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Evaluating the Impact of Technology-Supported Personalised Learning Interventions on the Mathematics Achievements of Elementary Students in India

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ABSTRACT

Technology-supported personalised learning (TSPL) refers to the use of technology to personalise a learner's experience by adjusting the pace and relevance of content based on the learner's age, capability and prior knowledge (FitzGerald et al., 2018). Although technology has been epitomised in creating personalised and effective learning experiences for students, there are perennial debates on its role in enhancing quality, productivity and learning (Payal Arora, 2019; Zierer, 2019). This review explores the effectiveness of TSPL on the mathematics achievements of elementary students in India. This review argues that while evidence on using TSPL at scale to benefit all learners remains mixed and inconclusive, with continued iterative research, TSPL holds promise in serving learners' needs irrespective of achievement level or socio-economic background. In doing so, this review outlines an agenda for future research to improve the efficiency, reach, and effectiveness of TSPL. This involves gaining a deeper understanding of whether TSPL works best as either a supplement or substitute in classrooms and the impacts of doing so in different quality schools. Mechanisms around how TSPL interventions can operate via low-tech mechanisms to better serve low-income communities and to advantage students of all learning abilities are also explored.

KEYWORDS

personalised learning, education technology, mathematics, elementary school, India

Introduction

Since The Right to Free and Compulsory Education Act took effect in India in April 2010 (Right to Education | School Education & Literacy, 2021), the number of children enrolled in elementary schools has significantly increased (School Enrollment, Primary (% Gross) | Data, 2020). However, the quality of India's schools has been compromised with accessibility,1 leaving schools with teacher shortages, multi-grade classrooms, and low student achievement levels (Singh, 2012). For example, just 28 per cent of grade three students in India's government schools could do a numerical subtraction problem (Annual State of Education Report (Rural) 2018, 2019).

The increasing availability of technology, coupled with its ability to personalise learning for each student more efficiently than a teacher (Major & Francis, 2020), has made its use compelling in tackling high student-teacher ratios and mixed-attainment classrooms. It is also considered an attractive solution in overcoming the 'one-size-fits-all' approach (FitzGerald et al., 2018) that is often observed in resource-stretched classrooms that are prevalent in India.

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1 In this review, the terms access and accessibility to education refers to a student's ability to gain school admission regardless of their family income, caste, religion, gender, geographical location, and perceived intellectual ability. These terms do not regard access in the context of sexual orientation, disability, and special education needs.

Although technology has been epitomised in creating personalised and effective learning experiences for students, there are perennial debates on its role in enhancing quality, productivity, and learning (Payal Arora, 2019; Zierer, 2019). To address this discourse, this review concentrates on the effectiveness of technology-supported personalised learning (TSPL) on the mathematics achievements of elementary students in India. Though evidence on using TSPL at scale to benefit all learners remains mixed and inconclusive, with continued iterative research, TSPL holds promise in serving learners needs irrespective of achievement level or socio-economic background.

The remainder of this review is organised as follows. First, the term personalised learning is defined and its association with technology is described. Next, the methods used to collate literature for this review are outlined. Following this, the effectiveness of TSPL for different groups of learners and the external factors that can influence TSPL are discussed. In the subsequent sections the effectiveness and sustainability of TSPL is scrutinised. To conclude, areas for future research are suggested.

Defining personalised learning

Personalised learning is not a new concept as teachers have continuously tried to respond to the shifting needs, aims, and desires of their students (Holmes et al., 2018). Although a key concept in the global education technology community, there is no universally agreed definition of personalised learning. This review considers personalised learning as a means of adjusting the learning experience and pace of new content based on the learner's age, capability, and prior knowledge, offering resources that are relevant and important to the learner (FitzGerald et al., 2018).

Why use technology for personalised learning?

There is a growing body of evidence to support the use of technology in classrooms over traditional 'chalk and talk' teaching methods (Holmes et al., 2018), as it reduces the time taken to learn content (Karnati, 2008), nurtures a positive attitude towards learning (Alcoholado et al., 2012; Brunskill et al., 2010), and allows learners to work at their cognitive level (Osin, 1998). The following sections details two key principles that underpin technology's success in education. These include the cognitive theory of multimedia learning and the approach of teaching at the right level (TaRL).

The cognitive theory of multimedia learning

The cognitive theory of multimedia learning is grounded in the belief that multimedia instruction can lead to permanent and effective learning (Mayer, 2014). According to Mayer (2014, p. 43), the theory is built upon three assumptions: "the human information processing system includes dual channels for visual/pictorial and auditory/verbal processing (i.e., dual-channel assumption), each channel has a limited capacity for processing (i.e., limited-capacity assumption), and active learning entails carrying out a coordinated set of cognitive processes during learning (i.e., active processing assumption)." As technology can store audio, video, and text files (FitzGerald et al., 2018), it can offer learners multimodal forms of interaction that can effectively support learning if incorporated into pedagogy successfully.

Teaching at the right level

The TaRL approach, pioneered by the Indian NGO Pratham, focuses on grouping learners based on their learning needs rather than age or grade (Teaching at the Right Level - Strengthening Foundational Skills, n.d.). This enables students who are falling behind to acquire foundational literacy and numeracy skills quickly. From several randomised evaluations in India (Banerjee et al., 2007, 2016; de Barros & Ganimian, 2021; Linden et al., 2003; Muralidharan et al., 2019) and an increasing body of evidence in Africa (TaRL in Action, n.d.), this approach has demonstrably improved the learning outcomes of children.

A systematic review of literature

This essay has been established upon a rigorous and systematic exploration of literature. Existing reviews in the field were leveraged such as the EdTech Hub's rapid evidence review on TSPL (Major & Francis, 2020), and an extensive search of evidence in the field was also carried out. Major and Francis's (2020) scoping review more broadly covered literature across low- and middle-income countries (LMICs), proving useful for retrieving key interchangeable terms for personalised learning. These were leveraged when conducting the literature search to ensure all bases of personalised learning were included. The key terms were combined with others more directed for the context of India and mathematics education.

Table 1 shows all search strings used for different sources to navigate the evidence of TSPL interventions in India. This was the prime methodology used to collate studies for this review; however, many studies were also collected through the snowball effect. Evidence primarily used in this review dates backs to 2006. Due to the smaller amount of research in this area, greater importance was found in observing how the methodologies and outcomes of studies had advanced alongside the development of technology.

Table 1

Search strings used from different databases and sources to find TSPL interventions in India

Source	Search terms
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Computer-assisted learning AND India AND Mathematics
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Computer-aided learning AND India AND Mathematics
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Computer-aided instruction AND India AND Mathematics
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Intelligent tutoring system AND India AND Mathematics
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Cognitive tutoring system AND India AND Mathematics
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Individualised instruction AND India AND Mathematics
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Individualized instruction AND India AND Mathematics
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Individualised instruction AND India AND Technology
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Individualized instruction AND India AND Technology
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Personalised learning AND India AND Mathematics
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Personalized learning AND India AND Mathematics

APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Personalized learning AND India AND Technology
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Adaptive learning AND India AND Mathematics
APA PsycInfo, ERIC, Education Abstracts (H.W. Wilson), British Education Index	Adaptive learning AND India AND Technology
Google Scholar (GS)	"Computer-assisted learning" in "India" "mathematics"
GS	"Computer-aided learning" in "India" "mathematics"
GS	"Computer-aided instruction" in "India" "mathematics"
GS	"Intelligent tutoring system" in "India" "mathematics"
GS	"Cognitive tutoring system" in "India" "mathematics"
GS	"Individualised instruction" using "technology" in "India" "mathematics"
GS	"Individualized instruction" using "technology" in "India" "mathematics"
GS	"Personalised learning" using "technology" in "India" "mathematics"
GS	"Personalized learning" using "technology" in "India" "mathematics"
GS	"Adaptive learning" using "technology" in "India" "mathematics"

How effective is TSPL and who benefits?

Measuring the learning outcomes of students using standardised testing has been under perennial debate due to the extent that it simplifies and quantifies learning (Breakspear, 2014). Despite this, it is still the most common method of monitoring student learning achievements. Therefore, many studies that fall under the purview of this essay naturally use quantitative methods primarily in the form of randomised controlled trials (RCTs). These have enabled researchers to make direct comparisons of pre- and post-test mathematics scores between control and treatment groups, where TSPL acts as a direct input.

While most RCT studies evaluated in this essay claim an overall improvement in mathematics because of TSPL inputs, each does so with a varying degree of confidence. Assertiveness varies depending on the levels of attrition, the length of the TSPL intervention, the learning software used and the comparability between control and treatment groups. Due to the variance in experimental conditions of RCTs conducted, the act of comparing effect sizes is equivocal and the consideration of methodologies is critical.

Although results show consistency at the surface level, further analysis of the data produces controversy. A large amount of evidence concludes that the effects of TSPL are highest amongst students with low pre-test scores and less significant for students with higher pre-test scores (Banerjee et al., 2007; Brunskill et al., 2010; Linden, 2006; Muralidharan et al., 2019). However, Kumar's (2018) intervention finds that the average student2 benefits most, while in opposition, de Barros (2021) claims that the improvement in achievement is null for the average student. Although these results appear contradictory, the differences in methodology can account for the disparity in findings.

For example, Muralidharan (2019) and de Barro's (2021) use the same learning software (Ei Mindspark) in their studies, yet the former includes teacher instructional time as part of the TSPL intervention whereas the latter does not. It is reasonable to assume that this was in part intentional due to the collaborative relationship between both research teams and the pursuit of observing the effects of TSPL using technology in isolation. However, these differences in methodology make direct comparisons more difficult and differentiating the impacts of technology and teacher instruction in isolation becomes problematic.

As evidence surfaces that TSPL interventions unequally benefit students, this begets the question of how students with medium-high mathematics levels can progress to similar extents. The software used to develop personalised homework in Kumar's (2018) study sheds light on why medium-high attaining students may not receive similar benefits. The algorithm used strictly offers 50 per cent of easy category questions. For high achievers who require more challenging questions, this ratio does not capture the full potential of the individual. This suggests that mathematics software used for TSPL may need further development and testing to advance the progress of learners at all levels.

Although there appears to be an unequal benefit of TSPL, researchers have made efforts to experiment with personalised learning to address children that fall into marginalised groups.3 In her study of a computer-aided learning (CAL) programme in Andhra Pradesh (2008), Karnati, to some degree, demonstrates how TSPL improves the efficiency of learning foundational mathematics for out-of-school children. This spotlights a beneficial use case of TSPL for reintegrating children into schools.

Kumar also validates the effectiveness of TSPL while controlling for the 'IT effect' (2018, p. 11). This involves implementing personalised homework for learning in a less engaging and interactive manner by removing entertainment applications and multimedia functionalities from laptops. This importantly distinguishes that personalised learning can effectively occur through low-tech mediums which can be more suited for classrooms with a lack of technology resources. However, it is important to note that the relative gains in mathematics achievements in this study are weaker than those in Banerjee's (2007) and Muralidharan's (2019) research, which Kumar (2018) recognises.

Addressing marginalised learners through TSPL: Supplement, integration, or substitute?

There is a wide variance in the experimental conditions of studies conducted around TSPL. An important factor is whether TSPL is used as a supplement to teaching, integrated into classroom teaching, or substituted for teaching. Supplementary methods would offer additional opportunities for children to use learning software outside of regular classroom instruction. Integrative methods would require teachers to use technology to assist with teaching and learning while substitution would use learning software in place of teaching (Major & Francis, 2020). Due to both convenience and utility, most studies have used TSPL as a supplement. As a result, there is little research to support how learning outcomes are affected when TSPL acts as a substitute and how this may differ with context.

The latest study in the field shows that using TSPL as a substitute continues to improve mathematics

2 In this review, the average student refers to those that sit within the middle tercile of a pre-test score distribution.
3 This refers to children marginalised by poverty, gender, language, disability, displacement and being out of school (Hennessy et al., 2021).

achievements, yet primarily for low performing students (de Barros & Ganimian, 2021). Although the effect size in de Barros (2021) study is lower than that observed in Muralidharan's (2019) where TSPL acts as a supplement, de Barros claims that learning gains "are commensurate with the lower dosage that students receive in this model" (2021, p. 7). Though there is some evidence that steers towards the success of TSPL when used both as a supplement and substitute, whether this is realistic and scalable remains ambiguous.

Firstly, the schools used in de Barros' (2021) RCT were purposively selected due to the presence of computer labs with continuous electricity supply and internet connectivity that enabled students to access one computer each weekly. However, not all schools are as well-equipped, particularly those serving marginalised students. In this context, higher student to computer ratios and lower exposure times to learning software is more likely to be relevant.

In response to this scenario, research has begun to display the potential of personalised learning via multi-user technology (Alcoholado et al., 2012; Brunskill et al., 2010; Karnati, 2008). Although multi-user systems can address the resource and financial constraints of deploying technology in schools, power hierarchies and different behavioural interactions between students can also manifest. For instance, multi-mouse configurations are deemed to reduce the domination of learning (Alcoholado et al., 2012), yet evidence shows that children who quickly grasp either technology or content will frequently dominate learning activities (Moed et al., 2009).

In studies that have used TSPL as a supplement in the form of before or after school programmes (Banerjee et al., 2007; Muralidharan et al., 2019), it becomes difficult to decipher the extent of the impact if this same time was removed from teacher instructional time. It can also remove accessibility for students from financially strained households who require time before or after school to assist with household or financial duties. In this respect, TSPL programmes that are substitutive rather than supplementary can have greater benefits for marginalised students that attend school regularly. However, one could argue that in schools with fewer technological resources, supplementary programmes could be more effective as they can host smaller classes where students have more opportunities to use learning software individually rather than in a shared environment.

Assessing the external factors that can impact TSPL outcomes

As most studies in this review are quantitative, factors which cannot be objectively measured have been overlooked in some cases; for example, learners' familiarity with using digital devices and behavioural elements of using technology. The next two sub-sections discuss how these factors have somewhat introduced bias and ambiguity into the results of the studies under purview.

The 'techno-educational threshold'

The concept of the 'techno-educational threshold' is introduced in Alcoholado's work (2012, p. 301). This references the time taken for an RCT participant to be familiarised with the technology implemented. Although this expression was not actively used in the remaining literature, it highlights an important component of TSPL in low-income contexts. Many participants involved in RCTs had no prior exposure to technology. Although learning software has been intently designed with a simple user interface, students without prior experience with digital devices would have required familiarisation time. During TSPL experiments, some students without prior exposure initially answered questions incorrectly due to technical difficulties, however, most were able to become acquainted by the second trial (Alcoholado et al., 2012).

As suggested in Alcoholado's (2012) work, students with little or no prior exposure to technology could have struggled to make intended achievements, particularly for interventions that had no teacher instruction. For studies that recognised participants had some computer skills from school classes (de Barros & Ganimian, 2021), the 'techno-educational threshold' was understandably not factored in. However, this was neglected for remaining studies that conducted RCTs with participants from low-income households who were less likely to own or know others that owned a computer. Whether the remaining experiments did not mention these effects due to longer periods of exposure or it was not considered a significant contributing factor, it is sensible to interpret the effect sizes from RCTs in the field as a lower bound estimate for learning gains.

Positionality and mixed method approaches

Leveraging the positionalities of researchers becomes important when critiquing evidence. For instance, economists Banerjee's (2007) and Muralidharan's (2019) work holds greater concern for the productivity of technology for personalised learning in comparison to traditional teacher instruction. Alternatively, those that identify as technology educationalists (Alcoholado et al., 2012; Brunskill et al., 2010; Pal et al., 2006) stress more importance on the practicalities of using technology in classrooms. This has led to a clear-cut distinction between quantitative and qualitative research in the field with few mixed method studies to contextualise the experiences of RCT participants.

Due to the dominance of quantitative research in the field, there is little insight on how the psychological behaviours of participants in RCTs impact their learning gains in mathematics. For example, Pal (2006) and Banerjee's (2007) studies are just two experiments that acknowledge the impacts of the Hawthorne effect.4 Particularly for shorter TSPL interventions, there is potentially a proportion of learning achievements that were subject to Hawthorne effects. This is just one aspect that remains unknown due to the lack of complementary qualitative research to RCTs.

It seems there is a greater need for a mixed methods approach when assessing the impacts of TSPL on mathematics learning outcomes. Karnati's (2008) study does well to illustrate how mixed methods can be beneficial in assessing personalised computer-aided instruction for out-of-school children. Although her RCT results lacked some reliability due to differences in control and treatment groups and a small sample size, she also collected qualitative data via descriptive surveys. These obtained insights on the socio-economic backgrounds, motivations, and opinions on schooling from RCT participants which effectively supplemented her quantitative data.

TaRL vs technology: What is driving higher learning achievements?

There is a growing body of evidence that channels TaRL approaches through TSPL to improve mathematics achievements. However, other studies have demonstrated that employing non-tech solutions, coupled with TaRL, can similarly be effective in improving mathematics achievements. Banerjee's (2016) evaluation of randomised studies of TaRL in India proved that students made significant learning gains in mathematics when grouped by ability and instructed by government teachers and trained volunteers.

In addition, studies that use CAL without personalised content have found that teaching mathematics using traditional methods is equally as effective as solely using CAL (Ramani & Patadia, 2012). However, the success of technology interventions for personalised learning depends largely on the baseline quality of school education (Linden, 2006). Linden (2006) reveals that implementing a CAL

4 The act of students modifying their behaviour and efforts while learning and completing tests due to their awareness of being observed.

programme as a substitute for good quality teaching led students to learn significantly less than they would have otherwise. Therefore, we cannot guarantee whether the teaching quality in Ramani and Patadia's (2012) study feeds into the results of this experiment, yet current evidence favours the personalisation element of TSPL rather than technology as a standalone tool, where the role of the teacher remains paramount.

Longevity of technology-supported personalised learning

Assessing whether mathematics learning gains from TSPL persist remains an enduring issue as most studies in the field are impermanent interventions. Although evidence remains inconclusive, some research has monitored the progress of children one year after exposure to TSPL. Banerjee (2007) shows that gains reduce when a student is removed from a TSPL experiment, where gains are conserved most for students with initial low attainment that benefitted most from the experiment. Though some effects persevere, Banerjee claims that the rapid rate of decay of learning gains is of concern and "if the decay continued at this rate, the intervention would very soon have had no lasting impact" (2007, p. 1256). As one of the first large-scale studies in the field, this is a grand statement to make. The fact that researchers who have pursued this area of interest highly referenced Banerjee's work and used similar experimental methods (de Barros & Ganimian, 2021; Muralidharan et al., 2019) have made no efforts to reference the longevity of TSPL experiments is unanticipated and questions the intentions of adapting this research into practice.

When using TSPL to enhance student mathematics achievements, short-term novelty effects can be equally as important as long-term attrition. For instance, participants with no prior exposure to technology may find it a novelty when first brought into the classroom (A. Kumar & Mehra, 2018). In some cases, this can cause children to engage more during TSPL interventions, increase efforts to learn and therefore make greater mathematics achievements. As a result, effect sizes from existing studies may not be truly representative of the real impacts of TSPL and the chances of the novelty effect wearing off could present limitations. In addition, software learning activities can, in some cases, be fairly repetitive leaving learners with a heightened familiarity of the software to cheat the system and achieve higher scores (Mutahi et al., 2017).

What defines achievement and learning?

In essence, personalised learning aims to challenge the notion of the average student as it acknowledges that all learners have individual needs, strengths, prior experiences, and interests. It also allows the notion of success to be challenged (Holmes et al., 2018). This conflicts with the studies primarily evaluated in this review as most use competency-based learning for the development of software and assessments, leading students to be assessed against certain criteria (Holmes et al., 2018). Evidently, researchers in this field have not questioned pedagogical practice but rather have aimed to examine the efficiency and effectiveness of TSPL based on current curricula. Many studies absorb TaRL approaches within their methodologies, yet it seems that this is where the element of personalisation stops. However, personalisation beyond the Indian national curriculum can seem idealistic and ambitious given the number of challenges the Indian education system currently faces. These include, but are not limited to, the prominent issue of rote learning, students falling behind their respective grade level and the lack of financing of public education.

Many studies in this review use pre- and post-tests to monitor learning achievements, yet all used different forms of assessment. While some used grade-level standardised tests (Brunskill et al., 2010), others developed internal tests devised from content most students had covered (Muralidharan et al., 2019). Although the effect sizes were the most imperative metric to the experimental studies, in some regard, the different assessment methods limited the comparability of results. Using grade-level standardised tests acted as a limit as the total learning gains could not be captured if the child showed improvement yet still performed below grade level. Only Muralidharan (2019) acknowledges this discrepancy and counteracts this flaw using an internal and reflective form of assessment.

Using competency-based learning methods in tandem with TSPL has proven to enhance student mathematics achievements. However, concerns remain whether learning software can foster cognitive learning and critical understanding for students or whether the repetitiveness of learning software is enforcing rote learning. While mathematics is built upon deep reasoning, this can be obscured behind algorithms which risk mathematics being portrayed as a remote and inaccessible subject (Nardi & Steward, 2003).

Conclusion

A wealth of instructive research has been produced over the past two decades providing evidence that TSPL approaches can be beneficial in boosting the mathematics achievements of learners. Although existing studies are informative, the weaknesses found in methodology and sampling has curbed their usefulness to policymakers considering whether TSPL approaches would be an effective investment at scale.

The limitations in experimental conditions identified throughout this review have cultivated an agenda for further research. This focuses on using a more holistic approach to research with particular attention to the implementation of TSPL approaches in low-income contexts. Academics have evidently iterated studies, increasing the robustness of data and deepening the understanding of the successes and limitations of TSPL. While these elements have been identified, there remains a need to explicitly test these successes and limitations against other control factors to address unresolved questions.

This would involve further experimentation of using TSPL as either a supplement or substitute and how the successes of these interventions can vary dependent on the type of school, set of students and teaching quality. Though this becomes difficult due to the multitude of inputs that can affect learning outcomes, the optimal relationship between teacher instruction and TSPL essentially needs to be recognised and how this relationship adjusts depending on context. Where the importance of TSPL may be more significant in schools of poor-quality teaching, it is important to note that the role of teachers remains crucial.

Low-cost personalised learning mechanisms also need to be explored further to understand the capabilities of TSPL in low-resource settings and how this can modify learning outcomes. Early evidence using multi-user learning software and low-tech personalised learning programmes to enhance mathematics achievements frame this as a promising area of research. While reducing the role of technology in TSPL may not be an attractive proposition for all stakeholders, exploring this avenue can have overarching benefits on implementing TSPL approaches at scale. Finding low-tech methods to implement personalised learning that achieves similar learning gains to high-tech solutions would ultimately minimise per pupil costs. Besides low-tech solutions being desirable for scalability, it is also critical to ensure equitable learning. For instance, having TSPL programmes that successfully function on a spectrum of low- and high-technology will mitigate the digital divide that is present in India's schools (B. S. Kumar & Kumara, 2018).

An area of research that is absent in the field is how TSPL can advance the learning of students at all achievement levels, particularly those with high attainment. Existing evidence indicates that students with high attainment levels are not benefitting significantly, or at all, from exposure to TSPL. This highlights the need for further interrogation of learning software content, how new content is generated based upon learner needs, and the extent to which this is challenging each learner. This could involve modifying the pace of new content displayed by the software or providing access to content from higher grades. In this scenario, future RCT studies must use assessments that are reflective of the attainment levels of all participants and can capture the learning gains of all students.

While empirical studies in the field have highlighted the capabilities of TSPL in improving mathematics achievements, it seems a much broader view of TSPL is needed to pull TSPL approaches into practice. Mixed-methods research would be highly valuable in this transition to ensure the views of students, teachers and parents are considered when introducing TSPL methods in schools. This is key for the long-term success of TSPL as teachers will ultimately be required to manage classroom technology. Though future studies may continue to be dominated by large scale RCTs, it is increasingly evident that all factors cannot be tested and controlled for. Therefore, future research must methodically consider which elements of TSPL should be tested and combine successful elements to work towards a flexible version of TSPL that can cater to all learners.

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