Growth Mindset Predicts Student Achievement and Behavior in Mobile Learning

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ABSTRACT

Students' personal qualities other than cognitive ability are known to influence persistence and achievement in formal learning environments, but the extent of their influence in digital learning environments is unclear. This research investigates non-cognitive factors in mobile learning in a resource-poor context. We surveyed 1,000 Kenyan high school students who use a popular SMS-based learning platform that provides formative assessments aligned with the national curriculum. Combining survey responses with platform interaction logs, we find growth mindset to be one of the strongest predictors of assessment scores. We investigate theory-based behavioral mechanisms to explain this relationship. Although students who hold a growth mindset are not more likely to persist after facing adversity, they spend more time on each assessment, increasing their likelihood of answering correctly. Results suggest that cultivating a growth mindset can motivate students in a resource-poor context to excel in a mobile learning environment.

KEYWORDS

Mobile Learning, Africa, Mindset, Self-efficacy, Expectancy-value theory, Learning Analytics

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1 INTRODUCTION

Sub-Saharan Africa has the lowest rate of educational access in the world. One in five children between the ages of 6 and 11 are out of school, and one in three youths between 12 and 14 are not in school [23]. The region also faces the greatest shortage of teachers worldwide and available teachers confront overcrowded, multi-grade classrooms with limited access to books or electricity [22]. Physical access to schools is further limited by financial and geographic barriers, especially in more rural areas [25]. In contrast, mobile connectivity is rapidly expanding and empowering people to use education and health services, as well as utilities for everyday financial transactions. In 2017, the mobile adoption rate in sub-Saharan Africa reached 44% [26]. Technological developments are paving the way for affordable mobile learning tools to support millions of students in poorly resourced contexts.

The use of mobile learning in Africa dates back to the early 2000s when it was introduced as a form of e-learning that is more widely available because it works with minimal infrastructure and can be accessed on the go [8, 47]. Early mobile learning projects in Africa targeted middle-aged full-time workers who were also the first to own mobile devices. Over time, as phones became cheaper and more widely adopted, mobile learning started appearing in formal school environments, where it was used as an aid for teachers in classrooms [46]. Nowadays, mobile learning is increasingly in the hands of students themselves, acting as a remote tutor outside of school even in rural parts of the continent [9]. A majority of phone plans in Africa are pre-paid and still relatively costly, which has prompted several programs to ease the financial burden of access. For example, the largest telecommunications provider in Kenya, Safaricom, partnered with a mobile learning provider to subsidize subscriptions that provide SMS-based content including Internet-less access to Wikipedia articles [11]. SMS-based mobile learning achieves high levels of accessibility and low costs by transmitting content through a series of short messages that even basic phones can receive.

Yet the flexibility of the format also poses challenges. Access to immediate feedback from teachers is limited and an unguided learning design requires students to be self-directed. Whereas in the classroom a teacher can ensure that students remain focused on the learning task, in the mobile learning setting the motivation and self-regulation must come from the student. Reasons for dropping out are manifold and hard to quantify, in part because student motivations for engaging in mobile learning vary; the complexity in understanding engagement and dropout resembles the focus of early research on massive open online courses [27, 28, 31]. Education research has made significant strides in developing learning theories and pedagogical designs for mobile learning over the last decades that can inform ways to improve engagement and learning outcomes [32, 35, 43]. Addressing the engagement problem may require a better understanding of students' personal qualities other than cognitive ability [14]. Non-cognitive factors such as a *growth mindset* (the belief that one can increase one's intelligence [15]), *self-efficacy* (the belief in one's ability to perform the actions needed to attain outcomes [5]), and positive *outcome expectancies* (the expectation of attaining outcomes by performing goal-directed actions [4]) are established predictors of academic achievement in formal learning environments. This research examines their role in student achievement and behavior in mobile learning.

The context of this research is a mobile learning service locally known as Shupavu291 that provides mobile tutoring in Kenya, Ghana, and Cote d'Ivoire. The parent company, Eneza Education[1], was founded by Kenyan teachers to improve student learning by providing quality educational resources using SMS technology. In 2019, it serves nearly 5 million learners including students, teachers, and parents, who seek additional tutoring outside of school or an alternative to grade school. Anyone can subscribe by sending an Unstructured Supplementary Service Data (USSD) code, which gives them access to course content that is aligned with the national curriculum for various grade levels and subjects. After signing up, the learner receives a text message with a numbered menu of options and responds by SMS with a number to select an option. This way a student first selects a grade levels and then a topic of study in subjects ranging from history, English and Kiswahili to sciences including mathematics, chemistry, biology, and physics. They then receive a brief tutorial followed by quiz containing several questions (multiple choice or short answer). Students answer questions one by one and receive feedback on whether their answer was correct and an explanation for the correct answer. They receive points for answering correctly and can either reattempt the quiz if they get it wrong, or move on to another topic. It is in this mobile learning context, that we investigate the role of high school students' beliefs and expectations on achievement and engagement. This research makes the following contributions at the intersection of learning at scale and educational psychology:

(1) Three quarters of Kenyan high school students using mobile learning reported a growth mindset.
(2) Growth mindset is a significant predictor of achievement in this context; self-efficacy and positive outcome expectancies are not.
(3) Growth mindset students spend more time answering assessments right on the first attempt and take longer to return after failing.
(4) Female students and students with better school grades achieve higher assessment scores in mobile learning.

2 RELATED WORK

This study investigates the role of three personal qualities other than cognitive ability: growth mindset, self-efficacy, and positive outcome expectancies. In this section, we review the theory and related empirical work on these three non-cognitive factors, which are established predictors of academic achievement in formal learning environments.

Growth Mindset

Mindsets are implicit theories, or lay theories, about aspects of the self such as one's level of intelligence [15, 18]. People who hold a growth mindset believe that intelligence is malleable, it can be improved through effort, for example by studying outside of school. In contrast, those who hold a fixed mindset believe their intellectual ability to be constant and outside of their control. Numerous studies have found students who hold a growth mindset to exhibit higher academic achievement, tenacity, resilience, and self-regulation [7, 17, 19, 50, 51]. Research shows that mindsets matter in different parts of the world and they are associated with socioeconomic status. A study in Chile found that high school students from low-income households on average had lower academic achievement and held more fixed mindsets than students from high-income households [12]. However, low-income students with a growth mindset performed as well as students in the top 20% of households by income. While a recent meta-analysis suggests that the link between growth mindset and academic achievement is weak [45], numerous studies have found links to various student performance indicators (for a review, see [20]). We therefore state the following hypothesis:

H1. Students with a stronger growth mindset score higher on assessments in mobile learning.

Mindsets can act as a lens through which to interpret everyday situations, especially when facing adversity like failing a quiz: those with a fixed mindset may conclude that

[1] https://enezaeducation.com/

they are simply not smart enough and give up, while those with a growth mindset conclude that they need more practice to solve it. How student behavior in mobile learning environments correlates with their mindset is not well understood. A set of studies investigated the possibility of encouraging the development of a growth mindset in an educational game by incentivizing effort, incremental progress, and strategy use [36, 37]. The "brain points" incentive increased overall persistence and perseverance following challenge among low-performing students. Targeted behavioral incentives were more effective than random ones and more effective than an animated lesson to explain growth mindsets. These findings highlight the potential of tailoring game dynamics to improve persistence. Whether the observed change in behavior is related to a change in student mindsets warrants further investigation. We therefore pose the following research question:

RQ1. Which mobile learning behaviors does a growth mindset predict?

Self-Efficacy

Self-efficacy is the belief in one's capability to organize and execute actions to achieve specific goals [5]. In an educational setting, students with high self-efficacy believe in their *ability* to prepare for quizzes and perform well in the class. This includes the organization and execution of assignments. Self-efficacious students tend to frequently review study materials and learn from their mistakes [5, 40, 52]. In contrast, students with low self-efficacy are less likely to follow through with preparation for assessments as they do not believe in their ability to overcome difficult situations, or avoid them completely. The role of self-efficacy beliefs in computer-based learning is particularly important, because some students face additional difficulties learning in these environments [33]. Numerous studies have found self-efficacy beliefs to predict academic motivation, effort, and achievement [34, 38, 42]. Accordingly, we arrive at the following hypothesis:

H2. Students with higher self-efficacy score higher on assessments in mobile learning.

Outcome Expectancies

Expectancy-value theories posit that student motivation to achieve a learning goal depends on the presence of positive outcome expectancies (beliefs about the likelihood of achieving a goal given commensurate effort) and the goal's subjective value (its importance to the individual) [4, 48]. Value can be derived from the satisfaction of completing the goal, the process itself, and extrinsic rewards. Without value, students may not see any reason to put effort into learning. Outcome expectancies are beliefs about whether the goal can be achieved as a function of performing a behavior. Students who both see value in the goal and hold positive outcome expectancies are motivated to engage in goal-directed behavior that supports learning and performance [2, 49]. In contrast, a lack of either subjective value or positive expectancies can cause reduced motivation and underperformance. This theory of academic motivation and achievement was developed and empirically tested in formal learning environments. In the context of a mobile learning system, the fact that students voluntarily seek out learning opportunities implies a high level of subjective value. We therefore focus in this study on positive outcome expectancies and their link to achievement, as stated in the following hypothesis:

H3. Students with more positive outcome expectancies score higher on assessments in mobile learning.

3 METHODS

In this research, we investigate links between survey data and behavioral logs for a subset of Eneza users. The study was conducted in coordination with Eneza employees who provided de-identified data on student engagement with assessments and fielded a survey to collect self-report data. Moreover, content experts at Eneza helped with tailoring the phrasing of survey questions and response options to an audience of Kenyan high school students. The study protocol was initially approved by the Institutional Review Board at Stanford University and then re-approved at Cornell University.

Participants

The final study sample consists of 942 students in Kenya (30% women). Recruitment and survey completion was done via SMS. An invitation to take the survey was sent to 4,000 high school users (i.e. those primarily consuming high school content). As an incentive, students received 20 Kenyan Shilling (KES; approx. 10c in US Dollars at the time) in airtime credit for completing the survey. Between 27 April and 8 May 2018, 1027 students responded to the survey. We excluded 85 students from the analysis because they either had not engaged with assessments or they engaged to a large extent with lessons intended for teachers and parents, which suggests that they are not high school students.

Survey Measures and Development

The survey comprised 19 questions including some that were added by Eneza for product research. Eneza content experts checked the phrasing and suggested modifications to improve comprehension among Kenyan high school students. Due to technological limitations, each survey item had to fit in the SMS character limit and have no more than four response options (unless it was an open response item). The following ten questions are relevant to this study (response options italicized):

(1) What is your gender? [*Male; Female; I prefer not to say*]
(2) How often do you go to school? [*Daily; 3-4 times a week; 1-2 times a week; I don't go to school*]
(3) My school average performance in all subjects usually ranges between: [*75 to 100%; 55 to 74%; 35 to 54%; 0 to 34%*]
(4) Who normally helps you study outside of school? [*Tuition teacher; Friends/siblings or classmates; Parents; I don't study outside of school*]
(5) Whose phone do you use to study on Shupavu291? [*Mine; Parent; Friend; Sibling*]
(6) What category of phone are you using to study on Shupavu291? [*Basic e.g. Mulika Mwizi; Smartphone/Touch screen; Tablet; I don't know*]
(7) On a scale of 0-10, how likely are you to recommend Shupavu291 to a friend, where 0 is 'Not at all and 10 is 'Extremely Likely'? Please reply with a number.
(8) Do you agree or disagree with the statement: "I cannot improve my inborn intelligence"? [*Agree Strongly; Agree; Disagree; Disagree Strongly*]
(9) Do you agree or disagree with the statement: "I know what I need to do to be a successful student"? [*Agree Strongly; Agree; Disagree; Disagree Strongly*]
(10) Do you agree or disagree with: "I can understand difficult topics if I put in more effort"? [*Agree Strongly; Agree; Disagree; Disagree Strongly*]

Items 2-4 are about formal school practices and achievement. Items 5-6 are about technological access. Item 7 is the "Net Promoter Score" question, a widely used measure of user satisfaction. The remaining items assess three personal beliefs: intelligence growth mindset (item 8; reverse coded), self-efficacy (item 9), and positive outcome expectancies (item 10). Conducting this survey at scale in a resource-poor mobile learning context requires a trade-off between response rate/quality and psychometric robustness. We developed the items on mindset, self-efficacy, and outcome expectancies with the goal of i. encapsulating the core idea of each construct based on established questionnaires and ii. ensuring comprehension in a population that differs from the Western context where questionnaires were developed. As described below, our starting point for each construct was an established questionnaire from which we selected items with high face validity and contextual relevance; we combined the items into one that meets the SMS space constraint with input from Kenyan content experts who write content for students of the target age group.

Growth Mindset. To assess growth mindset, students rated their agreement with "I cannot improve my inborn intelligence". Carol Dweck [16] states, "Individuals with a fixed mindset believe that their intelligence is simply an inborn trait–they have a certain amount, and that's that." Two recent articles published in leading journals by Dweck and colleagues also use only two reverse-coded items to measure mindset due to resource constraints [12, 39]. Their items, which were too long for SMS, were almost identical to ours and have strong construct validity and internal reliability: "intelligence is something that cannot be changed very much", and "you can learn new things, but you can't change a person's intelligence."

Self-efficacy. To assess self-efficacy, students rated their agreement with "I know what I need to do to be a successful student." Albert Bandura [6] originally defines self-efficacy as "People's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances" (p. 391). Our self-efficacy item is adapted from an established questionnaire by Pintrich and De Groot [40], which includes the following statement: "I know that I will be able to learn the material for this class." We adapted the statement for the broader context of a mobile learning platform.

Outcome expectancies. To assess positive outcome expectancies, students rated their agreement with "I can understand difficult topics if I put in more effort." Expectancy-value theorists define outcome expectancies as people's expectations of obtaining particular outcomes as a function of performing a behavior [4, 21]. We adapted items on outcome expectancies from an established general efficacy scale by Sherer et al. [44], including "When I make plans, I am certain I can make them work," and reverse-coded "If I can't do a job the first time, I keep trying until I can." We combined, shortened, and focused these items to ask students about the outcome of understanding difficult topics.

Behavioral and Achievement Measures

Behavioral and performance measures are derived from assessment interaction log data, which records the timing and outcome of each (re)attempt on a quiz. The following groups of metrics are calculated for each student. Descriptive statistics are provided in Table 1.

- **Achievement:** average final quiz score, average quiz score on the first attempt.
- **Engagement:** number of quizzes completed, number of days active, average number of seconds spent on the first attempt.
- **Response to failure:** after failing a quiz (<60% correct), what is the (a) average number of seconds until the next attempt of any quiz, (b) the probability of reattempting the same quiz within 1 hour, (c) the probability of attempting a different quiz within 1 hour, or (d) the probability of being inactive for at least 1 hour.

Table 1: Descriptive statistics omitting groups with <4% for categorical variables and providing mean $\bar{x}$, standard deviation σ, five-number summary q for continuous variables.

Variable	Distribution
Gender	67% male, 30% female
School frequency	88% daily, 3-4 times/week 9%
School grade	40% 75-100, 46% 55-74, 13% 35-54
Study help	53% friend, 23% tutor, 18% parent, 6% no
Whose phone	62% parent, 32% own
Phone type	75% basic, 21% smart phone
Growth mindset	$\bar{x}$=3.1, σ=1.1, q=[1, 3, 4, 4, 4]
Self-efficacy	$\bar{x}$=1.3, σ=0.6, q=[1, 1, 1, 2, 4]
Outcome expectancies	$\bar{x}$=1.4, σ=0.7, q=[1, 1, 1, 1, 4]
Satisfaction (NPS)	$\bar{x}$=8.2, σ=2.9, q=[1, 8, 10, 10, 10]
Avg correct initial	$\bar{x}$=0.5, σ=0.2, q=[0, 0.4, 0.6, 0.7, 1]
Avg correct final	$\bar{x}$=0.6, σ=0.2, q=[0, 0.4, 0.6, 0.7, 1]
Number of quizzes	$\bar{x}$=696, σ=1239, q=[1, 64, 222, 805, 14206]
Number of days	$\bar{x}$=60, σ=71.7, q=[1, 15, 34, 79, 539]
Avg secs initial*	$\bar{x}$=2.8, σ=0.4, q=[1.4, 2.5, 2.8, 3, 5]
Avg secs next | fail*	$\bar{x}$=3.3, σ=0.7, q=[1.4, 2.8, 3.1, 3.7, 6.8]
Pr(redo quiz | fail)	$\bar{x}$=0.1, σ=0.1, q=[0, 0.03, 0.07, 0.1, 1]
Pr(diff quiz | fail)	$\bar{x}$=0.6, σ=0.2, q=[0, 0.5, 0.7, 0.8, 1]
Pr(inactive 1hr | fail)	$\bar{x}$=0.3, σ=0.2, q=[0, 0.1, 0.2, 0.4, 1]

Note: *variable is $\log_{10}$ transformed

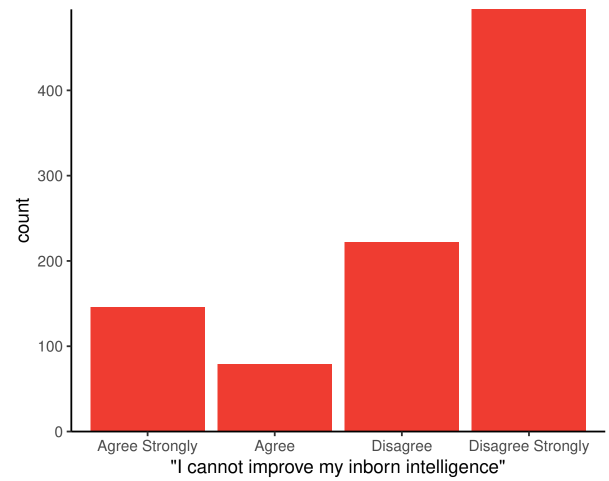

Figure 1: Distribution of intelligence growth mindset.

Analytic Approach

The primary method of analysis is multivariate OLS regression. There are some missing values due to survey non-response, ranging from 4 missing values for grades (one of the first survey items) to 68 missing values for NPS (the final survey item) out of 942 responses. We therefore apply multiple imputation forty times and conduct pooled analyses of regression models that account for uncertainty due to missingness [10]. This technique is preferred over complete-case analysis because it reduces non-response bias. We do not conduct mediation analyses to avoid any false impression that we are identifying causal relationships.

4 RESULTS

For an overview of the student sample in this study, Table 1 contains descriptive statistics for measured variables with Likert-scale response options converted to continuous values (*Agree Strongly*=1, ..., *Disagree Strongly*=4). The descriptive statistics show that students in the sample go to school daily or almost every day, but their grades are mixed. Most seek study help outside of Eneza from friends, tutors, or parents. A majority of them uses a basic phone from their parents for mobile learning, though a third owns a phone. Mindset beliefs (Fig. 1) are more spread out than outcome expectancies and self-efficacy; student satisfaction with Eneza is high. In terms of the behavioral and achievement statistics, it stands out that this is an active group of students, typically receiving 60% on quizzes. When students fail a quiz (score < 60%), most move on to a different one or stop practicing for a while, instead of reattempting the same quiz again.

Achievement Predictors

We investigate predictors of achievement in terms of the average final quiz score using multivariate regression analysis. Table 2 shows three models with different predictors: model (1) contains gender, formal school practices, and technological access; model (2) contains the four personal, non-cognitive qualities; and model (3) combines both sets of variables. The results indicate the following relationships:

- Students with a stronger growth mindset score higher quiz scores (H1).
- Students with higher self-efficacy or more positive outcome expectancies do not score higher quiz scores (H2, H3).
- Women have higher quiz scores than men.
- Students with higher school grades also have higher quiz scores.
- Students who receive study help from parents or a tuition teacher have lower quiz scores than those who receive help from friends or classmates.
- Students who are more satisfied with the learning environment score higher on quizzes.

Continuous dependent and independent variables are z-scored to facilitate comparisons of the strength of associations. In the full model, a 1 SD increase in growth mindset predicts a 0.18 SD increase in quiz scores, which is remarkably larger than the 0.12 and 0.10 increase associated with respective increases in school grades and satisfaction. In absolute terms, given model (3), the average score of a fixed

Table 2: Multivariate regression models predicting average quiz score on the final attempt (z-scored).

	Outcome variable: Average Quiz Score		
	(1)	(2)	(3)
Gender=female	0.23^{***}		0.23^{***}
	(0.07)		(0.07)
Gender=prefer not to say	-0.42^{**}		-0.28
	(0.18)		(0.18)
School grade†	0.12^{***}		0.12^{***}
	(0.03)		(0.03)
School frequency†	0.01		-0.01
	(0.03)		(0.03)
StudyHelp=parents	-0.33^{***}		-0.27^{***}
	(0.09)		(0.09)
StudyHelp=tuition teacher	-0.28^{***}		-0.17^{**}
	(0.08)		(0.08)
StudyHelp=no	0.03		-0.04
	(0.14)		(0.14)
PhoneType=smart phone	-0.12		-0.15^{*}
	(0.08)		(0.08)
PhoneType=tablet	-0.42^{*}		-0.28
	(0.23)		(0.23)
PhoneType=don't know	0.27		0.31
	(0.29)		(0.28)
WhosePhone=parent	0.07		0.02
	(0.07)		(0.07)
WhosePhone=friend	-0.37		-0.35^{*}
	(0.20)		(0.20)
WhosePhone=sibling	0.06		0.01
	(0.19)		(0.19)
Growth Mindset†		0.20^{***}	0.18^{***}
		(0.03)	(0.03)
Self-efficacy†		0.02	0.04
		(0.03)	(0.03)
Outcome Expectancies†		-0.04	-0.04
		(0.03)	(0.03)
Satisfaction (NPS)†		0.11^{***}	0.10^{***}
		(0.03)	(0.03)
Constant	0.06	0.00	0.06
	(0.07)	(0.03)	(0.07)
Observations	942	942	942
Pooled R^2	6.68%	6.87%	11.7%
Residual Std. Error	0.97 (df = 928)	0.97 (df = 937)	0.95 (df = 924)
F Statistic	5.08^{***} (df = 13; 928)	17.18^{***} (df = 4; 937)	7.04^{***} (df = 17; 924)

Note: $^{\dagger}z$-scored; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

mindset ("agree strongly") student is 51% compared to 60% for a comparable growth mindset ("disagree strongly") student. Moreover, it is worth noting that the association between mindset and mobile learning achievement stays relatively large and statistically significant even when adjusting for nine other variables including satisfaction, structural factors (school frequency), and proxies for cognitive ability (school grades) and income (phone type, study help). There is no evidence of multicollinearity (the presence of extremely correlated predictors) between the non-cognitive predictors: growth mindset significantly correlates only with satisfaction, $r = 0.22, t = 6.9, p < 0.001$, and self-efficacy correlates with outcome expectancy, $r = 0.25, t = 7.9, p < 0.001$.

Behavioral Manifestations of a Growth Mindset

The relative strength of growth mindset as a predictor of quiz scores raises questions about the behavioral mechanism through which these beliefs may lead to higher scores (RQ1). Although this correlational analysis cannot yield causal evidence, the deterministic relationship of the outcome variable with observables allows for an investigation into likely causal paths. First, consider that 96.1% (95% CI=[95.6, 96.6]) of the variance in the average final quiz score is explained by the average initial quiz score. The correlation between mindset and either outcome variable is practically identical (Pearson's $r = 0.232$, $t = 7.1$, $p < 0.001$) and thus students with a stronger growth mindset tend to already score higher on the first attempt (Fig. 2 top).[2]

One potential explanation for scoring higher on the first attempt is that students spend more time on the quiz, for instance reading more carefully and thinking harder about the solution. Indeed, there is a strong correlation between mindset and time spent ($r = 0.487$, $t = 17.1$, $p < 0.001$) as shown in Figure 2 (bottom). Students with a growth mindset spend 18% more time on their first quiz attempts than those with a fixed mindset ($t = 4.72, p < 0.001$), grouping students by agreement versus disagreement. Beyond the amount of time spent, growth mindset students could be more engaged on the mobile learning platform along other dimensions. We examine how the total number of quizzes and number of active days varies by student mindset. Surprisingly, there is no difference between the two groups in overall engagement outcomes ($|t|$s<1, ps>0.32). In fact, gender was the only significant predictor of overall engagement outcomes with women being more engaged than men ($|t|$s>3.3, $p < 0.001$, using model (3) in Table 2).

According to mindset theory and prior studies, a growth mindset shapes people's responses to challenge. We therefore

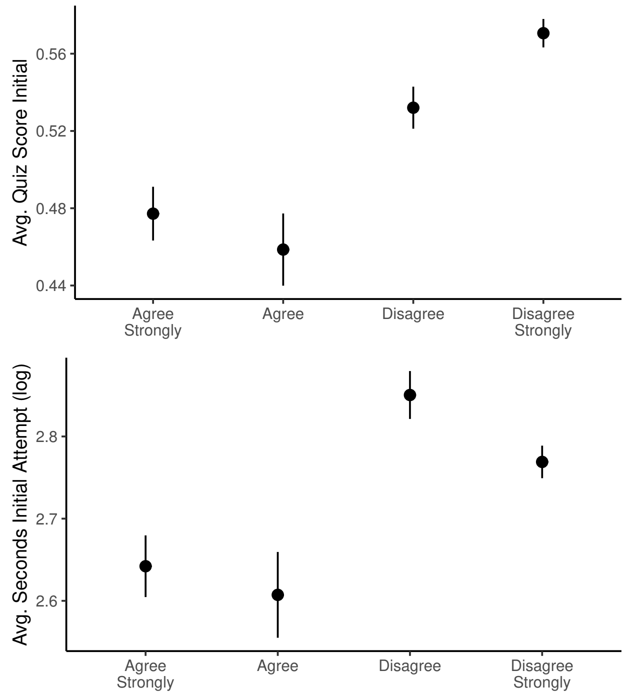

Figure 2: Behavioral outcomes by strength of growth mindset: average initial quiz score (top), average log number of seconds spent on initial quiz attempts (bottom). Showing pooled means and standard errors.

examine how students react after failing a quiz: do they retake it, do they move on to another quiz, or do they leave for some time? As shown in Figure 3, growth mindset students are not significantly more likely to redo the quiz right away (11 vs. 10%, $t = 0.895, p = 0.371$); instead, they are 16% more likely to leave (29.5 vs. 26%, $t = 1.95, p = 0.051$) and 7% less likely to attempt a different quiz right away (64 vs. 60%, $t = -2.29, p = 0.022$). Seeking distance from the source of failure, and perhaps consulting with friends or classmates, may be a self-regulatory action that students with a growth mindset take in order to gain new perspectives and re-approach the problem with fresh eyes.

5 DISCUSSION

This research provides new insight into the role of personal qualities other than cognitive ability in the behavior and achievement of Kenyan high school students who use a popular mobile learning application. In partnership with Eneza, an SMS-based learning platform, we surveyed 1,000 students about their personal beliefs on (1) the nature of intelligence (growth vs. fixed mindset), (2) their capability to act in ways to achieve outcomes (self-efficacy), and (3) the attainability

[2] The 0.23 correlation between mindset and quiz scores we find is almost identical to the 0.22 correlation between mindset and high school GPA found in the National Study of Learning Mindsets with a representative sample of 14,000 9th-grade students in U.S. public schools [20].

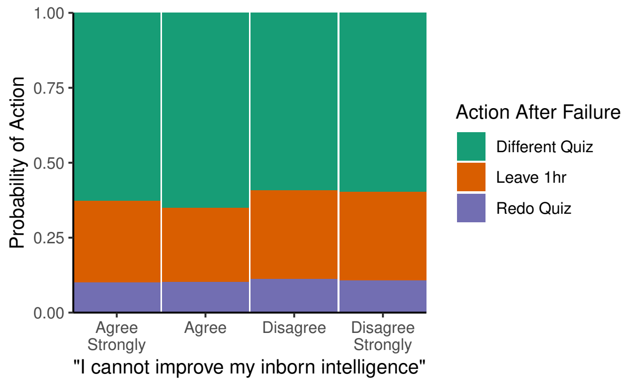

Figure 3: Probability distribution of possible next actions after failing a quiz by strength of growth mindset.

of outcomes through personal action (outcome expectancies). Prior studies in formal learning environments in the US and parts of the Global South have established the importance of these beliefs for academic achievement. This research contributes to educational psychology and the science of learning at large by studying a hard-to-reach population in a resource-constrained setting. Moreover, our findings may also be useful to researchers working on HCI for development, a rapidly growing community with strong interests in education [13].

Some of the study findings reaffirm our current scientific understanding of non-cognitive factors such as the hypothesized link between a growth mindset and academic achievement and effort (H1). However, the study also reveals several unexpected deviations from established findings. We hypothesized that both self-efficacy (H2) and positive outcome expectancies (H3) would predict achievement in mobile learning. Yet we saw no evidence that it predicts achievement or engagement. To address our research question, RQ1, we examined several behavioral mechanisms associated with holding a growth mindset. In contrast to prior work in educational games or classrooms [19, 36, 51], we found that holding a growth mindset did not predict higher persistence in mobile learning overall or after facing adversity (i.e. failing a quiz). Instead, students who hold a growth mindset appear to answer assessments diligently as they spend 18% more time completing them; and instead of reattempting quizzes after failure right away, students with a growth mindset are 7% less likely to immediately move on to another assessment and 16% more likely to leave the platform for a while before resuming learning. Findings of these exploratory analyses add to a limited but growing pool of evidence on the behavioral mechanisms of growth mindset in real-world learning contexts.

Limitations

When interpreting and generalizing from the study's findings, researchers and practitioners should consider several limitations. First, the research occurred on a particular mobile learning platform that delivers content via text message on a subscription basis. Platform design and content can significantly affect student behavior and achievement [29, 30, 36]. Second, the study sample is subject to standard response bias, which in this context manifests as a bias towards including more engaged users in the sample. Third, the study presents a correlational but not causal account of growth mindset and other beliefs. This account offers concrete ideas for intervention studies to investigate the causal effects of a growth mindset in this mobile learning context. Fourth, psychometrically robust measurement presents a significant challenge in this context and necessitates trade-offs: we do not have a validated measure of student learning and instead focus on quiz scores; our survey measure needed to be adapted from established questionnaires and shortened to one item per construct due to technological and resource constraints. The items have face validity and closely resemble established items, however their validity was not formally tested in this setting (and it would be a complex, costly enterprise to perform a formal validation in the current population). While the explanatory power of the mindset measure aligns with prior work [20], the surprising lack of correlation for self-efficacy and outcome expectancies may indicate a psychometric shortcoming.

Implications

A number of the trends we found confirm basic intuitions, such as that students with higher school grades also achieve higher scores in mobile learning. This result lends support to the construct validity of mobile learning quiz scores as a proxy for cognitive ability and knowledge states. We also observe that female students are underrepresented and yet outperform male students. Female underrepresentation in mobile learning is consistent with evidence on the digital gender divide [1]. According to UNICEF statistics for Kenya[3], the secondary school enrollment rate (50%) and participation rate (40%) does not differ much by gender: women are slightly less likely to be enrolled but more likely to attend school. Thus, why women outperform men in this mobile learning context warrants further research. In contrast to the UNICEF statistics on school attendance, students in our sample indicated extremely high attendance rates (97% attended daily or 3-4 times per week). This suggests that this mobile learning platform is not yet reaching students with significant barriers to access, as this large of a discrepancy cannot be explained by response bias alone. Based on conversations

[3]https://www.unicef.org/infobycountry/kenya_statistics.html

with Eneza employees, we assumed that high school students would use either their parents' or their own phone, and that phones would mostly be basic (i.e. not smart phones). These assumptions were confirmed by the survey findings.

For the non-cognitive factors it stands out that most students expressed high self-efficacy and positive outcome expectancies. Together with the high satisfaction scores (NPS), these findings speak to the quality of the implementation of the mobile learning platform. Notably, the low spread in responses to the self-efficacy and outcome expectancies questions can partly explain why they were not predictive of outcomes. In contrast, there are a substantial number of Kenyan high school students in our sample who agree (many strongly) that they cannot improve their inborn intelligence. It highlights the potential for growth mindset interventions in this learning context and also more broadly. These interventions could be delivered in the traditional way as a lesson about the malleability of the brain [20] or through behavioral nudges such as the "brain points" incentives [37]. This type of incentive structure can be readily implemented in mobile learning applications that provide targeted practice with immediate feedback.

A key finding in our study is that high school students in Kenya who hold a growth mindset score higher on mobile learning assessments; in fact, the strength of the association we found in this study is equivalent to the correlation found in a recent nationally representative study of 14,000 9th-graders in the United States [20]. However, this does not directly imply that students on Eneza with a growth mindset are learning more [24]. Inferring learning (gains in knowledge) from quiz performance data alone is challenging in the absence of reliable meta-data on the knowledge components that are being tested in each quiz [3]. Mobile learning providers like Eneza can only realize the potential benefits of learning analytics if their systems are designed and instrumented to collect meaningful information about learning processes. As Eneza's content is aligned with the national curriculum for each grade level, it may be possible to map quizzes to subject-specific mastery goals in future research.

6 CONCLUSION

The spread of mobile learning technologies in Sub-Saharan Africa can provide affordable, supplemental access to education for students, teachers, and parents. However, low rates of persistence and performance on these platforms call into question the efficacy of this approach as was the case for massive open online courses (MOOCs) [28, 41]. There are a variety of reasons why a learner seeks out and eventually drops out of an informal learning environment. This study highlights the role of growth mindset in how students engage on the platform, suggesting that attention to personal qualities other than cognitive ability is warranted. Specifically, our findings call for more research on the assessment and cultivation of growth mindsets in digital learning environments.

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