.6

Student Quote Examples with Corresponding Codes

Quote	Antecedent Condition(s)	Mediating Variable(s)
"I think that's mostly down to I just know that I have to get this done and if I don't do it, I'm going to have consequences later. Y'all made it pretty clear what I had to do and I knew what I had to do. And it was just a matter of me doing it really."	Desire for Good Grades	Clarity of Expectations
"Yeah. So you can kind of gauge a sense of your progress, not just in the class, but in like fitness. If I was maybe less fit when I started, which I wasn't very fit when I started, but it probably would have been a bigger impact, I think. But you can kind of	Initially Less Fit	Ease of Task

tell just like, "Oh, you know, when I first started, I was doing like a hundred minutes and now I'm doing like 300 and they were comparatively the same difficulty. So maybe I've gotten more fit."		
"Honestly, the widget was extremely useful just for gauging where I was at. Just because I work on the weekends, so I would try to get my walking done early in the week. But I have a little bit of time on Sunday where I could walk if I needed extra time."	Use of Widget	Time Management

Academic-Oriented Outcomes

The most common outcomes associated with use of the physical education widget were academic-oriented outcomes. Most commonly, students reported the use of the widget leading to successfully meeting course goals. There were three antecedent conditions and four mediating variables that students indicated as leading to their meeting the course goals. A smaller number of students reported occasionally not meeting course goals. Participants indicated one antecedent condition and two mediating variables in cases where goals were not met. Figure 4.1 gives an overview of academic-oriented outcomes along with their mediating variables and antecedent conditions.

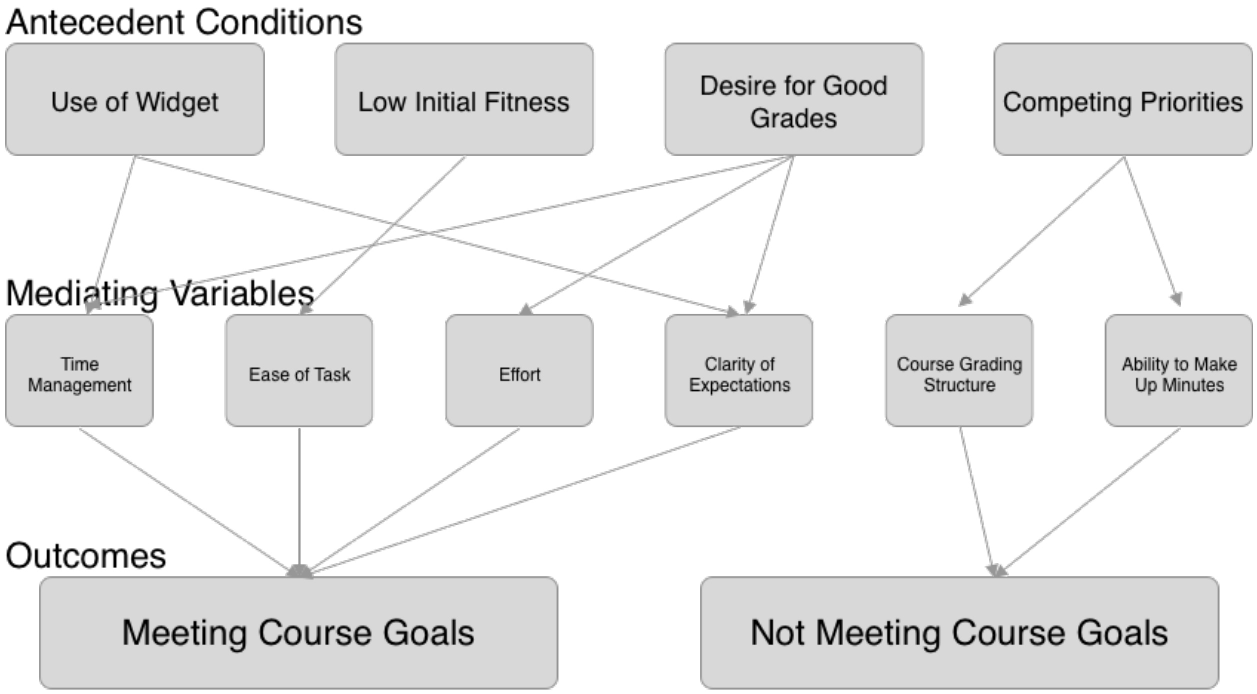

Figure 4.1. Antecedent Conditions, Mediating Variables, and Academic-Oriented Outcomes

Time Management. One mediating variable that several students reported as leading them to the successful completion of course goals was time management. That is, use of the widget and a desire for good grades (antecedent conditions) enabled students to more effectively practice good time management (mediating variable), which resulted in them meeting course goals (outcome). For example, Respondent 17 reported:

> ...the last two, three days of the module, I'd look at it and then check where I was at and base how long I walk to be off of that. So, if I had maybe like a hundred minutes left, I would try and split that into three parts. And so, it was helpful for me to know that so I could base like, okay, I have four days left. I need to walk at least 30 minutes each day.

Similarly, other participants reported that the visual of the dial filling up helped them gauge the amount of time they would need to dedicate to completing their required work for the week. Respondent 13 said:

> I can see what I did each day and keep doing what I did. Like the previous days that I got a lot of minutes in because my heart rate would be higher and it counts more if your heart rate's over 75%. So as the dials filled up, it helped me know like, “Okay, it's almost the end of the week, so I need to do a little bit more before Sunday, so I can get my points.”

Likewise, Respondent 8 found the visual of the gauge useful:

> So it's just like the little thing at the top. It shows you the percentage and going around. So if I have logged in, I've only worked out three days that week, but it was already to that. I'd be like, “Okay, if I have something to do tomorrow, I don't have to figure out how to fit in the gym.” But if it was only showing the thing 25% full, I'd be like, “Oh, I need to go and work out a couple more days this week.”

Interestingly, some students reported that while the widget helped with time management, their performance and motivation was internally attributed. Talking about how the widget informed class performance, respondent 3 said that, “it really just helped with time management for the class, not as much my performance.” Later in the interview, Respondent 3 reiterated this attribution, stating, “a lot of it was just consistency on my part for walking, but also the time management and the widget really helped with the time management.”

Clarity of Expectations. Another mediating variable made possible by the widget was “clarity of expectations.” Many students reported that the physical education widget helped make the expectations for success in the class clear and easy to understand. Respondent 3 summed up the issue of clarity succinctly, stating that “with the widget, it would just be very straightforward about how much I had left to walk and really put it in perspective." Similar to time management, students attributed the clarity of expectations to the use of the widget, but they attributed their success in the course to their open effort. For example, respondent 1 said:

> I think that's mostly down to I just know that I have to get this done and if I don't do it, I'm going to have consequences later. Y'all made it pretty clear what I had to do and I knew what I had to do. And it was just a matter of me doing it really.

The sense of internal, unstable attribution was also shared by Respondent 5, who also indicated the desire for good grades as an antecedent condition when asked to attribute success in the course:

> Well, definitely the structure of the class, it was really nice having a Fitbit and having your grades based upon achieving these minutes, so I would say I was primarily successful based upon the motivation to want to get my PE credit.

Respondent 7 also felt that the widget fostered a sense of internal attribution toward achieving the class goals:

> The Fitbit also made it easy because it was easy to look at it and the widget, everything just worked really well because I felt like I was working towards something specific that I knew I could achieve.

In each of these examples, students reported that the widget helped bring clarity to what was expected of them, which mediated their desire for academic achievement and helped bring about success in meeting course goals.

Effort. As described earlier, students' discussion of time management and clarity of expectations was often wrapped with caveats that they primarily attribute their outcomes to their own effort. These attributions were made clear in other statements as well, particularly as related to the desire to make good grades. For example, Respondent 8 demonstrated pride in receiving a high score in the class as a result of their own effort:

> I ended up with a 105 in the class. And even though that doesn't matter, because all you have to do is make an 80 to pass. It's still like, "Oh I made a 105, I can't get that in any of my academic classes." So it was nice to be like, "Oh I did it all consistently enough to make a 105 even though I'm not a particularly athletic person."

Respondent 12 echoed the effort attribution, citing an internal motivation, “I just have personal drive and I like getting things done, and I like doing everything to my full potential.”

Ease of Task. Another mediating variable that came up several times was the perceived ease of the task the students were being asked to do. Several students acknowledged not having a high fitness level, which allowed them to hit their heart rate goals with less perceived effort, particularly early in the class. For example, Respondent 7 said:

> I was living a fairly sedentary life… so my heart rate didn't have to go as high doing regular exercise, just walking around, as it did when I first started. I was more unhealthy when I first started… the farther I got into the class, it was harder to get into that fat burn zone doing what I had been doing. I had to move into more vigorous exercise.

Course Grading Structure. Interestingly, the course grading structure occasionally mediated the outcome of students not meeting course goals. The grading policy in online physical education courses have a couple of elements that allow students to miss goals and still succeed in the class. For example, students can miss minutes in the middle of the course and make them up at the end. Also, the courses use a pass/fail grading structure where the students have to accumulate 1,300 total points to pass. Given the structure of the class, it is possible for a student to accumulate enough points to pass while missing 150 total points during the course.

Respondent 12 reported falling short on the last goal because they knew that had achieved enough minutes to pass the class:

> I met all of my goals except for the last one because I determined that I did everything else to get a satisfactory done anyway and I was working doubles that week. So I was just like okay, I got everything I had to get done.

Similarly, when faced with competing priorities, respondents 13 and 17 both decided to skip minutes on the final module of the course. Respondent 13 stated:

> So Module Seven was around the time I was working. So those 300 minutes, I had to really fight to get those in, too. But then the last week I did not make up that time only because it was only 30 minutes and I had already far exceeded the 1,300 minutes that were required. I have been exercising after the class but during that week it was the last week of my internship and I did not really have much time. So I figured it would be okay because I exceeded everything else in the course with 100. So I felt that it would've been okay to just miss those 30.

In each situation where course goals were not met, the student cited that the course grading structure was the main mediating variable.

Personal Fulfillment Outcomes

Several students indicated personal fulfillment as an outcome of using the physical education widget. This fulfillment was most often reported as a sense of accomplishment, but some students also reported a sense of enjoyment and an increase in personal fitness. While enjoyment of exercise and an increase in personal fitness are academic goals for students participating in the course, these factors are aligned with students' intrinsic feelings of improved fitness. The mediating variables for personal fulfillment outcomes were the representation of physical activity in the widget, seeing data in the context of the course, and autonomy with meeting course goals.

Representation of Physical Activity in the Widget. Several students talked about how seeing their physical activity represented in the widget brought about a sense of accomplishment as they made progress toward class goals. Respondent 10 reported a sense of accomplishment at meeting one of the more difficult goals in the class (300 minutes), and reported that seeing minutes earned beyond the goal led to an even greater sense of accomplishment:

> I felt accomplished once I got it done and it was nice to see I did 300 minutes this week of exercise. And even if you go over it, it shows you that, too. You don't get an extra credit, but it says you did 383 minutes this week. So you definitely get a sense of accomplishment with that. And I guess it makes you keep wanting to do it the next couple of weeks as well.

Respondent 8 indicated a sense of accomplishment at seeing their effort represented concretely in the course after an intense exercise session:

> I would know I'm really out of breath or I've been working really hard but I just wouldn't know where my heart rate is at or my calorie count or any of that. So it was just, I want to say it was motivating to me because as I also see the dial turn around, I get to the end.

Additionally, Respondent 8 felt accomplished at knowing the representation of their physical activity was accurate, as opposed to students not using heart rate tracking who do not necessarily know if they have met heart rate goals:

> ...because you know sometimes some students will be like, "Oh yeah, I did that." And it's not accurate. So I feel that app is an accurate way of showing what students have done and their progress and stuff like that.

There was also a sense with some students that, similar to the academic outcomes, the personal fulfillment outcomes were attributable to effort, even when the mediating variable was something intrinsic to the widget. For example, Respondent 8 connected the representation of their physical activity associated with meeting a goal to a strong sense of accomplishment, which they attributed to their own effort in outpacing the goal:

> Whenever I would have weeks where I was over a hundred minutes over the goal, just because I was getting double minutes because I was in the right heart rate zone and that I'd be like, even though I'm not like, Oh, I'm, I'm a fitness guru. I'm doing so good. I'm outpacing it by so much. So that was kind of nice, but I mean, overall I wouldn't attribute that to the widget. I would just attribute it to doing better than the goal, but the widget kind of, because it told you, it would say minutes required 350 and then it would say minutes achieved and it would be 475 or something. And so that would be a nice way to see it without having to calculate it yourself. But it's not the widget itself was what did it, it was just knowing I surpassed the goal, which the widget kind of told me in a way.

Data in the Context of the Course. While it was possible for students to see their activity data within the Fitbit app, the widget put the relevant activity data into a format that was meaningful for participation in the course. For example, while the native Fitbit app might show activity data on a monthly or weekly basis, the widget displayed activity data in alignment with the course's modules. Likewise, where the native Fitbit app highlights metrics like steps (which are meaningless in the online course), the widget put emphasis on displaying accumulated heart rate data as related to course goals. Respondent 8 found that motivation to complete the tasks wasn't directly tied to the widget but was instead related to what the widget represented:

> So there was some personal factor, but it was also the grade incentive and the point incentive and just like, this sounds so corny, but just knowing you did good at something, that's kind of an incentive. But I know this is kind of about the widget. It wasn't so much the widget, but what the widget represented. So if it was full, then I got a hundred. And so that was kind of a nice feeling.

Autonomy with Meeting Course Goals. Some students reported a sense of autonomy that was fostered by use of the widget. Because the structure of the course allowed students to meet goals on a weekly basis, it was up to each student to plan how to meet those goals. While this made time management an important mediating variable for academic outcomes, it also allowed for autonomy to become a mediating variable for personal fulfillment outcomes. For example, Respondent 10 was a former athlete who had some previous injuries and physical limitations. They reported that while participating in the class "it was nice that I could pace myself and do what I needed to do for me." Respondent 17 reported that before the class started there was initial anxiety over the potential for rigid daily requirements in an online physical education class. They reported that:

> Being able to have that freedom to choose when I was going to do everything or if I was going to do it every day or every other day, or take the weekend off or something like that, that was really nice and it made it a lot more enjoyable.

While this autonomy was primarily an aspect of the course design, the students' use of the widget fostered their autonomy by helping them to stay up-to-date on their progress with no intervention from the instructor.

Discussion

The interview results indicate that students attributed the observed outcomes in the physical education widget to internal, unstable mediating variables. A common view of the widget was that it was a time management tool, enabling students to more effectively apply their effort to achieve course outcomes. This aligns with existing research that finds that a student's ownership of learning is a key factor to success in online courses (Yu & Richardson, 2015). The contribution of the physical education app to students' feeling of ownership over their learning indicates that the physical education app specifically, and learning analytics tools generally, could facilitate increased learner autonomy as framed by transactional distance theory (Moore, 2019). This indicates that the design conjectures implemented support student agency and a mastery-orientation toward the results seen through the use of the app.

Each student interviewed for the study met all of their heart rate goals except in cases where they deliberately did not participate in a module because they already had enough points to pass the class. Students felt as though the presentation of information in the widget made course expectations clear, so that, as one participant said, "[it was] pretty clear what I had to do… and it was just a matter of me doing it." This result suggests that the physical education app helped students focus their effort toward achieving their goals. This finding is further supported by students use of the widget to determine how much of a given activity helped them make progress toward their goals. The breakdown of heart rate zones by activity in the widget made clear for students how the time they spent exercising contributed to meeting their goals. This suggests that providing students with representations of their activity that they can connect with their own lived experiences can help inform and improve future performance.

These two findings, clarity of expectation and representations of data in the context of the course, also align with the ideas of structure and dialogue found in transactional distance theory (Moore, 2019). The clarity of expectations found in the widget provides structure for the course. It lets students know *how much* to do and *by when* they should do it. Likewise, representing concrete student activity as data in the context of the course provides a foundation for more meaningful dialogue. With earlier versions of the widget that did not provide the same detailed information as the version in this study, interactions between students and instructors often centered around the mechanics of submitting activity data to the course. By making that submission process seamless and providing the activity data to students in a way that aligns with course goals, the widget facilitates more meaningful dialogue.

One example of this more meaningful dialogue was found where participants in the study remarked on the ease of meeting heart rate goals, particularly early in the course. When the students can see their heart rate for each activity, they can more readily connect time spent in higher heart rate zones to a lower level of personal fitness. This becomes apparent as students' fitness improves over time during the course, when they find that working at the same level of perceived intensity does not yield the same heart rate results. As one participant said, "it was harder to get into that fat burn zone than what I was doing before, I had to move into more vigorous exercise."

The tool used in this study was the result of seven years of iterative design based on student and instructor feedback. While attribution theory and transactional distance theory help explain the app's use by students and its effect on learning design, other design principles have also emerged that influenced the app's design. This tool could not have come into being without an instructional designer and a faculty member being willing to take a risk on an innovative idea.

The design of this tool is not merely the creation of an online learning experience. It is an exploration of what is possible to do in online learning that has evolved and adapted along with consumer and internet technology. This exploration inherently involves the risk of failure and this design effort was no exception. We experienced many times while the app was being developed where its use and performance were problematic. For example, earlier versions of the app did not have the capability to show students their own data, and the app would sometimes timeout (i.e., fail as a result of taking too long) while fetching data. A very recent example of a design shortcoming occurred while the app was being scaled up in response to the COVID-19 pandemic. During the first few interviews, students reported that they felt like the data needed to update more frequently. In response, I adjusted the underlying data-fetching mechanism to pull data on a constant rotation rather than resetting daily in order to help students see the most up-to-date data possible (for more details on overcoming failures in the app's design, see chapter 3).

Implications

While the results of the MMCS indicated that overall study participants leaned toward more internal, unstable general academic attributions, there were individual participants who displayed strong tendencies toward external, stable attributions. However, the interviews indicated that the participants viewed their success in the course as a result of their own effort, stating repeatedly that their outcomes were due to their own consistency and performance, with the widget simply helping to inform their effort. This suggests that the physical education widget plays an important support role for students. An opportunity for future research might be to investigate student use of learning analytics tools as support mechanisms in other disciplines. Additionally, analyzing student use of learning analytics tools through the lens of transactional distance theory could prove useful, particularly given the finding regarding student autonomy and ownership of learning.

Limitations

The most obvious limitation of this study is the use of convenience sampling with a small sample size. The small sample size and the specific context of online physical education make it impossible to generalize the results beyond the scope of this research context. The purpose of the study was to examine how students perceived attributions of outcomes observed in the physical education app. The use of quantitative measures to ensure the interview sample was not significantly different from the overall class sample strengthened the results. Providing rich description of the online physical education context with extensive quotes from the interview participants established credibility for the qualitative results (Lincoln & Guba, 1986; Merriam & Tisdale, 2016). The steps taken to establish reliability and validity in this study strengthen its ability to contribute to the literature on learning analytics and student data use.

Ethical Considerations

There were no reasonably foreseeable risks or discomforts involved with this research procedure. The survey data were collected anonymously, and direct identifiers from the interviews were replaced with codes. Students were informed that their decision to participate in the study would not affect their course grade. In an effort to increase participation, students who completed participation in the study were entered in a drawing for one of six $50 gift cards purchased by the researcher.

All interviews were conducted via the Zoom video conferencing platform. Participants were reminded of the informed consent guidelines and affirmed their consent to participate in a recorded interview before the interviews began. The consent forms included contact information for The University of Georgia's Institutional Review Board.

The key to the direct identifier codes was kept only long enough to create a complete record of data for each participant. The interview videos were uploaded privately to the institution's media management platform for transcription using the platform's transcript editor. Transcripts were then loaded into Atlas.ti on a password-protected computer for analysis. Additionally, survey results were exported from the Qualtrics survey platform into a Google Spreadsheet for analysis using an account protected by two-factor authentication.

Researcher Subjectivities and Assumptions

This project reflects a nexus of my personal interests, both professional and personal. My interest in using data to improve teaching and learning began when I was a middle school teacher, and later a P-12 instructional technology specialist (ITS). During my time as an ITS, I spent a considerable amount of my working time helping teachers derive meaning from performance data to help plan and improve instruction. When I moved into higher education, I found the landscape around using data to inform instruction to be quite different from P-12. However, in both P-12 and higher education, I saw that students rarely engaged with data reflecting their own performance. This reality is even evident in the first two versions of the physical education app, where students only received feedback about their performance after the data had been filtered through the instructor. However, contrary to those early designs of the app I do believe that self-efficacy and learner autonomy are important for success in educational endeavors. It was with that belief that I helped bring the student-facing side of the app into existence. I hoped that by exposing students to data regarding their own performance, they would be able to more successfully meet their goals in the course.

I also have a personal interest in fitness and exercise. Although it was truly by chance that I was assigned as an instructional designer to the course that ended up growing into this project, I have participated in structured exercise such as weightlifting and high intensity interval training since I was fourteen years old (twenty-seven years as of this writing). I am currently an active member at a small gym in my community, and I use a heart rate tracking device during my workouts. In short, I believe that the subject matter being taught in the online physical education classes is of great importance to the students, and I am proud to have enabled them to participate in meaningful physical education from a distance.

The design of this study has also been influenced by my experiences. In addition to being the person researching student use of the physical education app, I am also its designer and primary technical developer. However, my pragmatic approach to this research has helped me avoid unduly influencing the research with my own subjectivities (Shannon-Baker, 2015). During data analysis, I consciously avoided identifying only instances that supported my belief for how students might experience the app. I worked to represent the students' portrayal of their experiences as faithfully as I could. I believe that I have been fair in my representation of the data collected.

Conclusion

Learning analytics is thought of as the measurement, collection, analysis, and reporting of data about learners and their contexts for the purposes of understanding and optimizing learning and the environments in which it occurs (Siemens, 2013). This definition of learning analytics does not specify to whom the data are reported, but much of the literature on learning analytics has focused on how instructors and institutions use data to inform decisions (Jimerson, 2014; Ikemoto & Marsh, 2007; Gummer & Mandinach, 2015; Bertrand & Marsh, 2015; Coburn, Toure, & Yamashita, 2009; Faber, Glas, & Visscher, 2018). Fewer studies have reviewed how students use their own data for learning. One study that looked at student use of learning analytics examined the effect of simply making a learning analytics tool available (Broos, Verbert, Langie, Van Soom, & De Laet, 2017). Other studies have looked at using learning analytics to track time on task (Tabuenca, Kalz, Drachsler, & Specht, 2015) or the effects of prompting on metacognitive processes (Sonnerberg & Bannert, 2015). This study indicates that the learning analytics tool used in the online physical education classes fostered an internal, unstable attribution toward class achievement by helping set clear expectations and facilitating effective time management. An alternative line of research could be to focus on how students use tools like the physical education app to foster autonomy and ownership of learning processes. This could help further understanding of the elements of learning analytics tools that support student success across disciplines.

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Appendix A

Interview Protocol

1. Tell me about your experience tracking your heart rate in the online physical education course.

2. How did the data presented in the course widget inform your performance?

3. What did you do that was successful? To what do you attribute it to?

4. What did you do that was not successful? To what do you attribute it to?

5. How did it feel to meet your heart rate goal for a module?

6. Tell me about a time that your heart rate data showed an unexpected outcome..

7. Did anything surprise you about the exercise data presented in the widget?

Appendix B

Multidimensional-Multiattributional Causality Scale (Achievement)

1. When I receive a poor grade, I usually feel that the main reason is that I haven't studied enough for that course.

2. If I were to receive low marks it would cause me to question my academic ability.

3. Some of the times that I have gotten a good grade in a course, it was due to the teacher's easy grading scheme.

4. Sometimes my success on exams depends on some luck.

5. In my case, the good grades I receive are always the direct result of my efforts.

6. The most important ingredient in getting good grades is my academic ability.

7. In my experience, once a professor gets the idea you're a poor student, your work is much more likely to receive poor grades than if someone else handed it in.

8. Some of my lower grades have seemed to be partially due to bad breaks.

9. When I fail to do as well as expected in school, it is often due to a lack of effort on my part.

10. If I were to fail a course it would probably be because I lacked skill in that area.

11. Some of my good grades may simply reflect that these were easier courses than most.

12. I feel that some Of my good grades depend to a considerable extent on chance factors, such as having the right questions show up on an exam.

13. Whenever I receive good grades, it is always because I have studied hard for that course.

14. I feel that my good grades reflect directly on my academic ability.

15. Often my poorer grades are obtained in courses that the professor has failed to make interesting.

16. My academic low points sometimes make me think I was just unlucky.

17. Poor grades inform me that I haven't worked hard enough.

18. If I were to get poor grades I would assume that I lacked ability to succeed in those courses.

19. Sometimes I get good grades only because the course material was easy to learn.

20. Sometimes I feel that I have to consider myself lucky for the good grades I get.

21. I can overcome all obstacles in the path of academic success if I work hard enough.

22. When I get good grades, it is because of my academic competence.

23. Some low grades I've received seem to me to reflect the fact that some teachers are just stingy with marks.

24. Some of my bad grades may have been a function of bad luck, being in the wrong course at the wrong time.

CHAPTER 5

CONCLUSION

The purpose of this dissertation research was to better understand how students used a learning analytics tool in an online physical education class. The learning analytics tool, which appeared as a widget, an area on a course's online homepage that presents information for students, was developed as a means to enable the use of heart rate metrics as achievement measures in the online class. This design, development, and research effort began as an idea shared by a faculty member and myself, an instructional designer in 2013 assigned to this course. The idea was developed over the course of seven years into a tool with an accompanying pedagogical approach that is used in many courses to help facilitate physical education at a distance.

The chapters in this dissertation highlight different elements of the physical education widget. Chapter 2 outlines a conceptual and theoretical framework for the dissertation. Important concepts outlined include learning analytics generally, data driven decision making in education, and a review of wearable technology in physical education. The theoretical foundation for the research consists of attribution theory, which helps explain how students perceive their academic outcomes, and transactional distance theory, which provides a framework for explaining the critical factors in distance education.

Chapter 3 is a design case that details four major iterations of the physical education widget, tracing its development from a rough proof of concept to a fully realized tool. The design case is meant to document the process and outcome of the design, paying particular attention to the shortcomings addressed by each successive iteration and how the student experience was shaped by the eventual design. Additionally, Chapter 3 details how the design work put into the physical education widget enabled mass participation in physical education at a distance during the COVID-19 pandemic, even though the widget was not designed with such an event in mind. Ultimately, this design case is a story of forging a path where there was not one before, and it is intended to contribute to a knowledge base for other designers who might be facing similar projects.

Chapter 4 is a mixed-methods study that seeks to better understand how students use the data presented to them by the physical education widget. The study examines how students attribute their successes and failures as presented to them in the widget. The interview data collected during the study facilitated the synthesis of antecedent conditions, mediating variables, and outcomes for students using the widget. The results indicate that students generally perceive data shown through the physical education widget as reflecting their own effort, and the widget itself is viewed primarily as a time management tool to help students stay on track for meeting course goals.

The framing of learning analytics as a time management tool for students is a novel contribution to the literature on learning analytics, and could serve to inform others who seek to design tools that expose students to data about their own learning for the purpose of improving course achievement. This chapter provides a reflection on the design process, summarizes the most critical design elements, and provides implications for future practice and research.

The Design Process

The design opportunity and process that culminated in this dissertation is unusual. As an instructional designer, I was fortunate to work with a faculty member with an innovative vision for what online physical education could be. I was equally fortunate to be employed in a context that allowed me to remain engaged with the project over a number of years, nurturing and iterating on the idea to help it become a more fully realized online learning experience for students. Finally, I worked with leadership who valued the time that I spent to become technically proficient enough with a range of technologies to make this project possible. When the project began, I did not have the technical skills needed to create the widget as it exists today. Over a number of years, I was given space to learn programming language, such as python and JavaScript, alongside the other design work I was assigned. Those languages are both used in the infrastructure of the widget, and without those skills I would not have been able to see this project through to completion.

Critical Design Elements

The first critical element of both the design and research presented here is that it casts students in an active role as related to both their data and their learning. This study was concerned primarily about how students experience and use data for online physical education. The interviews conducted with students indicated that the clarity of expectations communicated in the physical education widget facilitated student achievement of course goals. In fact, all participants I interviewed were able to meet a module's heart rate goal except in cases where they chose not to participate because it would not impact their course grade.

Students primarily saw the widget as a means for time management, allowing them to apply their effort where it would best contribute to success in the course. This point is important because it indicates that students did attribute the outcomes observed in the widget to their own effort. This is an important finding because academic outcomes attributed to effort indicate self-efficacy, which is a key factor for success in learning, both online and otherwise (Leasure et al., 2020; Tsai et al., 2020; Yu & Richardson, 2015).

A final critical design element from this dissertation is the importance of contextualizing data for educational experiences. The data that are presented to students in the physical education widget is technically also available in the standard Fitbit mobile app. However, the physical education widget presents this data within the context of course goals and progress, showing students how each completed activity contributes to their overall success in the course. Each version of the app refines the contextualization of the data within the course, first refining how instructors interact with data, then enabling students to become users of their own data.

Implications for Practice

While this dissertation is focused on a particular application of learning analytics (i.e., online physical education), a broader implication for practice is clarifying the audience for learning analytics tools. Most commonly, learning analytics tools are seen as driving institutional or instructor decisions. This begs the question: Why not put the data in the hands of those to whom it most closely affects? Students generate the data found in learning analytics tools. It reflects their own activity. While it is valid for administrators and instructors to use these data to improve practice, we should also use the data to help students more effectively direct their own effort. This helps guard against objectifying students and helps us consider who should benefit from student-generated data.

This research also demonstrates that learning analytics tools are not a magical cure or silver bullet to improve student outcomes. Their application is subject to longstanding theories of academic motivation (e.g., attribution theory) or of distance learning (e.g., transactional distance theory). While learning analytics can provide a clearer picture of student engagement and student achievement, they do not bypass existing knowledge about teaching and learning.

The manuscripts presented in this dissertation suggest that the design of learning analytics tools should reflect their use as practical instruments from which actionable steps can be taken. In physical education, it was relatively easy to help students understand the action to take to show more success in the physical education widget: exercise more, or exercise with more intensity. However, this implication should be seriously considered for learning analytics in other areas. When students show a deficiency in a particular context, how can a learning analytics tool inform decision-making to help the student progress? While learning analytics tools have enjoyed a large amount of fanfare as dashboards representing large swaths of student data, casting them as time management tools for helping students effectively direct effort might be more efficacious at producing improved student learning outcomes.

Recommendations for Future Research

Much of the existing research on learning analytics has focused on how administrators and instructors use data. This study highlights the need for research to further explore how students use learning analytics tools. In the case of online physical education, they used the tool as a time management tool to plan how they will apply their physical effort toward class progress. Future research should examine student use of similar tools in the cognitive domain. For example, how might a student use data that reflects their progress in a mathematics class to improve performance? Likewise, different contexts should be explored from a design perspective as well. We should not assume that the design principles for the physical education app will map exactly onto a learning analytics tool for a different subject area. However, there is an opportunity to examine the efficacy of learning analytics tools across disciplines and distill common design principles that apply to student use of data in multiple contexts. Finally, there is more work to be done around how learning analytics tools help shape the overall design of a course through the framework of transactional distance. Upon reflecting on the current iteration of the physical education app's design, it is clear that it does have some impact on all three of the critical factors outlined by transactional distance (Moore, 2019). However, future research might examine each of these factors more closely. For example, research could focus on how students experience learner autonomy in courses that use learning analytics tools. Such research would help contribute further to the use of learning analytics for helping students improve their own performance.

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