# Student Engagement in Mobile Learning via Text Message

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## ABSTRACT
Mobile learning is expanding rapidly due to its accessibility and affordability, especially in resource-poor parts of the world. Yet how students engage and learn with mobile learning has not been systematically analyzed at scale. This study examines how 93,819 Kenyan students in grades 6, 9, and 12 use a text message-based mobile learning platform that has millions of users across Sub-Saharan Africa. We investigate longitudinal variation in engagement over a one-year period for students in different age groups and check for evidence of learning gains using learning curve analysis. Student engagement is highest during school holidays and leading up to standardized exams, but persistence over time is low: under 25% of students return to the platform after joining. Clustering students into three groups based on their level of activity, we examine variation in their learning behaviors and quiz performance over their first ten days. Highly active students exhibit promising trends in terms of quiz completion, reattempts, and accuracy, but we do not see evidence of learning gains in this study. The findings suggest that students in Kenya use mobile learning either as an ad-hoc resource or a low-cost tutor to complement formal schooling and bridge gaps in instruction.

## Author Keywords
Mobile Learning; Student Engagement; Clustering; Learning Curves; Kenya

## INTRODUCTION
Rapid developments in mobile technology have increased the viability of mobile devices as a medium for education. The ubiquity of mobile devices has the potential to shift traditional practices in education that are tied to specific locations, mostly schools and homes [50]. Mobile technology is more affordable for people in developing countries and it does not demand high levels of literacy and training compared to desktop computers [39]. Especially for families with very limited disposable income, the accessibility of mobile education can help them accrue human capital at low cost while maintaining a high level of physical mobility relative to learning with desktop workstations. The role of technology in education is constantly evolving, especially for mobile technology as traditional desktop computers or laptops are not economically feasible in many parts of the world [51].

Sub-Saharan Africa has the lowest level of educational access in the world. Nearly one in three youths of primary, lower secondary, or upper secondary school age are unable to attend school, while the average rate across the rest of the world is less than one in five [17]. The region faces extreme shortages of both teachers to meet universal education standards and essential physical resources to provide access to education [18, 19]. While physical resources such as classroom space are scarce, over half of Sub-Saharan Africa will have mobile connectivity by 2025 [20]. This will improve connectivity within the region and facilitate access to information from around the world, as well as add $150 billion to the local economy [21]. It also expands access to learning opportunities via mobile devices.

There are numerous ongoing efforts to implement mobile learning platforms, but little empirical evidence has been published on how students engage with these platforms, how their learning behaviors develop over time, and whether there is evidence of learning gains from using mobile learning. In this study, we analyze the behavioral learning patterns of three cohorts of Kenyan students (6th, 9th, and 12th graders) who use Shupavu 291, a text message-based mobile learning platform that acts as a study tool. The tool serves pupils from primary school to high school, parents, and teachers in Kenya, Ghana, and Côte d'Ivoire. Shupavu 291 was created by a group of teachers to improve educational quality and access through mobile technology.

This research contributes the first large-scale empirical account of mobile learning in the developing world. We find that students in Kenya are using mobile learning as an ad-hoc resource or as a low-cost tutor to complement formal schooling, bridge gaps in instruction, and prepare for exams. More students are engaged during school holidays and leading up to exam periods, but only a quarter of students who start using the platform return to it the next day. A small cluster of highly engaged students exhibits adaptive learning behaviors and strong performance on assessments, but we do not find evidence of learning gains.

## RELATED WORK
Early work in mobile learning has focused on building theory and developing taxonomies of various case studies. Traxler defined mobile learning as "any educational provision where the sole or dominant technologies are handheld or palm-


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top devices” [47], and categorized emerging types of mobile learning: “technology-driven mobile learning”, “miniature but portable e-learning”, “connected classroom learning”, “remote/rural/development mobile learning”, to name but a few [48]. In contrast, Sharples and colleagues [43], who studied technology-assisted conversational learning, argued that mobile learning is a natural extension of existing learning practice because education is a conversive process that can occur in any context, and as such, it can take the form of reading a street advertisement or using a language learning application. Research on mobile learning in 2005 analyzed the market potential for mobile learning and suggested that developers target “life-long learners in full-time employment,” partly because mobile learning is most accessible to them financially [5].

Socioeconomic disparities have challenged the accessibility of mobile learning for many years. In contrast to applications that requires bespoke technologies, text message-based platforms like the one studied here have several benefits. Most notably, they are “socially inclusive” to people who cannot afford a smart phone [49], but the choice of mobile technology involves a trade-off between increasing accessibility and incorporating advanced functionality that may aid learning [46]. While physical classroom design has received much research attention, there has been much less work on effective (and inclusive) designs for mobile learning platforms [33]. Many mobile learning platforms have been designed for self-directed learners who take learning into their own hands [23]. Moreover, mobile devices are personal unlike classrooms, which has raised questions for instructional designers and learning engineers around effective ways to design for more personalized use of mobile learning platforms [32].

Many empirical studies on mobile learning have focused on the design of the physical hardware. For example, Corlett et al. [13] recruited 17 MSc students for a study, in which students were loaned a Compaq iPaQ course planner and asked to report their attitudes towards the mobile learning device. Much of the empirical work in this literature has focused on small-scale studies: for instance, interviews involving a group of 57 users within an educational program [37] or 60 trainee teachers who tried a mobile technology [4]. In contrast, there are many recent empirical studies with large amounts of students data on online learning, especially studies seeking to understand patterns in student engagement (e.g. [1, 12, 26]). In anticipation of more large-scale empirical work in mobile learning, recent conceptual work has proposed models for applying big data analytics in a mobile learning environments [44] and for assessing the quality of mobile learning platforms [42].

Numerous case studies have demonstrated that mobile learning platforms can increase access to education across a variety of domains [14, 3]. To help Syrian refugees adjust to Turkish culture, Castillo examined a mobile language learning application that became highly accessible because mobile phones were already essential for Syrian refugees [7]. Likewise, a mobile learning application developed to train farmers in the developing world was found to substantially increase communication and productivity among members of the food supply

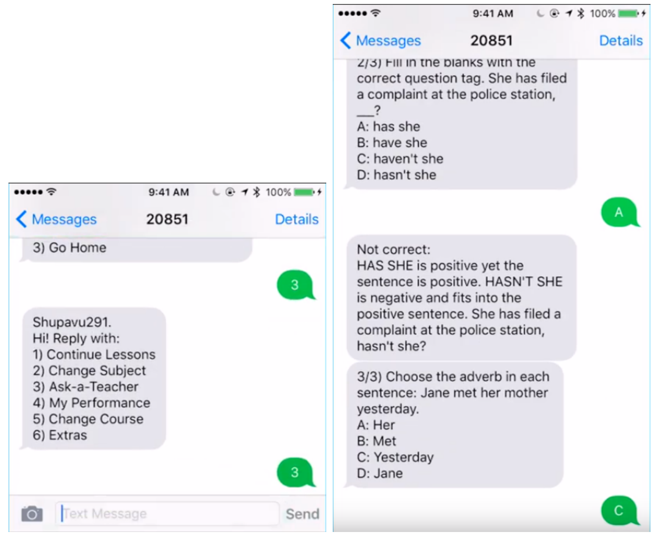


**Figure 1. Screenshot of Shupavu 291 text-message interactions: main menu options (left) and quiz questions with feedback (right).**

chain, and even increase economic activity [8]. Another application that was integrated into a local park system provided outdoor education instructors an accessible medium to teach personalized curricula and projects to students who reportedly felt a strong sense of ownership and pride in their work [40].

Several studies have examined how traditional study habits are affected by mobile learning. One study concluded that mobile applications can encourage students to diversify their study locations and achieve higher academic performance [10], pointing to prior work that found a link between study context diversity and cognitive performance [45]. Another study found that mobile learning encourages “microlearning” sessions that enable students to learn “on-the-go,” which students welcomed [15]. This was echoed by a cohort of healthcare profession students who perceived mobile learning as an improvement to both the process of learning (e.g., more self-assessment opportunities) and their own learning outcomes [30]. Students’ learning behaviors and performance in mobile learning environments were also recently linked to a well-established socio-emotional component of learning: students with more of a growth mindset were found to perform higher on assessments and exhibit more adaptive learning behaviors compared to those with more of a fixed mindset [24].

Prior research on mobile learning has come a long way from purely conceptual frameworks to laboratory and field studies that explore attitudinal and behavioral responses to mobile technologies and their socioeconomic implications. However, considering the rapidly expansion of mobile learning across educational domains, there is still a need for large-scale empirical studies to understand students’ real-world engagement with mobile learning. In particular, an important question is how students integrate mobile learning technology into their daily lives, especially in developing areas such as Sub-Saharan Africa that represent understudied learning contexts [31]. To advance our understanding of student engagement in mobile learning, we leverage a large mobile learning log dataset of

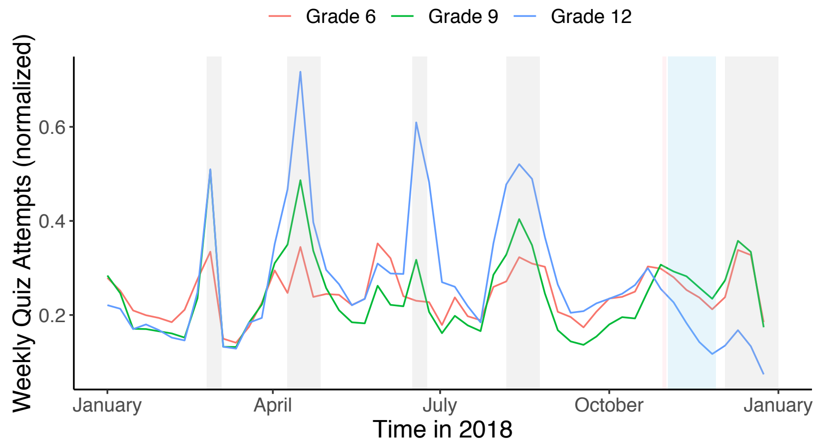


**Figure 2. Aggregate number of quiz attempts by 6th, 9th, and 12th graders in Kenya in 2018. Gray bars: half-term and full-term holidays. Blue bar: days of KCSE examination. Red bar (thin line left of the blue bar): days of KCPE examination.**

primary and education students in Kenya. We define student engagement in the behavioral tradition as interaction with the learning environment, which in this case is predominantly interaction with quizzes. We specifically address the following research questions:

1. How do students engage with mobile learning over time?
2. Does their engagement vary by grade level?
3. How do more versus less active students engage on the platform?
4. How much do students learn using mobile learning?

## MOBILE LEARNING CONTEXT

This research examines an SMS-based mobile learning platform called Shupavu 291 developed by Eneza Education/[1] Shupavu 291 is primarily used by Kenyan students, but its reach has expanded to Ghana and Côte d'Ivoire. The platform was designed by a group of Kenyan teachers to be used as a study tool and as a resource in regions where education is less accessible. The learning materials are developed by qualified teachers and they align with the topics and stated learning outcomes of the Kenyan national curriculum for numerous subjects at most levels of primary and secondary education. In 2019, the platform had 5 million unique learners and offered content tied to 844 distinct curricula, according to its official homepage.

Students find out about the platform through marketing campaigns via billboards or radio ads, and through word of mouth from friends, family, or teachers. They can accesses the learning application by dialing "*291#" on their mobile phone using a Safaricom line. Safaricom is the major telecommunication provider in the region. All interactions are via text message (SMS), as illustrated in Figure 1. Students navigate the menu by sending a text message containing a number corresponding to a menu item from the options provided in the message they received. Students register for a specific grade level and choose from a variety of grade-specific subjects, such as "The Covenant" and "Chemistry." For a given subject, they choose a specific topic and receive a tutorial (compact lecture notes) followed by a quiz (generally five multiple-choice questions). Quiz questions are sent one-by-one; students respond with their selected answer and receive instant feedback on correctness with an explanation. Correct question answers are awarded points on a platform-wide leaderboard that students can view via the "Extras" menu item. Students can retake any quiz as many times as they like. They can also use the "Ask-A-Teacher" feature to ask for help and get a response from a teacher working with the platform.

[1]https://enezaeducation.com/

## DATASET

The mobile learning platform stores a record for every interaction between the student and the application. Our dataset comprises 28,410,376 platform actions, including 1,515,550 quiz attempts by 93,819 unique students in Kenya in grades 6, 9, and 12 in 2018. Of the 93,819 students, 15,271 are in grade 6, 55,284 in grade 9, and 23,264 in grade 12. For the purpose of this research, we exclude students who never interacted with a quiz, the central feature of the platform, during the first two weeks (14 days) after registering. This yielded a focal sample of 77,337 students we use for analysis. This de-identified dataset contains information on each action taken on the platform including quiz correctness and quiz start and end timestamps.

## RESULTS

### Engagement Over the Academic Year

To understand how engagement with mobile learning evolves over time and particularly in relation to the academic calendar, we examine weekly student activity in 2018. Figure 2 shows the number of quiz attempts made by 6th, 9th, and 12th graders in Kenya (normalized by grade). Important dates in Kenya's academic calendar are indicated by shaded areas, including several school holidays (grey bars) and the final exam period (red and blue bar).[2]. We see clear evidence that engagement is aligned with the academic calendar, especially for 12th graders

[2]https://publicholidays.co.ke/school-holidays/

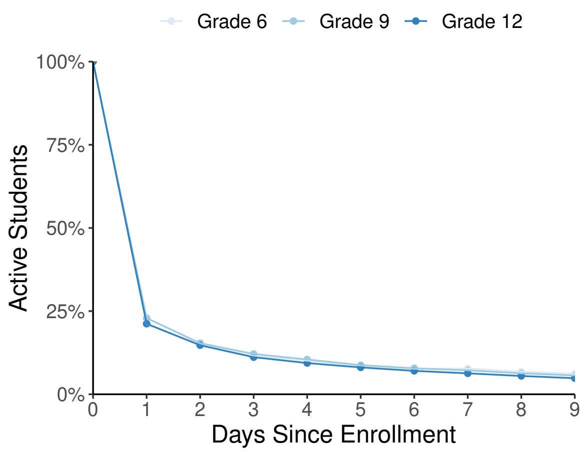


**Figure 3. Kaplan-Meier survival curves by grade level.**

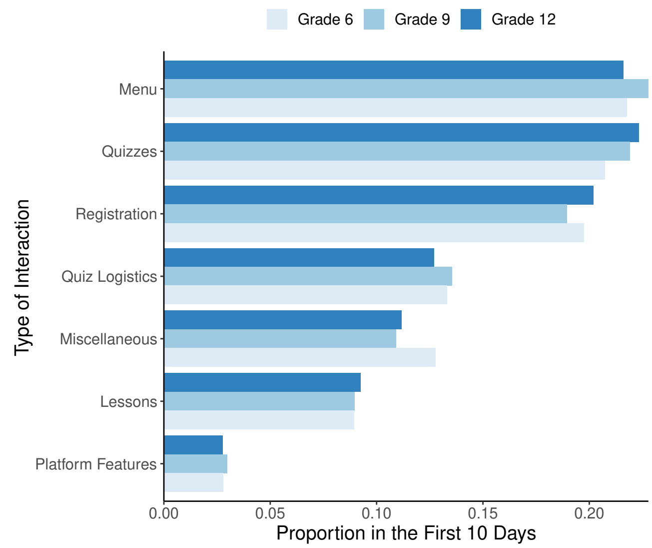


**Figure 4. Distribution of time spent on different platform actions in the first ten days by grade level.**

who exhibit the highest level of activity overall. Activity spikes during both term and mid-term holidays, and leading up to the exam period. Some of the remaining variation throughout the year may be induced by timed marketing campaigns.

The observed activity pattern suggests that students in Kenya use mobile learning to complement formal schooling, prepare for examinations, and bridge gaps in instruction. The platform may serve students as an ad-hoc resource to revisit specific topics and also as a low-cost tutor for an extended period of time. Distinguishing between the two uses is not possible in Figure 2, as it shows aggregate activity. The remainder of our analyses therefore examine patterns in engagement and performance for students relative to when they started using the platform.

### Grade-level Variation in Student Engagement

To understand how students in different grades use mobile learning, we examine the first ten days after a student starts using the platform. First, we examine the rate of attrition using a Kaplan-Meier plot (Figure 3). A student is defined to be active if they have at least one quiz interaction on a given day. The plot shows that less than 25% of students return to the platform the day after they begin using it and less than 10% remain active nine days later.

The survival curves are virtually identical for 6th, 9th, and 12th graders. We fitted a Cox survival model to test for variation in the hazard function by grade level, defining students who were inactive for five consecutive days as having "stopped out" (results are similar for a 2, 3, and 4-day threshold). Relative to sixth graders, ninth graders were not less likely to stop out (95% CI = [0.984, 1.000], $z = -1.84$, $p = 0.065$) and twelfth graders were 3.5% more likely to stop out (95% CI = [1.025, 1.044], $z = 7.29$, $p < 0.001$).

While there may not be notable variation in attrition by grade level, students may engage in different kinds of mobile learning behaviors on the platform. We therefore examine the nature of student engagement on the platform in more detail. To this end, we define seven types of interaction:

- *Registration:* registering on the mobile learning platform, or managing their subscription.
- *Menu:* navigating in the menu structure.
- *Lessons:* using course materials, e.g., reading a tutorial.
- *Quiz Logistics:* managing quizzes, e.g., starting quizzes or checking quiz grades.
- *Quizzes:* answering quiz questions.
- *Platform Features:* using special Shupavu 291 resources, e.g., the dictionary or ask-a-teacher feature.
- *Miscellaneous:* any other interaction.

Figure 4 shows how students in different grade levels distributed their time on the platform during their first ten days in terms of the seven interaction types. Students spent the most time navigating the menus, answering quizzes, and in the registration process. The prevalence of registration and navigation is consistent with the observation that many students do not return after the day they register. Students' early actions are relatively similar across grade levels. Given the minor influence of grade-level variation in student behavior we have observed thus far, we collapse data for all three grade levels for the remainder of the analysis and instead identify student groups empirically.

### Variation Across Student Engagement Clusters

Despite the rapid decline in student activity on average, there may be a small subset of students who are highly engaged and persistent. Adapting the approach of prior work that has "deconstructed disengagement" in massive open online courses [26], we use longitudinal clustering to identify groups of students based on their trajectory of activity. Specifically, we calculate how much time students spent on the platform on each of their first ten days (i.e. a vector with ten values per student), and use k-Means clustering (using a L2 distance metric and averaging over 100 random starts), setting $k =$

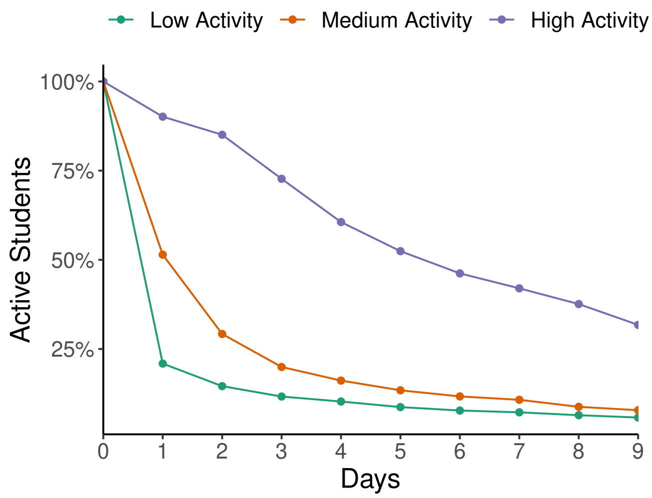


**Figure 5. Kaplan-Meier survival curves by activity cluster.**

3 based on the Elbow method and to prioritize parsimony. We label the three resulting clusters 'Low Activity' (64,403 students), 'Medium Activity' (11,120 students), and 'High Activity' (1,814 students), based on the cluster centroids. As expected, highly active students constitute the smallest group.

To compare how students across the three clusters engage on the platform, we first examine their trajectories of disengagement using another Kaplan-Meier plot (Figure 5). As expected, each cluster has a distinct pattern of attrition: 90% of students in the High Activity cluster returned the next day, but only 51% in the Medium Activity cluster and 20% in the Low Activity cluster returned. However, even among High Activity students, 68% stopped using Shupavu 291 by day ten. We fitted a Cox survival model as described above to test for between-cluster variation in the hazard function. Relative to High Activity students, Medium Activity students were 7.38 times as likely to stop out (95% CI = [7.005, 7.784], $z = 74.39$, $p < 0.001$) and Low Activity students were 9.95 times as likely to stop out (95% CI = [9.442, 10.479], $z = 86.38$, $p < 0.001$).

Beyond variation in attrition, we investigate trends in students' learning behaviors and performance on the platform over their first ten days. We focus our analysis on six metrics that are commonly used in learning analytics:

- *Time Spent (Log):* average number of seconds a student spent engaging with Shupavu 291, log-transformed
- *Courses Accessed:* average number of unique courses a student accessed
- *Unique Quizzes Attempted (Log):* average number of unique quizzes a student attempted, log-transformed
- *Quiz Completion Rate:* average proportion of quizzes a student starts and completes
- *Initial Accuracy:* average correctness of students' first attempts on quizzes
- *Attempts per Quiz:* average number of times a student attempts a quiz

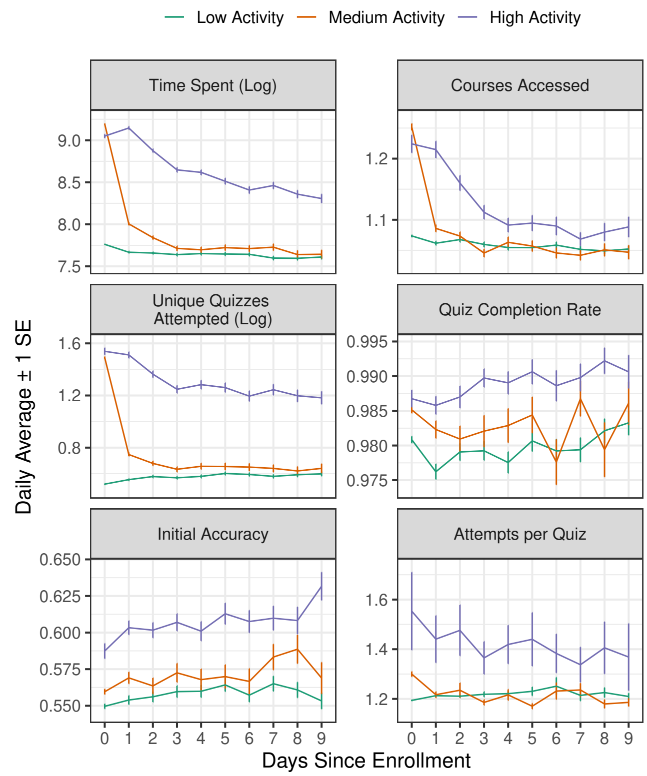


**Figure 6. Longitudinal trends for six learning behavior and performance metrics by activity cluster. Showing means with standard error bars.**

Figure 6 illustrates the longitudinal patterns for each metric across the three activity clusters among students who used the platform on any given day (i.e. not imputing a zero value for students who did not use Shupavu 291 that day). We find that High Activity students exhibit persistent effort and their quiz performance notably improves over time in terms of initial accuracy, completion rate, and the need for re-attempts. High and Medium Activity students behave similarly on their first day in terms of time spent, course exploration, unique quiz attempts and completion. However, Medium Activity students are less accurate and make fewer attempts on the first day, and their engagement substantially drops in subsequent days to the level of Low Activity students. Low Activity students start off with the lowest level of engagement and performance, and it remains low over time.

### Learning Curve Analysis

The finding that students in the High and Medium Activity clusters improve over time in terms of their quiz performance could be evidence of learning gains. However, students may be taking a variety of quizzes that happen to yield this pattern. To better assess if there is evidence of learning on the platform, we construct learning curves for four popular subject areas: Fractions, Numbers, Body Systems, and The Covenant. Learning curve analysis assumes that as students learn a component skill, their likelihood of answering questions incorrectly goes down [29]. We conduct two learning curve analyses. The first is more traditional and shows learning curves for a set

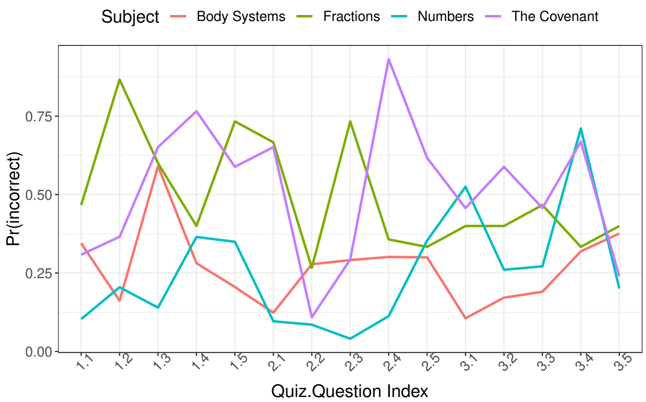


**Figure 7. Learning curves showing the likelihood of an incorrect response for questions across the same three quizzes (five questions each) in four subject areas;** $n$ **= 1,284 unique students.**

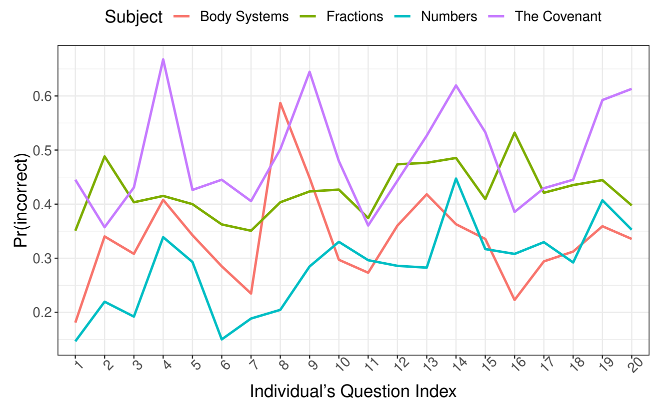


**Figure 8. Learning curves showing the likelihood of an incorrect response for 20 questions in the order that students attempt them in four subject areas;** $n$ **= 2,526 unique students.**

of three sequential quizzes (five questions each) on closely related component skills in each subject area (Figure 7). The second accounts for the flexibility in the learning environment and shows learning curves for 20 questions in each subject area in the relative order that each student answered them (Figure 8). The fact that students can take questions in any order limits the number of students who take the same quizzes in the same order, which is traditionally assumed in learning curve analyses.

We manually confirm that the quizzes selected for each subject area are conceptually closely related. For the subject Fractions, the three quizzes are entitled "Multiplication of fractions by fractions", "Multiplication of mixed numbers by fractions", and "Division of mixed numbers by a fraction". For the subject Numbers, the quizzes are "Place and Total Value", "Reading and Writing Numbers in Symbols and Words", and "Rounding Off Numbers". For the subject Body Systems, the quizzes are "Parts of the Reproductive System: Male (Testis, Urethra, Penis)", "Functions of Some Parts of the Reproductive System", and "Changes During Adolescence (Male and Female)". For the subject The Covenant, the quizzes are "The Making of the Sinai Covenant (Exodus 19; 24:1-8)", "The Breaking of the Sinai Covenant (Exodus 32:1-35)", and "The Renewal of the Sinai Covenant (Exodus 34:1-35)".

The learning curves shown in Figures 7-8 do not exhibit the downward slope that is characteristic of learning gains. Instead, they show mostly flat trends with several spikes for particularly difficult or confusing questions. Overall, we find no clear evidence of student learning gains from this learning curve analysis. Potential explanations and limitations of this finding are discussed in the next section.

## DISCUSSION

This work provides the first large-scale empirical analysis of how students use mobile learning in the context of Sub-Saharan Africa. We conduct longitudinal analyses to understand patterns in engagement, learning behaviors, performance, and learning gains. The findings address key questions about the rate of adoption, continued use, and efficacy of a mobile learning platform designed to complement and (when necessary) temporarily substitute formal schooling. Unlike many mobile learning platforms, Shupavu 291 offers learning materials and assessments that are aligned with a national curriculum via text message. This model of mobile learning that offers access to curriculum content and test preparation in resource-constrained settings has received substantial interest from researchers, policy-makers, and philanthropists. Yet how students learn using basic mobile phones in real-world contexts has nonetheless eluded systematic scientific investigation. We find that Kenyan students use mobile learning to complement formal schooling, bridge gaps in instruction, and prepare for standardized exams. The majority of students use it as a short-term study resource for a day. A smaller subset of students use it over extended periods like a low-cost tutor, and they exhibit promising learning behaviors and performance, even though we do not find formal evidence of learning gains in this study. We discuss the implications and limitations of our findings, and highlight promising areas for further research.

### Mobile Learning and Formal Schooling

The degree to which student usage of Shupavu 291 was responsive to the government-mandated school schedule is evidence that mobile learning is already complementing formal schooling in Kenya in 2018. The uptake in usage towards the end of the year may be to prepare for two important examinations in Kenya's education system, the Kenyan Certificate of Primary Education (KCPE) and the Kenya Certificate of Secondary Education (KCSE), which both take place at the end of the school year. The KCPE marks the transition from primary to secondary education after 8th grade, while the KCSE marks the end of secondary education to conclude 12th grade. This could explain why trends in activity were strongest for 9th and 12th graders who are closest to the KCPE and KCSE exams.

Mobile learning activity was higher during school breaks, which may be evidence of self-directed learning or external encouragement from parents or teachers to use the time between terms to study. The interdependence of this mobile learning platform with the school calendar suggests that students find it helpful and that it is sufficiently accessible to them. This can be a valuable insight for policy-makers looking for affordable ways to improve access to education and develop solutions to support students during times of teacher shortages or strikes. Qualitative research can help illuminate how students, teachers, and parents think about mobile learning in relation to formal schooling and inform the implementation and marketing of mobile learning platforms [35].

### Deconstructing Mobile Disengagement

The mobile learning platform we studied here is used by students in their own time and so it is not surprising that we observe substantial variation in engagement. In fact, our findings are reminiscent of prior work on understanding student engagement in massive open online courses [26, 16]. The current clustering analysis revealed three levels of student engagement, including a small group of highly engaged students that accounted for 2.3% of all students in the study sample. Those students were more persistent and successful on the platform in terms of their learning behaviors and performance. Their behavior may be influenced by a distinct set of motivations for adopting mobile leaning, such as a desire for affordable tutoring, or contextual factors that support persistence, such as using mobile learning together with a peer [28]. Further research into student motivation and contextual factors through interviews and surveys can help illuminate what supports persistence in mobile learning. For example, a recent survey of 1,000 Kenyan high school students on Shupavu 291 found that students with a growth mindset performed significantly better on quizzes [24]. A qualitative interview study of a related mobile learning system for early literacy in Côte d'Ivoire concluded that parental involvement was a critical enabling factor [35].

Although some students were highly engaged with the platform, the majority of student stopped using it shortly after registration. Our cluster analysis suggests that it is still worth distinguishing between two groups of less active students. One group uses the platform just like the highly engaged students but only on their first day. It is possible that these students got what they needed out of this experience, for instance reading up on a specific topic covered in class that day. It may also be the case that they had a bad experience after trying it out for a day and therefore decided to drop out. The significantly lower average initial quiz accuracy and re-attempting rate of this group compared to the highly engaged students can provide evidence to that effect.

The largest group of students are minimally engaged on the platform, even on the day of registration, and they stop using Shupavu 291 almost immediately. This group resembles "Sampling" learners in MOOCs, who enroll out of curiosity to see what the learning experience is like [26]. This type of engagement pattern is likely to be observed with any new educational technology that has a low barrier to entry. Survey research can offer valuable insight into why students drop out. For example, a survey of disengaged students in MOOCs found that besides a lack of time, which was the most commonly reported reason for dropping out, students also reported finding the content too difficult or having "learned all they intended to learn" [25]. These are also plausible reasons for disengaging from Shupavu 291, for example when students require human tutoring to understand concepts, or they completed a practice test for their upcoming exam. Surveys of disengaging students to identify reasons for drop out in this context can inform interventions to improve persistence.

At the time of this study, Shupavu 291 employed a mix of evidence-based strategies to improve persistence, including text-message nudges, financial incentives, and motivational messages to keep students engaged [9, 36, 34, 22]. Specifically, students would receive regular text-message reminders to study, daily phone credit incentives for completing quizzes with a minimum accuracy, and feedback after a completing quizzes would add positive reinforcement and growth mindset messages. These strategies would generally be expected to increase persistence, but the effects may be heterogeneous depending on characteristics of students and their context [27]. For example, not all students on Shupavu 291 have their own mobile phone and need to use their parent's phone, which can moderate intervention effects [24]. More research to evaluate the efficacy of these intervention strategies in this context is needed, especially in combination with survey research that examines reasons for enrolling and dropping out. This can answer questions about the need to target interventions to subgroups of students based on, for instance, their motivations for registering or their level of access to a mobile phone. Moreover, studies examining longer-term (dis-)engagement patterns are needed to understand cyclical patterns in individual engagement that may align with the academic calendar, such as regular albeit infrequent revision during holiday periods. Predictive modeling can help identify longer-term behavioral patterns such as disengagement and re-engagement early to inform the targeting of interventions [11].

### Learning with Mobile Learning

Establishing that an educational technology facilitates learning in the formal sense of measurable knowledge gains is difficult to achieve in an observational field study. This usually requires a pre- and post-test that has undergone psychometric evaluation. Alternatively, research on knowledge tracing has shown that learning gains can be modeled as a latent variable as students engage with a cognitive tutor, where the assessment questions are carefully curated to measure a specific knowledge component [2]. We use a technique that is commonly used to evaluate learning progressions in cognitive tutors to search for evidence of learning gains and encountered several challenges. First, and not surprisingly given the rate of disengagement, there were few students who consistently answered quiz questions in the same topic. Out of all 93,819 students in the sample, only 1,284 completed the specific sequences of three quizzes (15 questions) across the four most popular topics. For this reason, we also examined learning curves for a relative ordering of quiz questions within the same popular topic areas. The second challenge with learning curve analysis in this context is that the quizzes were not designed with the goal of isolating specific knowledge components, even though they were on specific, closely related topics such as different manipulations of basic fractions. Nevertheless, the learning curve analysis might have yielded different results if individual quiz questions had been tagged with relevant knowledge components by hand. Alternatively, novel techniques like Deep Knowledge Tracing could be used to infer the underlying knowledge graphs of Shupavu 291 content to facilitate this process [38].

In light of these challenges to conducting a traditional learning curve analysis in this context, it remains unclear if the lack of evidence for learning gains in our results means that students are not learning on the platform. The learning design of Shupavu 291 is grounded in repeated practice with immediate and constructive feedback (see Figure 1), which is considered to be a highly effective approach for learning [6]. To gauge the potential learning benefits of this mobile learning platform, and others like it, future research could implement pre- and post-tests (e.g. [41]) or link mobile learning records with official KCPE/KCSE exam scores.

## CONCLUSION

Early work on mobile learning argued that it is a promising innovation for expanding access to education, even though it offers limited ways to deliver content [5]. Fifteen years later, mobile technology is ubiquitous and powerful enough that it can offer rich and personalized learning experiences to millions of learners. Mobile learning can provide students with continuous tutoring or ad-hoc study resources to prepare for exams, and provides adult learners (including students' parents and teachers) flexible access to professional development and life-long learning opportunities.

The mobile learning platform under investigation here provides broad access to study materials for students in Sub-Saharan Africa, many of whom do not own a smart phone and whose parents may not be able to afford private tutoring. Students are evidently integrating mobile learning into their formal academic schedule and especially rely on it during scheduled school holidays. In regions where access to schools and qualified teachers is volatile due to lacking infrastructure, teacher strikes, or political unrest, mobile learning may provide students with a back-up plan to avoid falling behind in the curriculum and jeopardizing their academic pathway. More empirical studies of mobile learning usage in the wild are needed to develop evidence-based mobile learning design guidelines and to better inform policy-makers on how this technology can be leveraged to improve academic outcomes.

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