Dosage Patterns and Associations with Reading Comprehension in Click Learning's Reading Programs

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By Lissett Babaian

Executive Summary

Although research shows that early literacy and numeracy are foundational to later achievement and employment, in South Africa, 82% of children in Grade 4 cannot read for meaning (Spaull, 2023) and 63% of learners in Grade 5 have no basic mathematical knowledge (HSRC, 2020). These educational deficits compound as learners move through the education system and contribute to South Africa's high youth unemployment rates (Click Learning, 2024; O'Neill, 2024).

Given the complexity and magnitude of the learning crisis, traditional change efforts have often fallen short. Educational technology (edtech) has emerged as a promising solution to enhance learning outcomes and promote equity at scale. However, there is limited evidence regarding which programs are truly effective, for whom, and under what conditions. Although some intriguing trends highlight emerging best practices—like supplemental or after-school interventions and adaptive or personalized technologies—there are also common pitfalls. These include a mismatch between products and learners' needs, particularly concerning language, as well as various contextual factors that can impede the effectiveness and sustainability of edtech interventions.

These considerations are particularly vital in South Africa, where schools serve multilingual learners and grapple with infrastructure and human resource constraints. In this complex landscape, organizations like **Click Learning**, a South African NGO, play a crucial role in delivering locally led and contextually relevant solutions.

Click Learning's mission is to equip learners with the foundational literacy, numeracy, and digital skills necessary to build sustainable livelihoods in the future. Employing a holistic approach, Click Learning offers underserved schools access to top-notch digital learning programs, along with vital infrastructure (such as hardware, connectivity, and backup power) and essential human resources (including lab facilitators). By facilitating the integration of edtech in low-resourced schools, Click Learning is paving the way for thousands of children to succeed in school and beyond.

In the last ten years, Click Learning has collaborated with more than 340 schools, benefiting 230,000 literacy learners and 50,000 numeracy learners. Inspired by findings from a recent study indicating a significant link between enhanced learning outcomes and learners' cumulative time spent on Click Learning programs (Firdale, 2022, p.13), Click Learning partnered with a team of LEAP Fellows to investigate the most effective ways to structure learners' usage for optimal gains. This investigation aimed to determine the minimal or optimal time learners need to meet global proficiency standards in literacy and numeracy by Grade 3. Such insights would enable Click Learning to estimate the ideal balance between the number of sessions and the time spent per session and ensure that the time allocated for Click Learning results in high-quality learning.

During a three-month sprint, the team conducted a literature review to understand the evidence base related to edtech dosage and learning outcomes. After reviewing several studies, including multiple meta-analyses, the evidence remains limited, particularly within the South African context, regarding the impact of dosage, intensity, or duration of use on learning outcomes. This underscores the importance of studies like the present one.

The team also explored the data available for two of Click Learning's programs, Reading Eggs and Reading Eggspress, examining associations between students' use of the platform and their gains in reading comprehension from one year to the next. Below is a summary of our findings:

- The study uncovered significant variability in weekly logins and platform usage among individual students, between students, and across schools, highlighting inconsistent patterns likely influenced by both internal (e.g., student preferences) and external (e.g., school policies) factors. Such variation can be leveraged in analyses of the links between time spent and performance gains, but variation driven by students indicates that confounding variables related to both time spent and performance may bias such analyses.
- In non-regression-adjusted results, platform usage variables from Reading Eggs were negatively associated with reading comprehension scores from Click Learnings's equiz, whereas those from Reading Eggspress showed positive associations. These perplexing results may stem from outliers or students accessing the platform beyond their grade level. For instance, our analysis focused on grades three through five, although Reading Eggspress targets grades six and seven. This suggests that students using Reading Eggspress in lower grades may be unusually proficient, or Reading Eggs might be too elementary for them. Further investigation is necessary for clarification.
- There was substantial agreement between the data mined Reading Eggs time-on-platform variable and Click's previously calculated platform time variable. However, this agreement was not found for the time-on-platform variable in Reading Eggspress. This suggests that an aggregated variable, such as the previously calculated one, may not capture the nuances in the time spent on specific programs within Click Learning.
- In the regression-adjusted results, time on either Reading Eggs or Reading Eggspress was associated positively with score on the external reading comprehension test. For both programs, when students spent a standard deviation more time on the program each week (approximately 10 minutes per week), they gained one-fifth of a standard deviation (0.20) in reading comprehension score. This is a meaningful effect size in the context of reading instruction within South Africa.
- From these analyses, it appears that for this sample, longer sessions are associated with greater gains in reading comprehension. For both programs, the time per login variable was a positive statistically significant predictor of reading comprehension score, with a beta of 0.07 for Reading Eggs and 0.11 for Reading Eggspress. Examining this balance of number of logins by time spent through an interaction term, the interaction of time by logins was only statistically significant for the Reading Eggspress model. In these data, it appears that the association between time spent on Reading Eggspress and reading comprehension score is stronger for those students who have fewer logins. This indicates that students should be given more time per session to engage with Reading Eggspress. These results should only be interpreted as preliminary given that there were a number of extremely short logins (less than two minutes) that may be skewing results.

Based on insights gained during this sprint, and informed by the literature reviews, the report offers customized recommendations related to:

- the data collection and analysis of Reading Eggs and Reading Eggspress;
- further exploration of the connection between dosage and learning outcomes;
- the broader language and learning context of the Click Learning program; and
- enhanced program implementation and evaluation.

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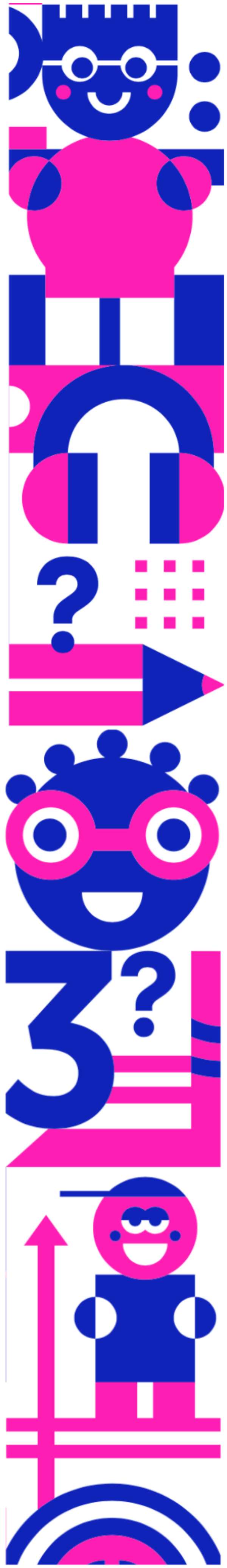

Setting the Context: Edtech and the Language & Learning Nexus in South Africa.

By Barbara Trudell

Setting the Context: Edtech and the Language and Learning Nexus in South Africa

Edtech has been described as the use of computer hardware, software, educational theory and on-the-ground practice to facilitate learning (Robinson et al., 2008). Edtech as a learning approach holds both potential benefits and potential drawbacks, a number of which are relevant to the siting of edtech in, or alongside, the formal classroom.

Edtech is also described as "the study and ethical practice of facilitating learning and improving performance by creating, using and managing appropriate technological processes and resources" (Richey, 2008, p. 24). Along with the more program-related ethics of data privacy and use, the ethics of access—providing pupils and teachers in under-resourced learning contexts with access to new learning options—are a powerful motivator for certain edtech programs in the global South, including the South African NGO, Click Learning. Click Learning's aim is to *"help under-serviced primary schools in South Africa improve foundational literacy, numeracy and digital skills through the deployment of relevant online programmes."*[2]

Edtech has the potential to support learning by "providing high quality content, enhancing motivation, providing time for practice and feedback, and individualisation or personalisation (i.e., self-led learning)" (Cheung & Slavin, 2013). However, as Borole and colleagues (forthcoming) note, the promise of edtech may not always be met in reality. This is why assessing the effectiveness of edtech solutions is both appropriate and important, especially in the low-resourced contexts that can be found in parts of South Africa (Borole et al., forthcoming); the lack of other learning resources, often including textbooks, and the limited competencies of teachers in many cases, can easily give rise to the untested assumption that edtech will provide the "learning solution" in such contexts. However, Borole et al. (forthcoming) note that many edtech interventions are either not evaluated at all, or evaluated by their creator organizations; this limits the accumulation of critical knowledge regarding which edtech interventions work, and for whom.

The Classroom Context in Which Click Learning is Working

The curricular goals around which Click Learning operates include English-language literacy and numeracy. For many of Click Learning's target audience, the literacy goal also necessarily includes an English language-learning component.

South Africa's Department of Basic Education (DBE), which sets curricular expectations for the nation's primary schools, recognizes the language context of young South African learners. Expectations of pupil language fluencies thus vary. Some South African primary schools are designated for the use of English as the pupils' home language throughout their educational career; other schools are designated for the use of a South African home language of instruction in the early grades, with English language learning (as the "first additional language") provided in those grades. A recent report (Firdale, 2022, p.17) notes that, of the schools in which Click Learning operates, 23.7% assume English to be the learners' home language and 76.3% assume English to be a first additional language. In the 23.7%, close to none of the pupils actually speak English adequately to learn in that language.

[2] Click Learning | Reviews 2024: Features, Price, Alternatives (edtechimpact.com). Accessed 9 March 2024.

Thus, for all of the schools, Click Learning's task includes support for the strengthening of pupils' literacy and numeracy skills—but also their English skills. In the 76.3% of the schools that Click Learning works in, some pupil literacy in a South African language may exist. Click Learning's task here includes strengthening pupils' English fluency, so that they can transfer their existing literacy knowledge from the home language to English (Nakamura et al., 2023, p. 5). So the goal for these schools is to facilitate pupils' learning to read English as an additional language. For the remaining 23.7% of the schools, a significant additional learning challenge is that much of the curricular content being conveyed in the classrooms—including reading and mathematics skills—is not being mastered, due to lack of pupil fluency in the language of instruction (English). Click Learning's task in these schools is to provide greater focus on the pupils' English language fluency, as well as strengthening whatever literacy and numeracy knowledge they have gained through English-medium teaching.

The Language Component of Reading Acquisition

In the primary schools of South Africa, as elsewhere, children's reading skills depend a great deal on whether they speak and understand the language of instruction. The DBE takes a holistic approach to reading acquisition:

> How well children learn to read depends on how well they are taught to read, how many opportunities they are given to read and write every day, how much access they have to a wide variety of high quality reading materials, whether they are encouraged and motivated to read, and whether they have reading role models to emulate (DBE, n.d., p. 12).

The DBE's perspective on language learning assumes a "natural" approach to second language learning that parallels the ways children learn their first language:

> In the first years of their lives, children hear huge amounts of simple language, which enables them to gradually absorb the grammar and vocabulary of their home language. After a year or so, children start speaking their home language, but not in full sentences. They begin by producing one or two words, which they use to express a range of meanings and purposes. . . . It is important for teachers to keep this in mind when children are learning an additional language (DBE, 2011, p.10).

A significant challenge to this naturalistic approach is its mistaken assumption that South African children are learning English in the same ways and to the same level of fluency that they have learned their home languages.

An additional challenge in this context has to do with pupils who do not gain strong reading skills in their own home languages before transitioning to English-medium learning. Castillo (2017, p.83) argues that "learners who do not demonstrate decoding proficiency in the mother tongue beyond the lower proficiency level may struggle to develop similar skills in a first additional language." Castillo estimates that, in the South African context, "more than a quarter of learners may be advancing into instruction in a first additional language without establishing sufficient foundational reading skills in their mother tongue" (p. 84). Castillo also argues that "reading performance can be enhanced through well-developed and contextualized digital material in under-resourced settings with diverse learner needs" (p. 86).

The Benefits and the Limitations of Edtech in Diverse Contexts

Much has been written about the role of edtech in assisting—or replacing—classroom teaching. Particularly in low-resourced contexts of the global South, edtech is seen to provide what institutional services cannot. An All Children Reading posting notes that "providing early access to reading materials in local languages . . . . gives them the opportunity to learn to read and develop social and cognitive skills to interact with the world around them." [3] The post notes further that technology-based reading projects have "effectively disseminated new or existing learning materials to underserved populations in languages they use." [4] All Children Reading also cites a World Bank study showing that Nigerian children who received preloaded smartphones saw significantly improved learning outcomes: "After using the apps for an average of around 8 hours during the first week, the children scored higher in a series of Early Grade Reading Assessment (EGRA) modules." [5] In a more explicit expression of this perspective, the Global Learning XPRIZE of 2019 challenged learning software developers to "develop open-source, scalable software that empowers [Tanzanian] children to teach themselves basic reading, writing and arithmetic within 15 months" and "take control of their own learning." [6]

However, a cautionary thread runs through research findings on this subject, regarding the adequacy of edtech to produce good results when used without reference to a classroom and a teacher. Sherman et al. (2007) express this caution:

> This framework for technology is based upon a critical assumption: Knowledgeable and dedicated teachers are the critical element in successful reading instruction programs. While technology can support these teachers and help them be more successful with all children, it can never replace qualified teachers because teaching children to read is too complex.[7]

Indeed, the website for Reading Eggs (one of the main apps used in Click Learning programs) notes that "The important thing to remember is that Reading Eggs is a supplemental. It is not intended to act as the be all and end all of reading success." [8]

Further studies are also cautionary. Shyamlee (2012, p. 153) notes that edtech today should be serving as an assisting instrument rather than a stand-alone tool for English language learning. Zainuddin (2023, p.20) comments on the reality that students using edtech "tend to pay more attention to the tools and resources available to them than they do to the material being taught." Altavilla (2020, p.19) observes that implementation of English language-learning tech "has tended to race out ahead of the research into whether, or under what conditions, [English language learners] benefit from the same technology-based instruction as other students."

[3] Using EdTech to advance learning in languages children use and understand - All Children Reading: A Grand Challenge for Development.
[4] ibid.
[5] Recent World Bank study provides compelling evidence that EdTech has big impact on literacy, improving reading outcomes within days - All Children Reading: A Grand Challenge for Development
[6] Overview | Global Learning XPRIZE | XPRIZE Foundation.
[7] Peterson (ed.gov) https://files.eric.ed.gov/fulltext/ED485613.pdf.
[8] Reading Eggs | Tried and Tested | Teach Primary

Conclusion: Edtech, but not Alone!

The utility and relevance of edtech in the low-resourced, multilingual contexts of South African schools depend on its designers' responses to those contexts. If designed to support and supplement classroom learning among learners with varied language abilities, edtech can be a valuable tool for teachers and learners alike. However, attention to learners' language abilities is crucial; as Zhao and colleagues (2024, pp. 24-25) note, " just because a program is well-designed for use by English speakers, that doesn't necessarily mean it will work well for ELs [English learners], or for ELs from particular language backgrounds."

Click Learning's experience with low-resourced South African primary students is a clear example of edtech being used to address the challenges of learning in formal education settings. To the degree that Click Learning is attentive to the language and learning issues that are affecting teachers' effectiveness and learners' classroom success, its edtech offerings hold an important degree of relevance. The challenge for Click Learning is to continue ensuring that its software is meeting the most urgent learning needs of its target audience: low-resourced South African children with varying levels of English fluency, and the teachers tasked with helping those children succeed in school.

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Introduction to Click Learning.

By Lissett Babaian

Introduction to Click Learning

Today, with just a *click* of a button, children should be able to readily access the information they need to learn and benefit from personalized support to make concepts *click* into place.

Click Learning was founded with the bold mission of harnessing the transformative potential of technology to combat South Africa's learning crisis. Through a full-service model, Click Learning provides underserved schools with access to world-class digital learning programs and comprehensive support tailored to the specific needs of South African schools. This support encompasses access to critical infrastructure, including hardware, connectivity, backup power, security, and insurance, as well as essential human resources, such as a virtual support desk and lab facilitators. Together, these resources create an enabling environment for the deployment of edtech in low-resourced public schools, while simultaneously generating hundreds of jobs for previously unemployed youth (Click Learning, 2024).

Over the past decade, Click Learning has forged partnerships with education departments and districts across four provinces. Through its integrated approach, Click Learning has established computer labs in more than 340 partner schools and reached over 230,000 literacy learners and 50,000 numeracy learners (Click Learning, 2024). A recent study underscores the effectiveness of Click Learning's approach, indicating a strong correlation between improved learning outcomes and the cumulative time learners spent on Click Learning programs (Firdale, 2022, p.13).

Building upon this success, Click Learning recently set an ambitious goal to reach 1 million learners in South Africa by 2030, teaching them to read for meaning and calculate with confidence (Click Learning, 2024). To ensure its approach is evidence-based, Click Learning employs a Sandbox Method. This approach allows Click Learning to rapidly learn and adapt its intervention in a subset of schools before rolling them out across all its partners.

In line with its ethos of "think big, start small (to learn and adapt), and relentlessly seek impact," Click Learning is conducting various experiments using its Sandbox to test new learning programs and implementation strategies (Click Learning, 2024, p.9). Nonetheless, a pivotal question remains:

If spending more time on Click Learning programs improves performance, what is the minimal or optimal time learners need to meet global proficiency standards in literacy and numeracy by Grade 3?

Over the course of a three-month sprint, Click Learning partnered with LEAP Fellows to investigate this question. This report outlines our findings and offers recommendations for Click Learning as it continues to explore the most effective ways to structure learners' usage for optimal gains.

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Literature Review: Relationship between Dosage and Learning Outcomes in Education Technology.

By Tony Senanyake

Literature Review: Relationship between Dosage and Learning Outcomes in Education Technology

Click Learning has a core focus on students engaging with their edtech intervention for at least 18 hours in a school year. However, an open question remains regarding the optimal amount of time a student should interact with the intervention to maximize learning outcomes. An understanding of this optimal time would help inform the appropriate deployment of the intervention at the school level. Such knowledge may influence decisions around intervention deployment, specifically focused on:

- **Dosage**: total hours of usage
- **Intensity**: minutes of use per week/session
- **Duration**: the total number of weeks the intervention is delivered

Improvements in learning outcomes may accrue through direct interaction with the intervention. However, this learning may come at the cost of improved learning outcomes that may otherwise have accrued through standard teacher-led learning in the classroom, given that the intervention is a partial substitute for teacher-led instruction. Therefore, the optimal amount of time interacting with the edtech intervention cannot be considered in a vacuum without also understanding the existing teaching environment. This literature review has not considered the value of existing teacher-led instruction that is being substituted.

The literature does not identify a correlation between dosage, intensity or duration of edtech interventions (similar to that delivered by Click Learning), and changes in learning outcomes.

There are two caveats that we would like to highlight on this overall finding:

1. The available evidence is almost all based on comparisons of different peer-reviewed impact evaluations (mainly randomized controlled trials) as opposed to an explicit testing of a single edtech with various dosages under otherwise controlled situations (exogenous variation). Therefore, the high-level finding is weak because the different studies have very different contextual environments, making it difficult to attribute differences in learning outcome changes to dosage.
2. The studies that comprised the various meta-analyses were all fully implemented. This means that the interventions were deployed for the full duration and intensity for the research period. The existing research currently is unable to inform the marginal value of intervention deployment characteristics if an edtech intervention is implemented at a level which is lower than the intended level.

The literature identifies a statistically significant, positive correlation between use of edtech interventions and learning outcomes. Therefore, it is safe to presume that there must be some correlation between intervention deployment characteristics and learning outcomes; however, the existing literature base has not identified what this may be.

The general literature on the correlation between dosage and learning outcomes of phonics and reading interventions suggests that between 30 and 40 hours per year may be the optimal amount of time for early primary level grade students. The context of the studies within this literature is not highly comparable to the Click Learning context, so these figures should be taken with caution.

Summary of Meta-Analyses Comparing Edtech

A handful of recent meta-analyses have tackled the question of whether there may be a correlation between elements of intervention deployment and learning outcomes.

Sampson et al. (2019) considered 14 studies that covered 27 interventions. All studies were from low and middle-income countries, with computer-based, edtech interventions. All studies employed randomized designs. Overall, the meta-analysis found a positive relationship between learning outcomes and use of edtech. However, when the authors sought to disaggregate the findings they concluded that "[e]ffect sizes from edtech do not correlate with dosage, intensity, or duration of use" (Sampson et al, 2019, p. 14).

Major et al. (2021) considered 16 randomized controlled trials across five countries. These studies covered 53,029 learners aged six-15 years. The authors, similar to Sampson et al. (2019), found an overall positive effect on learning in the order of 0.18 standard deviations. The authors then split the studies into interventions whose intensity was considered "strong"---where the total duration of the intervention was greater than or equal to 4.5 months with at least 75 minutes of usage per week—or otherwise "moderate." Ten of the studies were considered to have strong intensity and six were of moderate intensity. The authors stated (Major et al., 2021, p. 1,935),

> *…meta-regression reveals how there is no statistical difference between studies categorized based on the intensity and duration of the intervention. This suggests that technology implementation for more than 4.5 months with an intensity of greater than 75 min a week may be similarly effective to that of a more moderate duration and intensity (between 2 and 4.5 months and of 45–75 min a week), although further research is needed to confirm this.*

Cheung and Slavin (2013, p. 12), in an earlier meta-analysis using the same intensity metric, came to a similar finding: "no significant difference was found between the two intensity categories [strong and moderate intensity]. This result suggests that more technology use does not necessarily result in better outcomes."

The lack of evidence around optimal intervention deployment of edtech interventions has been highlighted in various reports. Rodriguez-Segura (2022, p.193) states,

> *The suitability of the treatment for the specific context, adaptability for different learning levels, and crucially, the right dosage for everyone's needs are pivotal elements to ensure that self-led interventions can cater and boost educational outcomes for all students.*

Comparison of Dosage within a Single Intervention

The first study (and only one identified at this point in time) to attempt to attribute exogenous changes in usage levels of an edtech intervention on learning outcomes is Bettinger et al. (2022). The authors found that doubling usage time per week either had no (or even potentially negative) impacts on learning outcomes.

The study was based in Russia and investigated the impact of a computer assisted learning (CAL) intervention on learning outcomes. The study contained three groups, one control group and two treatment arms. One treatment arm received what was considered a low level dosage of the intervention, which was 20-25 minutes per week of both mathematics and language (40-50 mins per week total). The other treatment arm received a high level dosage, which was double the low level, or 40-50 minutes per week of both mathematics and language (80-100 minutes per week total). The study contained 343 schools with 6,253 students from Grades 2–4.

The authors found

> *…positive effects of CAL on math test scores at the base dosage level. Doubling the amount of CAL input, we find similar effect sizes relative to the control. We thus find evidence that is consistent with a concave relationship between CAL and educational production. … For impacts on language achievement, we find positive effects of CAL at the base level, but stronger evidence consistent with concavity. We find that CAL is a positive substitute when moving from zero to the base level of CAL, but a negative substitute when moving from the base level of CAL to the higher level. The findings clearly indicate that there is an optimal amount of CAL use for language that represents a relatively balanced approach instead of one with very high levels of usage (or no usage) (Bettinger et al., 2022, p. 15).*

The study only contained two treatment arms, and therefore we are unable to deduce where within the usage curve optimal learning may have lay for this initiative. However, the study provides the only direct empirical evidence we are aware of that there may be an optimal amount of usage time for edtech interventions.

Bettinger et al. (2022) went on to consider whether there may have been different results for various subgroups. The authors did not find differences in the overall conclusions when focusing on either gender nor when they considered the students' baseline knowledge level.

Summary of Meta-Analyses Comparing General Correlation between Dosage and Learning Outcomes

A larger body of literature has investigated the association between phonic and reading instruction dosage on learning outcomes. The interventions within this analysis are not edtech interventions, but there may be something learned regarding the general understanding on optimal time. The general observation in this literature base is that there appears to be a non-linear relationship between dosage and learning outcomes. This means there may be an optimal dosage for instruction time.

Roberts et al. (2022) conducted a meta-analysis of 26 studies that covered 186 separate effect sizes. The interventions were all focused on reading, and studies targeted students between Kindergarten and Grade 3 in high-income contexts. The authors estimated that the maximal effect size peaked at 39.92 hours of instruction. They also noted that students who had 1:1 instruction with teachers did appear to display a linear relationship between dosage and reading learning outcome attainment, depending on the amount of time they worked with the teacher. Erbeli et al. (2024) conducted a similar meta-analysis, focused on early phonemic awareness instruction in preschool and grade 1 students in high-income contexts. They similarly observed a non-linear relationship between dosage and learning outcomes with a peak at 10.2 hours of instruction.

Another body of evidence that we have briefly investigated is related to time on task. Time on task may be understood as the amount of time a learner is actively engaged in the learning task they have been assigned (this may be any task, not necessarily an edtech intervention). This literature is somewhat tangential to the primary research question. However, it is interesting to note that even within this literature there is a lack of evidence suggesting that greater time spent on a task correlates with improved learning outcomes.

Karrie et al. (2021, p. 2) in a meta-analysis of time on task-related studies found that

> *…the relationship between time and learning remains elusive as prior research has obtained mixed findings. In the prior literature, a positive association between time spent on-task and achievement has typically been found, yet the correlation strength vacillates dramatically across studies. Indeed, in our review we found estimates for the correlation strength between measures of time and learning/performance ranged between -.23 and .78.*

Other Potentially Relevant Considerations

When considering the ideal implementation deployment characteristics, there are a number of factors that the literature highlights as being of potential relevance (Abbey et al., 2024; Major et al., 2021; Rodriguez-Segura, 2022). These include:

- Implementation quality of the technology: underlying logistical issues tend to be the main barrier to edtech intervention effectiveness.
- Whether the intervention is substituting existing learning time or supplementing it through after-school interventions: after-school interventions are more likely to show positive effects. This may be because they do not replace teaching time. In-school interventions are more likely to show positive impacts when the quality of traditional instruction time that they replaced was low (Montoya et al., 2021; Sampson et al., 2019).
- Adaptivity: interventions that leverage adaptive technologies to match instruction to the learning-level of the user have shown the largest effects. These adaptive products do not consistently benefit lower or higher performers more (Sampson et al., 2019).
- Incentives: there is some evidence suggesting that incentivising and focusing on time spent iterating within the edtech intervention lead to greater learning gains than rewarding the change in learning outcomes itself (Rodriguez-Segura, 2022).

This literature review helped to inform the key questions and recommendations articulated in the following sections. Indeed, the overall paucity of evidence regarding the correlation between dosage and learning outcomes gives additional value to the data collected by Click Learning and its subsequent analysis, below. The evidence generated by this work can help to enhance the impact of edtech interventions, particularly in the identification of optimal dosage targets.

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Study Methods & Results.

By Teomara Rutherford

Study Methods & Results

Motivation for Analysis

Click Learning expressed to the LEAP Fellows a desire to understand how usage (time on platform/dosage) of the Click Learning platform programs could be structured to result in optimal learning gains for students. For example, longer usage time per login might allow students to work more intensely on content, but may push against the bounds of young children's attention. As Click Learning had access to data from within the learning programs used within their platform (e.g., Reading Eggs), it would be possible to examine associations between students' use of the platform and their gains in reading comprehension from one year to the next.

The data analysis and results reported here were undertaken contemporaneously with the creation of the literature review on dosage. Therefore, certain insights from the literature review, such as the need to examine non-linear associations between dosage and achievement, could not be realized. What is reported herein is an initial exploration of the data available from two programs, Reading Eggs and Reading Eggspress. The exploration includes: examination of the structure of the data; how the data align with assumptions regarding school schedules and users; examination of variance in usage among students, classes, and schools; and associations between patterns of use and reading comprehension performance. Particularly detailed information is provided regarding the initial data examination. The intention is that these steps can serve as a model for both Click and other platform providers in vetting, organizing, and analyzing data derived from student interactions with educational technology.

Data Sources

Click Learning provided platform data that were structured so that each row provided data on a week of logins for a particular program (e.g., Reading Eggs, Matific). Only data on Reading Eggs and Reading Eggspress contained viable entries for both time played (in seconds per week) and number of logins (calculated by using a "sessions" variable that counted up from 1 for the first session a student played). Multiple sessions (i.e., logins) could be present per student, program, and week. Within the original dataset, there were data on 248,662 students across 35,120,674 observations of which 106,568 were complete duplicates. Dates ranged from Jan 1, 2023 to Dec 31, 2023.

The below shows data descriptives for 11,050,113 observations (students BY weeks) each for Reading Eggs and Reading Eggspress, with 234,883 students. There were some dates in the data that weren't when school was in session, so the data were limited to only Jan 8 (the week starts on Sunday) through Dec 13. After removing dates outside this range there were: 234,826 students with 10,213,898 observations for each Reading Eggs and Reading Eggspress.

Means are followed by standard deviations in parentheses with ranges below.

	Weekly Logins	Weekly Time (secs)	Tot Logins Per Student	Time/Login (secs per login)
Reading Eggs	0.40 (0.81) 0-119*	582.27 (1,246.78) 0-84,220	17.25 (18.54) 0-331	1,645.67 (1,068.97) 0-13,344
Reading Eggspress	0.20 (0.67) 0-48	165.97 (622.22) 0-47,722	8.58 (17.04) 0-252	920.21 (837.86) 0-9,600

Note. The data above are after data-cleaning steps taken below to rid the dataset of out-of-range values for dates.

**Each student's first week in the data was assigned a weekly login equal to their session number; this 119 outlier is from this assignment*

Additionally, there were some abnormalities in the data impacting a handful of students. These abnormalities showed the students restarting their "session" variable during a given week. Therefore, weekly logins and time for these students could not be calculated and they were dropped from the analysis dataset. This impacted 504 students for Reading Eggs and 278 students for Reading Eggspress. Given this was 0.02% and 0.01% of the students, respectively, they were dropped from the data, resulting in new samples of 234,257 students each for Reading Eggs and Reading Eggspress and 10,191,849 observations each.

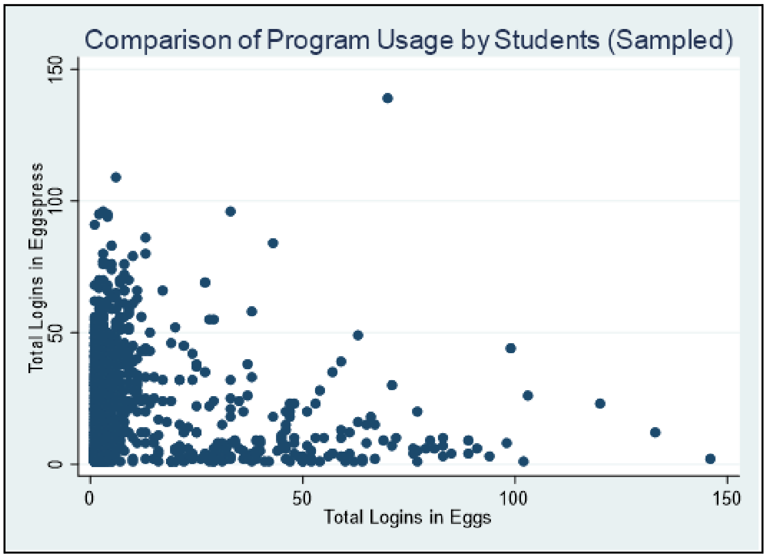
Click Learning also provided data on school demographics and student performance (the equiz data). These data included information on school language instruction, province, and resource quintile (based on socioeconomic background of the school). These data also included student information, including the student grade-level, reading comprehension scores from both 2022 (pretest) and 2023 (posttest), and a time-on-platform variable calculated by Click Learning's data analyst. The equizes were developed and administered by Click Learning as a way to measure impact on learning outcomes over time. The equizes of interest for the current analysis include the reading comprehension task from the Foundations of Literacy 2022, which is included as the pre-test reading comprehension score. The second equiz is the Comprehension equiz from 2023, which is the posttest score and outcome variable in the current analysis. These tasks are from separate equizes and are, therefore, not directly comparable. However, both tasks measure reading comprehension.

The equiz and program datasets were merged. The data were then limited to the 181,583 students who could be merged as their IDs were present in both datasets. These students had 8,117,625 observations for Reading Eggs and Reading Eggspress each. The students were nested within 336 schools and 4,672 classes. Each class had, on average, 38.87 students (SD=9.82, range 1-85). Each school had, on average, 540.43 students (SD=296.28, range 1-1,539) and 13.90 classes (SD=6.72, range 1-38).

Preliminary Analyses

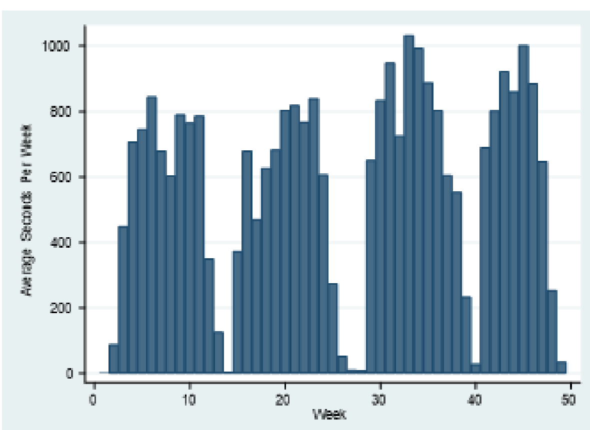
In these data, 161,290 students had logins for both Reading Eggs and Reading Eggspress. Of those students with logins for both, the mean number of logins for Reading Eggs was 13.89 (SD=10.51, range 1-42) and for Reading Eggspress was 6.58 (SD=8.20, range 1-44).

Below is a random sample of 1,000 students who have login data for each and a scatter plot illustrating the relationship between number of logins for each program.

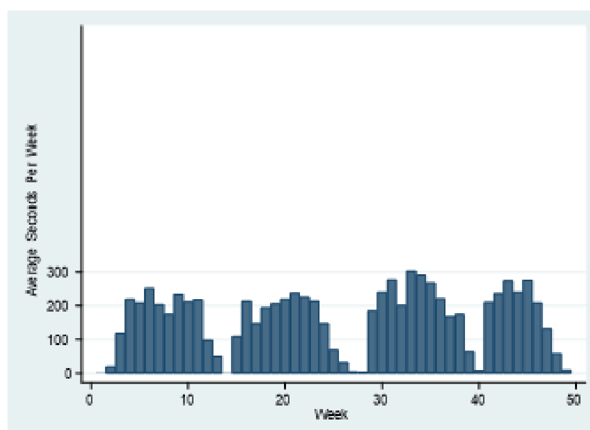


As an initial analytic step, the play data were examined to reveal patterns of play across the year. In particular, we were looking for play patterns that corresponded to school holidays, which would strengthen assumptions of data veracity.

Average Seconds Per Week Played in Total



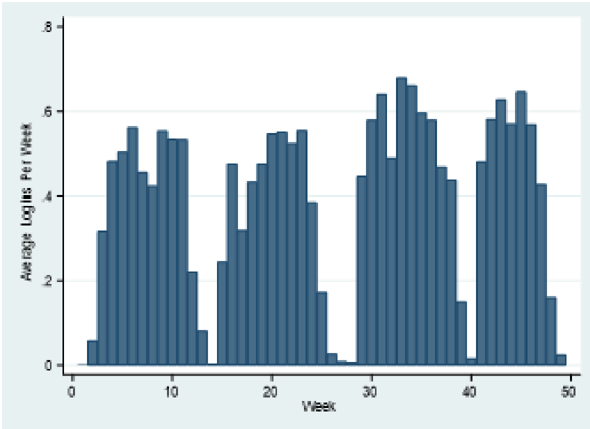
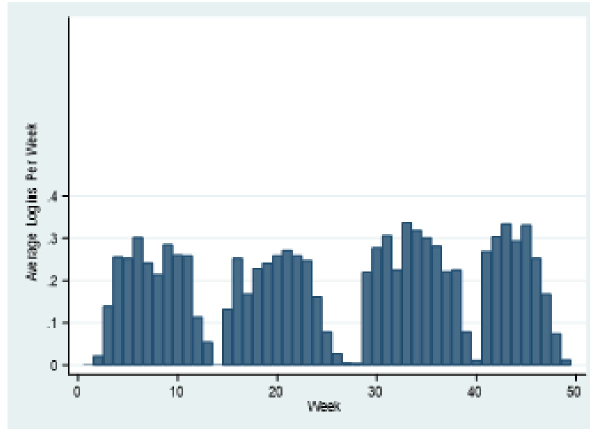
Reading Eggs



Reading Eggspress

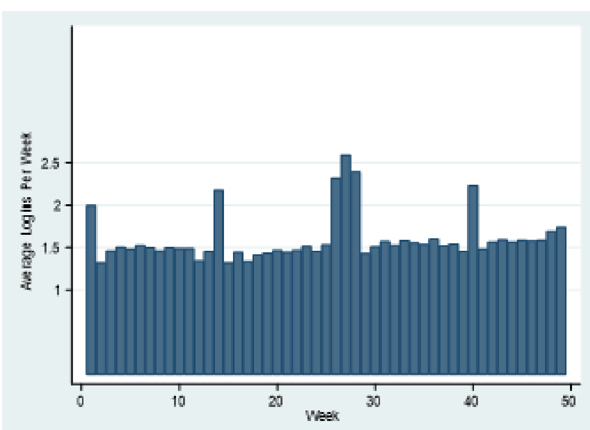
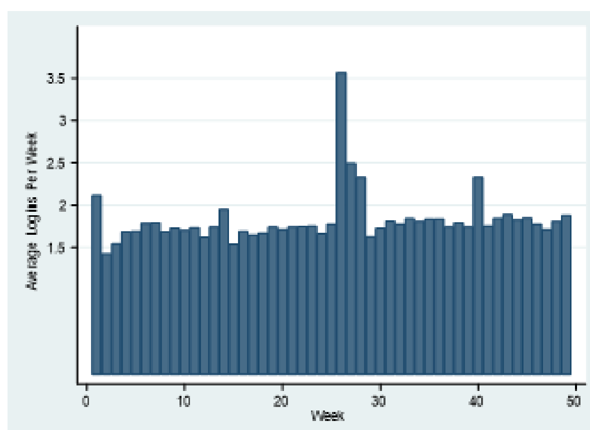
On average, there are more seconds played for Reading Eggs compared to Reading Express, as in the table above; but the patterns are very similar, with dips in play during school holidays. On the next page, similar graphs are created with logins per week. The average number of logins per week are less than one, because many weeks there are no logins. The second set of graphs reduces the data to only those weeks where there was at least one login for a given student.

Average Logins (Sessions) Per Week Played in Total

Reading Eggs	Reading Eggspress
	

The graphs below show that in weeks where students logged in, they tended to login around 1.5 times, with some high login weeks. In these high-login weeks there were fewer students playing. For example, most weeks had 50K or more students playing Reading Eggs. Weeks 26 and 27 had fewer than 1K playing and week 25 had 2,502 playing. These weeks may have been holidays or other instances where there weren't students in school.

Average Logins (Sessions) Per Week Played When There Was at Least One Login

Reading Eggs	Reading Eggspress
	

The structure of the data was such that each student had multiple weeks (as rows) of data. This allowed examination of within student variability in logins. For both programs, approximately 30% of the variance in weekly time was attributed to the student. This meant that the majority of the variance in weekly time spent on the program was within student—a given student would vary widely from week to week in how much time they spent on Reading Eggs or Reading Eggspress.

For number of logins per week, the variance explained by student was even lower, 24% for Reading Eggs and 28% for Reading Eggspress.

Proportion of Variance Explained by Student

Per Week:	Reading Eggs	Reading Eggspress
Seconds	.29 (29% of variance)	.30 (30% of variance)
No. Logins	.24 (24% of variance)	.28 (28% of variance)

For the remaining analyses, the data were collapsed to the student by program level, so that each student only had one or two observations (one for each program, Reading Eggs or Reading Eggspress). In the collapse, means of weekly seconds and weekly logins were created along with totals of seconds and logins spent on the particular program.

The data contained 181,583 students and 363,166 observations, 169,693 had at least some time on Reading Eggs and 136,762 had at least some time on Reading Eggspress. The data contained students who were labeled as participating in Core, DC Literacy, and DC Numeracy.

Examining the data, there were a number of students who had very low logins and then a number who had over 200 logins during the year. Both are included in the descriptive statistics below, but for future analysis, it might be a good idea to exclude these outliers after identifying potential reasons for these very low or very high numbers. Visually examining the data, it appears highly skewed. This is reflected in the extremely large standard deviations in the descriptive statistics below.

Descriptives for Those with at Least Some Time on Reading Eggs

	Core		DC Lit		DC Num	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Mean Weekly Time	696.24	693.43	1,819.97	1,572.84	882.36	805.08
Min/Max	0.04	7,937.24	0.29	7,010	0.08	6,557.25
Mean Weekly Logins	0.47	0.41	1.49	1.17	0.53	0.42
Min/Max	0.02	9.21	0.04	5.71	0.02	5.44
Total Time	31,976.67	32,891.45	35,973.21	31,585.91	37,735.52	36,251.61
Min/Max	2	332,334	6	147,210	4	246,618
Total Logins	21.48	19.27	29.42	23.34	22.4	18.65
Min/Max	1	331	1	120	1	145
N	**146,414**		**1,836**		**21,443**	

Descriptives for Those with at Least Some Time on Reading Eggspress

	Core		DC Lit		DC Num	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Mean Weekly Time	158.87	345.61	54.72	54.72	129.36	301.53
Min/Max	0.04	5,493.14	0.11	600.44	0.04	2,943.02
Mean Weekly Logins	0.2	0.35	0.13	0.11	0.18	0.32
Min/Max	0.02	5.14	0.03	1.33	0.02	3.2
Total Time	7,432.6	16,479.17	1,077.08	1,056.27	4,950.01	12,089.3
Min/Max	2	269,164	2	10,808	2	144,208
Total Logins	9.44	16.44	2.65	2.17	6.74	12.12
Min/Max	1	252	1	24	1	157
N	**118,110**		**1,535**		**171,17**	

Within the school data, there was already a variable for total time in hours, 2023. This may combine time on all platforms, so may not be an exact correlation of the calculated login and time spent variables above. Comparing this to the weekly time variable calculated from the in-platform Reading Eggs data, the two correlated at .70; however, comparing this 2023 variable to the in-platform Reading Eggspress data, the two correlated only at .19. This does not mean that either variable is wrong, but it does suggest that there are differences between looking at total time on the platform and actual time on specific programs, especially for Reading Eggspress.

In order to examine variable correlations, these data were reduced to the 90,136 students who had Reading Eggs data and data for the Reading Comprehension percentage score and the 82,374 for Reading Eggspress who had data for the Reading Comprehension percentage score. Correlations were examined between logins, time spent, reading scores, and school information, separately for Reading Eggs and Reading Eggspress.

In the correlations tables below, even though the mined data from Reading Eggs positively correlated with the 2023 Time Variable, the mined time variables negatively related to pre (2022) and post (2023) reading comprehension from Click Learning's eQuiz, whereas the Click-provided 2023 time variable positively related. In the Reading Eggspress data, these variables were less correlated, but both positively related to reading comprehension.

	Reading Eggs	1	2	3	4	5	6	7	8	9	10	11
1	**Mean Weekly Time**	1										
2	**Mean Weekly Logins**	0.868***	1									
3	**Mean Time/Logins**	0.636***	0.302***	1								
4	**Total Time**	0.988***	0.848***	0.626***	1							
5	**Total Logins**	0.866***	0.973***	0.302***	0.879***	1						
6	**2023 Time Variable**	0.764***	0.662***	0.325***	0.784***	0.701***	1					
7	**English: Both**	0.004	0.005	-0.008*	0.003	0.005	-0.005	1				
8	**English: FAL**	0.074***	0.027***	0.063***	0.083***	0.047***	0.090***	-0.312***	1			
9	**English: Home**	-0.078***	-0.011***	-0.091***	-0.089***	-0.037***	-0.105***	-0.113***	-0.759***	1		
10	**School Quintile**	0.048***	0.077***	0.001	0.038***	0.060***	0.030***	0.085***	-0.407***	0.387***	1	
11	**Reading Comp 22**	-0.076***	-0.071***	-0.058***	-0.074***	-0.071***	0.015***	0.0003	-0.202***	0.209***	0.190***	1
12	**Reading Comp 23**	-0.026***	-0.031***	-0.033***	-0.026***	-0.032***	0.062***	-0.007*	-0.194***	0.197***	0.199***	0.476***

	Reading Eggspress	1	2	3	4	5	6	7	8	9	10	11
1	**Mean Weekly Time**	1										
2	**Mean Weekly Logins**	0.932***	1									
3	**Mean Time/Logins**	0.675***	0.524***	1								
4	**Total Time**	0.997***	0.928***	0.671***	1							
5	**Total Logins**	0.930***	0.995***	0.523***	0.934***	1						
6	**2023 Time Variable**	0.120***	0.094***	-0.003	0.127***	0.104***	1					
7	**English: Both**	-0.005	-0.001	0.003	-0.006	-0.002	-0.005	1				
8	**English: FAL**	-0.048***	-0.049***	-0.039***	-0.048***	-0.047***	0.075***	-0.313***	1			
9	**English: Home**	0.044***	0.042***	0.027***	0.045***	0.040***	-0.094***	-0.112***	-0.754***	1		
10	**School Quintile**	0.075***	0.068***	0.066***	0.074***	0.066***	0.025***	0.080***	-0.411***	0.394***	1	
11	**Reading Comp 22**	0.217***	0.189***	0.225***	0.217***	0.189***	0.017***	-0.004	-0.207***	0.215***	0.194***	1
12	**Reading Comp 23**	0.204***	0.176***	0.214***	0.205***	0.177***	0.058***	-0.008*	-0.201***	0.204***	0.203***	0.483***

*$p < .05$, **$p < .01$, ** $p < .001$

In addition, intraclass correlation coefficients (ICCs) were examined for these new collapsed datasets, estimating the variance that was explained by class and school for the program time variables and for the student equiz variables. The high amount of variance explained by class was likely due to the confounding of class and grade-level, as schools were assigned to use Click Learning for a particular grade.

ICCs Reading Eggs

	Proportion Explained by School	Proportion Explained by Class
Mean Seconds	.27 (27% of variance)	.87 (87% of variance)
Mean No. Logins	.41 (41% of variance)	.86 (86% of variance)
Time/Logins	.13 (13% of variance)	.80 (80% of variance)
Total Seconds	.19 (19% of variance)	.85 (85% of variance)
Total Logins	.26 (26% of variance)	.82 (82% of variance)
2023 Time	.54 (54% of variance)	.78 (78% of variance)
Reading Comp 22	.13 (13% of variance)	.30 (30% of variance)
Reading Comp 23	.16 (16% of variance)	.24 (24% of variance)

ICCs Reading Eggspress

	Proportion Explained by School	Proportion Explained by Class
Mean Seconds	.22 (22% of variance)	.76 (76% of variance)
Mean No. Logins	.24 (24% of variance)	.78 (78% of variance)
Time/Logins	.11 (11% of variance)	.38 (38% of variance)
Total Seconds	.22 (22% of variance)	.75 (75% of variance)
Total Logins	.23 (23% of variance)	.77 (77% of variance)
2023 Time	.53 (53% of variance)	.77 (77% of variance)
Reading Comp 22	.13 (13% of variance)	.29 (29% of variance)
Reading Comp 23	.16 (16% of variance)	.24 (24% of variance)

Analytic Plan

The analysis was structured to answer the following research questions separately for Reading Eggs and Reading Eggspress:

(1) What is the association between weekly time spent on the program and performance?
(2) What is the association between weekly logins on the program and performance?
(3) What is the association between average session length (time per login) on the program and performance?
(4) What is the association between total time (as calculated by Click) on the platform and performance?

Before conducting analyses, the sample was limited to those with valid data on both the pretest (2022) and posttest (2023). In addition, the sample was limited to the 55,020 students in the target grades (grades three through five). It is recommended that all the data examination above be replicated with the final reduced analysis sample, but given time constraints, this could not be accomplished for the current report.

In addition, once these constraints were applied, no students in the double click literacy program were included in the sample. School demographics for the analysis sample by target program are below:

	Eggs	Eggspress
Eastern Cape	13%	14%
Gauteng	51%	49%
Mpumalanga	16%	17%
Western Cape	19%	20%
English: Both	5%	5%
English: FAL	69%	69%
English: Home	20%	20%
Core	88%	88%
DC Numeracy	12%	12%
Quintile 1	14%	15%
Quintile 2	25%	24%
Quintile 3	34%	35%
Quintile 4	18%	18%
Quintile 5	9%	9%
N	**52,975**	**48,581**

A series of multilevel regressions predicting 2023 reading comprehension score were run separately for Reading Eggs and Reading Eggspress data. For each regression, three levels were estimated: students nested within classes nested within schools. Control variables included grade level, English status, program (DC vs. Core), school quintile, province, and 2022 reading comprehension test. Regressions first were run separately for the time, logins, and time/logins variables. Then, the time and logins variables were included together. Finally, an interaction between time and logins was included.

Descriptive Statistics for Analysis Sample for Reading Eggs

	GR3				GR4				GR5			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Weekly Time (seconds)	1303.36	617.30	0.08	4853.39	991.84	701.90	0.08	6478.12	853.29	671.97	0.08	5033.02
Weekly Logins	0.77	0.37	0.02	4.00	0.62	0.41	0.02	4.53	0.54	0.39	0.02	3.71
Time By Logins	1880.74	514.69	4.00	3946.50	1636.79	687.06	4.00	4946.00	1517.06	721.85	4.00	4064.00
Reading Comp Pretest	34.98	36.57	0.00	100.00	47.44	38.36	0.00	100.00	57.64	38.39	0.00	100.00
Reading Comp Posttest	34.38	27.00	0.00	100.00	42.97	29.12	0.00	100.00	50.47	29.61	0.00	100.00
N	**19,090**				**19,114**				**14,771**			

Descriptive Statistics for Analysis Sample for Reading Eggspress

	GR3				GR4				GR5			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Weekly Time (seconds)	57.27	165.21	0.04	3340.08	243.00	412.11	0.04	4034.57	385.41	507.08	0.04	5493.14
Weekly Logins	0.10	0.17	0.02	2.92	0.28	0.41	0.02	3.57	0.42	0.48	0.02	4.51
Time By Logins	423.41	312.43	2.00	4180.00	635.30	464.64	2.00	3496.00	765.21	499.65	2.00	6292.00
Reading Comp Pretest	34.77	36.65	0.00	100.00	47.99	38.53	0.00	100.00	58.09	38.45	0.00	100.00
Reading Comp Posttest	34.22	27.07	0.00	100.00	43.14	29.49	0.00	100.00	50.77	29.74	0.00	100.00
N	**17,008**				**17,094**				**14,479**			

Results

Reading Eggs

The first large table below displays the results of multilevel regressions for Reading Eggs time variables predicting 2023 reading comprehension performance. The first model shows only pretest and control variable predictors. Pretest score was a statistically significant positive predictor of posttest. Standardized beta coefficients were calculated using the formula (B*sdx)/sdy to place the effect sizes in standard deviation units to allow them to be comparable across programs and with other studies. Although pretest was predictive of posttest, the standardized beta (β) was 0.38, indicating for each standard deviation unit higher scored on the pretest (about 39 points), it could be expected that a student would score a more than a third of a standard deviation unit higher on the posttest (just over 11 points).

In considering mined platform variables, when time and logins were entered separately, only time was statistically significantly associated with performance with an effect size of β = 0.05, indicating a standard deviation increase in weekly seconds (about 11.5 minutes) would bring 5/100th of a standard deviation improvement in performance (about 1.5 points). Although the coefficient for number of weekly logins was negative, when modeled alone, this association did not attain statistical significance (p value was > .05). However, when both variables were entered into the model (model 5), coefficients for each were statistically significant. Association between weekly time and performance was strengthened to β = 0.20, indicating that each standard deviation increase in weekly seconds was associated with one fifth of a standard deviation increase in performance (just under six points). Conversely, for every one standard deviation increase in weekly logins (just under half a login), students could be expected to perform worse, β = -0.18 (just over five points reduction).

These results indicate that longer logins were more important for performance gains. This was supported by the results for the time-by-logins variable, which was calculated by dividing each week's time by that week's number of logins and creating a mean average for each student. A higher number indicates that the student spends more time, on average, per login. Those students who had higher time-by-logins performed higher on the posttest β = 0.07, such that for each standard deviation increase in this variable (about 10 minutes per login), students gained just under two points on the posttest. This association was also explored in a model interacting weekly time and logins, but the interaction term was not statistically significant.

The Click Learning 2023 time variable also showed positive associations with performance. An additional 8.7 hours of total usage across the year (one standard deviation) was associated with a performance gain of four points (β = 0.14).

These standardized coefficients are summarized in the table below.

Standardized Coefficients from Reading Eggs Regressions

	Beta	SD X	Points Y
Pretest	0.38	38.80	11.14
Weekly Time	0.05	689.59	1.46
Weekly Logins	*not statistically significant*		
Time By Logins	0.07	658.17	1.92
Click Time (sec)	0.14	31,490.48	4.03
Weekly Time (2)	0.20	689.59	5.85
Weekly Logins (2)	-0.18	0.40	-5.23

Note. Weekly Time and Logins (2) are results from model 5, where both were included.

Reading Eggspress

The second large table below displays regression results for the Reading Eggspress data. There were some similarities in results between the Reading Eggs regressions and the Reading Eggspress regressions. The pretest association with posttest was replicated, with only slight differences in the coefficient likely due to sample differences. As with the Reading Eggs regressions, weekly time was positively associated with performance, but the beta value was higher in the Reading Eggspress data, $\beta = 0.15$. As a more striking difference, in the model where it was entered without other mined platform variables, weekly logins was positively associated with performance—for every standard deviation increase in weekly logins, students would gain 3.35 points on the posttest ($\beta = 0.11$). However, when both weekly time and weekly logins were entered in the model together, the association between logins and performance became negative ($\beta = -0.06$). As with the Reading Eggs models, in this regression (model 5), the coefficient for weekly time increased from model 2, with an association between weekly time and performance jumping to $\beta = 0.20$, the same as in the Reading Eggs model.

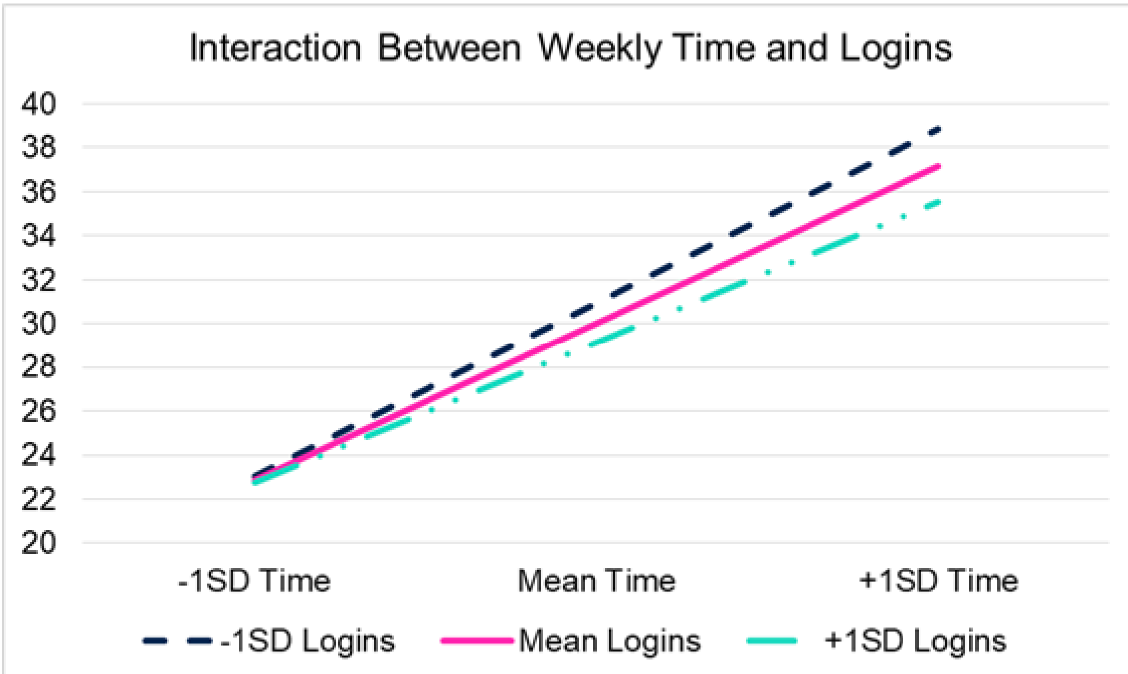
Also similar to the Reading Eggs models, the ratio of weekly time to weekly logins had a positive association with performance, although the beta of 0.11 was higher than the 0.07 beta in the Reading Eggs models. Rounding out the similarities, Click's calculated time variable had a beta association with performance of 0.14, the same as the Reading Eggs models.

Standardized Coefficients from Reading Eggspress Regressions

	Beta	SD X	Points Y
Pretest	0.38	39.01	11.27
Weekly Time	0.15	404.24	4.57
Weekly Logins	0.11	0.39	3.35
Time By Logins	0.11	451.55	3.32
Click Time (sec)	0.14	31,561.32	4.04
Weekly Time (2)	0.20	404.24	5.90
Weekly Logins (2)	-0.06	0.39	-1.67

Note. Weekly Time and Logins (2) are results from model 5, where both were included.

Unlike the Reading Eggs models, the interaction of weekly time and logins was a statistically significant predictor of performance (*p* < .001). The tables aren't displayed for space reasons; however, the graph below displays the interaction results. **The gain from more time is attenuated by the number of logins such that those who have higher amounts of logins gain less from increased time on the platform.**



Note. Y-axis displays results of unstandardized regression coefficients added to the constant. The original scale of the assessment is zero to 100; the data mean is 46.34.

Regression of 2023 Reading Comprehension on Time Variables and Controls for Reading Eggs

	(1)		(2)		(3)		(4)		(5)		(6)	
Weekly Time			0.002***	(0.0003)					0.009***	(0.0005)		
Weekly Logins					-0.770	(0.437)			-12.60***	(0.782)		
Time By Logins							0.003***	(0.0003)				
Click Time Var											0.0001***	(<0.0001)
Pretest	0.287***	(0.003)	0.286***	(0.00306)	0.287***	(0.003)	0.285***	(0.003)	0.283***	(0.003)	0.279***	(0.003)
Grade 4	5.380***	(0.372)	6.125***	(0.382)	5.260***	(0.378)	6.157***	(0.382)	6.214***	(0.385)	6.731***	(0.381)
Grade 5	9.821***	(0.413)	11.010***	(0.436)	9.623***	(0.428)	11.05***	(0.431)	11.04***	(0.438)	11.56***	(0.425)
English: Both	-2.719	(2.272)	-3.057	(2.271)	-2.657	(2.280)	-2.736	(2.293)	-2.967	(2.328)	-3.870	(2.413)
English: FAL	-4.784***	(1.169)	-5.051***	(1.169)	-4.751***	(1.173)	-4.865***	(1.180)	-5.243***	(1.198)	-5.820***	(1.241)
Eastern Cape	-3.357*	(1.599)	-3.782*	(1.599)	-3.225*	(1.606)	-2.825	(1.614)	-2.756	(1.639)	-4.717**	(1.695)
Gauteng	-3.665**	(1.216)	-3.799**	(1.216)	-3.610**	(1.221)	-3.707**	(1.227)	-3.239**	(1.246)	-3.031*	(1.290)
KwaZulu-Natal	-5.749	(8.476)	-4.972	(8.478)	-5.872	(8.495)	-3.533	(8.545)	-4.873	(8.621)	-8.112	(8.831)
Mpumalanga	-5.128***	(1.376)	-5.683***	(1.377)	-4.985***	(1.383)	-5.004***	(1.389)	-4.851***	(1.411)	-6.737***	(1.459)
Quintile 2	0.145	(1.333)	0.590	(1.334)	0.0804	(1.338)	0.198	(1.345)	0.761	(1.366)	2.666	(1.417)
Quintile 3	2.389	(1.445)	2.242	(1.444)	2.431	(1.450)	2.273	(1.458)	2.518	(1.480)	2.414	(1.532)
Quintile 4	4.598**	(1.665)	4.537**	(1.664)	4.616**	(1.670)	4.537**	(1.679)	4.649**	(1.704)	5.328**	(1.766)
Quintile 5	14.580***	(2.001)	14.660***	(2.000)	14.640***	(2.007)	15.28***	(2.019)	15.78***	(2.049)	14.57***	(2.120)
DC Numeracy	1.767	(1.523)	1.048	(1.524)	1.850	(1.529)	0.944	(1.538)	0.441	(1.563)	0.226	(1.620)
Constant	27.660***	(1.586)	25.100***	(1.612)	28.150***	(1.615)	22.35***	(1.666)	26.17***	(1.650)	18.85***	(1.724)
Variance:												
School Variance	37.210***	(3.994)	37.110***	(3.989)	37.500***	(4.025)	37.86***	(4.062)	39.25***	(4.183)	42.65***	(4.535)
Class Variance	27.602***	(1.718)	28.020***	(1.733)	27.670***	(1.720)	28.83***	(1.766)	28.75***	(1.754)	29.15***	(1.771)
Residual	567.50***	(3.566)	566.50***	(3.561)	567.40***	(3.566)	565.50***	(3.555)	563.20***	(3.540)	560.90***	(3.527)

Note. N = 52,820. Unstandardized regression coefficients displayed; standard errors in parentheses. Reference group is third graders who are in schools where English is taught at the Home Language level, who are in Quintile 1, who are in the Core Click program, and who are in the Western Cape province.

*** p < .05, ** p < .01, *** p < .001**

Regression of 2023 Reading Comprehension on Time Variables and Controls for Reading Eggspress

	(1)		(2)		(3)		(4)		(5)		(6)	
Weekly Time			0.011***	(0.0005)					0.015***	(0.001)		
Weekly Logins					8.539***	(0.483)			-4.250***	(0.887)		
Time by Logins							0.007***	(0.0003)				
Click Time Var											0.0001***	(<0.0001)
Pretest	0.289***	(0.003)	0.279***	(0.003)	0.284***	(0.003)	0.279***	(0.003)	0.278***	(0.003)	0.281***	(0.003)
Grade 4	5.390***	(0.384)	3.706***	(0.402)	4.106***	(0.397)	4.129***	(0.387)	3.846***	(0.401)	6.740***	(0.393)
Grade 5	9.936***	(0.421)	6.649***	(0.455)	7.420***	(0.451)	7.714***	(0.431)	6.931***	(0.457)	11.72***	(0.434)
English: Both	-2.608	(2.291)	-2.972	(2.426)	-2.868	(2.380)	-2.782	(2.316)	-2.953	(2.393)	-3.728	(2.424)
English: FAL	-4.790***	(1.179)	-5.011***	(1.247)	-4.904***	(1.224)	-4.873***	(1.191)	-5.022***	(1.231)	-5.779***	(1.247)
Eastern Cape	-3.358*	(1.606)	-1.833	(1.701)	-2.463	(1.668)	-2.423	(1.624)	-1.825	(1.678)	-4.707**	(1.698)
Gauteng	-3.822**	(1.226)	-1.964	(1.300)	-2.707*	(1.275)	-2.593*	(1.240)	-1.967	(1.282)	-3.232*	(1.296)
KwaZulu-Natal	-6.053	(8.511)	-13.83	(8.899)	-12.42	(8.760)	-8.469	(8.565)	-12.99	(8.811)	-8.344	(8.850)
Mpumalanga	-5.521***	(1.387)	-4.741**	(1.466)	-5.215***	(1.439)	-4.920***	(1.401)	-4.658**	(1.447)	-7.162***	(1.465)
Quintile 2	0.317	(1.342)	0.932	(1.420)	0.783	(1.393)	0.148	(1.356)	0.883	(1.401)	2.820*	(1.421)
Quintile 3	2.451	(1.456)	1.728	(1.541)	1.928	(1.512)	1.902	(1.472)	1.770	(1.521)	2.494	(1.539)
Quintile 4	4.697**	(1.679)	4.531*	(1.776)	4.582**	(1.743)	4.324*	(1.697)	4.532**	(1.753)	5.425**	(1.775)
Quintile 5	14.67***	(2.016)	12.52***	(2.134)	13.33***	(2.094)	12.99***	(2.039)	12.54***	(2.107)	14.70***	(2.130)
DC Numeracy	1.695	(1.536)	2.215	(1.628)	2.205	(1.597)	1.845	(1.554)	2.116	(1.606)	0.134	(1.628)
Constant	27.65***	(1.593)	26.42***	(1.685)	26.40***	(1.655)	24.52***	(1.615)	26.68***	(1.664)	18.78***	(1.730)
Variance												
School	37.50***	(4.035)	42.45***	(4.568)	40.82***	(4.388)	38.50***	(4.134)	41.19***	(4.448)	42.64***	(4.552)
Class	27.93***	(1.797)	32.15***	(1.967)	29.97***	(1.879)	28.23***	(1.801)	31.55***	(1.944)	29.67***	(1.858)
Residual	571.1***	(3.755)	562.0***	(3.700)	566.3***	(3.726)	564.2***	(3.710)	562.0***	(3.700)	564.2***	(3.712)

Note. N = 48,427. Unstandardized regression coefficients displayed; standard errors in parentheses. Reference group is third graders who are in schools where English is taught at the Home Language level, who are in Quintile 1, who are in the Core Click program, and who are in the Western Cape province.

$*\ p < .05$, $**\ p < .01$, $***\ p < .001$

Summary of Results

This report presents a preliminary analysis of one dataset from one set of programs (Reading Eggs and Reading Eggspress) implemented within the Click Learning platform. Results revealed that the number of weekly logins and time spent on the platform varied substantially within an individual student—within an individual student some weeks they logged on frequently and others they logged on less frequently. Differences between students also were associated with frequency and duration of logins—nearly 30% of the variance in time and logins was between students.

Additionally, there was variance in usage explained by school—not all schools spent equal time on the programs. This indicates that there are likely both external and internal forces driving engagement with the platform and programs within, such as students who enjoy the platform more spending more time on it or schools dedicating different time to engagement with Click Learning. Such variation can be leveraged in analyses of the links between time spent and performance gains, but large student-level ICCs indicate that confounding variables related to both time spent and performance may bias such analyses.

Although the data analyzed in this report were messy, with a number of outliers and some unexplained cases, such as those discussed in the *Data Sources* and *Preliminary Analyses* sections, there was substantial agreement for the data mined Reading Eggs time-on-platform variable and Click' Learnings previously-calculated platform time variable (the two variables were correlated at .76). This was not the case for the data mined Reading Eggspress time-on-platform variable, which only correlated with Click Learning's previously calculated variable at .12. This suggests that an aggregated variable, such as the variable previously calculated, may miss nuances in the time spent on specific programs within Click Learning.

Examining bivariate correlations between platform engagement and school demographics also revealed differences between Reading Eggs and Reading Eggspress. For Reading Eggs, students in schools where English was a first additional language had higher Click Learning use than those in schools where English was the primary language of instruction. For Reading Eggspress, this pattern was reversed. For both programs, higher school quintile was associated with more time on Click Learning and more logins. In these zero-order correlations, data mined platform use variables from Reading Eggs showed negative associations with the external reading comprehension score; these same variables from Reading Eggspress showed positive associations. These differing associations are puzzling, but may be driven by outliers or by those using the platform outside of the recommended grade level. For example, the analysis sample was exclusively in grades three through five and Reading Eggspress is designed for students in grades six and seven. Therefore, the young students using Reading Eggspress may be unusually high performers or Reading Eggs may be too easy for third through fifth graders. Further investigation is necessary to separate out these causes.

In the regression-adjusted results, time on either Reading Eggs or Reading Eggspress was associated positively with score on the external reading comprehension test. **For both programs, when students spent a standard deviation more time on the program each week (approximately 10 minutes per week), they gained one-fifth of a standard deviation (0.20) in reading comprehension score.** This is a meaningful effect size in the context of reading instruction within South Africa. Taylor et al. (2016) found that students who were exposed to two years of English language instruction during grades one through three scored 0.15 standard deviations higher than those who were not. An extra ten minutes a week on Click Reading programs appears to be associated with comparable gains. A meta-analysis of reading interventions in low- and middle-income countries may also help contextualize the results herein: Kim et al. (2020) found an average effect size of 0.25 of interventions on reading comprehension, although interventions focused on technology had smaller effect sizes that did not attain statistical significance. Contextualizing this effect size further within Click Learning's provided data, the difference in mean reading comprehension score between third graders and fourth graders was approximately eight points. The nearly six points gained from 10 more minutes a week of Reading Eggs or Reading Eggspress is 75% of this age-related difference.

Finally, Click Learning began the LEAP sprint with a question regarding how to structure student engagement with its programs, specifically asking the ideal balance of number of logins to time spent during each login. **From these analyses, it appears that for this sample, longer sessions are associated with greater gains in reading comprehension. For both programs, the time per login variable was a positive statistically significant predictor of reading comprehension score, with a beta of 0.07 for Reading Eggs and 0.11 for Reading Eggspress.** Examining this balance of number of logins by time spent through an interaction term, the interaction of time by logins was only statistically significant for the Reading Eggspress model. **In these data, it appears that the association between time spent on Reading Eggspress and reading comprehension score is stronger for those students who have fewer logins. This indicates that students should be given more time per session to engage with Reading Eggspress.** These results should only be interpreted as preliminary given that there were a number of extremely short logins (less than two minutes) that may be skewing results.

Recommendations from Data Analysis

This report illustrates some of the affordances and challenges with using mined data from programs within a digital learning platform, such as Click Learning. There are a number of recommendations for similar work in the future:

Data Collection Recommendations

In order to replicate the analyses conducted in this report, data need to be organized such that each student login date and time is captured or a weekly summary of number of logins and time spent is captured. The former will allow more nuanced analyses of exact time spent per login.

Linking logins to specific content will enable Click Learning to answer questions beyond dosage to explore which content has the greatest time engagement and association with learning gains.

Enhancing data collection with sub-topic benchmark assessments or measures of motivation, affect, or engagement would enhance Click Learning's ability to answer questions regarding student engagement, including the ideal length of session time.

There were some apparent errors in data collection, such as the cases of students whose logins reset while playing. Click Learning can work with program providers to understand and correct these errors.

Data Cleaning/Organization Recommendations

A number of researcher decisions were documented in this report, including identifying and handling outliers, determining sample characteristics, constructing variables, etc. At each of these decisions, the data need to be examined thoroughly to both inform the decision and to determine if intended actions were carried out correctly. Click Learning should engage in thorough data vetting procedures when using mined data from their programs.

Although this report provides examples of these decisions, each dataset is different and the process of cleaning, vetting, and preparing for analysis will vary across data sets. In addition, the steps undertaken in the current report were necessarily constrained by the speed of the LEAP sprint and fellow time. These steps should be viewed as a minimum.

Finally, data organization includes the construction of variables, such as the weekly time and login variables used in this report. Future efforts may include different variable operationalizations. Click should document their creation of these variables and decisions between competing variable constructions.

Analysis Recommendations

As with data cleaning, there were a number of researcher decisions in the analyses. The specific control variables included in the model will impact results. Click Learning may determine that different variables are necessary to produce the most unbiased estimates. It will be important to document and justify included variables in future analyses.

Given time constraints, we were unable to include student-level demographics in the analyses within this report. Click Learning may wish to run additional analyses including these student-level variables.

It is likely that there are omitted variables that predict both a student's engagement with Click Learning programs and their performance on the reading comprehension exam. Click Learning should consider models utilizing multiple years of data and student fixed effects to garner more unbiased results about the link between platform time and reading comprehension score. Alternatively, Click Learning may use their existing assignments to programs, such as through Double Click, to increase internal validity in analyses of platform time and score. To examine the association between actual platform usage and student outcomes within this experiment, Click may wish to use methods such as *instrumental variables* (Angrist et al., 1996) to estimate effects of treatment on the treated.

Finally, as revealed in the literature review, it is likely that the association between time spent on programs within Click Learning and reading comprehension is not linear. Click Learning can investigate non-linear associations in future analyses.

If Click Learning is able to collect data from multiple platforms and link data with unique student IDs, there are a number of additional questions that may be informative, such as:

- What are the characteristics of students in grades three through five who use Reading Eggs vs. Reading Eggspress?
- What balance of Reading Eggs vs. Reading Eggspress results in larger reading comprehension gains?
- Do students who use both math and reading programs within Click Learning spend more time on the platform? What is the balance of time between math and reading programs? What student and school factors predict this balance of time?
- Does the balance of time on reading and math programs differentially predict reading and math outcomes?

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Recommendations.

Compiled by Tony Senanyake, with input from Barbara Trudell, Lissett Babaian, and Teomara Rutherford

Recommendations

The LEAP Fellows admire Click Learning's mission and the data-driven, empirical approach the team is taking towards maximizing its impact. Based on research and analysis insights, as well as the literature reviews undertaken, the team has outlined four sets of recommendations:

1. **The data collection and analysis of Reading Eggs and Reading Eggspress**
   a. **Data collection**
      i. Collect detailed login and usage time metadata for all programs used within Click Learning, at either a per-login or per-week level.
      ii. Instrument additional data collection within the programs or within the platform, including more targeted performance assessments and motivation/engagement/affect surveys.
      iii. Query program providers on data structures and any inconsistencies within the data.

   b. **Data analysis**
   The following could warrant further analysis and explanation:
      i. What is driving the negative bivariate correlation between time usage and reading comprehension for Reading Eggs?
      ii. Why is there such a high level of variation in usage characteristics at the student level?
      iii. Why are so many third through fifth graders using Reading Eggspress?

   c. **Implementation**
      i. When negotiating timetables with schools, seek to ensure that longer sessions are specified for learners using Readers Eggspress.

2. **Further exploration of the connection between dosage and learning outcomes**
   a. **Rethink the balance between the classroom and the learning lab.**
   Intentional alignment between classroom learning needs and what Click Learning can offer could enhance Click Learning's impact on overall student learning. For example:
      i. supporting classroom teachers and curriculum, through edtech offerings that extend children's learning in more curriculum subjects than just reading and mathematics;
      ii. permitting learners more leeway in how they are allowed to use the apps that Click Learning is providing: e.g. allowing freer access to a range of learning apps, rather than restricting their access to certain apps at certain times to align with the classroom learning topics. This could energize learners to use them more intensively for effective learning.

   b. **Consider greater classroom teacher support.**
   As Click Learning has described the classrooms alongside which its program runs, it appears that teacher competencies, in either teaching principles or subject content, are not always very strong. Rather than considering this a reason to intensify Click Learning's impact on student learning as compensation for poor teacher quality, Click Learning might consider a focus on enhancing teachers' own

competencies in teaching reading and mathematics. Click Learning's existing apps might be very helpful in supporting teacher learning in important areas of reading, English language and mathematics.

c. **Take pupil language fluencies into account where the learning apps are concerned.**
The English language fluencies of pupils in their programs appear to vary widely - and more often than not, the pupils are weak in both oral and written English. This speaks to the value of including their own home languages in the learning process. Even teaching English as a second language can be enhanced by using the language the child speaks as the medium of learning. Digital reading materials in those languages could be provided to help learners improve their reading skills. In addition, English as a Second Language apps could be used to make the English language learning process explicit and systematic, and more efficient than simply providing English-language text at various levels of difficulty.

3. The broader language and learning context of the Click Learning program

a. **Conduct an evaluation to identify any relationship between dosage and learning outcomes.**
There is a gap in the current literature on the relationship between dosage and learning outcomes for edtech interventions, similar to that delivered by Click Learning. Click Learning may be well-placed to generate evidence that will both:
   i. inform the optimal level of dosage, intensity and duration within its existing deployment context; and
   ii. develop the international body of knowledge around optimal dosage of edtech interventions among vulnerable populations in lower-middle income and middle-income contexts.

There are many potential experimental designs that Click Learning may consider: e.g., alpha/beta testing, pre-post evaluation, difference in difference, randomized controlled trial. We recommend beginning with a clear research question of interest, and then identifying the experimental design approach that is best suited to answering that question, given the logistical and practical constraints in place.

One potential research question may be, *what is the impact of differential dosage targets on learning outcomes?* If that were the question, then Click Learning may consider randomly assigning different students to two dosage targets. Click Learning could consider providing Double Click randomly to one treatment arm and the standard Click Learning intervention to another treatment arm and then observing if there are differential learning outcome changes between these two groups. If feasible, we would advise randomly assigning a control group of students who did not receive either Click Learning intervention and served as a control. In Bettinger et al. (2022), students were exposed to the intervention for a period of 10 weeks, which also matches closely to one school term. It is our understanding that Click Learning has begun some of this work already with their Double Click program. Click Learning may wish to partner with an external evaluator and/or preregister their analyses for this experiment to maximize credibility of findings.

Based on the findings from this initial evaluation, Click Learning may then consider a secondary evaluation that could focus on a research question such as, *what is the optimal* *dosage of the Click Learning intervention?* This question would require a more nuanced evaluation design, whereby students were exposed to many different levels of dosages, durations and intensities of the intervention. Such an evaluation may be feasible, but we would recommend focusing on this as a secondary activity after evaluating the primary question around higher level dosage targets.

b. **Collect learning outcome data on non-Click learners.**
We recommend collecting data on students who are not receiving the Click Learning intervention and who are otherwise as similar as possible to those receiving the intervention, using the same data collection tool that Click Learners are tested with. We recommend collecting baseline and endline data on this group to better understand the effect of teacher-led instruction on learning outcomes and, therefore, whether (and to what extent) Click Learning may serve as an effective substitute to teacher-led instruction.

c. **Consider increasing the annual dosage target.**
There appears to be weak evidence to suggest that Click Learning may observe positive impact benefits from increasing its target annual dosage from 18 hours per year to closer to 30 hours per year. This is a weak recommendation for the following reasons:
    i. The opportunity cost of the existing teacher-led learning that would be substituted needs to be evaluated.
    ii. There are a myriad of practical and logistic challenges that may make this infeasible. Some examples include: scheduling / timetabling, availability of Click Learning staff to facilitate these sessions, willingness of school leaders to accept Click Learning's intervention at a higher dosage level.
    iii. The recommendation is based on optimal time evidence from non-EdTech literature, and therefore may not convert to EdTech interventions like Click Learning's.

4. Enhanced program implementation and evaluation

a. **Updates to the selection and testing product framework**
Click Learning may consider updating its product selection framework to thoroughly assess key stakeholders' preferences and learners' levels of engagement with different products. Additionally, Click Learning may evaluate the suitability of the language of instruction, the effectiveness of the product's pedagogy, and alignment between the product's content and learning objectives outlined in the national curriculum.

b. **Expand the Sandbox to include iterative user testing.**
Many edtech companies, such as Sesame Street and Ubongo Learning, prioritize human-centered design research and iterative user testing to promote adaptive learning. Through this approach, organizations can employ a range of qualitative and quantitative methods (e.g., distractor tests, observations, pre- and post tests, co-creation/prototyping, A/B testing) to conduct rapid tests and enhance interventions before investing in costly experimental studies.

c. **Experimentation with supplementary delivery mode.**
There may be scope (if not conducted already) to run a pilot to evaluate the impact of Click Learning's intervention if delivered as an out-of-school supplement to teacher-led instruction, as opposed to an in-school substitute. The literature tends to suggest that supplementary edtech interventions lead to greater learning outcome improvements

(Montoya et al., 2021; Sampson et al., 2019). However, this finding is highly dependent on the quality of the teacher-led instruction that may be substituted.

Thank you.