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Catherine Armstrong Asher
University of Michigan

Ethan Scherer
Harvard University

James S. Kim
Harvard University

Johanna Norshus Tvedt
Harvard University

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Catherine Armstrong Asher
Youth Policy Lab at University of Michigan's Institute for Social Research

Ethan Scherer
READS Lab and Center for Education Policy Research at Harvard University

James S. Kim
Harvard University, Graduate School of Education

Johanna Norshus Tvedt
READS Lab and Center for Education Policy Research at Harvard University

Abstract:

We leverage log data from an educational app and two-way text message records from over 3,500 students during the summers of 2019 and 2020, along with in-depth interviews in Spanish and English, to identify patterns of family engagement with educational technology. Based on the type and timing of technology use, we identify several distinct profiles of engagement, which we group into two categories: Independent Users who engage with technology-based educational software independently, and Interaction-Supported Users who use two-way communications to support their engagement. We also find that as the demands of families from schools increased during the COVID-19 pandemic, Spanish-speaking families were significantly more likely than English-speaking families to engage with educational technology across all categories of families, particularly as Interaction-Supported Users.

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Introduction

Families and schools are both important elements of children's educational success (Fan & Chen, 2001; Houtenville & Conway, 2008; Todd & Wolpin, 2007), and family educational engagement is an important factor in children's own engagement and learning (Raftery, Grolnick, & Flamm, 2012). As schools continue refining their efforts to engage families, one likely legacy of the COVID-19 pandemic will be an increased use of technology. Family engagement, or "parents' interaction with schools and with their children to promote academic success," (Hill & Taylor, 2004, p.1491) encompasses a variety of activities and mindsets (Epstein, 1990). Similarly, educational technology includes a broad array of interventions that target substantively different problems, from online learning to broadband internet access (Escueta et al., 2020). In this way, educational technology includes both specific learning resources, like app activities, and platforms for communication, like text-messaging.

Whether this increased reliance on technology (to both communicate and provide resources) will strengthen school-family ties remains an important question. While there is emerging evidence that school-based messaging can increase family engagement (Asher, Scherer et al., 2022; Doss et al., 2019; Kim et al., 2019; York et al., 2018), other resources like parent portals and virtual tutoring often suffer from low participation and inequitable access (Bergman, 2020; Kraft & Bolves, 2021; Robinson, Bisht, & Loeb, 2022). Prior work has documented variation in parental preference in school communication and resources (e.g., Cortes et al., 2019a, Cortes et al., 2019b), suggesting that blanket policies may not engage all families.

In this study, we investigate this heterogeneity in two forms of technology-supported family engagement: how families facilitate their children's learning outside of school when provided access to a free educational app and two-way texting. To do this, we leverage time-stamped app log data and the text message records from over 3,500 families during the summers of 2019 and 2020. We use Latent Profile Analysis to identify distinct family groups based on their patterns of technology engagement, and we complement these findings with in-depth interviews from a subset of Spanish- and English-speaking families.

Our analysis makes several contributions. It is the first, to our knowledge, to explore the variation in family engagement with education technology when offered both an educational app and a two-way texting intervention outside the app. In particular, our use of person-centered analyses differentiates us from most other rigorous analyses of educational technology that use variable-centered approaches. Second, we explore whether family engagement patterns shifted as school-provided resources changed in response to the COVID-19 pandemic. Finally, data from the app and messaging platforms allows us to move beyond families' self-reported feelings and activities; instead, we can directly observe their behaviors. Our results have implications for research and practice, and suggest that schools may need to employ a variety of strategies to connect with families with different engagement preferences.

Use of technology to facilitate family engagement

Technology could be a mechanism for encouraging family engagement in student learning. It can facilitate communication between schools and families and has the potential to be scaled at a low cost. Direct forms of communication, such as texting, have shown promise for increasing family participation in student learning (Escueta et al., 2020). Such initiatives reduce common communication frictions between parents and schools and provide parents timely, actionable information. Several studies show that providing information can change parents' educational decision and influence students' learning activities outside of school (Doss et al., 2019; Kim et al., 2019; York et al., 2018; Asher, Scherer et al., 2022, Cortes et al., 2019a; Cortes et al., 2019b; Kraft & Monti-Nusbaum, 2017). While there is excitement about technology's potential to transform school-family communication, questions remain whether all types of technology-supported communication are equally effective and whether the effects are equitably distributed among families. While many districts use portals to provide parents with information about their child, and sometimes facilitate two-way communication, these platforms often suffer from low take-up by families, even when behavioral nudges or technological support is provided (Bergman, 2020; Kraft & Bolves, 2021; Robinson, Bisht, & Loeb, 2022). Furthermore, there is often differential take-up by family income and race, which could further exacerbate existing gaps between demographic groups (Kraft & Bolves, 2021).

Another key component of out-of-school family engagement is the use of self-contained technological resources, such as educational apps, sometimes called "computer-assisted learning software" (Escueta et al., 2020). These are programs that focus on improving particular academic skills (Rouse & Krueger, 2004). Use of at-home software was already growing exponentially prior to the pandemic, and recent reviews indicate that some of these programs can improve achievement (Escueta et al., 2020; Kim et al., 2021). These resources could provide a tool for families to implement targeted practice at home, but have largely not been studied at scale. Moreover, during the pandemic, device use varied dramatically across families, often due to inconsistent Wi-Fi access or incapacity to support students' use, calling into question whether all families can access these resources.

Heterogeneity in family preferences and needs

The widespread variation in take-up of education technology may stem from variation in underlying family preferences for how to engage with children's education. For example, some families might appreciate a self-contained education app, whereas others appreciate being texted about activities that do not require any technology (e.g., questions to ask a child while reading a book) to support learning. Recent work on messaging interventions has also found that both the number of texts families receive per week (Cortes et al., 2019a) and the timing of the message (Cortes et al., 2019b) significantly affect engagement. Since prior research has often focused on one particular education technology solution, our understanding of engagement is one dimensional as opposed to multi-faceted. If the goal is to reach as many families as possible, technology-based interventions should factor in this variation.

Relatedly, in linguistically diverse communities, a school's ability to provide accessible and welcoming resources in families' home language is crucial (Linse, 2010; Quiñones & Fitzgerald, 2019). For example, if information on student behavior and performance is provided only in English, this could cause non-English speaking parents to feel unable to support their child. This might, in turn, disengage them from school communications, yielding the opposite of the intended effect. Recent studies focusing on younger children have shown that Spanish-speaking families appreciate receiving text and video messages in Spanish (Pila et al., 2019) and that a Spanish-language messaging intervention can improve parental engagement with literacy activities (Garcia et al., 2022). For Spanish-speaking families, the presence or absence of information and resources in Spanish could drive some of the variation in engagement observed in prior research.

Current educational context

While schools use a variety of means to provide educational resources and communicate with families during the school year, use of educational technology during the summer is a particularly helpful context to understand. Unlike during the school year, when all students have access to similar materials and reading instruction, both access to resources and the amount of time spent on learning varies considerably during the summer (Gershenson, 2013; Guryan, Hurst, & Kearney, 2008; Zvoch & Stevens, 2015).

In many ways, summer learning variability was mirrored in the early days of the pandemic in Spring 2020, when seventy-seven percent of schools moved to online formats (DOE, 2022). This abrupt and significant pull-back in school-provided resources left families scrambling to find additional supports to educate children at home (Bacher-Hicks et al., 2021). Given the unanticipated speed with which Spring 2020 closures unfolded and the uncertainty of how long they would last, most schools had no existing structures for how to best reach families during this time period – in essence causing a more extreme pullback of information and resources than what typically happens over summer. Moreover, the transition's urgency meant that some districts had less capacity to translate resources, and two-way conversations between teachers and caregivers were often conducted only in English, which may have had equity implications for Spanish-speaking families.

This study

In this study we utilize a mixed method approach to explore families' patterns of engagement when offered access to an educational app designed to improve reading engagement and comprehension along with two-way text communication in Spanish and English to parent cell phones. Specifically, we ask the following research questions:

1) How do families' patterns of engagement with an educational app and text messages during summer differ?

2) How did families' patterns of engagement with technology change after the start of the COVID-19 pandemic?

3) How are the engagement patterns different for families who speak English vs. Spanish at home and families living in different socioeconomic neighborhoods?

Methods and Procedures

Intervention

The intervention took place during the summers of 2019 and 2020. At the end of Spring 2019, first and second graders received access to an educational reading app containing short e-books along with leveled reading activities (Kim et al., 2023). Families received letters in children's backpacks with information about downloading and logging into the free educational app. Additionally, text messages were sent to families that provided direct links to download the app in the Apple Store/Google Play.

Throughout summer, these students' families also received a two-way text messaging intervention in Spanish or English that was sent to parents' cell phone numbers. The text messages covered a variety of topics, such as information about the educational app, resources and activities to help with summer reading, and general encouragement to engage their child in literacy activities (Asher, Scherer, et al., 2022) and were sent at various times Monday-Saturday, between 8am and 8pm. Families received, and could respond to, two messages per week over the course of nine weeks. All families received a similar proportion of texts during business and non-business hours. Text messages ceased during the school year, but students could use the app.

Despite interruptions in learning and the move to virtual instruction caused by COVID-19, students continued to receive access to the educational app during Summer of 2020, after it had been updated with new resources and activities. They again received two-way text messages with similar content and frequency.

Sample

This study contains a longitudinal sample of 3,602 students who attended 30 elementary schools in a large, Southeastern district for both the 2019 and 2020 school years.

The families in our sample are demographically diverse. Approximately 20% identify as White, 35% as Black, and 35% as Hispanic (see Appendix Table 1). Thirty percent of families reported speaking Spanish at home and received text messages in Spanish. Comparing active users to the full sample, families tended to receive the messages in Spanish and students were more likely to be designated with limited English proficiency status and Hispanic. The sample is also socioeconomically diverse: 40% live in low-income, 37% in medium-income, and 22% in high-income neighborhoods.

In the summer of 2020, a subsample of 51 parents was invited for interviews to understand how they adapted their daily routines under the constraints of the COVID-19 pandemic. To recruit families, the research team identified six representative elementary schools from the broader sample. Families were stratified by student gender, academic performance in reading, and whether they spoke Spanish; a subset was then invited via email to participate in interviews. The final interview sample included representation from second and third grade, communities of different socioeconomic status, and approximately even numbers of Spanish- and English-speaking families . The sample was also racially diverse, with just over half identifying as Hispanic, 35% as Black, 10% as White, and 4% as Asian or Native American. Interviews were conducted over Zoom in either English or Spanish, and usually lasted 60-90 minutes.

Data and measures

Qualitative data

The interview protocol had two components: one section containing close-ended questions about basic household information and one with open-ended questions adapted from Weisner's Ecocultural Family Interview (EFI) manual (1997). The coding strategy was modeled on the conceptual dimensions described in the manual, where each dimension "comprises a selection of the resources and constraints, goals and values, abilities and needs of families" (p. 16). Using these categories as a starting point, a coding scheme was developed after initial rounds of pilot coding and discussion. The coding team included four members; all interviews were coded by two individuals independently, and disagreements were resolved through discussion. Interviews conducted in Spanish were coded by two native Spanish speakers.

Quantitative data

We use log-level data from the educational app and text messages to characterize the nature of family engagement. The educational app tracks detailed information, including when students first logged in and when they completed each of the activities. The texting platform contains records of all text messages sent to and from families during the study period. We aggregated this data to the student-level with seven measures that capture the quantity, duration, timing, and interest of families' behavioral engagement with technology (see Grolnick and Slowiaczek, 1994 for a discussion on types of engagement) using the following constructs:

- Quantity: total number of app sessions and messages sent by parents
- Duration: number of weeks between the first and last app session and text message interaction
- Timing: proportions of app sessions and parental text messages sent during standard business hours
- Interest: whether families opted out of receiving text messages

Model Selection

In each year, we separated out "Non-Users," the sample who never engaged with either technological resource. The remaining sample, who used the app or responded to text messages at least once, were included in the Latent Profile Analysis (LPA). Using the "mclust" package in R, quantitative analyses were conducted using an increasingly complex set of person-centered analytical approaches (Nylund, 2007). Using the seven variables representing quantity, duration, timing, and interest of technology use described above, we fit a series of latent profile models with an increasing number of profiles (from K=1 to K=9) at each time point, under four different covariance matrix structures. We ultimately selected the "EEV" covariance model (see Appendix for details) and with this covariance structure in place, we evaluated the optimal number of latent profiles in 2019 and 2020 following the guidelines in Masyn (2013), which include both quantitative and substantive considerations. As described in the Appendix, we evaluated model fit according to several different indicators, and ultimately concluded that the fit statistics suggested a 6-profile solution for 2019, and an 8-profile solution in 2020.[1] Families were then assigned to their most likely profile.

Results

2019 Family Profiles

The 6-profile solution from the 2019 LPA corresponds to meaningfully distinguishable profiles among the families, which we have named based on qualitative differences (Figure 1). Panel A displays each profile's observed characteristics for quantity and duration of engagement, and Panel B shows the observed timing. Along the bottom of the graph we have separated the

[1]In both years, we observed a pair of profiles with identical mean characteristics and all individuals were more likely to belong to the first profiles than the second profile. We do not show the lower likelihood profile in our results, but include robustness checks in the Appendix.

profiles into those who tended to use the educational app (blue and red), profiles that focus more on text message response (green and orange), and non-users. In most profiles, we only observe positive values for characteristics associated either with the app or texting, showing that most families engaged with only one type of educational technology. Additionally, Panel B shows that most families either engaged exclusively during business hours or exclusively outside of business hours. The two largest app-using profiles were the Workday App Users (n=645) and the Robust App Users (n=510). The Robust App Users used the app more often and over a longer period of time compared with the other app user groups, Workday App Users and Downtime App Users (n=270), who used the app exclusively during business hours and non-business hours, respectively. A very small portion of the Downtime App Users did send texts that were exclusively during business hours. Families who only responded to text messages tended to do so only during business hours (Workday Texters, n=133). All in all, however, average usage rates were low across all profiles (Appendix Table 2).

The two user groups that break the "either/or" categorization are Non-Users (n=1720), who never engaged with either technology in 2019, and the Resource-Seeking Users (n=324), families who used both text messaging and the app. The Resource-Seeking families used the app less than the Robust App Users, but more than the other profiles, and they responded to text messages at similar levels of the Workday Texters. The Resource-Seeking and Robust App Users were also both likely to engage during business and non-business hours.

The content of family text messages, grouped in mutually exclusive categories, also revealed interesting patterns (Appendix Table 6). Most message themes were similarly present across profiles, but Resource-Seeking Users were significantly more likely to send messages asking about app technology or hardware than Workday Texters. Based on the content of these messages, we collectively categorize the app-only profiles as “Independent Users” of technology and the texting profiles as “Interaction-Supported Users.”

2020 Family Profiles

Figure 2 shows the profile mean characteristics for parental engagement in 2020. Many of the 2019 profiles are present, with similar engagement characteristics. However, we find a pattern where most groups, including “Independent Users,” are responding to more texts than in the prior year. Furthermore, the total number of families in the Independent-User profiles (Robust App Users, Workday App Users, Downtime App Users) decreased from 1,425 families in 2019 to only 381 families in 2020. The biggest difference in 2020 is that we observed two new profiles of Interaction-Supported Users who only engaged in text messaging. Downtime Texters (n=259) only sent messages outside of business hours, whereas Robust Texters (n=206) sent a relatively large number of texts during both business and non-business hours.

We leveraged multiple qualitative data sources to further unpack our engagement profiles. Table 1 explores the content of family text messages in 2020. Both Resource-Seeking Users and Robust Texters were significantly more likely than other profiles to ask questions about technology. While Resource-Seeking Users often focused on the inability to use technology and asked for help, Robust Texters were more likely than any other profile to inquire about physical resources like books. Thus, the Robust Texters were interested in using the app, but when faced with insurmountable issues, wanted to ensure that their child had access to physical books. A one-question multiple choice pulse survey about barriers to app use sent in late June (respondent n=382) indicated that a plurality (37%) of responding families needed additional help. Other common responses were not having enough time (19%) and not having a device that could run the app (17%).

Parent interviews provide additional information about family use and valuations of technology. All in all, families tended to view technology and educational apps in a positive light. Ninety-six percent of families (49/51) reported their children using any form of technology (e.g., kindle, apps, tv) while 57% (29/51) reported their child using educational software with some frequency. Sixty-five percent (33/51) discussed benefits of their children's technology use, particularly that children can learn a lot, in both educational and non-educational settings. One family member noted, "They can learn so many things, . . . with the apps. There are so many of them. So, it's kind of like no cap on what they can learn."

Theoretical appreciation did not necessarily correspond to engagement with our study's resources, however. Thirty-one percent (16/51) of parents indicated that they had not logged-in or had no interest in the app. Of these parents, about 20% (3/16) of parents were not interested in the app because they did not approve of online reading or thought it was too "basic" for their child. An additional 25% (4/16) mentioned technical issues, such as an inability to download, that prevented them from accessing the app. This was part of a larger pattern amongst all the interviewees, even those that had successfully logged-on, where more than a third of parents (18/51) spoke negatively about their own technology skills and did not feel prepared to support their child's technology use. One parent noted, "I don't understand the internet very much. So, it makes it a little difficult for me to help my kids."

Other families just never got around to using the app, even with help from text message reminders. Among the parents who had not logged onto the app at the time of the interview, 31% (5/16) indicated that they were too busy to act on the text when they received it. One parent noted, "You have done a wonderful job of sending reminders [...] but when I get them I'm typically doing something else." These attitudes and challenges provide some insight into why such a large proportion of our sample fell into the Non-Users category, and help us better understand the types of interaction or support families need to take advantage of technology-based educational resources.

Family Transitions from 2019 to 2020

Table 2 shows how families transitioned between profiles in 2019 and 2020. Across both years, the Non-Users were the modal family profile, representing 1,720 families (48%) in 2019 and 2,205 (61%) in 2020. However, these aggregate numbers mask important longitudinal patterns. While the pandemic resulted in many parents who engaged in 2019 to stop, there was an almost equally large group of Non-Users from 2019 who did engage in 2020. Only 1,191 (33%) never engaged with either technology across both years.

Approximately 900 families (25%) engaged with at least one technology medium in both years. Among these families, there was significant transition between the two years, typically from belonging to an Independent User profile to an Interaction-Supported User profile. For example, in 2019 approximately 900 families were either in the Workday App Users and Downtime App Users profiles. While about 60% of these families disengaged from any technology in 2020, 27% transitioned into one of the four Interaction-Supported User profiles. Additionally, we see that very few families of any type remained or became Independent Users in 2020 (11%). As school resources were pulled back, and families were faced with other challenges unique to the COVID-19 pandemic, families preferred the support and interaction associated with two-way messaging.

Language and SES Differences in Profile Membership

To understand the relationship between home language and engagement with educational technology, we fit a multinomial logistic regression predicting user type based on whether families received text messages in Spanish instead of English. The results of these analyses are presented in Table 3, which includes separate models for 2019 and 2020, with and without SES and additional covariates. The large, negative, and statistically significant constants in the bivariate model for both years provide the difference in log odds of being either an Independent User or an Interaction-Supported User among English-language families, reflecting our earlier finding that Non-Users were the modal profile in both years. The coefficients on Spanish-language messages represent the difference in log-odds of being categorized as either an Independent User or an Interaction-Supported User for Spanish-language families, with or without controlling for other covariates.

The positive coefficients on the Spanish language text messages indicate that these families were more likely to be both Independent Users and Interaction-Supported Users than similar families receiving messages in English. In 2019, these findings were significant for both user types, but, controlling for other baseline characteristics, only Independent Users. In 2020, however, families receiving Spanish-language messages were significantly more likely than English-message families to belong to both user types. Moreover, the magnitude of the log-odds differences are consistently larger in 2020 than in 2019, suggesting that differences between these groups of families increased in 2020.

Family interviews deepen our understanding of these patterns. Although many viewpoints were common across Spanish- and English-speaking families, obstacles experienced by Spanish-speaking families were exacerbated due to the reduction of resources available in Spanish during the pandemic. More than 50% of Spanish-speaking families (13/25) mentioned language or culture at some point during their interview. In addition to a reduction in Spanish-language resources sent home to families, parents also mentioned the inability to ask the teachers clarifying questions. For example, while parents from both groups struggled to upload their children's work online, a Spanish-speaking mother who called their teacher for assistance found it hard to understand the teacher's English-only responses. Relatedly, when talking about the text messages they received, another parent noted, "The messages were sent to me in Spanish. Yes, they [the messages] did support us a lot because with the calls I do stay at zero because, when I get the English calls from school, no, I don't understand anything." While the school district historically had been able to translate family resources to Spanish, the school system needed to suddenly adapt to the challenges brought on by the pandemic, investing more effort into providing Chromebooks, internet and food. With less time and resources available to translate materials, the two-way messaging in Spanish was able to fill an unmet need.

The covariate-adjusted models in Table 3 also provide some indication to whether there were socioeconomic differences in engagement. In both 2019 and 2020, we see that relative to a reference group of families in low-income neighborhoods, families in middle- and high-income neighborhoods were more likely to be Independent Users. In 2020, these families were also less likely to be Interaction-Supported Users, though the point estimate is only significant for families from high SES neighborhoods. Thus, lower socioeconomic status families tended to use two-way text messaging more. While our primary analyses collapsed family profiles into the broader user types, a less parsimonious analysis exploring predictors of individual profile membership can be found in the Appendix. We did not observe any actionable patterns beyond those described here.

Discussion

Leveraging latent profile analysis and time-stamped logs of app use and two-way text messaging, we identified distinct profiles of families. Most families chose to engage with one of the two resources. We also identified important differences in timing, as families usually engaged with technology either during or outside of traditional business hours, but rarely across both. The patterns of these profiles largely grouped families into three categories – Independent Users who took advantage of the app without additional messaging support, Interaction-Supported Users who tended to rely on the two-way text-messaging component of the intervention, often to help them access the app, and non-Users.

That families have different needs regarding technology use is not new. However, the stark divide of families using either the app or text messaging reinforces prior work showing the need to adapt to families' constraints and preferences, and that multiple media is one way to maximize engagement (Kim et al., 2019; Cortes et al., 2019b). For a subset of families, the opt-in resources and one-way messaging were sufficient to facilitate engagement. Our qualitative data suggest why a second technological medium, in particular, two-way text messaging, is important – approximately one third of families reported needing additional support accessing technological resources. In interviews, some parents struggled to use technology themselves, but still valued it for their children. Many portals offer help desks for support, but it is often more reactive rather than proactive – i.e. the parent must take initiative to seek support. Leveraging usage data and technology to target support to families who might need additional assistance could help engage these families. A friendly text or voice on the other end could easily remove some basic barriers.

While the need for technological assistance was widespread across our sample, exploratory analyses of family background provide some insight into which families were particularly likely to engage in specific ways. Families receiving Spanish-language messages were more likely to belong to all of the technology-using profiles, and these differences grew in 2020. Interview data indicated that while some of the resources and information shared by schools was provided in multiple languages, Spanish speaking parents faced additional barriers to using educational technology because follow-up communications happened almost exclusively in English. The two-way texting intervention, available in Spanish, mitigated some of these challenges. Our results also provide suggestive evidence that similar interventions could be particularly effective in smaller districts, where there might be less funding to translate resources in multiple languages, or in larger districts if a family's preferred language represents only a small proportion of the overall student population. The taxonomy approach, described in Linse (2010) emphasizes how even small changes in the linguistic and cultural responsiveness of school-home communications can yield important improvements.

We also found differences based on socioeconomic levels of families' neighborhoods that have implications for educational equity. Current research in education has shown that many opt-in technological resources are likely to increase equity gaps, as typically advantaged students and families take-up these interventions at higher rates (Kraft & Bolves, 2021; Robinson, Bisht, & Loeb, 2022). We saw similar patterns in that families in higher SES neighborhoods were more likely to be Independent Users. However, lower SES families were significantly more likely to be Interaction-Supported Users than the high SES families in our study. We suspect that the assistive nature of the text messaging component may offer a way to ensure more equitable takeup of and access to technology-based educational resources. This is particularly important during summer vacations, when the "resource faucet" from schools is turned off (Entwisle, 1997).

Beyond static family characteristics that might predict engagement, our study also shows that family preferences are dynamic and context-specific. Between 2019 and 2020, there was a strong shift away from independent use of the app towards two-way messaging. While this could feel like a game of whack-a-mole to education practitioners trying to anticipate family preferences, our study demonstrates one advantage of technology compared with other outreach tools (e.g., letters home or phone calls). Specifically, successful engagement can be assessed using the real-time data provided by technology platforms. Thus, schools and districts may want to consider tracking and measuring adoption of particular engagement approaches, and working with non-users to understand if they should consider changes. We acknowledge that the pandemic was unusually disruptive for schools and families, and typical year-over-year changes may not be as stark. However, we would still recommend tracking engagement unless a district finds evidence that family engagement patterns are no longer changing.

While our findings offer compelling insights into the variation in family engagement with educational technology, they are descriptive in nature and would benefit from additional causal research. For example, everyone in our study had the option to take advantage of two-way text messaging. Future research could compare family engagement with and without this second medium and collect more detailed family information to further refine what works for whom. Second, some non-users said they were “too busy” to log-on to the app during the summer time. One person noted that the timing of the text was not ideal and prior research suggests that timely text messages can be more powerful (Bergman, 2019). Though we varied the times and days of the week when families received text, future research could investigate whether asking families their preferred timing to receive messages would be helpful. Ultimately, by keeping in mind the heterogeneity of family preferences, and using data to adapt engagement strategies, policy-makers can target resources to the families who would benefit most.

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Table 1

Topics represented among family text messages in 2020, by profile membership

	Workday app users	Downtime app users	Resource-seeking users	Workday texters	Downtime texters	Robust texters
Confused (e.g., who is this) (%)	0.00	0.04	0.01	0.04	0.02	0.04**
	(0.00)	(0.19)	(0.11)	(0.19)	(0.12)	(0.20)
Opting Out (%)	0.05	0.04	0.02	0.18	0.07	0.08**
	(0.23)	(0.19)	(0.12)	(0.39)	(0.26)	(0.27)
Mention app, hardware, or technology (%)	0.16	0.15	0.5	0.12	0.13	0.4*
	(0.37)	(0.36)	(0.50)	(0.33)	(0.33)	(0.49)
Mention alt to tech (e.g., no screens) (%)	0.00	0.00	0.01	0.00	0.00	0.00
	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)
Request changes (e.g., updated phone number) (%)	0.00	0.07	0.02	0.01	0.02	0.01
	(0.00)	(0.27)	(0.15)	(0.10)	(0.14)	(0.10)
Responded to 2020 pulse survey	0.11	0.11	0.23	0.07	0.58	0.38**
	(0.31)	(0.32)	(0.42)	(0.26)	(0.50)	(0.49)
Mention resources (e.g., books)	0.26	0.15	0.29	0.2	0.05	0.38*
	(0.45)	(0.36)	(0.46)	(0.40)	(0.23)	(0.49)
Engagement (e.g., follow-up questions)	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)
Other content	0.39	0.41	0.45	0.26	0.19	0.56
	(0.50)	(0.50)	(0.50)	(0.44)	(0.39)	(0.5)

Notes: Sample includes families who texted-back in 2020. Means for each category are shown. Standard deviations are in parentheses. Each text was evaluated, and families were given an indicator if any text ever mentioned the following topic or sentiment. The categories are mutually exclusive; however, because the same family could have sent texts in multiple (or no) categories, the proportions do not total 100 percent. Standard errors for tests of difference between profiles are clustered at the school-grade level. Comparison of Resource-Seeking and Workday Texters + $p<0.05$; ++ $p<0.01$; Comparison of Resource-Seeking and Robust Texters * $p<0.05$; ** $p<0.01$

Table 2

Cluster Membership Transitions Between 2019 and 2020

	Cluster Membership in 2020								
		Independent Users			Interaction-Supported Users				
	Non-users	Workday app users	Downtime app users	Robust app users	Resource-seeking seeking users	Workday texters	Downtime texters	Robust texters	Total
Cluster Membership in 2019									
Non-users	1,191	50	35	41	58	130	126	89	1,720
	69%	3%	2%	2%	3%	8%	7%	5%	
Independent Users									
Workday app users	420	20	9	18	47	53	46	32	645
	65%	3%	1%	3%	7%	8%	7%	5%	
Downtime app users	151	17	16	12	20	18	22	14	270
	56%	6%	6%	4%	7%	7%	8%	5%	
Robust app users	244	37	29	46	67	38	29	20	510
	48%	7%	6%	9%	13%	7%	6%	4%	
Interaction-Supported Users									
Resource-seeking users	132	11	13	16	50	42	25	35	324
	41%	3%	4%	5%	15%	13%	8%	11%	
Workday texters	67	3	5	3	14	14	11	16	133
	50%	2%	4%	2%	11%	11%	8%	12%	
Total	2,205	138	107	136	256	295	259	206	3,602

Notes: Percentages refer to the proportion of that row's total number of 2019 families that transitioned to each of the 2020 profiles. For example, of the 1720 families who were Non-Users in 2019, 69% remained Non-Users in 2020. The sum of percentages across a row total 100%.

Table 3

Multinomial logistic predictions of profile membership based on messaging language

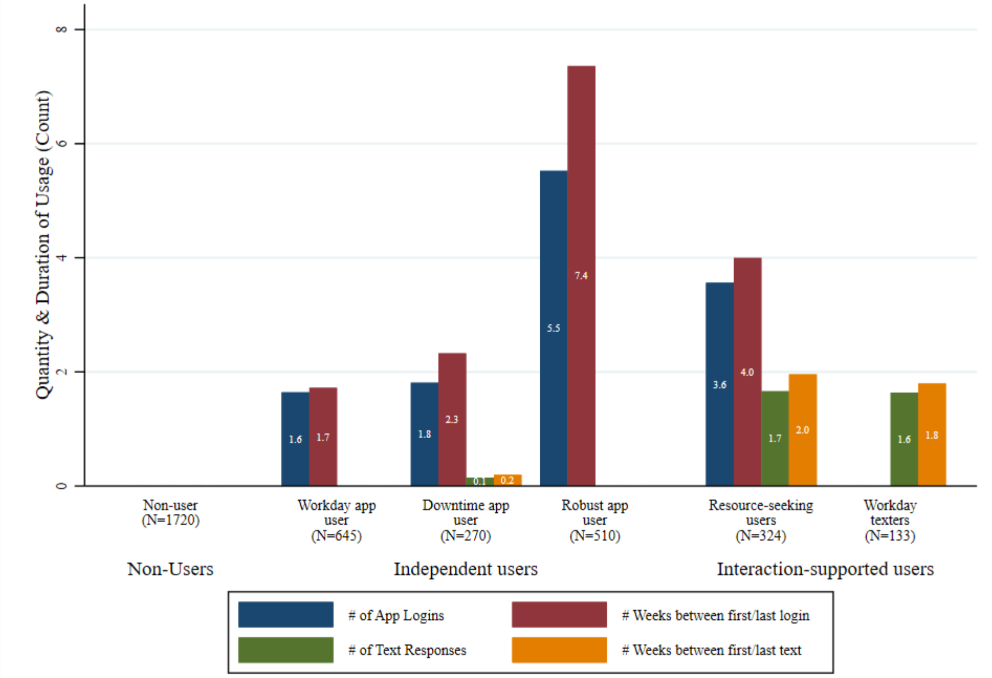
	2019 Unadjusted		2019 Adjusted		2020 Unadjusted		2020 Adjusted	
	Point Estimate	(SE)	Point Estimate	(SE)	Point Estimate	(SE)	Point Estimate	(SE)
Independent Users								
Received texts in Spanish	0.22*	(0.090)	0.56***	(0.150)	0.74***	(0.140)	0.86**	(0.290)
Moderate SES Neighborhood			0.28*	(0.130)			0.38*	(0.150)
High SES Neighborhood			0.46**	(0.140)			0.38	(0.220)
Constant	-0.25**	(0.090)	-0.91	(0.520)	-1.98***	(0.090)	-4.23***	(0.640)
Interaction-supported Users								
Received texts in Spanish	0.46***	(0.120)	0.03	(0.240)	0.92***	(0.120)	0.77***	(0.220)
Moderate SES Neighborhood			0.09	(0.110)			-0.22	(0.120)
High SES Neighborhood			-0.14	(0.220)			-0.44**	(0.160)
Constant	-1.45***	(0.080)	-0.69	(0.520)	-1.08***	(0.060)	-0.27	(0.530)
Observations	3524		3483		3524		3483	
Includes baseline covariates	No		Yes		No		Yes	

Note: Results come from a multinomial logistic regression model where Non-users are the base outcome profile. Standard errors, presented to the right of each point estimate, are clustered at the school-grade level. * p<0.05; ** p<0.01; *** p<0.001

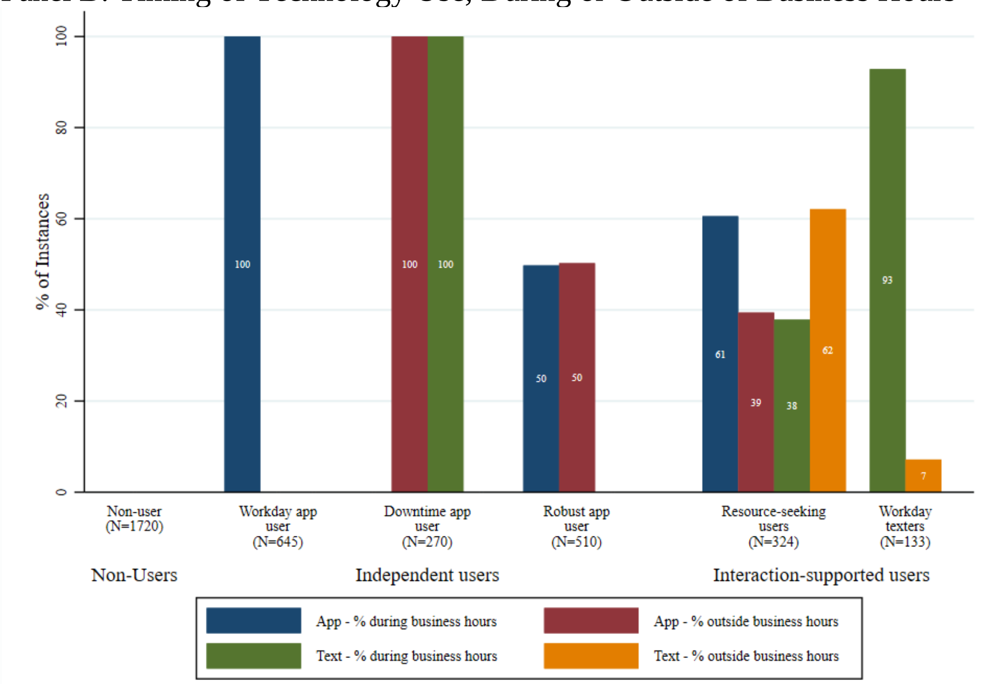
Figure 1

Mean Characteristics of the Families by Profile Membership in 2019

Panel A: Quantity & Duration of Technology Use



Panel B: Timing of Technology Use, During or Outside of Business Hours

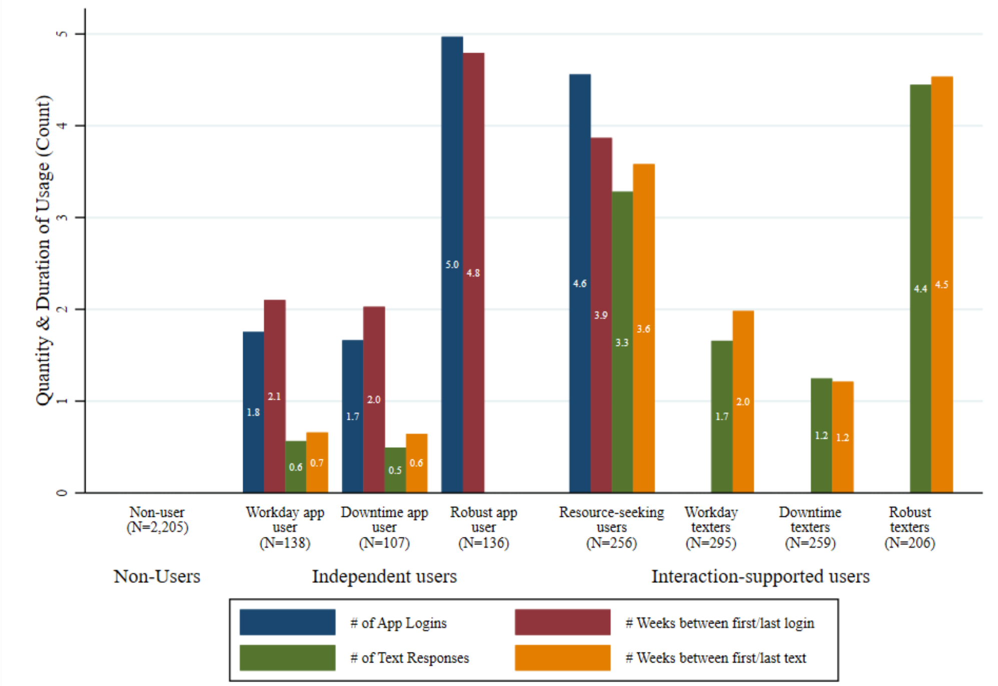


Notes: Graphs represent each profile's observed characteristics for quantity, duration, and timing after families have been assigned to their most probable profile. The sample size for each profile is presented below the name. At the bottom of the graph, we have separated the profiles into Non-Users, Independent Users, and Interaction-Supported users. The Non-Users did not engage with either technology medium and have 0s for all characteristics.

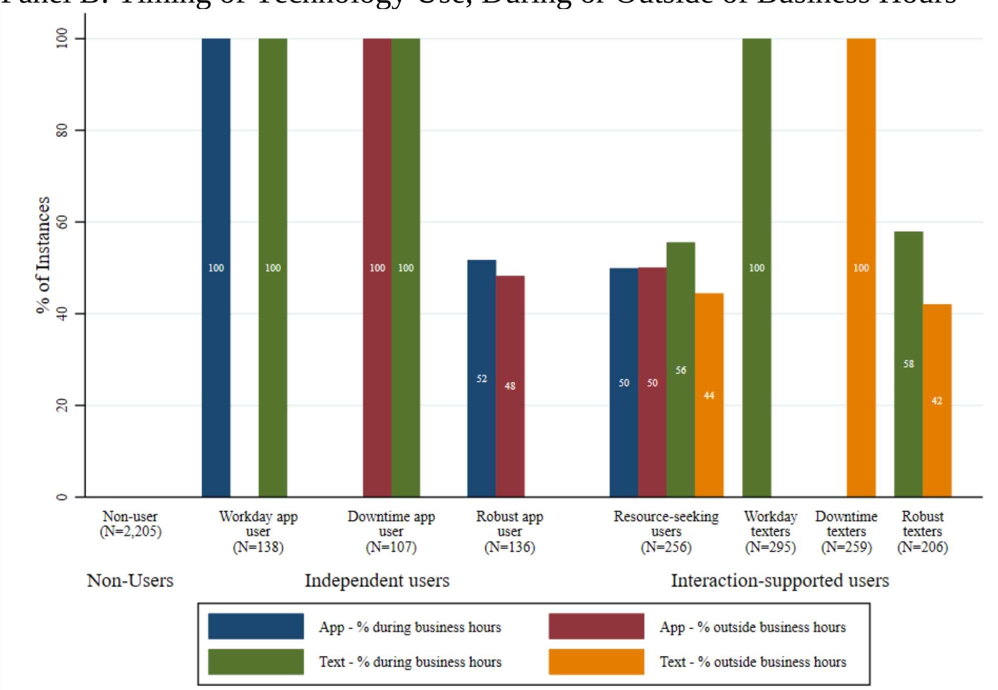
Figure 2

Mean Characteristics of the Families by Profile Membership in 2020

Panel A: Quantity & Duration of Technology Use



Panel B: Timing of Technology Use, During or Outside of Business Hours



Notes: Graphs represent each profile's observed characteristics for quantity, duration, and timing after families have been assigned to their most probable profile. The sample size for each profile is presented below the name. At the bottom of the graph we have separated the profiles into Non-Users, Independent Users, and Interaction-Supported users. The Non-Users did not engage

Online Methods Appendix

Sample Demographics

As further described in the main text of the article, the longitudinal sample of students included in this analysis is diverse in terms of racial/ethnic identity and socioeconomic status. Appendix Table 1 presents the sample means for the sample's demographic characteristics, along with other baseline information about students' participation in academic programs and performance on assessments. Six percent of the sample participated in an academic gifted program in 2019; 8% had an individualized education plan (IEP); and the mean baseline reading score on the MAP Reading is 175 for first graders and 182 for second graders and represents the 58th and 85th percentile using the national norming study, respectively (Thum & Kuhfeld, 2020).

Constructs for Measuring Engagement

We considered four distinct domains of families' behavioral engagement with technology, and measured each separately for their use of the educational app and participation in text messaging: quantity of engagement, duration, timing, and interest. Appendix Table 2 presents the variables associated with each of the domains, along with their original units. The majority of these analytic variables display long right tails. As described in more depth below, the model selection process fits a series of Guassian mixture models to identify profiles representing different types of families. To facilitate this process, we log-transform all variables to approach normal distributions before including them in our models to approach. In presenting our results throughout the paper, we re-transform output into raw units for ease of interpretation.

Modeling Approach

There are a wide variety of dimension-reduction procedures that can be used to classify data into meaningful groups. When the goal is variable reduction, approaches like Principal Component Analysis (Jolliffe, 2002) and Factor Analysis (Harman, 1976) are common in the social sciences. However, in this project, we were conducting a person-centered analysis, whereby we want to identify latent groupings of individuals within our data set. We ultimately selected Latent Profile Analysis (LPA) as our approach, which uses Gaussian mixture models to probabilistically assign individuals to a specific number of groups based on similarities in their observed values of pre-specified variables (Masyn, 2013). Aside from LPA, another common approach to assign observations to latent groups is to use algorithmic grouping procedures, such as k-means clustering, an unsupervised machine learning technique which calculates euclidian distance between each observation and the centroid of each cluster, and iteratively groups observations accordingly (Brusco et al., 2017).

In the current research context, latent profiles are philosophically and practically more desirable as a modeling choice. Unlike LPA, k-means algorithms result in a deterministic grouping and do not include measures of uncertainty about the clustering process. Additionally, because k-means cluster relies solely on squared Euclidean distance, clusters are ultimately spherical; using latent profiles allowed us greater flexibility in specifying the variance-covariance structures between the variables used to identify our groups. From a practical perspective, some recent comparisons have found that k-means clustering often produces similar, or noticeably worse, results than LPA (Brusco et al., 2017; Liu et al., 2022). Ultimately, the flexibility and robust performance of LPA models, along with the relatively low dimensionality of our data, made it a better choice for this analysis than k-means clustering.

LPA Model Selection

As described in the main paper, model selection was based on a data-driven approach, fitting a series of latent profile models with an increasing number of profiles (from K=1 to K=9). At the same time, we considered five different potential covariance matrix structures for our LPA models (listed in order of increasing flexibility: “EEI,” “EEE,” “VVI”, “VVV”, and “EEV”) and ultimately selected “EEV.” Appendix Figure 1 shows the Bayesian Information Criterion (BIC) for each model under different covariance structures. In 2019 (presented in Panel A), the “EEV” and “EEE” models performed similarly well across all numbers of profiles, with the “EEI” model only outperforming them for a very large number of profiles (7 or more). In 2020, the “EEV” covariance structure outperformed all others for any model with at least two profiles. Using the priorities of overall fit according to the BIC, and for consistency across years, we selected the “EEV” covariance structure. Under the value of parsimony (all else being equal, simple models are better), we did not consider more complex covariance structures.

We then evaluated the optimal number of latent profiles in 2019 and 2020 following the guidelines in Masyn (2013), which include both quantitative and substantive considerations. Appendix Table 3 presents model fit statistics for LPA models with a different number of pre-set profiles. We evaluated the models according to the following statistics: the Log Likelihood, the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the consistent AIC (CAIC), the sample size-adjusted BIC (SABIC), and the Bootstrapped Likelihood Ratio Test (BLRT) and its corresponding p-value. For each criterion, the best model will maximize each of these fit statistics; because they are all negative, except for the BLRT, this will be the smallest absolute number.[2]

[2] The typical formula for BIC is *df(log(n)-2(Loglikelihood)*, where df is the degrees of freedom and n is the sample size; however, the “mclust” packages calculates BIC as *2(Loglikelihood)- df(log(n)* This means that while typically one should minimize the BIC, we were looking to maximize this statistic.

In 2019, every statistic suggests that a 6-profile solution is the most appropriate. This is displayed most clearly with the BLRT results, which show that the decrease in the fit statistics from model to model is statistically significant for Profiles 1 through 6, but becomes insignificant for Profile 7. In 2020, the fit statistics do not show a clear local maximum across criteria, the way they did in 2019. Instead, the model fit statistics all continue to improve across the first 8 profiles, but are incalculable for 9 profiles. The inability of models to converge is often a case of weak- or under-identification – i.e. we don't have sufficient data to consistently estimate all the model parameters – but does not mean the model needs to be thrown out entirely (Masyn, 2013). In our case, we judged the instability of the 9-profile model as an indication of poor fit/underidentification, and decided to proceed with the model including 8 distinct profiles, which had the best fit statistics among the models that did converge.

With an LPA model, each observation is assigned a probability of belonging to each of the profiles. In the main text of the paper, our analyses describe profile characteristics after families have been assigned to their most probable profile. We also briefly mention that the optimal profiles identified through model selection (6 in 2019, 8 in 2020) included two pairs of identical profiles that were indistinguishable from one another. However, individual participants in our sample were always more likely to belong to the first member of the pair than the second; this resulted in an empty, or "ghost" profile in each year. We show this in Appendix Tables 4 (2019) and 5 (2020), where we include both the model predicted means for each variable, along with the sample size for each profile. We were concerned that the presence of this "ghost" profile indicated poor model fit; however, the uncertainty of profile assignment within the model did not exceed 15 percent for any of the profiles in either year. Typically, 80% certainty is considered sufficient and appropriate for grouping individuals into their most likely classification (Ferguson et al., 2020; Nylund-Gibson & Choi, 2018).

Robustness of model results

To further explore the potential concerns raised by the presence of "ghost" profiles in each year, we conducted two robustness checks to further assess our model fit. First, we compared the model-predicted variable means to the observed means of those variables once participants had been assigned to their most probable profile (the main results we present in Figures 1 and 2 in the paper). The results are what we would expect. Because the observed means we present in our main analysis are provided only by the individuals who are most likely to represent each profile rather than a weighted mean based on the probability of being in a particular profile, our main figures show a pattern of slightly intensified differences between the profiles relative to what we see in Appendix Tables 4 and 5. For example, among our Workday App users, they still only use the app during business hours; but, this group uses it slightly more (they have more logins over a longer number of weeks) than the weighted full sample. We see similar patterns across profiles and across years, indicating that the probabilistic assignments of individuals to profiles are reasonable and consistent with the rest of the model.

We conducted a second robustness check by limiting our sample to exclude individuals placed in the more-likely partner of the "ghost" profiles, which has no observations – in 2019, these were the individuals who were most likely to be a Workday App User, and in 2020, these were the Workday Texters. With this slightly smaller sample, we refit the LPA model using the same approach as for our primary analytic sample. In doing this, our 2019 results consistently suggested a different structure for our variance matrix ("EEI" instead of "EEV"). In our primary results, "EEI" had outperformed "EEV" with a large number of profiles as well, but as noted above we chose to use EEV for consistency across years. In 2020, the limited sample model once again identified "EEV" as the appropriate variance structure and identified a smaller number of optimal profiles – only 6. This is consistent with our primary results, as we removed the individuals who had contributed to the two additional profiles, one "ghost" and one observed. Overall, these results were reasonably consistent with our main sample findings.

Analyzing text message content

To provide additional information on the nature of the family's text message communications, we categorized text messages into a set of exclusive *content areas*. The most frequent content areas are listed in Appendix Table 6: confusion about the source of the intervention text messages; requesting to opt out of future messages; discussing technology hardware, such as the app; requesting changes to personal information, like a different phone number or language; mentioning specific resources, such as books. In 2020, we also administered a pulse survey, and categorized responses to that survey as their own content area. Several other topics were also covered by the text messages; these other, less frequently occuring message topics, were grouped together in the "Other" category.

After messages were individually coded, data was aggregated to the family level, indicating whether a family had ever sent a message for each of the coded *reasons* and about each of the *content areas*. Because of this, percentages across reasons and content areas do not sum to 100%. Appendix Table 6 presents summary statistics about family message patterns from 2019, which are also discussed briefly in the main text. In 2020, we compared message content across the profiles that included some text messaging (these results are presented in Table 1 in the main text). Comparing the Resource-Seeking and Workday Texters, the Resource-Seekers were more likely to send messages that related to the app, hardware issues, and technology (e.g., how to login, username and password) as well as more likely to ask questions related to the hard copy resource mailed to the students (e.g., books), compared to the Workday Texters.

Appendix References

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Appendix Tables and Figures

Appendix Table 1

Descriptive Statistics for the Longitudinal Sample

	Full Sample Mean	Full Sample SD	Never Users Mean	Never Users SD	Active Users Mean	Active Users SD	Interviewed Subsample
Race/Ethnicity							
White	0.19	0.39	0.23	0.42	0.18	0.38	0.12
Black	0.35	0.48	0.41	0.49	0.32	0.47	0.35
Hispanic	0.35	0.48	0.27	0.44	0.38	0.49	0.51
Male	0.50	0.50	0.47	0.50	0.51	0.50	*
Gifted	0.06	0.24	0.06	0.23	0.06	0.24	*
Individual Education Plan	0.08	0.27	0.08	0.27	0.08	0.26	*
Limited English Proficiency	0.24	0.43	0.17	0.38	0.27	0.45	*
Text/Interview Spanish	0.30	0.46	0.21	0.41	0.34	0.47	0.46
Neighborhood SES							
Low SES	0.40	0.49	0.39	0.49	0.40	0.49	0.33
Med SES	0.37	0.48	0.37	0.48	0.38	0.48	0.33
High SES	0.22	0.42	0.23	0.42	0.22	0.41	0.33
MAP Spring 2019 Reading (RIT)							
Grade 1	175.48	16.2	182.2	17.56	181.46	17.3	*
Grade 2	188.11	16.21	183	18.22	182.53	18.28	*
N	3602		1191		2411		51

Note. Table provides the summary statistics for never users (i.e., those who did not engage in either year), active users (i.e, those who ever engaged) and the interviewed sample. *The interviewed sample's data was de-identified after recruitment and was not connected to administrative records. For this table, we have provided information as closely aligned to the administrative variables as possible, but information for which the students were not selected are not available.

Appendix Table 2

Measures of Engagement, by Domain and Technology Medium

App										
			2019				**2020**			
Domain	**Original Units Before Log Transformation**	**Measure from App Activity**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Quantity of engagement	Count	Total number of app sessions	1.53	2.89	0	37	0.63	2.01	0	41
Duration of engagement	Weeks	Weeks between first and last app session	1.88	3.6	0	19	0.6	1.73	0	14
Timing	Percentage points	Relative proportion of app sessions began Mon-Fri 8am-6pm	29.22	41.1	0	100	9.33	25.7	0	100
Text										
Quantity of engagement	Count	Total number of text messages sent by family	0.22	0.74	0	12	0.75	1.7	0	19
Duration of engagement	Weeks	Weeks between first and last family-sent text message	0.26	1.12	0	16	0.81	1.93	0	11
Timing	Percentage points	Relative proportion of family-sent text messages sent Mon-Fri 8am-6pm	7.42	25.2	0	100	17.25	35.1	0	100
Interest	Binary indicator	Whether families ever opted out of receiving text messages	0.01	0.08	0	1	0.03	0.16	0	1

Appendix Table 3

Fit statistics for latent profiles

	Log Likelihood	AIC	BIC	CAIC	SABIC	BLRT	p
2019							
Profile 1	-13,352	-26,709	-27,112	-26,711	-26,703	NA	NA
Profile 2	-11,183	-22,374	-23,120	-22,378	-22,363	4,339	0.00
Profile 3	-10,063	-20,138	-21,227	-20,146	-20,122	2,239	0.00
Profile 4	-8,148	-16,313	-17,744	-16,322	-16,290	3,830	0.00
Profile 5	-6,981	-13,983	-15,757	-13,995	-13,955	2,334	0.00
Profile 6	-5,704	-11,432	-13,550	-11,447	-11,399	2,555	0.00
Profile 7	-5,783	-11,595	-14,055	-11,612	-11,556	-159	1.00
Profile 8	-5,784	-11,599	-14,402	-11,618	-11,555	0	1.00
Profile 9	-5,784	-11,603	-14,749	-11,625	-11,553	0	1.00
2020							
Profile 1	-12,948	-25,901	-36,297	-25,903	-25,895	NA	NA
Profile 2	-9,112	-18,233	-29,351	-18,238	-18,222	7,672	0.00
Profile 3	-8,896	-17,805	-28,425	-17,812	-17,788	432	0.00
Profile 4	-7,658	-15,333	-25,023	-15,342	-15,311	2,476	0.00
Profile 5	-5,838	-11,696	-22,033	-11,708	-11,669	3,641	0.00
Profile 6	-5,762	-11,548	-20,084	-11,562	-11,515	152	0.00
Profile 7	-5,762	-11,552	NA	-11,569	-11,513	0	0.00
Profile 8	-5,158	-10,347	NA	-10,366	-10,303	1,209	0.00
Profile 9	NA	NA	NA	NA	NA	NA	NA

Notes: AIC = Aikaike Information Criterion; BIC = Bayesian Information Criterion; CAIC = consistent AIC; SABIC = sample-size adjusted BIC; BLRT = Boot-strapped Likelihood Ratio Test; p-value corresponds to the BLRT.

Appendix Table 4

Mean characteristics for each 2019 LPA profile, including "ghost" profile

	Non-User	Independent Users				Interaction-Supported Users	
	Non-User	Workday app users	Workday app users (Alternate)	Downtime app users	Robust app users	Resource-seeking users	Workday texters
N	1720	645	0	270	510	324	133
Number of Text Responses	0.0	0.0	0.0	0.1	0.0	1.5	1.4
Number of App Logins	0.0	1.5	1.5	1.6	4.7	2.1	0.0
How many weeks did you use text	0.0	0.0	0.0	0.1	0.0	1.5	1.4
How many weeks did you use the app	0.0	1.4	1.4	1.7	5.9	2.2	0.0
Was the text an opt out?	0.0	0.0	0.0	0.0	0.0	5.4	5.4
Text - % during business hours	0.0	0.0	0.0	0.4	0.0	6.7	90.7
Text - % outside business hours	0.0	0.0	0.0	0.0	0.0	23.1	0.9
App - % during business hours	0.0	100.0	100.0	0.0	45.7	15.3	0.0
App - % outside business hours	0.0	0.0	0.0	100.0	46.4	6.6	0.0

Notes: Table represents the results from the Latent Profile Analysis model. The model assigns the likelihood that each family was in a profile and calculates corresponding weighted averages. For example, if family X had a 90% chance of being in the Robust App User profile and a 10% chance of being in the Downtime App User profile, their characteristics would contribute to the means presented in both of those columns here. This is different from Figure 1, which reports mean characteristics after families were assigned to their most likely profile. Thus, the numbers here will differ slightly from Figure 1 and percentages might not add to 100%. As noted in the main text, we observed a pair of profiles with identical mean characteristics where all individuals were more likely to belong to the first profile than the second profile (e.g., Workday App Users). This empty or "ghost" profile is shown here for completeness.

Appendix Table 5

Mean characteristics of each 2020 LPA profile, including "ghost" profile

	Independent Users				Interaction-Supported Users				
	Non-users	Workday app users	Downtime app users	Robust app users	Resource-seeking users	Workday texters	Workday texters (Alternate)	Downtime texters	Robust texters
N	2205	138	107	136	256	295	0	259	206
Number of Text Responses	0.0	0.3	0.3	0.0	2.7	1.5	1.5	1.2	3.9
Number of App Logins	0.0	1.5	1.5	4.3	3.5	0.0	0.0	0.0	0.0
How many weeks did you use text	0.0	0.3	0.3	0.0	2.7	1.5	1.5	1.1	3.8
How many weeks did you use the app	0.0	1.7	1.6	4.2	3.1	0.0	0.0	0.0	0.0
Was the text an opt out?	0.0	1.5	0.9	0.0	2.0	20.9	20.9	7.6	10.2
Text - % during business hours	0.0	2.6	2.2	0.0	24.2	100.0	100.0	0.0	55.3
Text - % outside business hours	0.0	0.0	0.0	0.0	17.7	0.0	0.0	100.0	38.6
App - % during business hours	0.0	100.0	0.0	48.7	26.1	0.0	0.0	0.0	0.0
App - % outside business hours	0.0	0.0	100.0	45.1	28.1	0.0	0.0	0.0	0.0

Notes: Table represents the results from the Latent Profile Analysis model. The model assigns the likelihood that each family was in a profile and calculates corresponding weighted averages. For example, if family X had a 90% chance of being in the Robust App User profile and a 10% chance of being in the Downtime App User profile, their characteristics would contribute to the means presented in both of those columns here. This is different from Figure 2, which reports mean characteristics after families were assigned to their most likely profile. Thus, the numbers here will differ slightly from Figure 2 and percentages might not add to 100%. As noted in the main text, we observed a pair of profiles with identical mean characteristics where all individuals were more likely to belong to the first profile than the second profile (e.g., Workday App Users). This empty or "ghost" profile is shown here for completeness.

Appendix Table 6

Topics represented among family text messages in 2019, by profile membership

	Downtime app users	Resource-seeking users	Workday texters
Confused (e.g., who is this) (%)	0.05	0.1	0.14
	(0.22)	(0.31)	(0.34)
Opting Out (%)	0	0.05	0.05
	(0.00)	(0.22)	(0.22)
Mention app, hardware, or technology (%)	0.38	0.27	0.14
	(0.50)	(0.45)	(0.35)
Request changes (e.g., updated phone number) (%)	0	0.02	0.02
	(0.00)	(0.15)	(0.12)
Mention resources (e.g., books)	0	0.08	0.05
	(0.00)	(0.27)	(0.21)
Other content	0.48	0.38	0.38
	(0.51)	(0.49)	(0.49)

Notes: Sample includes families who texted-back in 2019. Means for each category are shown. Standard deviations are in parentheses. Each text was evaluated and families were given an indicator if any text ever mentioned the following topic or sentiment. The categories are mutually exclusive; however, because the same family could have sent texts in multiple (or no) categories , the proportions do not total 100 percent. Standard errors for tests of difference between profiles are clustered at the school-grade level. Difference between Resource-Seeking Users and Workday Texters * $p<0.05$; ** $p<0.01$

Appendix Table 7

Multinomial logistic predictions of family profile based on family and child characteristics

	2019 Unadjusted		2019 Adjusted		2020 Unadjusted		2020 Adjusted	
	Point Estimate	(SE)	Point Estimate	(SE)	Point Estimate	(SE)	Point Estimate	(SE)
Independent Users								
Workday app users								
Received texts in Spanish	0.0873	(0.140)	0.188	(0.224)	0.850***	(0.214)	1.094*	(0.447)
White Student			-0.0502	(0.197)			-0.841**	(0.287)
Black Student			0.106	(0.165)			-1.064***	(0.260)
Hispanic Student			0.127	(0.226)			-0.788	(0.429)
Male Student			0.124	(0.0990)			0.397**	(0.149)
Individual Education Plan Student			0.207	(0.176)			-0.146	(0.388)
Moderate SES Neighborhood			0.258	(0.199)			0.163	(0.249)
High SES Neighborhood			0.481*	(0.237)			0.178	(0.299)
Spring Reading RIT score			0.00472	(0.00386)			0.0147**	(0.00541)
Constant	-1.009***	(0.132)	-2.259**	(0.714)	-3.039***	(0.131)	-5.386***	(0.960)
Downtime app users								
Received texts in Spanish	0.0377	(0.147)	0.562	(0.321)	0.574**	(0.207)	0.385	(0.440)
White Student			0.236	(0.244)			-1.549**	(0.517)
Black Student			0.0719	(0.193)			-1.072**	(0.337)
Hispanic Student			-0.411	(0.325)			-0.541	(0.510)
Male Student			0.173	(0.141)			-0.195	(0.219)
Individual Education Plan Student			0.131	(0.278)			-1.027	(0.591)
Moderate SES Neighborhood			0.321*	(0.150)			0.0865	(0.248)
High SES Neighborhood			0.419	(0.229)			0.246	(0.299)

Spring Reading RIT score			-0.0102*	(0.00444)			0.00812	(0.00653)
Constant	-1.856***	(0.0932)	-0.424	(0.815)	-3.187***	(0.124)	-3.778**	(1.179)
Robust app users								
Received texts in Spanish	0.458***	(0.109)	1.121***	(0.239)	0.750***	(0.184)	1.056*	(0.522)
White Student			-0.684***	(0.165)			-1.462***	(0.308)
Black Student			-0.493**	(0.154)			-1.007***	(0.225)
Hispanic Student			-0.945***	(0.251)			-0.809	(0.509)
Male Student			0.176	(0.110)			0.325	(0.190)
Individual Education Plan Student			0.163	(0.236)			-0.484	(0.444)
Moderate SES Neighborhood			0.286	(0.148)			0.867***	(0.226)
High SES Neighborhood			0.450**	(0.150)			0.742	(0.413)
Spring Reading RIT score			0.00685	(0.00374)			0.0201***	(0.00518)
Constant	-1.358***	(0.0882)	-2.499***	(0.690)	-3.014***	(0.144)	-6.685***	(0.982)
Interaction-Supported Users								
Resource seeking users								
Received texts in Spanish	0.607***	(0.124)	0.209	(0.265)	1.617***	(0.161)	1.448***	(0.338)
White Student			-0.417	(0.264)			-0.535*	(0.246)
Black Student			-0.0640	(0.260)			-0.633*	(0.304)
Hispanic Student			0.303	(0.321)			-0.414	(0.405)
Male Student			0.274*	(0.128)			0.327**	(0.114)
Individual Education Plan Student			0.314	(0.174)			-0.344	(0.277)
Moderate SES Neighborhood			0.207	(0.131)			-0.0706	(0.185)
High SES Neighborhood			0.0173	(0.235)			-0.402	(0.368)
Spring Reading RIT score			-0.00444	(0.00335)			0.000307	(0.00430)

	-				-			
Constant	1.856***	(0.0974)	-1.207	(0.631)	2.816***	(0.109)	-2.385**	(0.810)
Workday texters								
Received texts in Spanish	0.0884	(0.188)	-0.418	(0.384)	0.654***	(0.175)	0.379	(0.415)
White Student			-0.0995	(0.405)			0.151	(0.273)
Black Student			0.0948	(0.379)			0.302	(0.270)
Hispanic Student			0.427	(0.473)			0.277	(0.454)
Male Student			0.0652	(0.182)			0.106	(0.102)
Individual Education Plan Student			0.447	(0.332)			-0.599*	(0.284)
Moderate SES Neighborhood			-0.188	(0.184)			-0.182	(0.176)
High SES Neighborhood			-0.499	(0.359)			-0.634**	(0.246)
Spring Reading RIT score			-0.00536	(0.00592)			-0.0102*	(0.00455)
	-				-			
Constant	2.560***	(0.101)	-1.530	(1.067)	2.206***	(0.104)	-0.358	(0.832)
Downtime texters								
Received texts in Spanish					0.372*	(0.155)	0.499	(0.358)
White Student							0.0899	(0.261)
Black Student							-0.0176	(0.240)
Hispanic Student							-0.174	(0.460)
Male Student							-0.0795	(0.127)
Individual Education Plan Student							-0.0303	(0.260)
Moderate SES Neighborhood							-0.262	(0.146)
High SES Neighborhood							-0.259	(0.237)
Spring Reading RIT score							0.00367	(0.00487)
					-			
Constant					2.251***	(0.0772)	-2.718**	(0.917)
Robust texters								
Received texts in Spanish					1.046***	(0.167)	0.719*	(0.364)
White Student							0.139	(0.297)

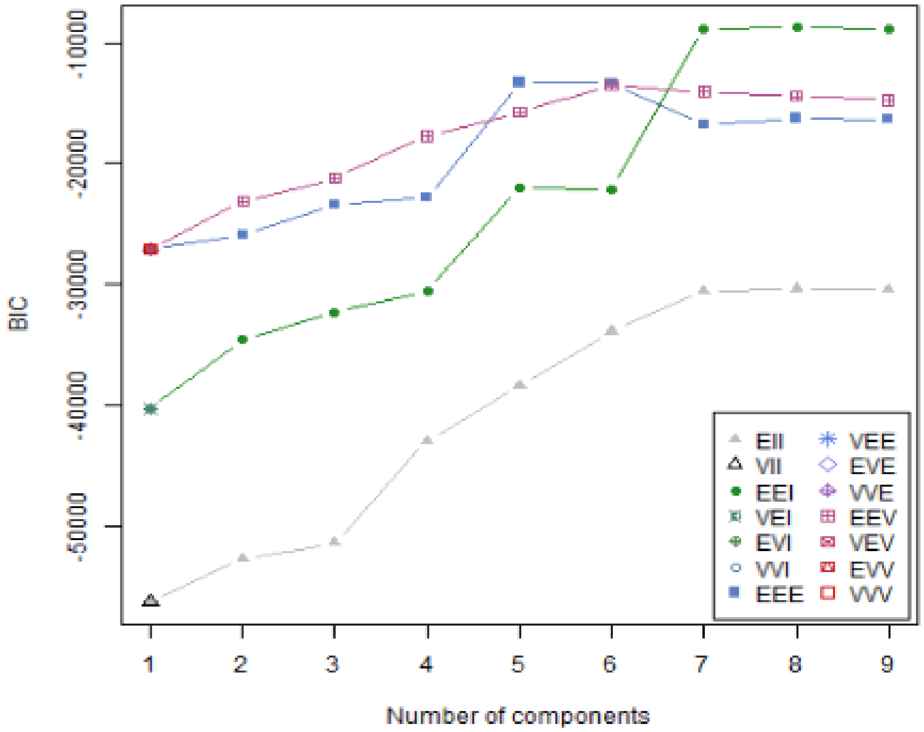
Black Student							-0.0214	(0.298)
Hispanic Student							0.142	(0.367)
Male Student							0.0483	(0.141)
Individual Education Plan Student							0.175	(0.260)
Moderate SES Neighborhood							-0.383*	(0.180)
High SES Neighborhood							-0.549*	(0.276)
Spring Reading RIT score							-0.00608	(0.00553)
Constant					- 2.721***	(0.124)	-1.389	(0.991)
Observations	3524		3483		3524		3483	
Includes baseline covariates	No		Yes		No		Yes	

Note: Results come from a multinomial logistic regression model where Non-Users are the base outcome profile. Standard errors, presented to the right of each point estimate are clustered at the school-grade level. * p<0.05; ** p<0.001; *** p<0.0001"

Appendix Figure 1

Bayesian Information Criteria (BIC) for profiles with differing covariance structures

Panel A: 2019 Sample



Panel B: 2020 Sample