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Rapid Evidence Review: Technology-supported personalised learning

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Version 1

This publication is one part of a series of rapid evidence reviews that has been produced by the EdTech Hub. The purpose of the rapid evidence reviews is to provide education decision-makers with accessible evidence-based summaries of good practice in specific areas of EdTech. They are focused on topics which are particularly relevant in the context of widespread global challenges to formal schooling as a result of COVID-19. All the rapid evidence reviews are available at edtechhub.org.

Abbreviations and acronyms

CAI	Computer Assisted Instruction
CTS	Cognitive Tutoring Systems
EdTech	Educational Technology
ICT	Information and Communications Technology
ITS	Intelligent Tutoring Systems
LMICs	Low- and middle-income countries
RCT	Randomised Controlled Trial
RER	Rapid Evidence Review
TaRL	Teaching at the Right Level

Summary

This Rapid Evidence Review (RER) provides an overview of existing research on the use of technology to support personalised learning in low- and middle-income countries (LMICs). The RER has been produced in response to the widespread global shutdown of schools resulting from the outbreak of COVID-19. It therefore emphasises transferable insights that may be applicable to educational responses resulting from the limitations caused by COVID-19. In the current context, lessons learnt from the use of technology-supported personalised learning — in which technology enables or supports learning based upon particular characteristics of relevance or importance to learners — are particularly salient given this has the potential to adapt to learners' needs by 'teaching at the right level'.

This RER provides a summary of the potential benefits of technology-supported personalised learning as well as identifying possible limitations and challenges. It intends to inform educational decision makers, including donors and those in government and NGOs, about the potential to use technology-supported personalised learning as a response to the current pandemic. The findings and recommendations are also anticipated to be of interest to other education stakeholders (e.g. researchers and school leaders).

The RER involved a systematic search for academic and grey literature to address the overarching question: **What is known about personalised learning through using technology that can be of value in responding effectively to mass school shutdowns in LMICs?** After a rigorous screening process, 24 studies (in 12 countries) published since 2006 were analysed. Details on the inclusion criteria, as well as the associated limitations, are explained in the methodology section. Two specific research questions (RQs) guided the enquiry:

- **RQ1**: How has technology-supported personalised learning been implemented in LMICs?
- **RQ2**: What key themes are reported in the literature that may inform a response to the COVID-19 pandemic?

While a number of potential research limitations must be taken into account, on the whole, an encouraging and positive impact on learning outcomes is reported. Indeed, the RER demonstrates that there is a growing base of strong evidence on the impact of technology-supported personalised learning to support school-age learners in LMIC contexts.

Research involving a range of digital technologies and learners of various ages is reported. Studies mainly target instruction in mathematics and science although there are examples of research involving the development of non-cognitive skills. Importantly, the RER corroborates previous research which suggests there is no agreed definition of technology-supported personalised learning. It notes that 'personalised learning' does not necessarily mean 'individualised learning'; it can include group-level adaptation and collaborative learning. Levels of personalisation also appear to fall on a continuum of being highly responsive to the user to less responsive. A further interesting finding is

that studies report using technology as either a supplementary (providing additional opportunities for students to practice instructional content outside of regular classroom instruction), integrative (using technology during instruction to facilitate teaching and learning), or substitute (investigating the possibility of using personalised technology in lieu of teaching) approach.

Structured according to four themes, the findings of the thematic analysis reveal further insights:

1. **Improving access to education and adapting to the diverse needs of learners:** This theme examines how technology-supported personalised learning enables access to quality educational materials, adapts to learners' needs by 'teaching at the right level', extends learning, and potentially closes educational gaps for the most marginalised.
2. **The role of teachers and appropriate professional development:** This theme examines the central role of teachers and teacher professional development in enabling technology-supported personalised learning in addition to addressing potential constraints on teaching and learning.
3. **Pedagogical and motivational affordances:** This theme examines the pedagogical affordances of technology-supported personalised learning and the impact this can have on learner motivation.
4. **Potential challenges and barriers in implementation:** This theme examines implications with regard to cost and infrastructure, in addition to potential issues for scalability and sustainability.

The key findings and recommendations from this review are:

1. **Technology-supported personalised learning appears to offer significant promise to improve learning outcomes**, including potentially 'out-of-class' and 'out-of-school' learning.
2. **The adaptive nature of technology-supported personalised learning to 'teach at the right level' is key** as it enables students to learn at their own pace and according to their current proficiency.
3. **Technology-supported personalised learning may be most beneficial in closing educational gaps for lower attaining students**, potentially including those returning to school after an absence.
4. **Any introduction of personalised learning technology should not be interpreted as decreasing the importance of the teacher**, but rather enhancing it.
5. **Implications for cost and infrastructure are unclear**, but using existing hardware solutions is likely to help to reduce costs and increase access.

1. Introduction

The COVID-19 pandemic has resulted in widespread and unprecedented global disruption to education.[1] Physical distancing policies to suppress the spread of

[1] See: en.unesco.org/covid19/educationresponse

COVID-19, which often advise that students and teachers cannot congregate in schools in the conventional manner, has led to a global expansion of the use of technology within education.

This RER provides a summary of existing research evidence on the use of technology to support personalised learning in LMICs. It offers insights and evidence that can assist in the development and implementation of effective EdTech interventions across the globe and in situations of disruption to education and distance learning within the current context.

Background

Personalising education by adapting learning opportunities and instruction to individual capabilities and dispositions has been a long-standing objective among educators (Natriello, 2017). Indeed, everyday practice in schools globally almost always involves a degree of personalisation as teachers and students respond to each other's constantly shifting needs, aims and desires (Beetham, 2005; Holmes et al., 2018). The idea of personalised learning is therefore not new. There are, however, variations in how personalisation is realised in practice.

Research on technology's role in enabling learning that is better suited to the characteristics and needs of learners can be traced back several decades (and even beyond, to groundbreaking work on 'teaching machines' by Pressey and Skinner in the 1920s and 1950s respectively: Holmes et al., 2018). In more recent years, stimulated by the increasing availability and sophistication of digital technology, it has been argued that the adaptive and personalisable affordances of EdTech offer a way of addressing challenges facing education systems around the world. Potentially these affordances can open up new, scalable opportunities for greater personalisation that adjust the learning experience (e.g. based on age, ability, prior knowledge and/or personal relevance; FitzGerald et al., 2018). They may also enable diverse representations of content that reflect learners' own preferences and cultural reference points, in addition to the ability to automatically capture and respond to students' learning patterns with data.

Purpose

In the context of LMICs in particular, personalised learning carries significant promise in improving the state of education (Zualkernan, 2016): for instance, with regard to identifying and teaching at the 'right' (i.e. the learner's current) level; reducing the negative effects of high pupil–teacher ratios; increasing access to education; and improving learning outcomes (Kishore & Shah, 2019). The COVID-19 global health emergency has accelerated interest in how EdTech can support personalised learning given the nature of schooling is likely to be seriously affected in the medium to long term due to the introduction of physical distancing, school closures and other policies intended to alleviate the impact of the virus. As a result, there is an urgent need to identify existing research on technology-supported personalised learning in order to inform an effective response to the crisis. This is particularly the case for LMICs where marginalised learners risk falling even further behind.[2] This RER, alongside others, contributes to an emerging evidence base on the use of technology for education during the COVID-19 pandemic, and organises the most relevant literature into coherent themes for the consideration of key stakeholders.

Application

This RER is intended to inform educational decision-makers, including donors and those in government and NGOs, about the potential to use technology-supported personalised learning as a response to the current pandemic. The findings and recommendations are also anticipated to be of interest to other education stakeholders (e.g. researchers and school leaders). Given that the circumstances surrounding EdTech interventions differ greatly across LMIC and other education systems, as with other related reviews (e.g. Escueta et al., 2017), focusing on research undertaken in LMIC contexts allows for the integration of findings in a way that can yield meaningful policy implications.

Research questions

This study asks the overarching question: **What is known about personalised learning through using technology that can be of value in responding effectively to mass school shutdowns in LMICs?**

Two specific research questions (RQs) guide this enquiry:

RQ1. How has technology-supported personalised learning been implemented in LMICs?

- Where has research been undertaken?
- Which learners have been involved in the researched interventions?
- What approaches to technology-supported personalised learning are reported?
- How does technology-supported personalisation relate to learning outcomes?

RQ2. What key themes are reported in the literature that may inform a response to the COVID-19 pandemic?

Definition and scope of the study

Like many concepts in education, there is no universal definition of personalised learning (Holmes et al., 2018). Indeed, Cuban (2018) describes personalised learning as "*like a chameleon; it appears in different forms*". According to Cuban, these forms can be conceptualised as a 'continuum' of approaches: from teacher-led classrooms to student-centred classrooms, with 'hybrid' approaches in between. Such ambiguity has led to the idea of personalised learning being conflated with individualised learning and differentiated learning, and sometimes also confused with problem- or inquiry- or project-based learning (Holmes et al., 2018).

Although definitions of personalised learning vary, broadly stated there is agreement

[2] Estimates suggest the pandemic could lead to approximately US$10 trillion of lost earnings over the lifetime of every primary and secondary student globally while substantial reductions in education budgets are also a possibility (Azevedo et al., 2020).

that it is learner-centred and flexible, and responsive to individual learners' needs (Gro, 2017).[3] As reflected by the keywords used to search the literature (encompassing areas such as computer-aided instruction and intelligent tutoring systems among others; see methodology), an intentionally broad view of *technology-supported personalised learning* as an 'umbrella' term was adopted from the outset. Influenced by FitzGerald and colleagues (2018), in this RER **we conceptualise technology-supported personalised learning as: the ways in which technology enables or supports learning based upon particular characteristics of relevance or importance to learners**. This may refer to technology-supported instruction in which: the pace of learning is adjusted; the instructional approach is optimised for the needs of each learner (e.g. through learning objectives, content or tools); learning is driven by learner interests; learners are empowered to choose what, how and when they learn (Office of Educational Technology, 2017).

Structure of the RER

Following this introduction, the methodological approach is discussed, including details of the scoping review, the literature search, eligibility criteria and possible limitations of the methodology. Then, detailed findings are presented in response to the research questions (including four themes that emerged from a thematic analysis of identified literature). The report concludes by providing a summary of key findings and recommendations.

2. Methodology

The methodological approach for this RER was informed by the Cochrane Collaboration Rapid Reviews Methods Group interim guidance on producing rapid reviews (Garrity et al., 2020) in addition to the framework for undertaking a scoping review (Arksey & O'Malley, 2005; Levac et al., 2010).

Scoping review

A rigorous and systematic form of secondary research, scoping reviews involve collecting, evaluating and presenting available evidence at a 'high level'. Differing from 'conventional' systematic reviews in that they are better able to account for studies with varying intentions and designs, scoping reviews provide an accessible and summarised overview of existing research to inform policymakers and other stakeholders (Levac et al., 2010).

Preliminary search terms were developed based on the research questions and after considering the titles, abstracts and keywords of research which was known beforehand to be important and relevant (even if not focusing exclusively on LMICs e.g. the review by FitzGerald et al., 2018). Search terms were iteratively refined during pilot searches that revealed potentially useful studies and terms (identified following further analysis

[3] While beyond the scope of the RER, note that the contentious and widely disputed idea of 'learning styles' does not feature in mainstream definitions or approaches to personalised learning, see: www.theguardian.com/education/2017/mar/12/no-evidence-to-back-idea-of-learning-styles

of titles, abstracts and keywords). Using this approach, a final set of 35 search terms was compiled (Annex B).

Literature search and eligibility criteria

Automated searches were undertaken during May 2020 using Google Scholar and the Searchable PUblication Database (SPUD), an extensive searchable publication database (3+ million records to date) developed by the EdTech Hub team. Unlike a 'traditional' systematic review, which may screen all search results, the rapid review methodology employed relied on a system of quotas. As such, only the most relevant results (up to a maximum of the first 20 pages of results as ranked by Google Scholar) were selected for the first round of screening. In total, the search strings returned 38,335 results across Google Scholar and SPUD, with 198 potential candidate studies being identified through the automated searches.

Figure 1 provides an overview of the search process. The title and abstract screening, as well as all other subsequent screenings, were conducted according to the eligibility criteria in Table 1. Where research was identified to be potentially important despite not strictly meeting the eligibility criteria this was retained in a complementary collection in case it was useful later. 'Grey literature' (e.g. non-peer reviewed reports) was accepted if relevant to the scope of the RER. All data were shared by the research team through online documents and folders (e.g. Google Docs, Zotero).

Figure 1: Literature search and screening process

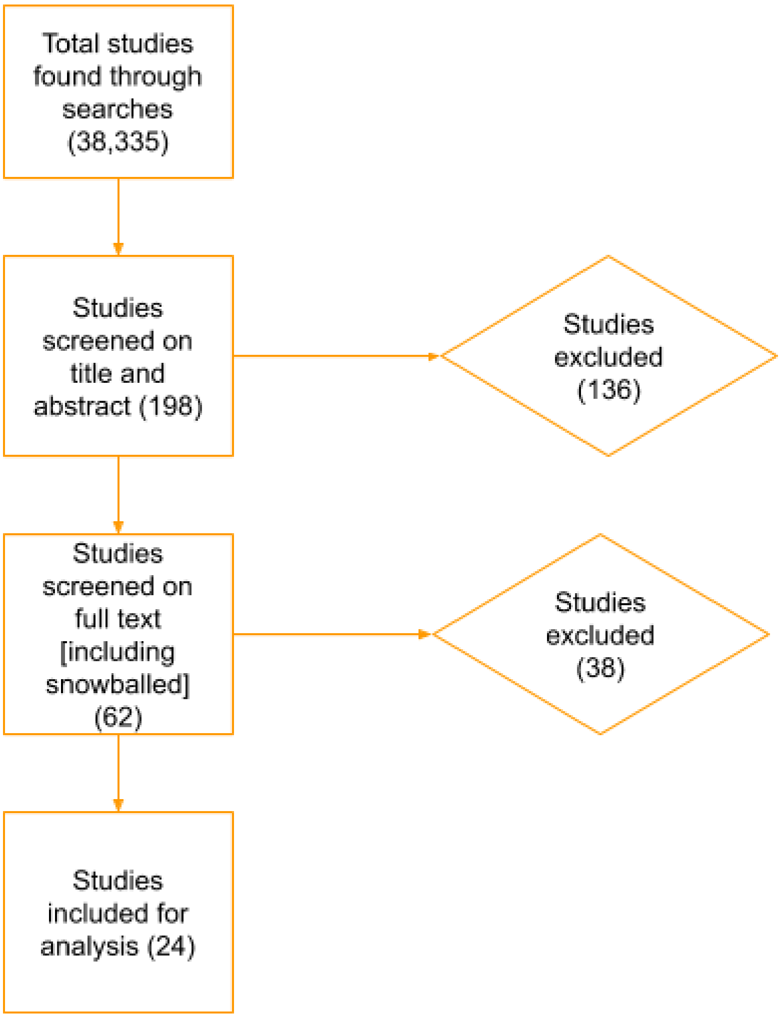

Table 1: Eligibility criteria for literature searches and screening

Criterion type	Inclusion criteria	Exclusion criteria
Population	Involving elementary and/or secondary school students (ranging from 5 to 19 years old) based in LMICs	Involving learners in higher or tertiary education only
Intervention	Falling under the broad 'umbrella' of technology-supported personalised learning	Studies focusing on access to technology with little consideration for how this is personalised to the needs of learners, or personalised

		learning with no use of technology
Outcomes	Reporting effects on academic performance (e.g. measured by grades or performance on tests) or relating to student needs/preferences (e.g. motivation to learn)	Focusing on the development and testing of software with no learner data
Study design	Describing primary empirical research (i.e., acquired by means of observation, experimentation or survey), both quantitative and qualitative	Reviews and meta-analyses or providing a 'lessons learned' account without presenting any empirical evidence
Date	Published 2006–2020	
Language	English-language only	

After full-text screening according to the eligibility criteria, 41 relevant studies were identified. Nonetheless, the reference lists of studies identified during the automated searches were also examined as a further check to ensure that relevant research was not missed. This 'backward snowballing' strategy resulted in 11 additional studies being identified. Further studies (n=10) were also identified via expert referral. In total, 62 studies were identified. Hassler and colleagues' (2016) adaptation of Gough's (2007) 'weight of evidence' framework was applied to determine those studies of most value. This involved one member of the research team independently scanning identified studies before making an evaluation of 'low', 'medium' or 'high' for each of the following criteria:

- *Methodological trustworthiness:* the trustworthiness of a study's results based on an evaluation of the research approach used.
- *Relevance to the RER:* relevance of a study for the specific purposes of this review, namely how technology-supported personalised learning can be of value in responding effectively to mass school shutdowns during COVID-19.

Any study categorised as 'low' for trustworthiness (n=19), relevance (n=12), or both (n=7) was omitted from further analysis (n=38). Thus these studies were excluded primarily because they reported only minimal empirical findings or considered technology-supported personalisation in a limited way. This process resulted in the inclusion of 24 studies that met a minimum threshold of 'medium trustworthiness' and 'medium relevance'.

To address RQ1, a process of data extraction involving the 24 included studies was undertaken. Initially, this involved extracting data to determine the key characteristics of studies (i.e. where has research been undertaken? Which learners have been involved in the researched interventions? What approaches to technology-supported personalised learning are reported? How does technology-supported personalisation relate to learning outcomes?). Having established this overview of the research landscape, thematic analysis was applied to address RQ2. Whereas data extraction (e.g., numbers of participants) is objective and not interpretive, thematic analysis (or 'thematic synthesis'; Thomas & Harden, 2008) involves telling the story that emerges across the findings reported by the included studies. Informed by established guidelines for narrative syntheses (Ryan, 2013), the research team: read studies to become familiar with their similarities and differences; discussed emerging relationships within and between studies; iteratively revised and refined themes to agree on a final set of themes.

Limitations

The search only considered English-language research published from 2007 onwards. The choice of keywords used or omitted, publication bias, or the selection and/or nature of digital libraries searched may have had an impact on the eventual findings. Due to the constraints of the RER timeframe, activities such as data extraction and quality assessment were necessarily undertaken primarily by one researcher in a short period of time, and thus some subjectivity or error may have been introduced. Time constraints also likely limited how comprehensively the research questions were addressed. It is also important to note that findings may not be generalisable to the current COVID-19 context, given the majority of reported research was undertaken in a school or 'school-like' context prior to the pandemic. Concerns have also been raised about whether learning gains from using personalised technology are actually attributable to the use of the software (e.g. as opposed to additional lessons conducted by a teacher; Buchel et al., 2020). A further limitation of research in this area is that the software is not always fully described; often the name of the software is omitted, and the full capacity of the software is not outlined. These factors may limit accurate inferences about the degree to which the reported software was personalised and how. Finally, the broad conceptualisation of technology-supported personalised learning employed resulted in the identification and analysis of a diverse range of heterogeneous studies of varying rigour which may have implications for the interpretation of findings.

Actions to mitigate the potential impact of these issues included undertaking pilot searches, examining the reference lists of included studies for other relevant work ('snowballing' — a process that revealed several commonly cited studies had already been identified thus demonstrating a degree of saturation) and maintaining frequent contact between researchers involved. While the findings of the RER are inherently limited by the quality of evidence available, the application of the quality/relevance assessment helped to mitigate the risk of low-quality or irrelevant research significantly impacting conclusions.

Theme identification

In the next section we present the findings of the RER. **RQ1** contextualises evidence available by outlining the characteristics of research on technology-supported personalised learning in LMICs, including how (and with what impact) this has been implemented. This contextual question provides the basis for informing the thematic outcomes in **RQ2**, which established four themes (and sub-themes):

1. **Improving access to education and adapting to the diverse needs of learners**
    - Enabling access to quality educational materials
    - Adapting to learners' needs by 'teaching at the right level'
    - Extending learning in new ways
    - Closing educational gaps for the most marginalised
2. **The role of teachers and appropriate professional development**
    - The central role of teachers and teacher professional development
    - Addressing constraints on teaching and learning
3. **Pedagogical and motivational affordances**
    - Peer interaction, scaffolding & productivity
    - Learner motivation
4. **Potential challenges and barriers in implementation**
    - Cost
    - Infrastructure, scalability and sustainability

3. Findings

RQ1. How has technology-supported personalised learning been implemented in low and middle-income countries?

See Annex C for a summary of information extracted from included studies.

Where has research been undertaken?

Evidence on technology-supported personalised learning is continually developing across LMICs. Identified research has assessed the implementation of technology-supported personalised learning in Asia (n=12), Africa (n=6) and Latin America (n=6).

This RER synthesises a total of 24 studies[4] from 12 countries during the period 2007 to 2020: India (n=5), Pakistan (n=1), Nigeria (n= 4), Kenya (n=2), Chile (n=1), Ecuador (n=1), El Savador (n=1), Cambodia (n=1), and rural China (n=6). Three additional countries are also reported in two comparative studies: Chile, Mexico and Ecuador were compared in

[4] Two interesting studies did not meet the formal inclusion criteria for RQ1 given their focus on the teacher and not students (Stott & Case, 2014; Zualkernan et al., 2013). Their reported findings are, however, considered in response to RQ2.

the same experimental study by Casas and colleagues (2014); Brazil, Mexico, and Costa Rica were also compared in the same case study by Ogan and colleagues (2012).

Research addressing technology-supported personalised learning is current and shows that work is ongoing in the field judging by the publication dates of retrieved studies: 2007 (n =1), 2008 (n=1), 2010 (n=1), 2011 (n=1), 2012 (n=2), 2013 (n=3), 2014 (n=2), 2015 (n=3), 2016 (n=2), 2017 (n=1), 2018 (n=2), 2019 (n=3), 2020 (n=2).

In addition, a range of research methods have been employed across different countries. Randomised Controlled Trials (RCTs) were the most common (n=12) and were conducted in rural China (n=6), India (n=4), Cambodia (n=1), and El Salvador (n=1). Quasi-experiments (n=8) were carried out in Nigeria (n=4), India (n=1), and the Latin American countries of Chile, Mexico, and Ecuador. There were 4 case studies; 2 from Kenya, 1 from Venezuela, and one study which compared Brazil, Mexico, and Costa Rica. Note, this classification of 'case study' was applied to studies designed to evaluate the development and implementation of specific personalised learning technologies in LMIC contexts. The four case studies collected both quantitative data (student learning outcomes) and qualitative data (teacher interviews) to assess the efficacy of personalised software (Andallaza et al., 2012; Mutahi, 2015, 2017; Ogan, 2012).

Which learners have been involved in the researched interventions?

Studies involved learners attending primary (n=15) and secondary schools (n= 9). The sample size of the studies overall are considered to be fairly large (minimum sample = 18, maximum sample = 21,936). For instance, an RCT in India by Muralidharan and colleagues (2019) sampled 619 participants, a quasi-experimental study sampled 734 learners across three Latin American countries (Chile, Ecuador and Mexico; Casas et al., 2014), and a case study by Andallaza and colleagues (2012) involved 143 learners from Venezuela.

What approaches to technology-supported personalised learning are reported?

A range of digital technologies are reported to deliver educational content to students in order to maximise opportunities for learning cognitive (test scores or learning outcomes) or non-cognitive skills (social skills, computer proficiency).[5] These have mostly targeted instruction in single subjects: mathematics (n=15), science (n=3), English (n=1), multiple subjects (n=4), and one study addressing social skills.

[5] Refer to Annex C (Data Description Spreadsheet) which includes a list of the personalised technology used in each study. In this context, 'cognitive skills' generally refer to assessment of learning outcomes using tests, and non-cognitive skills include social skills (e.g. Ige, 2019), computer proficiency skills (e.g. Mo et al., 2013), and affective skills (e.g. Andallaza et al., 2012). An interesting observation is the emphasis on assessing cognitive outcomes although learning is of course inextricably linked to non-cognitive skills like students' needs, preferences, socio-emotional development, etc.

The introduction to this RER pointed out how there is no agreed definition of technology-supported personalised learning. This is reflected in the varied terminology used by included studies. Common terminologies used to describe research related to 'technology-supported personalised learning' include:

- *Computer-assisted learning* e.g. Bai et al. (2018), Banerjee et al. (2007)
- *Computer-aided Learning* e.g. Muralidharan et al. (2019)
- *Computer-aided Instruction (CAI)* e.g. Carrillo et al. (2011); Ito et al. (2019)
- *Intelligent Tutoring Systems (ITS)* e.g. Andallaza et al. (2012)
- *Cognitive Tutoring Systems (CTS)* e.g. Ogan et al. (2012)

The studies which reported using either computer-assisted learning (n=9), computer-aided learning (n=3), or CAI (n=5) appear to use slightly different terms to describe a similar goal. While not all studies provide operational definitions for these terms, two common definitions were observed. Computer-assisted learning is characterised as a type of computer-aided learning which uses computerised instruction, drills and exercises, simulations, and instructional games (Gambari et al., 2016; Lai et al., 2013, 2015), or involves the use of a computer program that offers remedial learning materials in the form of interesting interfaces and games with the aim of improving educational outcomes and interest in learning (Bai et al., 2018; Mo et al., 2013).

In contrast, the studies which reported using ITS (n=3) and CTS (n=4) placed greater emphasis on the affordances the technology provided to the learner. These described how: responses to learner inputs (monitoring and feedback) were provided, content was adjusted to match the level of the learner, and a high volume of user data can be captured as feedback to the learner and teacher. Specifically, ITS are defined as "*computer applications that are capable of providing individualised instruction to learners through the use of artificial intelligence, thereby supporting the learner and facilitating the learning process*" (Andallaza et al., 2012, p.1). CTS are defined as a type of ITS that is capable of assessing skill mastery as a student solves problems, and provides context-sensitive hints, error feedback, and adaptive problem selection (Ogan et al., 2012). These adaptive softwares are specifically designed to facilitate self-paced learning through tailoring content to levels of learning (which can free teachers to act as classroom facilitators rather than teaching directly; Ogan et al., 2012).

There appears to be a link between the *level of personalisation* afforded by the technology and the reported approach to personalised learning. Three levels of personalisation afforded by educational technology were distinguished. Those with '*fewer personalisation affordances*' (n=8 studies), '*medium personalisation affordances*' (n=6 studies), and '*greater personalisation affordances'* (n=10 studies). The classifications *'fewer personalisation affordances'* and *'medium personalisation affordances'* can broadly be applied to studies reporting personalised learning using approaches like computer-assisted learning, computer-aided learning and CAI. By contrast, studies investigating technology-supported personalised learning using ITS, CTS, or other highly personalised technological software can be described as featuring *'greater personalisation affordances'*.

Software featuring fewer personalisation affordances may not use highly sophisticated intelligent software. Generally embedded in their design, however, is the explicit alignment of the software content to the local country's national curriculum, in addition to some level of personalisation that provides feedback to the learner to support monitoring of learning and progress. Technologies with *medium* personalisation affordances go beyond aligning the content of the personalised software to the curriculum but also try to coincide use of the software to ongoing class instruction. They also target the level of learner by presenting concepts according to task difficulty and facilitating interactive user feedback. Technologies involving *greater* personalisation affordances were: highly data driven;[6] had the potential for interaction (or responsive engagement) between the technology and the learner; involved educational content that was contextualised to meet the local context of the research.

In the present RER, the classifications of 'fewer-', 'medium-' and 'greater-' personalisation affordances are intended to indicate the differences in the extent to which personalisation is affected. Hence, levels of personalisation may fall on a continuum of being highly responsive to the user (e.g., scaffolding learning and providing hints to difficult questions), to less responsive (e.g., by providing activities like exercises for drill and practice, viewing videos linked to questions, and limited feedback such as indicating that user responses are correct or incorrect).

A further interesting finding is that studies implementing technology-supported approaches to personalised learning used the technology as either a *supplementary* (n=14), *integrative* (n=3) or *substitute* approach (n=2). Further, studies have compared these approaches: *supplementary/integrative* (n=1), *supplementary/substitution* (n=1) in addition to attending to *software evaluation* (albeit involving an analysis of learning outcome data, n=3).

Supplementary approaches provide additional opportunities for students to practice instructional content outside of regular classroom instruction. Such studies typically use additional learning opportunities to provide remedial support through independent practice using a learning software (e.g. Banerjee et al., 2007; Buchel et al., 2020). These have been trialled with software featuring fewer-, medium- and greater-personalisation affordances with content designed to target the different levels of the learner. Variations exist, however, in the extent and quality of engagement and feedback between the learner and the software. Supplementary approaches to personalisation thus complement the quality of instruction available to students. Students can therefore use such technology independently or with teacher guidance (Buchel et al., 2020).

Integrative approaches use the technology during instruction to facilitate teaching and learning. In this approach, the teacher and technology co-exist, where it is the teacher's role to facilitate and reinforce the learning process. They are designed not as supplementary, standalone systems but take into account the teacher, student and classroom interactions (Mutahi, 2015). For instance, the teacher uses technology to complement their lesson instructions by including time for students to use technology

[6] Examples include data drawn from interfaces and sensors that capture fine-grained user interactions (Mutahi et al., 2015), or that provide visual feedback on student progress using logs generated during a session (the Aplusix ITS in Andallaza et al., 2012)

(Gambari, 2016b). During this time the teacher may use the feedback data generated to adjust teaching and re-teach concepts.

Substitute approaches investigate the possibility of using personalised technology in lieu of teaching i.e. where instruction is delivered solely through technology. There is little evidence of technology-supported personalised learning successfully replacing certified teachers or regular teaching. Gambari and colleagues (2015) compared an individualised computer-assisted instructional program to two other non-computer assisted instructional programs. The researchers found no significant differences in learning outcomes among the three groups, implying that neither approach had an advantage.

Two studies designed interventions that compared these approaches with each other (Linden, 2008; Gambari et al., 2016a).[7]

In Table 2, an overview of the link between *fewer*-, *medium*- and *greater*-personalisation affordances and the ways in which technology-supported personalised learning has been implemented is outlined. It is worth recalling that the studies using software with greater personalisation affordances (ITS and CTS) have been the least researched. Further work is required to make affirmative conclusions about the use of any of these approaches.

Table 2. Summarising reported technology-supported personalised learning approaches by the nature of their implementation.

	Fewer personalisation affordances (n=8)	**Medium personalisation affordances (n=6)**	**Greater personalisation affordances (n=10)**
Supplementary (n=14)	3	6	5
Substitute (n=2)	2	0	0
Integrative (n=3)	1	0	2
Supplementary/ integrative (n=1)	1	0	0

[7] Linden (2008) evaluated a computer-assisted learning programme designed to reinforce Indian students' understanding of material presented in class and found this was a poor substitute for the teacher-delivered curriculum and was no better than a complement (supplement) programme delivered using an out of school model. Gambari and colleagues (2016a) study in Nigeria found that an integrative approach – integrating an interactive computer program into chemistry instruction – was no more effective than using conventional teaching methods or a substitute approach (using a computer tutorial instructional package).

Supplementary/ substitution (n=1)	1	0	0
Software evaluation [8] (n=3)	0	0	3

How does technology-supported personalisation relate to learning outcomes?

Studies report diverse but broadly positive relationships between technology-supported personalised technology and learning outcomes (Table 3).[9] It is striking how a relatively limited amount of qualitative or mixed methods research has been undertaken (although as discussed in the Limitations section, this lack of representation may be due to studies being inadvertently filtered out or missed).

Table 3. Summarising reported impact on students' learning (by research method)

	Studies	Positive outcomes	Mixed outcomes[10]	Negative outcomes
RCTs	12	10	2	0
Quasi-experiments	8	4	0	4
Case study[11]	4	3	0	1
Total	**24**	**17**	**2**	**5**

Of the studies featuring *fewer personalisation affordances* (Table 2, n=8), five report that the intervention had a negative impact on learning and three report a positive impact.

[8] These studies also attended to an analysis of learning outcomes (n=2).

[9] The learning outcomes are summarised to provide a broad overview. Ideally, a meta-analysis that compares effect sizes is a more appropriate way of determining the common effect across different studies and will be the next step towards extending this RER.

[10] The studies categorised as mixed outcomes generally found a positive effect on student learning from using the software. However, the effects were small over and above traditional pencil and paper learning (Ma et al., 2020) and the personalised approach was a poor substitute for the teacher-delivered curriculum in comparison to a complementary program which showed statistically significant gains for the weakest and oldest students in the class (Linden, 2008).

[11] The case studies were software evaluation studies which trialled newly developed personalised learning software with teachers and/or students to garner feedback on the useability of the tool and users' perceptions. Andallaza and colleagues (2012) collected quantitative data by observing students' affective states while using the software to determine if the software facilitated the development of affective skills. Mutahi and colleagues (2015, 2017) analysed qualitative data via teacher interviews to get feedback on the usability of the software and quantitative software usage data. Ogan and colleagues (2012) presents a qualitative case study featuring teacher interviews.

These three studies (all 'supplementary' approaches) were designed to provide remedial instruction that was tightly aligned to the curriculum, teacher instruction and learner feedback.

Similarly, the studies classified as featuring *medium personalisation affordances* (n=6) all used a supplementary approach that had a positive impact on learning. Moreover, it appears that the effort to contextualise the contents of the software so that it aligns with the national curriculum, classroom lessons or the level of the learner can have profound impact regardless of technology sophistication.

In terms of the impact on learning for studies classified as featuring *greater personalisation affordances* (n=10): five used a supplementary approach, all of which had positive impacts on students' learning; two used an integrative approach that also had positive impacts on students learning; and three were software evaluations that reported varying results in terms of impact on learning outcomes.

RQ2. What key themes are reported in the literature that may inform a response to the COVID-19 pandemic?

Building on RQ1, four interconnected themes identified in the literature are now considered. As outlined in RQ1, technology-supported personalised learning has been implemented in three main ways (as a supplementary, integrative or substitute approach). The reported synthesis is intentionally — and necessarily (given the constraints of the RER timeframe and the broad definition of technology-supported personalised learning) — 'high level' as it does not differentiate between the distinct ways in which technology has been used to support personalised learning. Further, the impact of cultural and social differences between different contexts, and the fact that the majority of research relates to mathematics and science education, must be considered when interpreting results from the reviewed studies. Despite these challenges, themes identified are intended to provide an accessible summary of existing evidence so that educators, policymakers and donors might make informed decisions about the potential role of technology-supported personalised learning as a response to the COVID-19 pandemic.[12]

Theme 1: Improving access and adapting to the diverse needs of learners

Enabling access to quality educational materials

Technology-supported personalised learning appears to offer an accessible means by which students can access instructional materials capable of enhancing learning. Thus, such technology can address severe teacher shortages (Ito et al., 2019) and the need for out-of-school learning (e.g. to support homework; Kumar & Mehra, 2018). Established

[12] Note, findings from two additional studies, that focus primarily on the role of the teacher, have also been incorporated into the thematic analysis given they provide insights complementing reported themes (Stott & Case, 2014; Zualkernan et al., 2013). Also included are findings reported in two other highly relevant studies undertaken in Latin America, originally published in Spanish, which were identified following the automated search (Perara & Aboal, 2017a, 2017b).

technology-supported personalised learning programs such as Mindspark offer a means to deliver educational content in a variety of settings (in schools, in after-school centres, or through self-guided study). Such solutions are being deployed across increasingly diverse platforms (including computers, tablets and smartphones; Muralidharan et al., 2019), and can be used offline as well as online (Bai et al., 2018; Ma et al., 2020).

In this context, 'quality educational materials' may be evaluated on two levels: (1) technological content carefully developed to be aligned with the curriculum and instruction at a level of instructional units (e.g. Carillo, 2011; Ito et al., 2019), and (2) lessons being delivered to students (e.g. Mo et al., 2014). As discussed in RQ1, so far much of the evidence points to positive gains when technology-supported personalised learning supplements classroom instruction (Lai et al., 2013; Mo et al., 2014). See Theme 4 for further discussion on potential barriers to equitable EdTech access that may be particularly relevant given the COVID-19 context.

Adapting to learners' needs by 'teaching at the right level'

Somewhat unsurprisingly, the adaptive nature of technology-supported personalised learning is a key emergent theme. For instance, the way this can enable students to learn at their own pace and according to their current proficiency (Ito et al., 2019), including collaboratively (Ogan et al., 2012). Allowing students to work at their own speed using personalised software pitched at their level can avoid potential negative status effects of them being labelled as being in a 'weaker' track, while the dynamic updating of content mitigates the risk of premature permanent tracking of 'late bloomers' (Muralidharan et al., 2019). Even more important is ensuring that the educational content is pitched at the learner's level of proficiency. Here, the technology is used to differentiate instruction in a way that meets the goal of remediation (Banerjee et al., 2007).

While there are several mechanisms by which computer-aided learning can improve teaching and learning, a particularly attractive feature is its ability to deliver individually customised content for Teaching at the Right Level (TaRL) for all students, regardless of the extent of heterogeneity in learning levels within a classroom (Muralidharan et al., 2019). This can help to directly address one of the main reasons for the general inability to meet desired learning outcomes in LMICs: the inability to meet the heterogeneous learning needs of a large student population with constrained educational resources (Kumar & Mehra, 2018).

Consider the following example reporting the use of a mathematics intervention in urban India. Addressed to all children but adapted to each child's current level of achievement, a technology-supported personalised learning initiative allowed each learner to be individually and appropriately stimulated (Banerjee et al., 2007). Specifically designed to address constraints on effective pedagogy in LMICs, such software may feature the use of an extensive item-level database of test questions and student responses to benchmark the initial learning level of every student; the material being delivered can then be dynamically personalised to match the level and rate of progress made by each individual student (Muralidharan et al., 2019). In addition to allowing for variation in academic content presented, other potential benefits include allowing different entry points and differentiated instruction without the need to reorganise peers in the classroom (including preserving the age-cohort-based social grouping of students; Muralidharan et al., 2019).

Extending learning in new ways

In addition to this capacity to support TaRL, technology-supported personalised learning appears to offer the potential to promote learning in other ways beyond those previously possible. A randomised controlled trial in Salvadoran primary schools, for instance, reveals not only how computer-assisted personalised learning produces substantial learning gains, but may actually outperform traditional modes of instruction (Buchel et al., 2020). Such a relative advantage seems to be driven by a mismatch between teacher preparation and the complexity of the concepts they have to teach: under traditional teaching models, it seems questionable that children are able to master what their teachers fail to understand. However, technology-supported personalised learning may allow learners to make progress beyond their teachers' content knowledge. Such approaches may thus help to teach or remediate critical deficiencies in both students' and teachers' understandings (Ogan et al., 2012). Researchers including Gambari and colleagues (2016a) have explored using personalised technology as an integrative or blended model where it is used as part of instruction in mathematics and science to address challenges such as a lack of instructional materials and to facilitate the teaching of constructs that are abstract and difficult to understand. While the researchers did not find using computer-simulated instruction during instruction to be more effective than traditional instruction, the study points to a need for research to detangle the contribution of delivering pedagogical content through the teacher versus through the technology.

Closing educational gaps for the most marginalised

Consistent with the promise of technology-supported personalised learning to customise instruction for each student, integrating a novel approach to implementing grade level appropriate material into existing teaching practice can substantially increase learning for students of all baseline learning levels (Muralidharan et al., 2019). Of particular significance during the current context of mass school shutdowns, given many learners will likely require additional support to get to the 'right level' upon returning to school, is a growing collection of evidence that indicates how technology-supported personalised learning may help most in closing educational gaps for marginalised learners. This is evident in examples of studies done in India, rural China and Latin American countries that deliberately target disadvantaged students from low-income backgrounds or aim to address issues relating to quality education (e.g. Carillo et al., 2011; Mo et al., 2013).

Many parents of the most marginalised learners have neither the skills nor the money to provide remedial tutoring, while many teachers often do not have time to give students the individual attention they need. The ability of personalised technology to teach all students equally effectively, for instance as a complementary input to using existing computer resources, has been reported as offering the potential to narrow the urban-rural achievement gap and help disadvantaged populations (Bai et al., 2018). Indeed, students from disadvantaged family backgrounds (Lai et al., 2013), or who have less educated parents (Lai et al., 2015), may benefit more from such programmes. In settings where students are more likely to be substantially behind grade level, or where there is substantial heterogeneity, the effects of adaptive technology might be larger because technology can personalise education (Ma et al., 2020). As a result, the relative impact of learning gains may be much greater for lower-attaining students (Muralidharan et al., 2019), although arguably such learners may be the most likely to have limited access to required technology.

Positive effects have also been observed with regard to gender, which is indicative of the promising use of computer simulation and tutorial instructional strategies to bridge the academic gaps that might exist between male and female secondary science students (Gambari et al., 2015). Note, however, that other research has reported no similar positive effect for girls, nor indeed for high-performing students irrespective of their gender (Ma et al., 2020). This is something also reported by Kumar and Mehra (2018), who, while finding students with low and medium mathematics attainment benefited significantly from the personalised homework, higher-attaining students did not to the same degree. This might have been because the algorithm offered too many easy questions that could be suboptimal for the learning needs of some high ability students. Other potential explanations include high-attaining students already knowing how to learn effectively (and hence are always more likely to do well), as well as the 'gap' being much smaller in terms of how much they can improve.

Theme 2: The role of teachers and appropriate teacher professional development

The central role of teachers and teacher professional development

While the exact ways in which technology-supported personalised learning is implemented vary, evidence on the role of the teachers in such implementation is overwhelmingly consistent: any introduction of personalised learning technology should not be interpreted as a loss of the importance of the teacher in teaching. For instance, Buchel and colleagues (2020) found that while students benefited from additional mathematics instruction, the learning gains were greater when this instruction was delivered using personalised learning technology with an experienced teacher over a supervisor who does not offer pedagogical support. It is possible that the availability of the teacher to provide immediate feedback is complemented by the potential of the technology to deliver individualised materials (at the pace and level of the learner) which has benefits for the progress of the whole class.

Overall, the majority of the research on technology-supported personalised learning in LMICs trials supplementary approaches where students used the personalised technology outside of class instruction and without input from the teacher (see RQ1). Importantly, it appears studies that report success typically rely on the teacher or a knowledgeable expert to ensure the quality of the software's instructional content and the alignment between class teaching and further practice for students. The few studies that have compared substitute and complementary approaches to using personalised technology have consistently reported no advantages when the technology replaces the teacher (Gambari et al., 2016a, 2016b; Linden, 2008).

Thus, reported research should not be interpreted as supporting a reduced emphasis of the role of teachers in education. Rather, since the delivery of education involves tasks that vary for individual students and situations, and requires complex contextually aware communication, technology should be viewed as a complement (rather than substitute) to teachers (Muralidharan et al., 2019). This is, of course, a common message emerging from EdTech research across recent decades and it is no less applicable here. Where a technology-supported personalised learning system is reported to have been used, learners have themselves recognised the role of the teacher as a helpful guide in the learning process (87% of 388 students; Casas et al., 2014).

Using technology in this way can include deploying it to perform routine tasks to free up teachers to spend more time on aspects of education where they have comparative advantages over technology (e.g. such as supporting group learning strategies that can help develop social and other non-cognitive skills; Perara & Aboal, 2017a). Personalised approaches using cognitive tutoring systems that provide self-contained lessons, can help to mitigate common barriers to using educational software (such as the preparation time teachers require; Ogan et al., 2012). In cases where teachers cannot be in class, such technology could potentially assist substitute teachers or aides and supplement existing lessons, thereby facilitating a dynamic interaction between the teacher, system and learner by tracking student engagement and learning (Mutahi et al., 2015). How personalised technology can provide analytics or support data-analysis-intensive tasks (Muralidharan et al., 2019) is also likely to be an important focus of future research, particularly in those contexts where it is not possible for teachers to be physically present with students. As also highlighted in Theme 1, student progress may be hampered by limited teacher knowledge; hence, investing in the skills of teachers through offering professional development programmes is important (Buchel et al., 2020; Mo et al., 2014). When integrating technology-supported personalised learning approaches, teachers should be trained on the effective pedagogical use of the technology (through seminars, workshops and conferences; Gambari et al., 2016a).

Additionally, there appears to be some limited evidence indicating the effectiveness of electronic tutoring as a tool for promoting conceptual change among in-service teachers themselves. Quantitative data collected from 1,049 South African science teachers who attended 54 in-service teacher workshops suggest that individual use of the software can be effective in developing new knowledge, especially for those who already have relatively high levels of prior knowledge (Stott & Case, 2014).

Addressing constraints on teaching and learning

Providing they are operational and available, reported personalised technological interventions appear to be well received by teachers (who broadly agree that they offer efficient and effective learning accompaniments; e.g. Mutahi et al., 2017). Teachers' intention to use such systems, however, is strongly dependent on how well the system is aligned with their teaching practices, students' learning habits, and whether the content on the platform is made available in a language that can be understood by students (Zualkerman et al., 2013). Teachers must also reconcile their usual one-size-fits-all delivery model, in line with the order in which their curriculum expects them to teach concepts, with the notion of different pathways for different students.

In addition to enabling 'teaching at the right level' (see Theme 1), personalised learning software may help in addressing other constraints on teaching and learning. For instance, in the case of the Mindspark software, the high quality of content, combined with effective delivery and interface, can help circumvent constraints of teacher human capital and motivation. Algorithms for analysing patterns of student errors and providing differentiated feedback, and follow-up content that is administered in real time, also enable more relevant and more frequent feedback (Muralidharan et al., 2019). As a result, promoting the targeted use of personalised learning technology may be an attractive option for governments and NGOs operating in settings with low teacher quality. This is because learning software can empower teachers to improve the quality of their teaching, particularly when they themselves struggle with particular concepts they have to teach (Buchel et al., 2020). Other ways in which technology-supported personalised learning may support teaching include outside of school uses (e.g. through easy-to-implement personalised homework; Kumar & Mehra, 2018), and by providing extensive information on student performance to better guide teacher effort in the classroom while not contributing to increasing teacher workload (Muralidharan et al., 2019).

Theme 3: Pedagogical and motivational affordances

There is a close link between the affordances provided by technology and the manner in which it is implemented. Complementing the previous discussion in Themes 1 and 2, in this subsection other potential affordances of technology-supported personalised learning are considered.

Peer interaction, feedback and scaffolding

While the idea of personalised learning may on the surface appear to relate to a more 'solitary' understanding of education, some evidence points to the potential benefits of personalised learning for collaborative working. Peer interaction can be promoted directly through personalised technologies or enabled offline as students use the technology to acquire core knowledge and skills that allows them to contribute to group-based work taking place outside of the technology itself.

For instance, in Ogan and colleagues' (2012) study on the use of mathematics tutoring software in middle schools in Latin America, students collaborated extensively while using a technology primarily designed for individual use; the pace of work was often interdependent, and work often occurred at classmates' computers in addition to their own. Further, the authors observed that the greater the (group) use in the class, the greater the advantage that the students obtained. Such findings have led to calls for research to explore how personalised technology may be used within classrooms to promote conceptual change through scaffolding and peer tutoring (Araya & Van der Molen, 2013), and active learner participation and classroom dialogue (Stott & Case, 2014). The way that technology-supported personalised learning can enable comparison and competition between peers has also been suggested as a contributing factor to positive learning gains (Brunskill et al., 2010; Bai et al., 2018). Consideration has also been given to how students' social skills might be fostered (Ige, 2019).

While the features of technology-supported learning initiatives differ according to many factors, including the intended audience and deployment location, a case study on how interactive adaptive tutor software (Wayang Outpost) has been used to support mathematics learners (Grades 5-12) in Pakistan is useful in demonstrating how such technology can be designed to support pedagogy by:

- Modelling (introduces the topic via worked examples, making steps explicit, and working through a problem aloud);
- Providing practice with coaching (offering multimedia feedback and hints to sculpt performance to match/resemble that of an expert's);
- Scaffolding (putting into place strategies and methods to support student learning);
- Providing affective support (via characters that reflect about emotions, encourage students to persevere and demystify misconceptions about mathematics problem solving);
- Encouraging reflection (self-referenced progress charts allow students to look back and analyse their performance) at key moments of loss or boredom (Zualkerman et al., 2013).

Such technology features have been reported to improve students' learning efficiency and productivity (Ito et al., 2019) and enable teachers to spend more time on supporting group-based learning strategies that may help build social and other non-cognitive skills (Muralidharan et al., 2019).

Impact on learner motivation

Technology-supported personalised learning appears to be well received by most learners and has a broadly motivational impact as well as improving subject learning. For example, after the implementation of a cognitive tutoring strategy for mathematics learners in Latin America, a high percentage (67%) of students in the intervention group (n=388) increased their motivation toward learning maths, felt more certain about their abilities to solve maths problems (68%), and viewed the technology as a useful tool that substantially helped their learning process (81%; Casas et al., 2014). Other evidence corroborates this conclusion. This includes a study showing that secondary school students in Nigeria performed better on chemistry achievement and motivation tests when compared to those taught without computer simulations (Gambari et al., 2016a). Positive effects on student interest in mathematics have also been found (whereas there was no effect on maths interest from extra time learning maths; Ma et al., 2020). Indeed, this 'interest-oriented stimulation' is regarded by some researchers as one of the main sources of improvement among students (Bai et al., 2018), although this may in part be due to a novelty effect.

A more general positive impact on student motivation as a result of technology-supported personalised learning is also reported. This includes the adaptive and/or gamified capabilities of technology increasing the probability that students will remain engaged and challenged (Brunskill et al., 2010; Ma et al., 2020), in a way that can significantly increase their interest in learning (Lai et al., 2015) and aspirations for their future education level (Bai et al., 2018; Ito et al., 2019). Trials of emotionally intelligent personalised mathematics software that provides encouragement and support while students learn algebra indicate the creative potential of technology-supported personalised learning to simulate interactions similar to that provided by the teacher (Andallaza et al., 2012). Other research also reveals a strong positive correlation between performance and engagement (Mutahi et al., 2017). Questions remain, however, about whether such motivational benefits manifest across different age and subject groups. For instance, Ito and colleagues (2019) reported only a very slight change in motivation and self-esteem in younger learners following the introduction of a computer-aided instruction programme. Other issues must also be considered, including the problem of questions that do not challenge those at higher attainment levels (Kumar & Mehra, 2018) or how to prevent learners from 'gaming' a system to get better results (Mutahi et al., 2017).

Theme 4: Potential challenges and barriers in implementation

Cost

As outlined above, due to the constraints of the RER process and scope, we do not differentiate between the distinct ways in which technology has been used to support personalised learning (i.e. whether this is implemented as a supplementary, integrative or substitute approach; see RQ1). Such heterogeneity presents a challenge to drawing firm conclusions about the costs associated with technology-supported personalised learning initiatives. Our findings in this regard are, therefore, tentative and further research is recommended to unpack such factors. Nonetheless, this initial exploration indicates that implementing technology-supported personalised learning need not be prohibitively expensive, even if it may be somewhat more expensive than non-technology based solutions.

Banerjee and colleagues (2007) reported the cost of a non-technology based tutor-led programme for developing primary school literacy and numeracy skills at US$2.25 per student per year, with technology-supported programmes costing $15.18 per student per year (including the cost of computers and assuming a five-year depreciation cycle). In terms of cost for a given improvement in test scores, therefore, scaling up the non-technology based programme would thus be much more cost effective (if it brings about a similar increase in test scores at a much lower cost). Other research has concluded that the implementation of one personalised-learning technology can be calculated as broadly on par with other interventions to improve student performance in LMICs (e.g. a girls scholarship program, cash incentives for teachers and new textbooks), though less cost-effective than remedial education and teacher training programmes (Linden, 2008). In an experiment by Ma and colleagues (2020), however, the researchers found that the marginal costs of paper workbooks are unsurprisingly lower than those associated with technology and lead to roughly similar effects on academic performance. Importantly they also do not require the high fixed costs and maintenance costs of computers, internet connections, and extra space to securely house such equipment.

Such findings have prompted interest in how lower cost (and less resource-intensive) technology-supported personalised learning initiatives may be implemented in LMIC contexts — for instance, an adaptive multi-user software that splits screen resources and pushes different questions to individual input devices (Brunskill et al., 2010). Beyond an upfront investment, such software can be provided at low cost or even open access, which improves its scalability potential. Another approach includes computer-generated personalised homework, which is reported to be both somewhat effective (showing a 4.16% improvement in exam scores in a study involving 240 students) and inexpensive as associated costs can be spread over a large number of students when applied on a large scale (e.g. less than $1.00 per student; Kumar & Mehra, 2018).

In summary, additional work is needed to explore the cost implications associated with technology-supported personalised learning initiatives. This is a complex matter that boils down to more than the cost of software development or purchasing of a device. Models of technology-supported personalised learning that charge fees may limit the ability of low-income students to access them (Muralidharan et al., 2019). Donated (up-to-date) hardware (Banerjee et al., 2007), 'online' programmes (e.g. Open Educational Resources or Massive Open Online Course) and government-led initiatives may all play a role in enabling greater access to personalised and adaptive learning technology (Muralidharan et al., 2019).

Infrastructure, scalability and sustainability

In a similar manner, further research is needed to determine other factors involved in the broader EdTech ecosystem (including in relation to the potential to scale and sustain technology-supported personalised learning initiatives).

Significant resource constraints and challenges (e.g. intermittent network connectivity, lack of battery power, etc) have been reported in the deployment of technology-supported personalised learning programmes, and this should be a consideration when developing systems for resource-constrained regions or countries (Mutahi et al., 2017). Weak technology infrastructure, poor equipment maintenance, poorly prepared technical support personnel, high frequency of electric supply problems, and unstable connections to the internet have all been reported to present problems; in addition, such technical difficulties may be more pronounced in students' homes (Araya & Van der Molen, 2013). 'Start-up' costs associated with the development and maintenance of adaptive software have also been flagged as a potential concern, indicating how more research is needed on the trade-offs between adaptive versus non-adaptive software (Ma et al., 2020). In addition to technological deployment (technical issues such as lack of local servers and networks because of poor internet bandwidth and lack of technical assistance for the setup of computer labs), the potential impact of changing political priorities and teachers' attitudes (owing to lack of confidence and engrained practices, particularly for more established teachers) for scalability and sustainability must also be considered (Casas et al., 2014).

While 'traditional' software-based technology-supported personalised learning programmes may sometimes be particularly difficult and costly to implement (compared to other EdTech uses that potentially do not require as high a learner-to-device ratio), solutions that bypass some of these problems have been proposed (e.g. 'online' computer-assisted learning; Bai et al., 2018). Such an approach is reported to eliminate the need to manually install and maintain software in addition to enabling the ability to log in 'anywhere and anytime'. Additional features, such as the integration of social functions (Bai et al., 2018), may open up new avenues for learning. Other personalised approaches, such as computer-generated personalised homework (Kumar & Mehra 2018), have also been reported as relatively easy to implement with minimal need for external monitoring. Moreover, one thing is clear from the literature: access to technology alone is insufficient (Ito et al., 2019).

4. Recommendations

Personalised learning in LMICs, as both a concept and a practice, remains in its infancy. In general, there is still much to learn about the potential benefits of personalised learning, including how learning environments that can adapt to the unique needs and strengths of students and allow them to have greater ownership of their learning may enable more meaningful and effective education (Gro, 2017). Nonetheless, this RER demonstrates that there is a growing base of evidence on the impact of technology-supported personalised learning to support school-age learners in LMIC contexts.

Following a systematic search of the literature since 2006, 24 studies in 12 countries were identified. On the whole, an encouraging and positive impact on learning outcomes is reported. As previously discussed, the limitations of the RER, heterogeneity of included studies, and fact that the majority of included research reports on the use of technology-supported personalised learning approaches in a school (or school-like) context must be considered when drawing conclusions. Despite these challenges, recommendations can be made to inform educational decision makers, including donors and those in government and NGOs, about the potential to use technology-supported personalised learning as a response to the current pandemic in LMICs:

- **Technology-supported personalised learning appears to offer significant promise to improve learning outcomes, including potentially 'out-of-class' and 'out-of-school' learning.** This has been successful in providing remedial instruction in mathematics and science. Further research is needed, however, to support these claims and it is important to note that most existing research conducted 'out-of-school' has been in classroom-type settings with support from facilitators. It is also unclear how long any learning gains persist over time.
- **The adaptive nature of technology-supported personalised learning to 'teach at the right level' is key as it enables students to learn at their own pace and according to their current proficiency.** It can deliver individually customised resources and activities for all students regardless of the extent of heterogeneity in learning levels in the class. Importantly, these adaptive features appear to make a difference to learning, while technology with fewer personalised affordances does not seem to positively impact learning in the same way. Of particular significance in the context of mass school shutdowns,

given that many learners are likely to require additional support upon returning to school, is that technology-supported personalised learning may help most in closing educational gaps for marginalised learners.

- **Technology-supported personalised learning may be most beneficial in closing educational gaps for lower-attaining students, potentially including those returning to school after an absence.** Much of the evidence points to it being an effective avenue for delivering remedial instruction. Questions remain, however, about whether the approach is as effective for higher-attaining learners. Moreover, 'personalised learning' does not necessarily mean 'individualised learning'; it can include group-level adaptation and some research points to the beneficial nature of student collaboration in this context (as in many others). Indeed, technology-supported personalised learning can also open up a range of other important pedagogical and motivational affordances (e.g. relating to feedback and the scaffolding of learning).
- **Any introduction of personalised learning technology should not be interpreted as decreasing the importance of the teacher, but rather enhancing it.** Technology-supported personalised learning approaches appear to have promise in helping to teach or remediate deficiencies in student understanding as well as in potentially helping teachers improve their subject and conceptual knowledge. This is particularly important to note when considering low-resource contexts where teaching quality may be low. Such approaches have potential to function as a medium for continuous learning beyond classroom instruction.
- **Implications for cost and infrastructure are unclear, but using existing hardware solutions is likely to help to reduce costs and increase access.** While significantly more research is needed into the costs associated with technology-supported personalised learning, a number of studies report that such an approach need not necessarily be prohibitively expensive. Whether the 'added value' of technology-supported approaches is sufficient to merit the additional expenditure remains to be determined. Using existing hardware solutions (e.g. mobile devices or desktop computers in those areas where these are readily available) can clearly help to reduce associated costs and enable greater numbers of students to access personalised learning through technology. In settings without sufficient infrastructure, it is likely that implementation costs will be high.

Further robust quantitative, qualitative and/or secondary research is needed to investigate the various complex and nuanced factors associated with technology-supported personalised learning presented in the RER. In addition to addressing questions relating to cost effectiveness, a particularly important consideration for future research is to understand which approach to the use of technology in personalising student learning will have the greatest impact on learning outcomes (including how this varies according to countries, culture and context). Integrated approaches to design, research and development (e.g. design-based research), that feature close collaboration with practitioners and learners as an integral part of the research process in order to solve 'real-world' educational problems, may be particularly fruitful. Such approaches can help to engender 'buy in' and avoid situations where personalisation technologies developed in higher-income countries are 'parachuted' into LMICs (Zualkernan, 2016). Other avenues of research could include: rigorous comparison of EdTech personalised adaptive learning and non-EdTech personalised learning approaches; greater consideration of differences in the use of personalised technologies in urban and rural settings; nuanced investigations into learning outcomes (e.g. broken down by gender and level of achievement over time); how the role of teacher may change in the presence of personalised technology; and consideration of the motivational affordances of technology-supported personalised learning from both teacher and learner perspectives (particularly in contexts where a teacher may not be physically present with students).

One important area noticeably absent from the analysis relates to the ethics of technology-supported personalised learning. There are, of course, many assumptions that underpin personalised technologies that warrant scrutiny. This includes whether there is a risk of perpetuating a narrow idea of what it means to 'succeed' academically (e.g. due to an overt focus on 'traditional' learning outcomes such as test scores); whether personalised learning risks promoting individualistic learning aspirations; whether valuing more 'closed' tasks over 'open' ones may be to the detriment of deeper learning experiences; and in what ways personalised data collection impinges upon students' privacy.

It is also worth noting how the majority of research to date has been undertaken in a school context. Many of the most disadvantaged learners will not have regular access to schooling in the traditional sense (much like in the present situation given the COVID-19 pandemic). Future technology-supported personalised learning initiatives should potentially look, therefore, to specifically target such learners, in particular lower-attaining students who are left behind in 'business-as-usual' instruction (Muralidharan et al., 2019

Annex A: Bibliography

N.b. Those items astericked (*) represent those included in the final set of 24 studies.

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Annex B: Search terms

Source	Search terms	Records returned	After screening
Google Scholar (GS)	"Personalised Adaptive Learning"	132	2
GS	"Personalized Adaptive Learning"	619	3
GS	"Personalised technology-enhanced learning"	34	4
GS	"Personalized technology-enhanced learning"	76	12
GS	"Technology-enhanced personalised learning"	18	6
GS	"Technology-enhanced personalized learning"	30	18
GS	"Personalised TEL"	13	5
GS	"Personalized TEL"	11	3
GS	"Personalised learning environment"	593	20
GS	"Personalized learning environment"	3490	5
GS	"Teaching at the right level"	266	5
GS	"Combined Activities for Maximized Learning"	15	1
	... ("Edtech" OR "Education technology" OR "digital learning" OR "eLearning" OR school) AND ("africa" OR "LMIC" OR "developing world" OR "developing country*" OR "ICT4D" OR "global south")		
GS	"Personalised education" AND	160	6
GS	"Personalized education" AND	626	6
GS	"Personalised learning" AND	1810	6
GS	"Personalized learning" AND	3660	5
GS	"adaptive learning" AND	6910	1
GS	"adapting learning" AND	396	5
GS	"Differentiated learning" AND)	1310	8
GS	"Computer-assisted instruction" AND	6160	27
GS	"Computer-assisted learning" AND	8130	10
GS	"Computer-aided learning" AND	1530	3
GS	"Intelligent tutoring system" AND	765	5
GS	"Exploratory learning environments" AND	33	0

GS	“Adaptive Educational Hypermedia” AND	112	2
GS	“Adaptive hypermedia” AND	414	1
GS	“Personalised Adaptive Learning” AND	7	3
GS	"Personalized Adaptive Learning" AND	43	3
SPUD (TE or (TT and PP))	Teaching at the Right Level	2	2
SPUD (TE or (TT and PP))	TARL	43	0
SPUD (TE or (TT and PP))	personalised	534	4
SPUD (GC.HM or GR or GD)	personalized	255	2
SPUD (GC.HM or GR or GD)	adaptive learning	42	3
SPUD (GC.HM or GR or GD)	intelligent tutoring system	76	8
SPUD (GC.HM or GR or GD)	computer assisted learning	20	4
TOTAL		**38,335**	**198**

Annex C: Data description spreadsheet

Available here