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Investigating Factors Associated with Student Use of Digital Tools for Learning

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Conclusions

This study examined individual and environmental factors that contribute to students' usage of digital tools for learning by extending the Technology Acceptance Model (TAM), a framework on how users decide on using a technology, with self-efficacy and cognitive engagement, as well as students' background variables. Using statistical modeling, usage for tools was predicted by students' attitude towards tools, and attitude was predicted by ease of use and usefulness of tools. Self-efficacy and cognitive engagement predicted ease of use and usefulness. Both predictors were stronger when it came to predicting ease of use. Background information had a differential effect on self-efficacy and cognitive engagement. This study showed that developing students' self-efficacy and cognitive engagement is imperative to their use of technologies for learning.

So What?

Research in effective student use of learning technologies proves to be challenging (e.g., oversaturation of digital tools in the market, lack of educator training and professional development for these tools, the digital divide in education). It is therefore important to identify the factors and context that may lead students to use learning technology more frequently and effectively in classrooms. Understanding the factors that influence students' use of technology would help provide them with proper support, both technological and non-technological.

Now What?

It is evident from the research that solely providing technology is not sufficient–that students' context matters on whether a tool is used and properly integrated in their learning process. It is recommended for education practitioners to be aware of these factors when integrating digital tools in their instruction so that they can have better insights on students' performance and engagement in their classrooms. Prior to introducing a tool for learning in classrooms, educators can likely increase acceptability and use of such tools by involving students in implementation plans and evaluating their perceptions, attitudes, and learning behaviors.

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Introduction

With the rapid advances in technology (e.g., the internet, hardware, and software), technology-supported learning environments have widely emerged in K–16 learning and instruction. A survey found that 73% of teachers had their students use smartphones to conduct internet searches, and almost half of students reported using e-readers and tablets to complete in-class assignments (Purcell et. al., 2013). More recently, a survey of high school students (Moore & Vitale, 2018) reported **daily** use of technology or technological devices for school-related activities, including checking grades, emailing the teacher, researching information, and using school related web-based applications.

The integration of educational technology (EdTech) or digital tools into learning and instruction is essential to education success (Cheung & Slavin, 2013; Craig et al., 2013; Darling-Hammondet al., 2014; Graesser & D'Mello, 2012). And this often involves developing students' technology literacy: their ability to understand, manage, and use technology for self-directed learning (ITEA, 2002). Despite this, research has shown that even students who are "digital natives" struggle to effectively work with EdTech for their learning (Keengwe & Onchwari, 2017). As recently as 2018, only 20% of 8th-grade students in the US could work independently with tools for information gathering and information management (U.S. Department of Education, 2018). While most students continue to gain access to the internet and technological devices (Liberman, 2021; U.S. Department of Education, 2018), access to such technology does not necessarily translate to actual and effective use for learning (Levin, 2014). Students still need guidance in using digital tools or EdTech effectively.

Conducting research in effective student use of learning technologies proves to be challenging. First, there is an oversaturation of digital tools in the market, making it difficult to determine which tools are most effective for which type of learning. Second, there is a lack of educator training and professional development in the topic, making it difficult to implement technologies in classrooms effectively (Granić & Marangunić, 2019; Johnson et al., 2016; Keengwe, et al., 2008; Khlaif, 2018). Third, the digital divide in education–the gap between people who have access to and sufficient knowledge of technology and those who do not–continues to exist, making it difficult for learning technologies to be fully accessed and used to their full potential by all learners (Lai & Widmar, 2021; Pick et al., 2018; Pierce, 2018). However, research shows that when the digital divide is reduced, where teachers are trained to use learning technologies and students end up knowing which technology works best for them, effective learning occurs (NAEP, 2019). Given these issues, it is therefore important to identify the factors and contexts that may lead students to use learning technology more frequently and effectively in classrooms. Prior research has shown that integration of EdTech in classrooms depends, to a large extent, on teacher and student use, as well as their attitude towards that use (Davis, 1989). Actual use of EdTech may be attributed to specific contexts and cultures and the specific purposes for their use. Understanding the factors that influence students' use of technology would help provide them with proper support, both technological and non-technological.

In this study, we aim to examine student factors that may contribute to their usage of EdTech or digital tools for learning by looking at students' self-reported usage of a wide range of tools designed to aid students in learning activities within their schools. Students' use of different learning technologies was examined in a model with three core constructs of the Technology Acceptance Model, two external constructs (i.e., self-efficacy and cognitive engagement), and three background measures (i.e., student-computer ratio at school, poverty level at the school, and students' high school grade point average).

Literature Review

Educators have used technology to teach since the 1920s, but it was not until the 1980s and 1990s that school reforms began utilizing computers to assist in teaching students and to individualize learning (Cuban, 1993). Computer teaching programs traditionally focused on facilitating lower-level cognitive skills through the rote memorization of facts and figures (Flick & Bell, 2000). Since then, the rapid progression of technology has shaped teaching and learning practices. Advances in information and communications technology (ICT)–particularly with computers, mobile phones, and the Internet–have helped a resurgence in education technology (EdTech: any ICT application that aims to improve education). Advents in digital tools have been shown to be efficient in building higher-level cognitive skills, such as problem-solving or critical thinking skills (Lucas & Kinsman 2016). Decreasing costs, lightweight laptops, and the growing availability of wireless connectivity all combine to make one-to-one digital initiatives feasible on a broad scale (Penuel, 2006).

A primary category of technology used by students is for learning, where they use basic software applications to extend their abilities to solve problems, access information and resources, create knowledge artifacts, support their thinking, self-reflect, build on knowledge, or communicate and collaborate with each other (Jonassen, 1995; Jonassen et al. 2008; Morrison and Lowther 2010). Examples include word processing, presentation software, databases, spreadsheets, Web 2.0 tools, and concept mapping software, etc. Bruce and Levin (1997) proposed a taxonomy of uses of technologies for learning based on the natural impulses of a child proposed by John Dewey (1943): inquiry, communication, construction, and expression. The diversity of uses of technologies for learning is captured by these four different mediums for learning based on the goals of the learner.

Research on Educational Technology in K–12 Classrooms

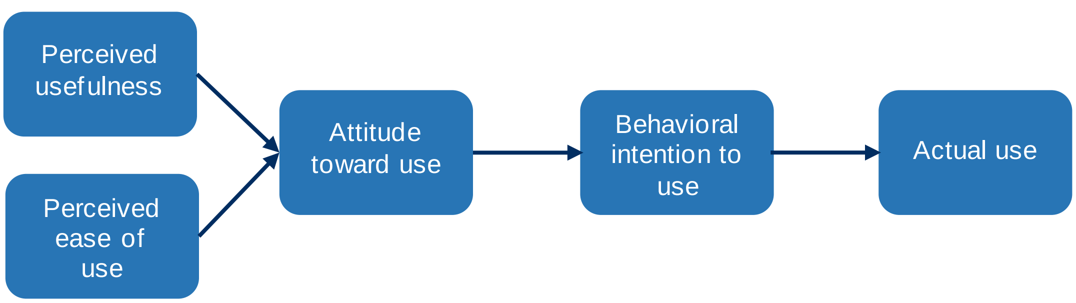
Much research on EdTech has been devoted to learning outcomes, for example: increased academic performance (Koedinger et al., 2010), enhanced higher order thinking skills (Shute et al., 2015), and learning motivation (Graesser & D'Mello, 2012; Pekrun et al., 2010; Miller et al., 2015). An extensive body of research has demonstrated that the use of technology in K–12 classrooms enhances learning and motivation (Cheung & Slavin, 2013; Craig et al., 2013; Graesser & D'Mello, 2012). For example, integrating the course tool WebCT has been shown to improve reading engagement and critical thinking skills (Burgess, 2009). Online courses (e.g., in Massive Open Online Courses or MOOCs) provide students with the opportunity to master their learning, learn at their own pace, and engage anonymously in online discussions (Adamopoulos, 2013; Zhenghao et al., 2015). Educational games and tutoring systems such as ARIES (Graesser & D'Mello, 2012), Reasoning Mind for Math (Miller et al., 2015), iSTART-ME for Writing (Jackson & McNamara, 2013), and Physics Playground for Science (Shute et al., 2015) have been found not only to enhance learning, but also to increase levels of enjoyment and motivation for student users. For certain adaptive technology, such as intelligent tutoring systems (e.g., ASSISTments, Cognitive Tutor, Wayang Outpost), empirical evidence within these environments has shown positive impacts on students' academic achievement and their attitudes toward learning (Arroyo et al., 2013; Koedinger et al, 2010; Pane et al., 2014).

Despite these known effects of EdTech on academic and non-academic outcomes, there are few instances of research that looks at students' actual usage of EdTech in K–12 classrooms and even fewer examples investigating precursors or factors that influence such usage from a student's point of view. Research has shown that users' psychological variables (cognitive ability, personality, self-efficacy, demographics, and user-situational variables, etc.) can have different levels of influence on user technology acceptance (Alavi & Joachimsthaler, 1992). However, few educational researchers have attempted to combine both technological (those pertaining to usage) and psychological (those pertaining to student skills or traits) variables into a framework for design and implementation purposes (Dillon, 2001).

Technology Acceptance Model

One model that explains and predicts behaviors of people in a specific situation and has been adopted by researchers to examine individuals adopting new information technology is the Technology Acceptance Model (TAM; Davis, 1989), a model derived from the theory of reasoned action (Ajzen & Fishbein, 1980). In TAM (Figure 1), perceived ease of use (PEOU) and perceived usefulness (PU) are two perceptions that reflect users' attitude towards technology. PEOU refers to what extent users believe that using a specific tool or system would be free from effort, while PU refers to the degree users believe that using a specific tool or system would improve their performance (Davis, 1989). TAM research shows that perceived ease of use has a positive relationship with perceived usefulness.

Figure 1. Technology Acceptance Model (Davis, 1989)



TAM has become one of the most widely used technology acceptance theories within information systems research (Lai, 2017). It offers a method to study the process of applying new technologies in the classroom or workplace. Many empirical studies have employed TAM with different technologies in different contexts (e.g., Liaw et al., 2008; Venkatesh et al., 2003), demonstrating that TAM can be a robust model to predict users' behavioral intention in adopting and using a new technology. However, TAM research has also generated inconsistent results and different effect sizes in different studies, which may be the result of different types of users, different types of task characteristics, and different types of technologies (Legris et al., 2003;

Šumak et al., 2011). To address these limitations, many researchers have attempted to extend this model by including contextual factors like cultural context (Huang et al., 2003; Straub et al., 1997), prior experience (Jackson et al., 1997), and self-efficacy (Holden & Rada, 2011). In addition, few studies have used TAM to examine the factors in technology use among K–12 students. Previous studies have found that high-performing students with high performance expectancy have more belief in the benefits of technology than that of their low-performing counterparts (Wang et al., 2009). This extension asserts that high performers tend to think EdTech in classrooms is more useful than low performers do, and thus is easier to use because they have higher self-efficacy.

Self-Efficacy in Academic Learning

Self-efficacy refers to an individual's perception and belief about behaviors that influence educational or occupational choices and participation in those choices (Bandura, 1977; Betz & Hackett, 1997). Such behaviors may include engagement in technology and learning activities in classrooms or after-school programs. These associations suggest that meaningful and effective learning can increase self-efficacy and in turn influence attitudes towards an activity. In computer-based learning environments, self-efficacy is defined as students' self-confidence in their capabilities to use computers by searching for information or help (Agudo-Peregrina et al., 2014). Self-efficacy has been used as an antecedent of academic performance in many studies. Within the learning context, the relationship between self-efficacy and academic performance had been explored across various subjects (including math, science, and general success) and in a range of learning environments (including early years, high school, and university populations). A meta-analysis of 12 years of related studies found that self-efficacy moderately correlated with academic performance (Honicke & Broadbent, 2016). However, the causality between self-efficacy and performance remains to be established since no consistent results were found. It is possible that in the context of learning with technology, students whose previous academic performance was better than others would believe themselves more capable of learning with new technology. Therefore, in our study, high-performing students are expected to have higher self-efficacy than low-performing students.

Cognitive Engagement in Academic Learning

Student engagement is a complex behavioral process (Fredricks et al., 2004; Linnenbrink & Pintrich, 2003) that has multiple components. Behavioral engagement includes observable behavior in students with respect to their effort, persistence, and help-seeking, as well as involvement in academic, social, or extracurricular activities. Emotional or motivational engagement includes positive and negative reactions that influence one's willingness to exert effort and display interest and value in their learning activities. Cognitive engagement includes active learning where students exert the effort to comprehend complex ideas and master difficult skills in a thoughtful way, such as using learning strategies and practicing self-regulation or meta-cognition.

Student engagement, learning, and achievement are reciprocally related to self-efficacy, where self-efficacy leads to more engagement and subsequently more learning and better achievement, which in turn increases self-efficacy (Linnenbrink & Pintrich, 2003). Students who are more engaged in school tend to have higher academic motivation and achievement

(Fredericks, et al., 2004; Pardos et al., 2013). Related to this, research studies on the relationships between engaged behaviors and learning have found that the academic emotion of engaged concentration is positively associated with learning outcomes (Craig et al., 2004; Csikszentmihalyi, 1990). Engaged concentration is related to Csikszentmihalyi's flow state (1990); it describes the state when a student has intense concentration, focused attention, and complete involvement in the task at hand (Baker et al., 2010).

In this study, we focus on cognitive engagement in relation to learning with technology use. Finn and Zimmer (2012) found behaviors that are suggestive of cognitive engagement, such as asking questions to clarify concepts, persisting with difficult tasks, reviewing materials, reading or studying sources of information beyond those required, and using self-regulation and other cognitive strategies to guide learning.

Research Model

Based on the theoretical background in the previous section, we hypothesize a research model where motivational and behavioral factors such as students' self-efficacy and cognitive engagement have positive effects on known factors from TAM that contribute to their actual usage of learning technologies. We investigate these relationships while also controlling for background variables (i.e., student GPA, school's student-to-computer ratio, and poverty level). Our model, in Figure 2, consists of actual usage of learning technologies (i.e., frequency of use of 14 tools), attitude towards use, perceived usefulness, perceived ease of use, self-efficacy, cognitive engagement, student GPA, school's student-to-computer ratio, and poverty level. We incorporate self-efficacy and cognitive engagement as precursors of the core TAM framework but bypassing intent to use since we are considering learning technologies used in classroom; even if a student has a positive attitude towards a learning tool, they may only be using it because the teacher requires it and the student may have no intention of using it in the first place (cf., Ngai et al., 2007, Sánchez & Hueros, 2010).

In this study, perceived ease of use (PEOU) of EdTech in classrooms is the level of effort a student considers needed for using digital tools. The perceived usefulness (PU) of EdTech in classrooms is defined as the degree to which users believe that using a tool would boost their learning. TAM postulates that perceived usefulness and perceived ease of use have direct effects on attitudes towards usage of new technology. This attitude is the degree to which a student is interested in a digital tool, and student usage of EdTech in classrooms is influenced by their attitude towards technology which is then influenced by their perceived ease of use and perceived usefulness. We hypothesize that:

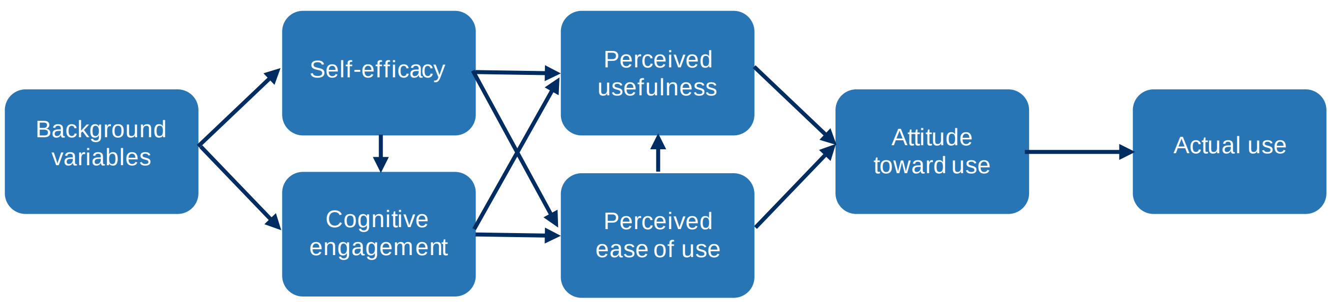
- Hypothesis 1. Attitude towards using EdTech in classrooms has a positive effect on their actual usage.
- Hypothesis 2. Perceived ease of use has a positive effect on attitudes towards using EdTech in classrooms.
- Hypothesis 3. Perceived usefulness has a positive effect on attitudes towards using EdTech in classrooms.

- Hypothesis 4. Perceived ease of use has a positive effect on the perceived usefulness of EdTech in classrooms.

Based also on our literature review on extended TAM in the context of EdTech in classrooms, this study also proposes the following research hypotheses on precursors of TAM's components.

- Hypothesis 5. Background variables of students' GPAs and their schools' student-to-computer-ratios and poverty levels have a significant effect on students' self-efficacy and cognitive engagement in classrooms.
- Hypothesis 6. Self-efficacy for learning has a positive effect on the perceived usefulness of EdTech in classrooms.
- Hypothesis 7. Self-efficacy for learning has a positive effect on the perceived ease of use of EdTech in classrooms.
- Hypothesis 8. Cognitive engagement in learning has a positive effect on the perceived usefulness of EdTech in classrooms.
- Hypothesis 9. Cognitive engagement in learning has a positive effect on the perceived ease of use of EdTech in classrooms.
- Hypothesis 10. Self-efficacy for learning has a positive effect on cognitive engagement.

Figure 2. Hypothesized Model for EdTech Use in Classrooms



Methods

Participants

The sample used for analysis in this study consisted of 3,460 U.S. high school students (62% female, 38% male) who completed the ACT® test in February 2020. Most of the participants were in their junior (56%) or senior (36%) year of high school with a smaller percentage (8%) in their sophomore year. The racial composition of students included: White (62%), Hispanic/Latinx (17%), African American/Black (14%), and Asian (7%), with the remaining students either indicating "other" (e.g., multiracial, Native American) or choosing not to respond.

Procedure

An online survey was administered to a random sample of 65,800 registered test takers out of 259,873 who had completed the ACT in February 2020. A total of 3,460 registered test takers responded to the survey ((5.3% response rate). An email invitation was sent in February 2020 to test takers asking them to participate in a survey about their use and perceptions of educational technology. No incentives were provided. Students spent approximately 12 minutes, on average, completing the survey. These survey responses were then matched with students' self-reported academic information (i.e., high school GPA), collected at the time of test registration, and school-level characteristics (i.e., poverty level, student to computer ratio) originating from MDR.

Measures

Technology Use

A total of 14 items were used to describe students' frequency of use of technology for learning during school. Items were generated from work conducted by Goodyear and Retalis (2010) and can loosely be categorized into four groups: technologies to access and study learning materials (e.g., learning management systems), technologies that enable learning communication and collaboration (e.g., cloud services that allow the simultaneous revision of a shared document or presentation), technologies for assessing learners (e.g., online tests), and technologies enabling a learning-by-doing approach through construction and programming (e.g., assembling and programming robotics). Because previous confirmatory analyses did not show good item fit to these four constructs, we measured technology use at the item level. Item examples include: "How often during school hours do you use learning management systems (i.e., Moodle, Canvas, Blackboard, Google classroom) for class-related work?" and "How often during school hours do you use file sharing tools (e.g., Google docs, Dropbox, iCloud) for class-related work?" A seven-point frequency scale was used: 1 = not at all, 2 = less than once a week, 3 = about once a week, 4 = 2–3 times a week, 5 = 4–6 times a week, 6 = about once a day, 7 = more than once a day.

Perceived Usefulness

A total of five items were developed to measure the perceived usefulness of using digital technologies to complete school-related requirements, based on Davis's perceived usefulness scale for employees as they did their work (1989). Example items in our study included: "Using digital technologies makes me more productive when doing school-related work" and "Using digital technologies helps me finish school-related work quickly." A six-point scale was used such that 1 = strongly disagree and 6 = strongly agree.

Ease of Use

Like perceived usefulness, four ease of use items were developed based on the theoretical and empirical underpinnings set forth by Davis (1989). Items in this study measured students' beliefs about the ease of using technology for learning. Example items included "I am able to accomplish school-related activities using digital technologies without any help from others" and "It would be easy for me to learn how to use school-related digital technologies that are new to me." A six-point scale was used such that 1 = strongly disagree and 6 = strongly agree. Cronbach's alpha was .94.

Attitudes Toward Technology

Four items were used to measure students' attitudes toward technology. Attitudes used in the items were defined as "psychological tendencies that are expressed by evaluating a particular entity with some degree of (dis)favor" (Albarracin, Zanna, Johnson, & Kumkala, 2005). An example item: "I would prefer using digital technologies for class-related work than not." A six-point scale was used such that 1 = strongly disagree and 6 = strongly agree. Cronbach's alpha was .64.

Cognitive Engagement

Items for cognitive engagement were based on school engagement research by Fredericks et al. (2005), where they define cognitive engagement as "being thoughtful and being willing to exert the necessary effort for comprehension of complex ideas and master of difficult skills." We measured this construct using 6 items. Example items include: "I talk with people outside of school about what I am learning in class" and "When I read a book, I ask myself questions to make sure I understand what it is about." A four-point scale was used: 1 = not true of me, 2 = somewhat true of me, 3 = moderately true of me, and 4 = very true of me. Cronbach's alpha was .77.

Self-Efficacy

Students' sense of efficacy was based on Bandura's definition of the concept "as one's belief in one's ability to succeed in specific situations or accomplish a task" (Bandura, 1977). We therefore measured students' sense of self-efficacy to succeed in a class where they used technology for learning. Students were asked to answer eight items, including "I believe I will receive an excellent grade in this class" and "I'm confident I can understand the basic concepts taught in this course." A four-point scale was used: 1 = not true of me, 2 = somewhat true of me, 3 = moderately true of me, and 4 = very true of me. Cronbach's alpha was .93.

High School GPA

Students were also asked to self-report their course grades in their high school classes taken. These grades were then converted to an overall GPA, which ranged from 0 to 4.00.

Poverty Level

The poverty level data is sourced from the U.S. Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program, which provides annual estimates of income and poverty statistics for all states, counties, and school districts. The poverty level code field was calculated by MDR by creating a ratio of the children in a district from families below the poverty line to all children in the district. The categories include: 0%–5.9% of the students are below the poverty line, 6%–15.9%, 16%–30.9%, and 31% or more.

Student-to-Computer Ratio

This ratio is determined by dividing the enrollment of a school by the total number of computers–all brands–in the school. High computer density (lower ranges) indicates fewer students sharing a computer, while low computer density (higher ranges) indicates more students per computer. These data are calculated by MDR and grouped into a seven-point scale: 1–3 computer density, 4–6 computer density, 7–9 computer density, 10–14 computer density, 15–19 computer density, 20–29 computer density, and more than 30 computer density.

Data Analysis Steps

Multiple Imputation

Missing data from our sample were accounted for using multiple imputation (Rubin, 1987). Imputation was conducted multiple times (five times, using Rubin's old rule of thumb of 3 to 10 imputations that typically suffice) to create estimates that pool across multiple data sets. The predicted values were estimated using all the variables to be used in the final structural equation model because it is important to include correlates of the dependent variable used in the primary analysis. It is worth noting that the intent of multiple imputation is not to guess an individual's response to a survey item; rather, the intent is to analyze data that maintain the variability and relationship of all the variables in the model. Calculations for multiple imputations were conducted in R (Version 4.0.1). A total of 33% of survey respondents had missing data on family income, followed by 25% missing on the school's poverty level. There was 21% missing on high school GPA, 18% missing on student to computer ratio, 16% missing on parents' educational level, and 8% missing on the school's zip code. Less than 1% was missing on the survey items and students' gender. There was no missing data on students' race.

Sample Weighting

Because we administered the survey to a stratified random sample based on students' high school GPA, and because a disproportionate number of female students participated in the study, we weighted the survey responses. Weighting reduces the chances for non-response bias, corrects for the stratified sampling and on key measures related to use of EdTech, and makes the survey respondents more representative of the February 2020 population to which they are being generalized. Propensity score weighting was used to create sample weights. Here, a logistic regression model was estimated predicting the probability of survey participation, given population characteristics. We used students' race/ethnicity, gender, parents' education level, high school GPA, and family income as predictors. Table 1 provides descriptive statistics for the unweighted sample, weighted sample, and the population.

Table 1. Background Descriptive Statistics of Sample and Population (Unweighted and Weighted)

Attribute	Value	Unweighted Sample (n = 3460)	Weighted Sample (n = 3460)	Population (n=259,873)
Family Income	Low (<$36,000)	667 (19.3%)	553.2 (16.0%)	42270 (16.27%)
	Average ($36,000-$100,000)	858 (24.8%)	860.9 (24.9%)	64228 (24.72%)
	High (>$100,000)	783 (22.6%)	988.1 (28. 6%)	73471 (28.27%)
	Missing	1152 (33.3%)	1057.8 (30.6%)	79904 (30.75%)
Race/ Ethnicity	White	1810 (52.3%)	1913.2 (55.3%)	142599 (54.9%)
	Black	491 (14.2%)	567.1 (16.5%)	41562 (16.0%)
	Hispanic/Latino	580 (16.8%)	481.7 (13.9%)	35975 (13.8%)
	Asian	246 (7.1%)	172.5 (5.0%)	13842 (5.3%)
	Other	186 (5.4%)	186.1 (5.38%)	14093 (5.4%)
	Missing	147 (4.2%)	137.5 (4.0%)	11802 (4.5%)
Parent's Education Level	High School Graduate	890 (25.7%)	1079.2 (31.2%)	77310 (29.8%)
	Some College or Less	843 (24.4%)	733.1 (21.2%)	55447 (21.3%)
	Certificate/Associate	327 (9.4%)	319.0 (9.2%)	24656 (9.5%)
	Bachelor's	825 (23.8%)	926.3 (26.8%)	70546 (27.2%)
	Missing	575 (16.6%)	402.4 (11.6%)	31914 (12.3%)
Gender	Female	2139 (61.8%)	1916.6 (55.4%)	145304 (55.9%)
	Male	1277 (36.9%)	1510.7 (43.7%)	113213 (43.6%)
	Missing	44 (1.3%)	32.7 (0.9%)	1356 (0.5%)
Mean HS GPA	–	3.4 (SD = 0.6)	3.52 (SD = 0.53)	3.52 (SD = .51)

Structural Equation Modeling

A structural equation model (SEM) was estimated to answer our central research question: What are the factors related to students' use of digital tools for learning? SEM allows for the simultaneous analyses of both antecedents and by-products of multiple mediating measures. For the purposes of this research question, a recursive equation model was estimated, which allows for the use of latent and measurement models to be estimated simultaneously. We hypothesized that perceived ease of use (PEOU) and perceived usefulness (PU) will both be predictors of actual usage. In previous studies, PEOU and PU were correlated with self-reported current and future usage obtained based on two separate studies (ex., Davis, 1989). PU had a significantly greater correlation with usage behavior than did PEOU. Regression analysis also suggests that PEOU may be a causal antecedent to PU as opposed to a parallel direction determinate of system usage. So, we tested this as well. Likewise, we investigated whether and to what degree students' sense of self-efficacy and cognitive engagement were related to students' PEOU and PU of technology. Students' GPA, proportion of students at school in poverty, and student to computer ratio at the students' schools were used as controls.

Results

Measurement Model

The descriptive statistics of mean and standard deviation (weighted) were calculated for the items measured (Table 2 and Table 3). The means of the 14 technology items that were on a one-to-seven scale ranged from 1.61 (tutoring systems; SD = 1.42) to 6.00 (search engines; SD = 1.64); 3.82 (attitude; SD = 1.56) to 5.09 (usefulness; SD = 1.15) for TAM-related items that were on a one-to-six scale; and 1.94 (cognitive engagement; SD = 1.04) to 3.51 (self-efficacy; SD = 0.74) for motivational items that were on a one-to-four scale. There is greater frequency in using digital tools to access student learning materials in classrooms, such as LMS, videos, and search engines (M = 4.38 to 6.0), as well as file sharing tools (M = 5.11). On the other hand, there seems to be a lesser frequency of usage in classrooms per week for tools that help build skills or those that are more specific to subjects.

Reliability was assessed using Cronbach's alpha to determine the extent to which measured items within the same construct were related to each other. Cronbach’s alpha coefficients, calculated for each of the constructs, ranged from .52 to .70 for the tech tools (not included in Table 2), .71 to .89 for TAM-related constructs, and .77 to .93 for motivational constructs, most of which exceeded the recommended cutoff of .7 (McCrae et al., 2011; Nunnally, 1978). Construct validity of the measurement model was assessed through a confirmatory factor analysis. The purpose was to determine whether the sample data provides empirical support for the proposed theoretical structure of the constructs. Convergent validity is shown when all indicator factor loadings within the construct exceed the conservative level of .7 at the significance level of $p < .05$. As listed in Table 3, most of the standardized factor loadings exceeded .7, and all loadings except for two were almost 0.5 (0.495 and 0.499). Even though there were below .7 factor loadings, the CFA model converged, with indices that indicated a good fit: $\chi 2(289) = 2962.95$ ($p < 0.001$), RMSEA = 0.052, SRMR = 0.04, CFI = 0.941, GFI = 0.986, NFI = 0.936, and TLI = 0.934. Discriminant validity was confirmed by examining correlations among the constructs. As a rule of thumb, a correlation of 0.85 or larger indicates poor discriminant validity in SEM (David, 1998). The results suggested an adequate discriminant validity of the measurement model. The correlation matrix between constructs is shown in Table 4.

Table 2. Descriptive Statistics of Technology Use Items

Items		Mean	Standard Deviation
Approximately how often during school hours do you use the following *digital technologies to access and study class-related materials* (1–7; Not at all, Less than once a week, About once a week, 2–3 times a week, 4–6 times a week. About once a day, More than once a day)	Q3_1: Learning management systems (i.e., Moodle, Canvas, Blackboard, Google classroom)	5.35	2.11
	Q3_2: Videos (e.g., YouTube, Vimeo, TED Talks, Khan Academy, etc.)	4.38	1.98
	Q3_3: Search engines (e.g., Google, iSEEK, ThinkQuest, Bing, Yahoo)	6.00	1.64
Approximately how often during school hours do you use the following *digital technologies to communicate and collaborate with others for class-related work*? (1–7; Not at all, Less than once a week, About once a week, 2–3 times a week, 4–6 times a week. About once a day, More than once a day)	Q5_1: File sharing tools (e.g., Google docs, Dropbox, iCloud)	5.11	2.01
	Q5_2: Web conferencing tools (e.g., Google Hangout, Skype)	2.10	1.91
	Q5_3: Social media tools (e.g., Twitter, Facebook, Schoology, Edmodo)	3.56	2.48
Approximately how often during school hours do you use the following *digital technologies to help build your skills for class-related work*? (1–7; Not at all, Less than once a week, About once a week, 2–3 times a week, 4–6 times a week. About once a day, More than once a day)	Q6_1: Mobile apps that aid in studying for a specific subject (e.g., Duolingo, Photomath, Quizlet, Flashcard apps)	3.93	1.97
	Q6_2: Educational games (e.g., MinecraftEDU, Kahoot, Zoombinis, iCivics, Wuzzit)	2.69	1.64
	Q6_3: Tutoring systems (e.g., iReady, ASSISTments, Cognitive Tutor, ALEKS)	1.61	1.42
Approximately how often during school hours do you use the following *digital technologies for class-related work*? (1–7; Not at all, Less than once a week, About once a week, 2–3 times a week, 4–6 times a week. About once a day, More than once a day)	Q7_1: Programming tools (e.g., Arduino, Raspberry Pi, Python, Java, C++)	1.68	1.53
	Q7_2: Office documents (e.g., Word, Spreadsheet/Excel, Prezi/PowerPoint)	3.86	2.15
	Q7_3: Note taking, bookmarking tools (e.g., OneNote, Evernote)	2.32	2.09
	Q7_4: Visual design tools (e.g., Adobe Spark, Photoshop, or Illustrator; Canva, Sumo Paint)	2.02	1.69
	Q7_5: Multimedia tools (e.g., iMovie, Adobe Premiere, Windows MovieMaker)	1.89	1.51

Table 3. Descriptive Statistics of Construct Items and Measurement Model Results

Construct	Items		Mean	SD	Factor Loading (Std)	Cronbach's α
Usefulness	Please indicate the extent to which you agree or disagree with the following statements about the *usefulness of digital technologies*. (1–6; Strongly disagree, Moderately disagree, Somewhat disagree, Somewhat agree, Moderately agree, Strongly agree)	Q16_1: Using digital technologies makes me more productive when doing school-related work.	4.54	1.34	0.759	0.89
		Q16_2: Using digital technologies helps me do well in school.	4.91	1.16	0.827	
		Q16_3: Using digital technologies helps me to learn more information for school.	5.04	1.16	0.771	
		Q16_4: Using digital technologies helps me finish school-related work quickly.	5.02	1.17	0.780	
		Q16_5: Using digital technologies makes it easy for me to complete school-related work.	5.09	1.15	0.803	
Ease of Use	Please indicate the extent to which you agree or disagree with the following statements about the *ease of use*	Q17_1: It would be easy for me to learn how to use school-related digital technologies that are new to me.	4.92	1.15	0.816	0.84

	of digital technologies. (1–6; Strongly disagree, Moderately disagree, Somewhat disagree, Somewhat agree, Moderately agree, Strongly agree)	Q17_2: I could find a new digital technology on my own to help me with school-related work.	4.61	1.34	0.689	
		Q17_3: It would be easy for me to become an expert in using digital technologies for school-related work.	4.67	1.32	0.791	
		Q17_4: I am able to accomplish school-related activities using digital technologies without any help from others.	4.97	1.14	0.712	
Attitude	Please indicate the extent to which you agree or disagree with the following statements about digital technologies. (1–6; Strongly disagree, Moderately disagree, Somewhat disagree, Somewhat agree, Moderately agree, Strongly agree)	Q18_1: I would prefer using digital technologies for class-related work than not.	4.34	1.43	0.800	0.71
		Q18_2: I tend to use digital technologies for class-related activities, even if my teacher does not tell me to.	4.12	1.50	0.583	
		Q18_3: I know a wide variety of digital technologies that can help me with class-related activities.	4.70	1.26	0.705	
Self-Efficacy	Thinking about this class, to what extent are the following	Q20_1: I believe I will receive an excellent grade in this class. (1)	3.35	0.82	0.809	0.93

	statements true for you? (1–4; Not true of me, Somewhat true of me, Moderately true of me, Very true of me)	Q20_2: I'm certain I can understand the most difficult material presented in the readings for this course.	3.07	0.89	0.767	
		Q20_3: I'm confident I can understand the basic concepts taught in this course.	3.51	0.74	0.737	
		Q20_4: I'm confident I can understand the most complex material presented by the instructor in this course.	3.11	0.89	0.802	
		Q20_5: I'm confident I can do an excellent job on the assignments and tests in this course.	3.28	0.82	0.846	
		Q20_6: I expect to do well in this class.	3.51	0.74	0.773	
		Q20_7: I'm certain I can master the skills being taught in this class.	3.23	0.83	0.782	
		Q20_8: Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.	3.40	0.78	0.825	
Cognitive Engagement	To what extent are the following	Q21_1: When I read a book, I ask myself questions	2.48	1.07	0.660	0.77

	statements true for you? (1–4; Not true of me, Somewhat true of me, Moderately true of me, Very true of me)	to make sure I understand what it is about.			
		Q21_2: I study at home even when I don't have a test.	2.12	1.05	0.682
		Q21_3: I talk with people outside of school about what I am learning in class.	2.89	1.00	0.495
		Q21_4: I check my schoolwork for mistakes.	2.94	0.97	0.571
		Q21_5: If I don't know what a word means when I am reading, I do something to figure it out, like look it up in the dictionary or ask someone.	3.09	0.97	0.499
		Q21_6: I read extra books to learn more about things we do in school.	1.94	1.04	0.655

Table 4. Estimated Correlations Among Constructs (All Have *p*-Values <.001)

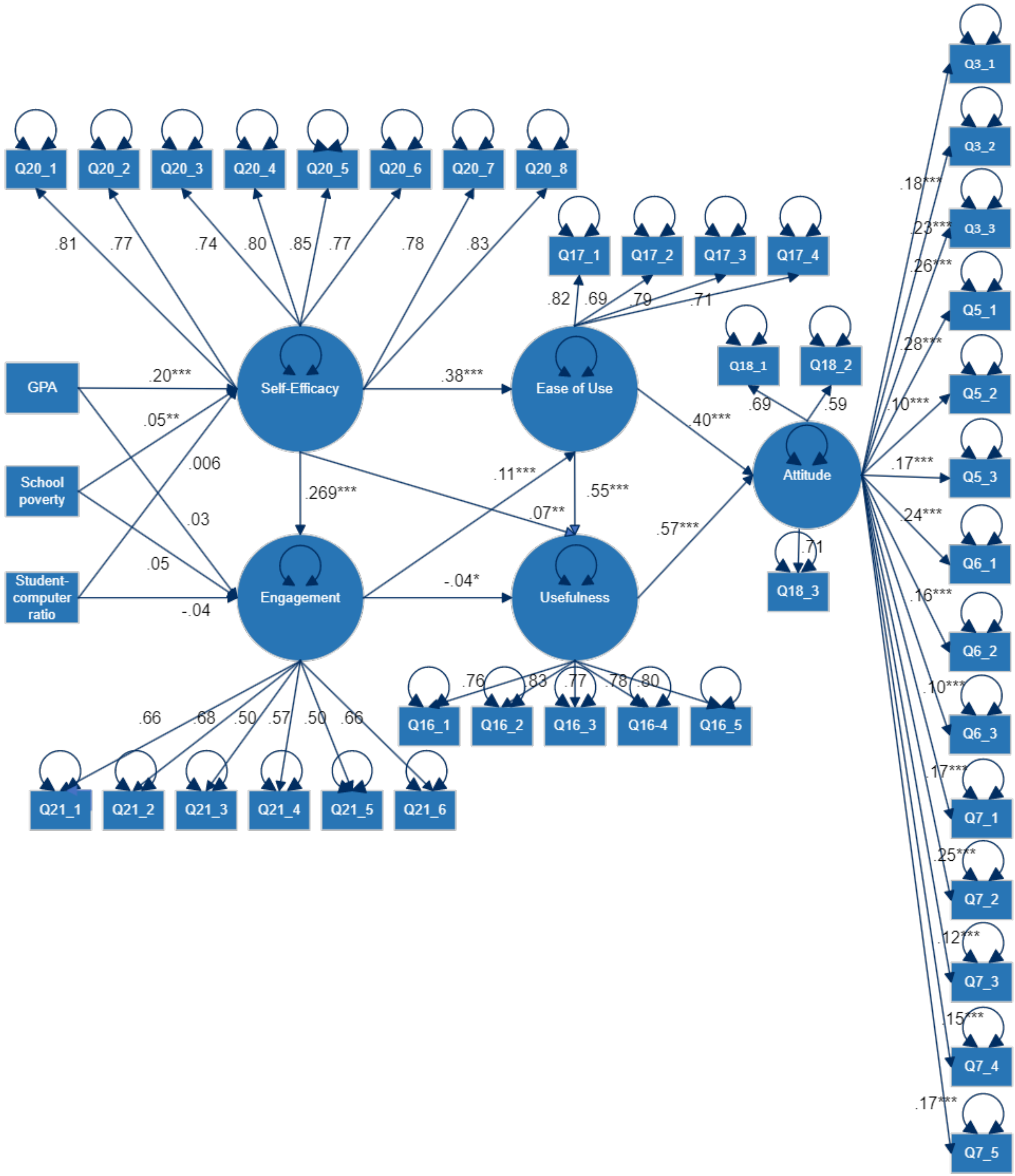
Construct	Usefulness	Ease of Use	Attitude	Self-Efficacy
Usefulness	1	–	–	–
Ease of Use	.584	1	–	–
Attitude	.805	.732	1	–
Self-Efficacy	.301	.409	.312	1
Cognitive Engagement	.172	.211	.203	.271

Structural Model (Hypotheses Testing)

Similar to the measurement model, this structural model was interpreted with a set of fit indices: $\chi 2(755) = 5029.58$ ($p < 0.001$), RMSEA = 0.04, SRMR = .046, CFI = 0.927, GFI = 0.981, NFI = 0.916, and TLI = 0.913. The overall results demonstrate an acceptable fit between observed sample data and the structural model based on various fit indices.

In testing the proposed hypotheses, the results of the structural model are illustrated in Figure 3. Note that all standardized beta coefficients of our factors are positive. The usage for each of the 14 tools was predicted by attitude at the $p < .001$ significance level, with a variance range of 1% to 8% that was accounted for by attitude (β coefficients ranging from .097 to 0.275, all with $p < .001$). In total, 75.3% of the variance in attitude was explained by ease of use (β = 0.402, $p < .001$) and usefulness (β = 0.569, $p < .001$). This relationship is consistent with the TAM framework (Davis, 1989). The influence of ease of use on usefulness was supported, as well as the influence of self-efficacy and cognitive engagement at the $p < .001$ level. Self-efficacy (β = 0.065, $p = .002$), cognitive engagement (β = 0.042, $p = .046$), and ease of use (β = 0.549, $p < .001$) accounted for 34.7% of the variance in usefulness, while self-efficacy (β = 0.377, $p < .001$) and cognitive engagement (β = 0.113, $p < .001$) accounted for 17.9% of the variance in ease of use. It is interesting to note that both self-efficacy and engagement have a stronger influence on ease of use than they do on usefulness. For the background variables, only GPA (β = 0.196, $p < .001$) and school poverty level (β = -0.053, $p = .007$) showed significant influence on self-efficacy at the $p < .01$ level, accounting for 4.5% of the variance in self-efficacy, while only self-efficacy (β = 0.269, $p < .001$) and school poverty level (β = 0.047, $p = .024$) showed significant relationships with cognitive engagement, accounting for 7.8% of the variance in cognitive engagement.

Figure 3. Resulting Structural Model of Technology Use



* $p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Discussion and Conclusion

In this paper, we investigated a combination of background variables and malleable factors that are observed during student's use of technology for learning (EdTech) in the classroom. Taking survey data from 3,460 students about their usage of learning technologies, behavior, and motivation during learning, we used structural equation modeling to modify the Technology Acceptance Model (TAM) to include constructs important to learning, as well as school and student information. We used TAM's core components of perceived ease of use, perceived usefulness, and attitude towards technology and combined them with students' self-efficacy, cognitive engagement, high school GPA, their school's student-to-computer ratio, and poverty level to model usage of 14 learning technologies.

Our results found that usage of EdTech in classrooms (frequency) is related to a combination of background (individual and environmental) variables used in the model, as well as motivational and behavioral factors. The goodness of fit of the resulting structural equation model indicates that our hypothesized model was robust and represented our data well, showing relations between students' actual usage of a variety of EdTech in classrooms and the hypothesized factors. Student GPA had a significant influence on self-efficacy but not on cognitive engagement, which may suggest that students' ability is not necessarily indicative of their effort to actively learn. It is plausible that cognitive engagement may be driven more inherently by their motivation to learn or self-belief than their innate cognitive ability (i.e., self-efficacy having a significant direct effect on cognitive engagement). While school poverty level, representing a student's access to classroom resources, significantly influenced both self-efficacy and cognitive engagement, it was a weak predictor of both. In addition, student-to-computer ratio at school did not have any significant influences on self-efficacy or cognitive engagement, which may be due to access to mobile devices as opposed to a computer, or self-efficacy and cognitive engagement for learning not necessarily being dependent on usage of technology.

Consistent with our hypothesized model, our results then showed that these external motivational and behavioral variables (self-efficacy and cognitive engagement) have significant influences on perceived ease of use and perceived usefulness of EdTech in classrooms. The weak influence of self-efficacy on perceived usefulness compared to perceived ease of use could be due to the actual design and function of a tool. Such tool design and functionality may determine one's perception of usefulness as opposed to being primarily determined by self-efficacy and cognitive engagement. And in accordance with the TAM framework, our results then revealed that students' perceived usefulness (PU) and perceived ease of use (PEOU) significantly predicted their attitude towards the tools which, in turn, influenced their actual usage of different learning technologies in classrooms. It is interesting to note that the beta coefficients of attitude towards technology are all significant with large magnitudes ($> .20$) on videos, search engines, file sharing tools, mobile apps, and programming tools, with PU and PEOU having large beta coefficients ($\geq .40$) on attitude towards technology.

Our model confirms both the core TAM framework (even without the construct behavioral intention to use) and the hypothesis that students may form their attitude towards EdTech in classrooms and eventual usage of these tools by relying on their assessment of how at ease they were when using them for learning and how useful the tools were in accomplishing the learning activities involved in the tools. This relationship may further be explained by attitudes towards technology usage behavior being extrinsically motivated by students' perception of its usefulness and ease of use. This instance of goal-oriented behavior (Deci & Ryan, 1985) when using technology may be driven by a student's expectation that using a tool would improve their understanding of how to use that tool to perform or accomplish a task.

The findings from this study are in line with previous research about technology acceptance in classrooms and confirm the influence of contextual factors on the perceptions of use of EdTech in classrooms (Granić & Marangunić, 2019; Ngai et al., 2007; Park et al., 2012; Sánchez & Hueros, 2010). More than that, this study contributes to the EdTech literature by extending our current understanding of learning technologies within the classroom from the student perspective by investigating students' actual learning experiences with a variety of EdTech and using their self-efficacy and cognitive engagement during learning, which has not been considered so far in the area of technology integration within classrooms. This study also examines technology acceptance research in a high school context, a setting of which has been scarcely looked at.

From this study, it is evident that solely providing technology is not sufficient–that students' context matters on whether a tool is used and effectively integrated in their learning process. This is particularly telling since the student-to-computer ratio was not important in our model. Instead, students' self-efficacy and cognitive engagement ought to be developed since both are directly related to PEOU and PU and indirectly to attitudes towards technology. This finding suggests that it is valuable to foster self-confidence and active learning in students so they can recognize how a tool can be easily and effectively used. It is recommended for education practitioners to be aware of these factors when integrating digital tools in their instruction, so they can have better insights on students' performance and engagement in their classrooms, beyond individual ability. Prior to introducing a tool for learning in classrooms, educators can likely increase acceptability and use of such tools by involving students in implementation plans and evaluating their perceptions, attitudes, and learning behavior.

Students' non-usage of tools may be a function of the tools themselves (i.e., usability), their lack of familiarity and proper guidance in using these tools, or even their own motivations and perceptions in using tools for learning activities. It would benefit students for education practitioners to adopt learning technologies in classrooms that have motivational or personalized elements, such as scaffolding, hints, and other feedback, to develop and sustain student engagement with these tools or effective guides and tutorials to aid students when they struggle with use.

Overall, the current study was modeled around the TAM framework to identify factors affecting acceptance and integration of different technologies in classrooms (i.e., through its frequency of use) in response to the growing value and benefit of technology in educational settings. We emphasized the motives of actual usage of EdTech from a student perspective, given its inherent value of aiding students to learn and assisting in their instruction. We wanted to know factors that can contribute to students using a digital tool for learning when they have access to it. This may lead to insights on what tools and tool features work and are preferred by students given the wide variety of EdTech in the market.

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