Centre for Financial and Management Studies (CeFiMS)

Analysing the readiness and effectiveness of the use of technology to provide continuity of learning amidst COVID-19 pandemic: Case Study of India

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To my rocket fuel, Swasti.

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Abstract

The research makes a considerable contribution to the academic literature which explores the use of technology in the public education system by analysing 'how effective the widespread use of technology has been for learning during COVID-19 in India'. The research develops a conceptual framework that outlines the readiness of states to adopt digital learning technologies and its effectiveness in terms of usage and impact on learning levels across states in India. The conceptual framework is used to analyse the variations across states in India in terms of availability of digital infrastructure, teacher preparedness, adoption of different tech-driven education initiatives, and its effect on the learning levels among students during COVID-19. The conclusions are drawn for key evidence driven policy decisions to ensure effective use of technology in providing quality learning to students. The results of the research are drawn using National Achievement Survey (NAS) data, ASER data, UDISE Report, TRAI Report and academic publications to assess the impact on learning outcomes of students for widespread use of remote and digital learning tools.

Keywords: education technology, digital learning, education during COVID-19 pandemic, India

1.0 Introduction

The severe acute respiratory syndrome coronavirus 2 (SARSCoV2), or COVID-19, was declared a global pandemic by the World Health Organization (WHO) on March 11, 2020 (WHO 2020). The pandemic caused unprecedented disruption in people's lives worldwide, and governments across the world sprang into action to mitigate the pandemic's catastrophic effects. Beginning in March 2020, multiple spells of lockdowns were imposed in India (Rao 2023). Despite these measures, India saw one of the highest rates of infections in the world, reporting around forty-five million cases between 2020 and 2023 that overwhelmed medical infrastructures (WHO 2023). The pandemic triggered severe economic repercussions, including widespread job losses, business closures, and financial instability. India's GDP contracted by 5.5% in the fiscal year 2021 on account of the pandemic (Rao 2023).

The pandemic's impact has been profound, hitting health systems, economies, and education. Due to its diverse effects on all areas of human life, and its unprecedented and global nature, it becomes very important to analyze the challenges faced during the pandemic and understand where responses fell short. These analyses are crucial to guide future capacity-building efforts.

The COVID-19 pandemic disrupted traditional education systems, leading to school closures and a shift toward remote learning. The closure of schools due to COVID-19 affected over 276 million children and adolescents attending primary and secondary schools in India. When considering tertiary education, the impact extended to around 311 million students (UNESCO 2021). The consequence was a rapid switch to EdTech learning interventions. The education sector witnessed the rise of numerous EdTech startups, attracting 4 billion USD in investments between 2020 and 2022. As of 2022, India had 4530 such startups, with over 400 founded after 2019. EdTech unicorns include Byjus, Unacademy, Emeritus, UpGrad, and Vedantu (HolonIQ 2022; Nag 2022).

In addition to these privately pursued EdTech ventures, government policies during the pandemic also keenly focused on EdTech. The National Council of Educational Research and Training (NCERT), along with the Ministry of Education (MoE) used the National Teacher Platform, Digital Infrastructure for Knowledge Sharing (DIKSHA) to offer teacher training, lesson plans, and curriculum-linked worksheets. The MoE (in collaboration with IIT Madras) also works to deliver educational content through the portal Study Webs of Active-Learning for Young Aspiring Minds (SWAYAM). Additionally, considering disparities in access to digital infrastructure, lessons were also broadcasted through TV channels and radio channels, in different languages of instruction to ensure access to educational resources (Capelle et al. 2021; Nag 2022).

The present research seeks to identify the readiness of Indian states to adopt technology for providing education and the effectiveness of these EdTech interventions rolled out by governments at the central and state levels in India during the pandemic. The paper has been structured in six chapters in order to provide the reader with an organized understanding of the knowledge contribution rendered by this research project.

After this short introduction, the second chapter reviews the literature available on the research topic. The literature review is divided into (a) the digital divide and barriers to learning via EdTech (b) Learning during the COVID-19 pandemic (c) teachers' perspectives and experiences with EdTech, and (d) examining the efficacy of EdTech initiatives for learning. Vast amounts of scholarly literature have thus reiterated the growing importance of digital learning in an evolving educational landscape and point towards creating an enabling ecosystem for preparing states to have equitable and efficient adoption of education technology.

The third chapter presents a background to the research problem, research questions, and a discussion on the research paradigms, approaches, and methodology that were employed during the research.

The fourth chapter delves into the conceptual framework developed for this study. This chapter forms a core part of the study, providing a structured methodology to answer the research questions and how a sound examination of these research questions can be undertaken.

The fifth chapter focuses on attempting to directly tackle the research questions. It includes empirical data analysis, drawing interpretations that allow us to score Indian states on their readiness to adopt education technology, and draw implications for the effectiveness of the edtech initiatives taken during the pandemic. Further, a simple two-variable linear regression analysis was conducted to evaluate how readiness correlates to effectiveness: whether readiness of a state can be used to predict the effectiveness of any EdTech interventions.

The sixth chapter presents the conclusions by providing an overview of the results, comparing observed results with the research questions, and drawing out implications of the research both in terms of its omissions and limitations and scope for further research.

2.0 Literature Review

This chapter is written with the aim of presenting an analysis of the literature available on the topic of the project. The analysis has been structured to focus on specific concepts falling under scope of the study. This allows us to narrow down our focus, enabling a greater understanding of the research topics under study.

The literature review has been structured in the following manner.

1. The digital divide and barriers to learning
2. Learning during the COVID-19 pandemic
3. Teachers' perspectives and experiences with EdTech
4. Examining the efficacy of EdTech initiatives

This structure allows us to broadly cover the major aspects of relevant literature, as well as move sequentially in a manner that would allow the researcher to arrive at a conceptual framework. Due to our analysis being centred on India, the point of view of developing countries is emphasized.

The first section focuses on describing barriers to the adoption of EdTech through the lens of different perspectives existing in the academic literature, and the varied challenges that researchers have highlighted. The focus on challenges to the adoption of EdTech in a broad context is justified as these descriptions of approaches create the right context for the exploration of the relationship between the prerequisites for Edtech in specific country or state contexts.

The second section covers the analysis of the literature exploring how COVID-19 has impacted the EdTech sector. The section focuses on different governmental initiatives, and the idea of readiness for online learning during COVID-19, as has been evaluated by previous studies. The section also focuses on how learning occurred during the pandemic and the challenges and perceptions of teachers and students. Thus, different aspects of EdTech use during the pandemic are brought out.

The third section narrows down on the stakeholders involved in the process, focusing on literature that explores teachers' experience, perceptions, and preparedness when it comes to utilizing EdTech within the classroom.

The fourth section focuses on literature that measures usage and the impact of EdTech interventions, and the methodologies various authors employ to do so. Effectiveness focuses on evaluating the results and consequences of integrating EdTech tools and strategies into the education system and the degree to which these accomplished their intended goals.

2.1 The digital divide and barriers to learning

While the benefits of EdTech are numerous and digitization is transforming societies and spurring digital economic growth in many parts of the globe, these benefits do not accrue evenly, being fractured due to digital divides globally. Some segments of societies continue to lag. The digital divide is digital inequalities or unequal diffusion, adoption of digital goods and services, based on economic, social, geographical, and generational divides (Van Dijk 2012; Maceviciute & Wilson 2018).

A strand of literature on the digital divide has focused particularly on developing economies. Subnational digital divides have received plenty of scholarly attention. Scholars argue that the gap within countries in access to Information and Communication Technologies (ICT) between the haves and the have-nots (the underprivileged class) is rather wide. Works in this area also emphasize that the digital divide must be seen as more nuanced than a reductive binary division with a singular determining factor of access/non-access (Warschauer 2002; Keniston and Kumar 2003; Venkatesh and Sykes 2013). Socio-economic factors that are implicated in the process of creating digital divides, such as rural/urban, gender, nationality, age, class, and caste, also influence how technology will be utilized, even once barriers to access are overcome. The usage of devices can be guided by patriarchal social norms (Damarin 2000; Dahya et al. 2019; Capelle et al. 2021). Thus, literature has also focused on how the digital divide has more dimensions than just access, extending to usage patterns and digital literacy levels.

Cross-country analyses have also occurred within the literature. Mathrani et al. (2021), focus on the digital divide in India, Pakistan, Bangladesh, Nepal, and Afghanistan during the COVID lockdown. They remark that "hurdles to access, affordability, lack of education, as well as inherent biases and socio-cultural norms" are further exacerbated in times of crisis, such as COVID-19. Various surveys carried out at national levels tell us about the extent of the digital divide in developing countries. These surveys reveal that 37.6% of households had access to the internet in Bangladesh, compared to 93% in the Maldives, 51.1% in Nepal, 34% in Pakistan, 53% in Sri Lanka, and 24% in India. Considering access to computers, only 5.6% of Bangladeshi households had access to a computer, compared to 59% of Maldivian households, 14% of Pakistani households, 22% of Sri Lankan households, and 11% of Indian households (ITU 2018; ITU 2019; MICS 2019; ITU 2020; Sri Lankan Government 2020).

Rodriguez-Segura's work (2020) synthesizes existing studies of EdTech interventions in developing countries. The review covers 67 studies across 29 low and middle-income countries since 2002. Rodriguez-Segura argues that the most pressing challenges for EdTech in developing countries are vastly different from developed countries. They argue that if the digital divide and technological barriers are overcome, EdTech could be leveraged to address problems that would be too costly or resource-intensive to solve through other channels. Additionally, Ganimian et al. (2020) show that EdTech programs can fail in developing countries because learners either lack access to hardware (such as laptops), or have poor internet connectivity. Educators may lack the requisite knowledge to deploy technologies and may not have access to adequate training or onsite support. In such contexts, even if access barriers are overcome, Gainimian et al. (2020) argue that technology can feel alien in schools, and solely introducing technology without additional challenges is unlikely to lead to improved learning outcomes. The authors argue that classroom technologies only matter if teachers and students feel comfortable utilizing them for learning.

In India, government interventions have acknowledged the existence of a digital divide. In August 2020, the Government of India issued remote learning guidelines where they acknowledged that access to technical devices and learning opportunities available to students varies greatly across the country (Ministry of Education 2020). Considering different levels of affordability of different technologies cause variations in learning opportunities, the guidelines offered different models for providing learning continuity during school closures. One of these diverse modalities was the radio, and radio programs were launched across various states. However, the percentage of enrolled children who did learning activities via radio broadcasting was less than 4% in each of the states, with the lowest at 0.5% enrolled children in Jharkhand doing learning activities via radio broadcasting (ASER 2020).

During the pandemic, NCERT acknowledged the lack of access to the internet to students, advising educational guidance through SMS, or phone calls (Capelle et al. 2021). Further, considering the lack of access to the internet and mobile phones, TV-based telecasting of learning programs was initiated. The learning program was telecasted for two hours and organized throughout the day for students in different grades on TV channels from Monday to Saturday. Students could ask their doubts after watching the TV program on a phone call. A similar approach was adopted by different state governments to provide learning on TV programs based on the SCERT curriculum and contextualized in local languages.

Thus, the concept of the digital divide during the pandemic has been widely discussed in scholarly literature. Digital divides have been studied within developing country contexts, including India, and for their impact in the sphere of EdTech. Adequate attention has not been paid to how this manifests into a tangible divide in readiness, and effectiveness behind learning through EdTech. This study attempts to conduct an empirical analysis across states in India to provide insights on readiness among states to adopt technology for learning, and effectiveness of such initiatives.

2.2 Learning during the COVID-19 pandemic

The COVID-19 pandemic induced school closures across the world. This compelled a rapid switch to EdTech driven learning globally. The main obstacle to e-learning during the pandemic was low-quality Internet services, requiring significant financial resources for improvement (Maatuk et al. 2020). Radha et al.'s study (2020), based on 175 responses from around the world, concludes that e-learning became a prominent trend during the pandemic. Abdelfattah et al.'s (2022) meta-analysis delves into the acceptance of e-learning systems before and during the COVID-19 pandemic, considering the pandemic an impactful year for the sector.

A branch of India-focused academic literature has analysed initiatives commenced by central and state governments, focusing on EdTech during the pandemic.

The PM e-Vidya program facilitates multi-mode access to digital/online teaching-learning content of various types among students and teachers. New learning guidelines were also released for students and teachers by the MoE and NCERT. These guidelines recognized the different circumstances in the country, including varying access to technology and educational opportunities for students. The main aim was to offer various approaches to support and continue learning during school closures for three groups of students: 1) those who had no access to any technological device 2) those with basic technological devices (such as radios televisions, and telephones), and 3) those who could access digital devices for learning (such as smartphones and computers). This provided flexibility in applying learning strategies and methods across different states in India (Ministry of Education, Government of India 2021).

Within low-tech modalities, television, radio, and telephonic assistance was provided through Swayam Prabha DTH channels, All India Radio, FM educational lectures and toll-free helpline numbers for resolving students' doubts. Medium tech modalities included smartphone applications, web repositories, and social media messaging platforms. Initiatives such as iScuela Learn, Unnayan: Mera Mobile Mera Vidyalaya, DIKSHA, e-Pathshala, Swayam and National Repository of Open Educational Resources (NROER), WhatsApp and SMS initiatives to connect students and teachers were those delivered through these medium-tech modalities. High-tech modalities (Learning Management Systems (LMS), Chatbots, Real-time video conferencing, AI/ML and Virtual Reality based virtual learning) were not widely adopted in government schools, and only saw limited adoption even in private schools (Ministry of Education, Government of India 2021).

Doraiswamy et al. (2020) have also studied the actions taken by seven states: Delhi, Gujarat, Himachal Pradesh, Kerala, Meghalaya, Rajasthan, and Uttar Pradesh. They interviewed senior government officials, organizations, agencies, and individuals involved in the implementation of the programs in those states. The study analysed these states' interventions, dividing them into high-tech (web content and apps), low-tech (WhatsApp, mobile, TV, radio), and no-tech (printed material). The authors reason that information and communications technology (ICT) interventions in India have been largely hardware-focused with the aim of improving students' digital literacy in schools, while at-home promotion and adoption of learning through technology has been rather limited. The initial responses by governments also did not consider the needs of marginalized learners, especially girls and disabled students. Crucially, they concluded that states that had before the pandemic invested in technology and the development of local-language content were more resilient to the shock and responded swiftly. The most resilient states were those that had the existing state capacity to mount a swift and comprehensive education response.

The education response programs were created and executed by senior officials from education departments, with some cases having assistance from external technical partners. The extent to which other stakeholders were involved in the process differed among states (Doraiswamy et al. 2020). However, these policies did not adequately and systematically consider the country's levels of preparedness for such initiatives.

Limited attention has been given to assessing a country's readiness for large-scale EdTech transformations, such as the one compelled by COVID-19. Works that discuss readiness include Adam et. al (2021)'s study which discusses countries' readiness, focusing on the Sub-Saharan African region. Additionally, Nag (2022) has undertaken an analysis of the infrastructural preparedness in India. This is measured in terms of the availability of electricity; internet connectivity, and digital resources. Nag's analysis occurs through the Objective and Key results method (OKR). In a similar vein, Ganimian et al. (2020) have argued for policymakers to understand the preparedness and capacity of a region's school system before the implementation of any ed-tech intervention. They recommend policy makers to : (a) understand the needs, infrastructure, and capacity of a school system; (b) survey the best available evidence on interventions that match those conditions, and (c) closely monitor the results of innovations before they are scaled up.

Due to the COVID-19 crisis, governments globally resorted to formulating ad-hoc policies and implementing them as rapidly as possible. The nature of the pandemic did not allow for systematic and wide-spread analysis. Future policies must be guided by evidence, and have a structured approach. This study aims to provide a unified framework that can systematically inform future

EdTech efforts in times of crisis. The conceptual framework developed here can aid state and national authorities to undertake analyses of (i)preparedness of infrastructure and stakeholders for EdTech interventions, and (ii) the effectiveness of the interventions once they are implemented.

Further, research on digital learning during the pandemic has given us valuable insights into the challenges faced by students and teachers. Reports and studies have shown the extent of the central and state government's involvement in this area. However, most of these studies relied on surveys, questionnaires, and interviews. These qualitative methodologies have not yet allowed for a comprehensive empirical analysis to take place. The author came across very few studies that looked at the efficacy and implementation of government-led EdTech initiatives for schools during the pandemic (see, for instance, Doraiswamy et al. 2020; Singh et al. 2021; Capelle et al. 2021; Nag 2022).

2.3 Teachers' perspectives and experiences with EdTech

There has been relatively limited research into teachers' vantage point and their preparedness for EdTech. Teachers encountered several challenges in the realm of online teaching, including a lack of technical facilities, interruptions from family, insufficient training, unclear direction, and a lack of technical knowledge. This was emphasized by Joshi et al. (2020), who collected data from various secondary sources, including reports, news articles, magazines, and online media. In addition to technical obstacles, difficulties in conducting online exams and assessments have been highlighted by Kamal & Illiyan (2021), who conducted an econometric analysis of teachers in Delhi schools.

Several studies on teachers' readiness or preparedness have also been conducted. Paliwal & Singh (2021) have looked at teachers' readiness to handle online education based on an online teaching readiness competencies model. This online teaching readiness competencies model included a measure of online course designing competencies, communication competencies, time management competencies, and technical competencies. Alimyar & Lakshmi G (2021) have attempted to understand teachers' preparedness, attitudes, beliefs, and difficulties across India and Afghanistan through the means of questionnaires fielded to English teachers that obtain responses on the Likert Scale—a study that stands out for its cross-country focus. Their findings revealed that lack of technological tools, time taken to adapt to technical tools, the sudden paradigm shift without systematic training, planning, and executing classes were among the challenges that teachers faced while using technology in their classes during the Covid-19 pandemic.

Mohalik & Sahoo (2020), employ a survey methodology, to look at the e-readiness of teachers enrolled in teacher education programs. The indicators in their questionnaire included e-readiness with digital devices, financial support, internet connectivity, adequate electricity supply, and personal space at home. Carried out via purposive sampling, their study is unique in its geographic focus, looking at teachers across fifteen states. These are: Jharkhand, Odisha, Tripura, West Bengal, Chhattisgarh, Madhya Pradesh, Telangana, Rajasthan, Uttar Pradesh, Arunachal Pradesh, Manipur, Haryana, Maharashtra, Kerala, and Sikkim.

A common trend across the studies on teacher preparedness is the overwhelming reliance on qualitative methodologies and the reliance on questionnaire/survey/interview responses for analysis. While these studies are immensely valuable for their contributions, and many rightly assess the metric of preparedness, a gap is palpable in the assessment of teachers' preparedness that (a) relies on "perceptions" or "experiences" and has not yet occurred on empirical lines, and (b) highlights the need for using more diverse, representative samples that can allow us to draw conclusions beyond grade levels, subjects, schools, and cities. The present study strives to fill this gap within existing research.

2.4 Examining the efficacy of EdTech initiatives

EdTech has been known to significantly expand the range of opportunities in the education field. Recognizing student diversity, and offering a more interactive and tailored learning experience have been emphasized as Edtech's key advantages over traditional 'chalk-and-talk teaching (see for instance, Christensen et al. 2011; Major & Tsapali 2021).

Christensen et al. (2011) argued that the educational system could be disrupted by leveraging student-centric technology. They examined different philosophies of education throughout history and identified that the element of individualized instruction was missing throughout. To address this, they advocate for the adoption of online learning, which they argue can offer more student-centric learning experiences, meeting the unique needs of each learner.

Major & Tsapali's meta-analysis (2021) focuses on the potential of digital technology to address educational challenges in resource-poor settings, specifically in low- and middle-income countries (LMICs). Through a rigorous examination of randomized controlled trials (RCTs) and meta-regressions conducted between 2007 and 2020, the study assesses the impact of technology-supported personalized learning on students' learning outcomes in LMICs. The findings provide compelling evidence for the effectiveness of personalized learning approaches, enabled by technology, in improving educational outcomes for learners in these contexts.

Very few studies have examined the efficacy of government-led EdTech initiatives during COVID. Studies have not adequately emphasized that the EdTech initiatives that were implemented were largely unilateral in action, without a beneficiary-oriented approach to their implementation. There was little to no feedback mechanism for beneficiaries on the programs implemented. A lack of adequate acknowledgment of this in the scholarly literature can be a barrier to responsive policymaking in the future. Capelle et al. (2021), who look at the Indian government's EdTech interventions during COVID focus on measuring three key variables – access to technology, their utilization, and perceived learning for different profiles of children. They evaluated 6 states in India and analysed the reach of different distance learning modalities during school closures. Beyond access, they argue that major variations occur in the parameters of adolescents' use of technology for learning purposes and their perceptions of learning. They argue that these variations are linked to the type of remote learning modality, gender, location, and type of school.

An area that has received significant scholarly attention is randomized experiments that analyse the impact of various EdTech offerings. These studies have been localized to a particular region, and specific to students of particular grades. For instance, Banerjee et al. (2007) conducted a randomized experiment in government schools in Mumbai and Vadodara to understand the impact of a computer-assisted remedial program. Private stakeholders such as Pratham, and tech firms such as Media-Pro assisted the intervention in government schools. The computer-assisted learning program was implemented in Vadodara government-run primary schools, while trained local teachers provided remedial education in Mumbai. Both programs were found to have substantial positive effects in the short run. Muralidharan, et al. (2016) conducted a randomized controlled trial on an after-school blended learning program that combined personalized, adaptive learning with available teaching resources. Another study by Muralidharan et al. (2019) examined a technology-led afterschool instructional program in Delhi. In this highly cited study, Muralidharan et al. (2019) studied the impact of a personalized technology-aided after-school instruction program in middle-school grades in urban India. They found that those who accessed the program, or lottery winners scored higher in math in Hindi over just a 4.5-month period. These studies collectively contribute to our understanding of the impact of educational technology interventions on student learning outcomes, however, disaggregated by state contexts, subject-specificity, and grade levels.

NITI Aayog' School Education Quality Index (SEQI) evaluates the performance of States and Union Territories (UTs) to identify their strengths and weaknesses and undertake requisite course corrections or policy interventions. This index is of immense value in assessing varied states' capabilities when it comes to delivering quality education. However, a similar state-level analysis has not been undertaken with a precise focus on EdTech interventions—a gap that the present study aims to fill.

Previous literature is somewhat limited in its approach due to constrained geographic focuses, focusing on limited EdTech interventions, and their methodologies. In their review, Rodriguez-Segura (2020) writes that out of all the studies that examine the efficacy of EdTech interventions, 80% of core studies had opted for randomized controlled trials as their methodology. RCTs, due to their specific inclusion and exclusion criteria, lack generalizability. The process of randomization also does not guarantee a representative sample. Furthermore, RCTs, due to their expensive and time-consuming nature, are rarely conducted in large geographical areas, or with a long-term focus.

Even while precise methodologies differ across studies, these do not offer a unified framework through which any EdTech intervention can be assessed, or its impact measured. Additionally, these methodologies are often excessively complicated (involving rigorous econometric analyses, regressions, and meta-regressions). In opting for these approaches, the already existing data, which is quite extensive in its focus has not been utilized to its potential. There is a lack of a comprehensive index for digital education.

The present research study is unique in several aspects. It stands out for its comprehensiveness with regard to geographical focus, and studying the various dimensions of education technology employed. The geographical scope of this study encompasses all Indian states. It explores the different technologies of televisions and smartphones at the household level, accompanied by the availability of internet and electricity at the household level. Using these indicators, the study investigates the infrastructural readiness of different states using a unified conceptual framework. The research examines teacher preparedness as a crucial factor in successful ed-tech integration, something that has previously received limited scholarly attention. It considers indicators such as the number of teachers trained in computers to do so. By exploring these aspects, the study provides insights into the readiness of educators and the readiness at a household level to effectively utilize technology for learning.

Additionally, the author did not come across research studies that attempt to describe how readiness contributes to efficacy, or draw a linkage (whether causal or correlational) between the readiness of any Indian state and the effectiveness of EdTech interventions in that state. To bridge this gap, this study conducts a two-variable linear regression analysis. The data and indicators for this analysis were obtained via the conceptual framework developed. The findings of this regression add to our knowledge about the pre-requisites of a successful EdTech intervention and affirm that the formulation of policies and EdTech interventions must take into account the capacities of a region.

Studying the effectiveness of Edtech is a significant focus of this research. This component goes beyond the question of access to technology to look at how many students were actually enrolled in and reported learning through EdTech interventions. To understand changes in learning outcomes, the study analyses the academic performance of students in Mathematics using data from the National Achievement Survey (NAS) in 2017 compared to the most recent survey in 2021.

3.0 Research Methodology

In this chapter, the approach taken to address the research questions is explained. Research methodology refers to a systematic, accepted, and verifiable approach to problem-solving. Conducting a research study to seek answers to research questions involve:

1. An adherence to certain philosophies (approaches);
2. Employing tested procedures, methods, and techniques for validity and reliability,
3. Ensuring an unbiased and objective design. (Opie & Brown 2019)

With these considerations, the research methodology is structured into five parts namely: (a) the problem background, (b) the research questions (c) the research paradigm and approach, (d) the scientific method and techniques, and (e) the sources of analysis employed to address the research question.

3.1 Problem Background

This section provides a rationale for the motivation leading to the selection of the topic of the research project.

During the writing of the paper, the author was involved in the formulation and management of various EdTech interventions in India. As most of these EdTech projects were related to reducing learning gaps and ensuring learning continuity that was disrupted by the pandemic, the opportunity to work on these projects was exploited to provide a good source of evidence. The research was undertaken to understand how prepared the states were to implement the Edtech interventions, and just how effective these were once implemented.

The motivation for this topic is derived from two major considerations. The first motivation, as discussed in the literature review, is that in the wake of the pandemic-induced global crisis, a renewed interest in EdTech interventions is palpable. This is visible among teachers, students, parents, academic circles, as well as private education firms, and government stakeholders. Conventional wisdom from a pre-COVID era, of ‘chalk and talk’ teaching as the only effective tool to disseminate educational content is being challenged as blended learning models see increasing popularity and become the subject of discourse.

The second motivation is that the design of the conceptual framework presented in chapter three provides a sound basis for development agencies and policymakers alike to draw conclusions regarding the role of EdTech in the Indian education landscape, which is incredibly diverse due to varied needs and contexts within each state.

Further, an analysis of empirical findings on components of readiness and effectiveness of the education landscape for EdTech is presented. It showcases the use of the framework, and quantitative data, an attempt to link readiness and effectiveness using a sound regression analysis. Following this, we attempt to draw conclusions on EdTech interventions—what it takes for a large-scale EdTech rollout to succeed, and areas where policymakers need to do better.

3.2 Research Questions

The research questions explored in this study are as follows:

1. How can we assess the readiness of Indian states to adopt education technology for learning during COVID-19?
2. How can we examine the effectiveness of the ed-tech initiatives taken by governments across states in India during COVID-19?
3. What is the relationship between readiness of Indian States to adopt education technology and effectiveness of the initiatives taken by the Indian state?

3.3 Research Paradigm and Approach

A research paradigm is a philosophical framework that guides how scientific research should be conducted. The philosophical approach of the researcher denotes how a researcher knows about the reality and assumptions; and what knowledge and assumptions they focus on. (Alharahsheh & Pius 2020). The two most important research paradigms available for research in the sphere of education are Positivism and Interpretivism.

Positivism is characterized by viewing reality as highly objective and governed by laws and mechanisms. In contrast, interpretivism adopts a subjective stance, perceiving reality as shaped by multiple mental constructs influenced by the researcher and their contexts. Positivism advocates unique research methods for different sciences, relying solely on empirical evidence to validate or refute scientific theories without relying on argumentation. Conversely, interpretivism emphasizes the ongoing generation of new knowledge through the researcher's experiences and highlights the active role the researcher plays in scientific inquiry (Alharahsheh & Pius 2020).

Given the fact that the author was interacting with the stakeholders involved in formulating and managing EdTech interventions, the research paper inclines more toward the interpretivism paradigm. The author's understanding of the research topic was enhanced through this research, fostering a continuous learning cycle as a result of the information collection process and utilizing different sources, thereby providing further support to the interpretivism character of the research.

After the research paradigm for the research project has been identified, there is a need for the identification of an appropriate research approach from the following three research approaches available to the researcher:

(1) induction approach,

(2) deduction approach and

(3) abduction approach (Agterberg , 2021).

Induction is a method of reasoning from premises that supply some evidence without full assurance of the truth of the conclusion that is reached. Deduction starts from premises that are correct and lead to conclusions that are certainly true. Abduction starts with observations from which it seeks to draw the simplest and most likely conclusion, moving between theory and empiric to draw the simplest conclusions (Agterberg, 2021). Induction is used frequently within the interpretivism paradigm, while deduction in the positivism paradigm.

The research work follows the abduction approach. The choice for this approach is largely because the author has not encountered a specific theory linking the concepts of readiness and effectiveness of EdTech paradigms in the post-COVID context for all Indian states. Therefore, the author uses both past studies through a focused literature review on the research topic and empirical data gained from various national surveys to gain necessary knowledge and investigate the research questions. The analysis oscillates between the studies and the empirical analysis to ensure a thorough analysis.

3.4 Scientific Method and Techniques

The scientific research methods can broadly be classified in the following two categories namely: (a) Qualitative and (b) Quantitative (Naibaho, 2022). The methods for data collection differ across the two approaches. Quantitative methods lead the researchers to rely on statistical analysis of data which is usually in numeric form. In qualitative research, the researcher analyses words (for example, transcription from interviews) or images (for example, photographs). Qualitative research employs an open-ended, subjective approach, emphasizing the researcher's perspective and interpretation of reality, rather than a direct observation of the reality itself. In contrast, quantitative research disregards the subjectivity arising from the researcher's interactions and approaches reality in an objective manner.

According to Naibaho (2022), there are three factors in deciding the use of a quantitative or qualitative approach: (i) match the approach to the research problem. Here, Naibaho reasons that problems that require the researcher to analyze trends, or seek explanations are better suited for quantitative research. In contrast, problems that need to be explored further to gain a deeper understanding are better suited to qualitative research. In addition, (ii) stresses on knowing the audience of the research report, and (iii) the degree to which the researcher can link the approach with their personal experience and training.

This research starts off as qualitative in nature. Initial research leans towards interpretivism, and the focus is on interpreting literature to devise a conceptual framework that will allow us to explore readiness and effectiveness in the EdTech landscape. The author starts with the "how" question to stress the explanatory dimension of the research. The setting being studied here is a very contemporary one, with countries still reeling from the effects of the pandemic, and with stakeholders in the education sector increasingly focusing their attention on EdTech approaches, as an effective tool to enhance learning.

Following the development of the conceptual framework, the author focuses on how the conceptual framework stands up against quantitative data collected through national-level surveys. A quantitative data analysis is thus performed using numerical data in conjunction with the conceptual framework to understand the level of preparedness of states for EdTech interventions, and the effectiveness of these interventions.

Further, the study attempts to determine whether the readiness of states for EdTech interventions has any correlation with the effectiveness of these initiatives for learning. While it intuitively follows that high levels of readiness will contribute to high effectiveness, we use the econometric tool of regression analysis to check for statistical significance for the relationship between two variables in India.

Econometrics is a discipline that deals mainly with the empirical verification of economic theory (Gujarati & Porter 2009). The term regression was first introduced by Francis Galton in 1886. A regression analysis is now regarded as an econometric tool. A regression analysis involves examining how one variable, known as the dependent variable, depends on one or multiple other variables called explanatory variables. The main objective is to estimate and/or predict the average value of the dependent variable within a population, based on the known or constant values of the explanatory variables when repeatedly sampled (Gujarati & Porter 2009).

For the purpose of this study, a two-variable linear regression model (a model in which the dependent variable is expressed as a linear function of only a single explanatory variable) is appropriate. The explanatory variable is readiness, while the dependent variable is effectiveness in our analysis. This linear regression analysis is used to drive correlation between readiness and effectiveness. However, it is important to note that a regression analysis does not necessarily imply causation. "A statistical relationship, however strong and however suggestive, can never establish causal connection: our ideas of causation must come from outside statistics, ultimately from some theory or other" (Kendall and Stuart 1961, p.279).

3.5 Sources of Analysis

The key data sources used for the study are:

1. **Unified District Information System for Education (UDISE) 2020-21** is one of the largest Management Information Systems (MIS) on school education in India covering more than 1.5 million schools. The platform collects data on a wide range of parameters from schools, infrastructure, teachers, enrolments, etc. This study particularly analyses data that describes Information and Communication Technology (ICT) related indicators. It includes the percentage of total teachers trained in computers.
2. **Annual Status of Education Report (ASER) 2021** reports on various indicators that measure how children (aged between 5 and 16 years old) studied during the pandemic and challenges faced by schools and households. In 2021, the ASER report surveyed 25 states, 3 UTs and 581 districts, 76,706 households, 75,234 children, and 7,299 schools through a phone survey format. This study analyses specific data related to the availability and usage of digital devices for learning. Indicators used include the percentage of enrolled children who have a smartphone available at home and the percentage of enrolled students who have a TV available at home
3. **National Achievement Survey (NAS) 2017 and 2021**: NAS is a large-scale survey conducted by the Ministry of Education, Government of India. In the 2017 survey, the learning levels of 2.2 million students from 1,10,000 schools across 701 districts in all 36 States/UTs of India were assessed. On the other hand, the 2021 survey assessed the learning levels of 3.4 million students from 1,18,274 schools across 720 Districts in all 36 States/UTs. The survey analyses the learning levels of the students at the district, state, and national levels

and gauges the competencies of students at various grades, and at an aggregate level provides a system-level reflection on the effectiveness of school education. This study looks at data pertaining to the learning achievements of students in Maths (across Classes of 5th ,8th and 10th). Learning outcomes based on the socio-economic background of students are also examined.

4. **Past scholarly literature:** These secondary sources are used as a reference point to make sense of quantitative evidence for the research, aiding researchers in the development of the conceptual framework.

4.0 Conceptual Framework

The conceptual framework is the representation of how variables are related. Thus, it is a researcher's map in conducting the research by identifying the variables required in the research investigation (Ravitch & Riggan, 2016). In this chapter, a conceptual framework is developed to study two variables - readiness and effectiveness for education technology integration at the state and national level. It forms the basis for measuring readiness and effectiveness for education technology as well as deriving a correlation between the two variables by regression analysis.

The chapter begins by defining the terms readiness and effectiveness in the context of this study. The concepts of readiness and effectiveness are further divided into different components and sub-components. These components are derived using past academic literature. The conceptual framework diagram has been developed to indicate all the components and sub-components used for analysing readiness and effectiveness within the scope of this study.

Further, indicators have been assigned to each sub-component to evaluate the performance of states for all the components. These indicators have been selected from various national surveys based on data availability. The measurement of state-wise performance in the next chapter for all the components lay a strong foundation for using the conceptual framework to provide empirical evidence.

This chapter also describes the scoring methodology to assign scores to each state for all the indicators of the sub-components and components used in the conceptual framework.

4.1 Readiness

Readiness is defined as the level of preparedness and capacities of Indian states to effectively use their resources to implement education technology solutions. A higher state of readiness indicates that the education system is well-equipped to smoothly transition to remote or blended learning methods, ensuring minimal disruption to students' learning experiences during the challenging circumstances posed by the COVID-19 pandemic.

For this study, the author has identified two key components for measuring readiness: Access to Digital Infrastructure and Teacher Preparedness, and the related sub-components and indicators for each component. The identified sub-components and indicators for measuring readiness are based on a review of existing literature around readiness, and based on the availability of data for Indian states at the household level.

1. **Access to Digital Infrastructure:** This component assesses the availability of essential digital resources at the household level, which were crucial for facilitating remote learning and online education during the pandemic.

   Nag (2022) identifies key parameters for measuring student readiness, and these include the availability of electricity, internet connectivity, and digital resources. Nag (2022), too, reasons that the availability of the internet and digital devices is of utmost importance, as they form the foundation for an effective EdTech-driven system. Without these resources, the functionality of any EdTech system becomes practically impossible. However, even before considering internet and digital devices, the most rudimentary factor to address is electricity. Without a stable electricity supply, powering up the necessary equipment becomes infeasible, rendering other resources futile. Hence, electricity, internet connectivity, and availability of digital devices stand as the primary determinants influencing the performance of an EdTech system, and their quantifiable nature allows for gauging progress towards achieving the desired level of "readiness" (Nag 2022). Additionally, a version of World Bank's EdTech Readiness Index (ETRI), proposed by Trucano & Cobo (2019), covered digital literacy for teachers, availability of devices, and internet connectivity.

   Based on the review of academic research by Nag (2022) and Trucano & Cobo (2019), following sub-components and indicators were included in the Access to Digital Infrastructure Component. In this study, the author has taken into consideration the indicators for which data was available at the household level. This is largely due to the nature of the pandemic that forced students to learn from their homes.

   The sub-components and indicators for 'Access to Digital Infrastructure' component include:

   a. **Access to Television at the Household Level:** This sub-component analyses the states performance on households having access to television sets, which can be used for broadcasting educational content.

      Governments across states in India adopted low-tech initiatives consisting of using facilities readily available in households such as Television (TV) and Radios in order to broadcast education programmes. However, the percentage of enrolled children who did learning activities via radio broadcasting (whether state's radio programme or national radio programmes) was extremely low, showing a low impact of radio broadcasting on students' learning continuity. The percentage of enrolled children who did learning activities via radio broadcasting was less than 4% in each of the states, with the lowest at 0.5% enrolled children in Jharkhand doing learning activities via radio broadcasting (ASER, 2020). Further, the radio learning initiatives were continued despite their low reach towards the target students (DoSEL, MoE, GoI 2021).

In this study access to radio at the household level has not been considered in the conceptual framework primarily due to very limited adoption of radio broadcast programs for learning purposes among students. The other reason is unavailability of data for this indicator at the household level.

In India, all the state governments launched state-wide educational classes broadcast via TV. While the TV broadcasts had a wider reach in being utilized for learning activities than did radio, the state-wise reach varied between different states. The percentage of enrolled children doing learning activities through TV broadcasts varied widely from the lowest of 6.4% enrolled children in Assam, to the highest observed of 57.7% enrolled children in Gujarat doing learning activities through televised programmes (ASER 2020). Therefore, this indicator has been analysed in detail in this study.

The indicator used to measure this subcomponent is : Scoring of states for having access to Televisions at the household level. The data is sourced from ASER 2020 Survey for this indicator.

b. **Access to Smartphones at the Household Level:** This sub-component measures the proportion of households that possess smartphones, enabling students to access digital educational resources and participate in online classes.

In India, the most popular and widely used mobile application is DIKSHA - Digital Infrastructure for Knowledge Sharing. While being a national web portal, DIKSHA has specific portals for e-content to be published from different Indian states. All states publish content on their specific DIKSHA portals, in local languages for all grades across various subjects. Currently, there are more than 337 crore learning sessions with an average daily page hits of more than 5 crores. Moreover, since May 2020, DIKSHA mobile app has been rated among the top-rated Free education apps on the Google Play store and the app has been downloaded more than 55 lakh times. Further, states have also developed their own web repositories to provide e-content developed at the state-levels itself (DoSEL, MoE, GoI 2021).

The ownership of mobile phones is wide-reaching in India with more than 80% mobile cellular subscriptions (ITU 2019-2020). Therefore, this indicator has been analysed in detail in this study to understand the use of mobile technology for learning during COVID-19 pandemic.

The indicator used to measure this subcomponent is : Scoring of states for having access to Smartphones at the household level. The data is sourced from ASER 2020 Survey for this indicator.

c. **Access to the Internet at the Household Level**: This indicator evaluates the percentage of households with internet connectivity, which is necessary for accessing online learning platforms and resources.

There is inadequate access of households to internet connectivity across states in India and only 24% households in India have access to the household internet (Digital Development Report by ITU, 2018). Therefore, this indicator has been analysed in detail in this study to understand the level of preparedness among states to have internet access as an enabling indicator to provide e-learning solutions. The indicator used to measure this subcomponent is : Scoring of states for having access to Internet at the household level. The data is sourced from TRAI, Government of India 2021 report for this indicator.

d. **Access to Electricity at the Household Level**: It examines the availability of electricity in households since digital devices such as TVs and internet access require a stable power supply. The indicator used to measure this subcomponent is : Scoring of states for having access to Electricity in both rural and urban areas at the household level. The data is sourced from Ministry of Power, Government of India 2021 report Power outage (2020-21) State-wise Average hours of Power Outage in an year for this indicator.

2. **Teacher Preparedness**: Considering the crucial role of teachers in the process of integration of education technology, teacher preparedness was considered as an important component to be

included for measuring readiness of a state. This component focuses on the readiness of teachers to effectively utilize technological tools and platforms for learning and teaching purposes.

The CLIx 2017 survey, conducted across Chhattisgarh, Mizoram, Rajasthan, and Telangana, found that in-service teacher education and use of ICT was minimal in the four states surveyed. 52% of teachers did not know how to use a presentation software such as Microsoft PowerPoint while 72% of teachers were not able to use an application for facilitating teaching. The survey highlights the importance of digital skills and knowledge among teachers to ensure the adoption of technology by teachers for teaching students.

Teachers trained in computers were thus selected as an indicator that would encompass all computer-related skills. The indicator for this component is:

a. **Teachers Trained in Computers**: It assesses the performance of states for teachers trained in using computers and educational technology, enabling them to effectively integrate technology into their teaching practices. The indicator used to measure this subcomponent is: Scoring of states for teachers trained in Computers. The data is sourced from the UDISE 2020 Report for this indicator.

4.2 Effectiveness

Effectiveness is defined as the efficacy of the EdTech interventions in terms of learning using digital devices and its impact on learning outcomes of students across Indian states. High level of effectiveness represents high usage of technology for learning and improvement in the learning levels of students

For this study, the author has identified two key components for measuring effectiveness: Effectiveness of learning through digital tools and Learning Outcomes, and the related sub-components and indicators for each component. The identified sub-components and indicators for measuring effectiveness are derived from thorough secondary research and also availability of information providing state-wise data.

1. **Learning through digital devices**: This component evaluates the degree to which digital devices were used by students during the pandemic. Various past studies have shown that only access to digital devices does not ensure its usage for learning (National Council for Education Statistics, 2018). Also ASER 2020 report, highlights limited adoption of technology for learning even for students with access to the digital infrastructure. In this respect, ‘Effectiveness of learning through

digital devices' was considered as a component by the author. The subcomponents and indicators for 'Learning through digital devices' component include:

a. **Children learning using television**: This sub-component analyses the performance of states for students who engaged in learning through televised educational programs during the pandemic. It assesses the reach and effectiveness of educational content broadcasted on television as a means of remote learning. The indicator used to measure this subcomponent is : Scoring of states for students learning using television. The data is sourced from ASER 2020 Survey for this indicator.
b. **Children learning using smartphones**: This sub-component analyses the performance of states who utilize smartphones to access digital learning resources and participate in online classes. The indicator used to measure this subcomponent is : Scoring of states for students learning using Smartphones. The data is sourced from ASER 2020 Survey for this indicator.

2. **Learning Outcomes**: This component focuses on the academic achievements and learning progress of students as a result of the widespread adoption of EdTech interventions. Measuring learning outcomes through a look at scores, while imperfect, has been a preferred method for testing the impact of EdTech interventions amongst scholarly literature (for instance, see Banerjee et al 2007; Naslund-Hadley et al. 2014; Johnston & Ksoll 2017; Muralidharan et al 2019). Therefore, the second component selected by the author to study effectiveness was Learning Outcomes. The indicators for this component are:

a. **Comparison of learning outcomes in 2017 (limited adoption of Ed-tech) and in 2021 (widespread adoption of Edtech):** This sub-component involves comparing the performance of states on learning outcomes of students in National Achievement Survey 2017, when EdTech was minimally used, with the learning outcomes in National Achievement Survey 2021, after the widespread adoption of EdTech. The comparison helps evaluate the impact of EdTech on student learning and academic performance. The indicator used to measure this subcomponent is: State Scores on difference in learning outcomes for Class 10 Students in National Achievement Survey in 2017 and 2021. The data is sourced from NAS 2017 and NAS 2021 Survey for this indicator.

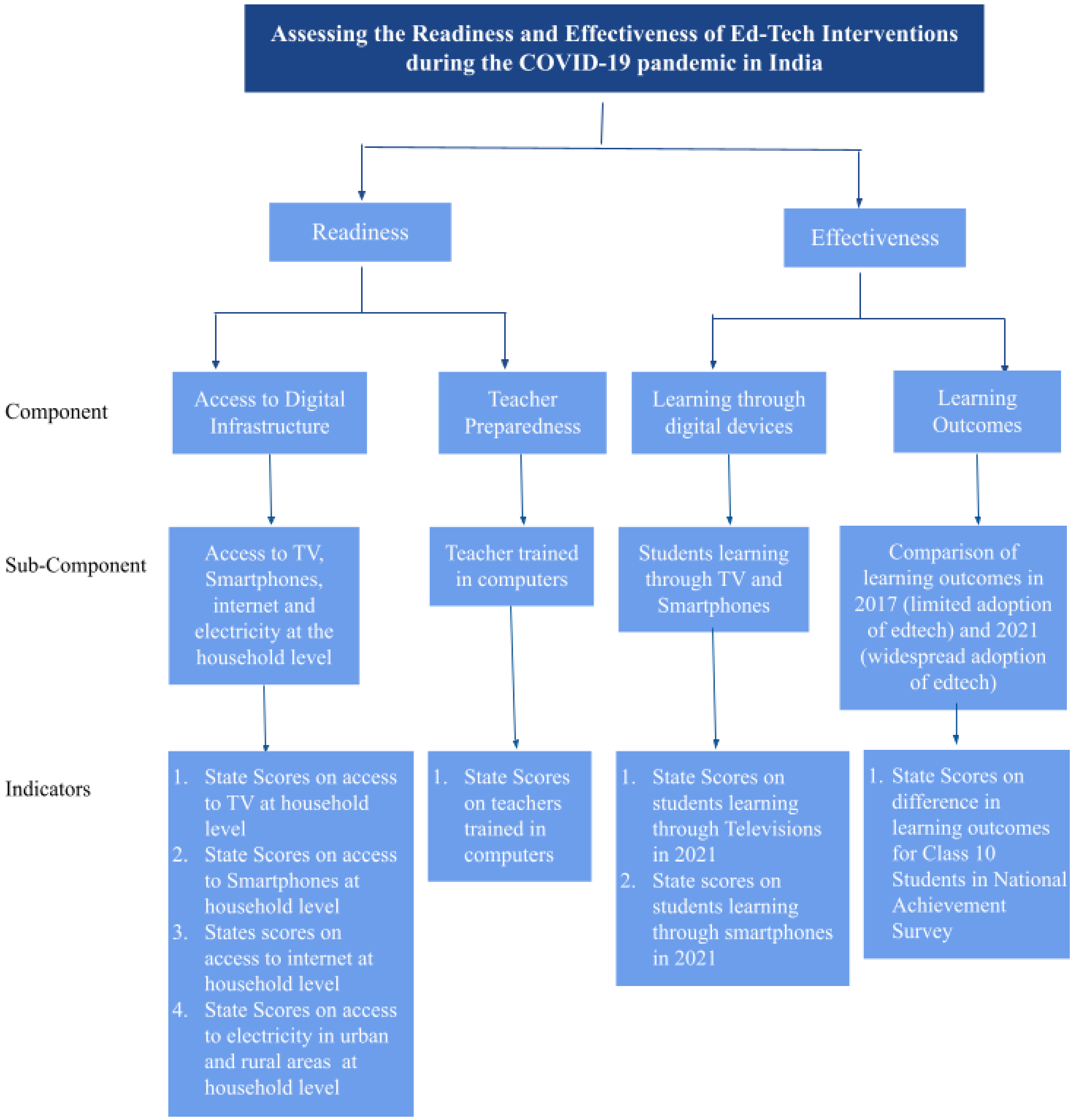

Figure 1: Conceptual Framework

4.3 Scoring Methodology

This section describes the scoring methodology used to measure components derived in the conceptual framework. All the data for indicators of various sub-components of the conceptual framework are collected and analysed using national level household surveys which were done by various agencies across states in India. The indicators for each sub-component considered in this study are selected based on the availability of data at the household level across states in the above-mentioned surveys to bring uniformity in the analysis. The scaled value for each indicator along with their assigned weights is used to measure the scores of state for each component.

This section also describes the methodology used to scale all the indicators for measuring state wise performance. Considering the variability in the measurement of the indicators (for instance, access to power is measured in hours whereas teachers skilled in computers is a percentage figure), it was necessary to scale every indicator within a score of 100 to ensure uniformity and allow a scoring index to be formed.

For indicators where a higher value signifies better performance. The scaled value (S) for the i^{th} indicator (S_i), for the State or UT (X) with data value (X_i), has been calculated as follows (School Education Quality Index, NITI Aayog, 2019):

$$Scaled\ value\ (Si) = \frac{[(Xi - Minimum\ value)\times 100]}{[Maximum\ value - Minimum\ value]}$$

Similarly, for indicators where a lower value signifies better performance (indicators with negative valence), the scaled value was calculated as follows (School Education Quality Index, NITI Aayog, 2019):

$$Scaled\ value\ (Si) = \frac{[(Maximum\ value - Xi)\times 100]}{[Maximum\ value - Minimum\ value]}$$

The minimum and maximum values of each indicator was obtained based on the values for that indicator across States. The resultant scaled value for each indicator lies between 0 and 100, with the best-performing State receiving a score of 100. Based on the scaled values (S_i), the overall performance on each sub-component, component, and readiness and effectiveness scores have been calculated based on the weights in table 1.

$$Readiness\ Score = \frac{\sum Wi * Si}{\sum Wi}$$

$$Effectiveness\ Score = \frac{\sum Wi * Si}{\sum Wi}$$

Parameter	Weights	Components	Weights	Sub-components and Indicators	Weights
Readiness	1	Access to Digital Infrastructure	0.5	Access to television at the household level	0.125
				Access to smartphones at the household level	0.125
				Access to Internet at the household level	0.125
				Access to electricity at the household level for rural areas	0.0625
				Access to electricity at the household level in urban areas	0.0625
		Teacher Preparedness	0.5	Teachers trained in computers	0.5
Effectiveness	1	Effectiveness of Learning through digital devices	0.5	Students learning using television	0.25
				Students learning using smartphones	0.25
		Learning Outcomes	0.5	Difference in learning outcomes post-covid (NAS 2021) and pre-covid (NAS 2017)	0.5

Table 1: Weights for Components, Sub-components, and indicators

5.0 Data Analysis

This chapter uses the conceptual framework developed in the above chapter to provide empirical evidence to measure the performance of Indian states for Readiness and Effectiveness. The scoring methodology described in the above chapter is used to measure state-wise scores for different indicators. For analysing the overall performance of states on Readiness and Effectiveness, weighted scores have been calculated using formula mentioned in the Scoring Methodology section. A quantitative data analysis is performed in this chapter to provide empirical evidence to understand the level of preparedness of Indian states to adopt education technology, and the effectiveness of the edtech interventions taken by states during COVID-19 pandemic.

This chapter also derives the relationship between Readiness and Effectiveness using simple two variable regression analysis. The results of correlation are used to understand how the readiness of a state to adopt education technology solutions is connected to the effectiveness of learning through educational technology interventions.

5.1 Readiness

Readiness Scores

The Readiness Scores are assigned to Indian states by analysing overall performance of states in the two sub-components of readiness: Access to Digital Infrastructure and Teacher Preparedness (as defined in the Conceptual Framework). The indicators used to measure these two sub-components include access to televisions, smartphones, internet, and electricity at the household level, and teachers trained in computers. The overall readiness scores were calculated considering the performance of states on all of these indicators.

Punjab, Gujarat, and Karnataka were the best-performing states for the readiness component, while Bihar, Uttar Pradesh, and West Bengal performed the worst. Maharashtra, Himachal Pradesh, and Telangana were among the states that performed moderately well on the readiness component, while Madhya Pradesh, Odisha, and Andhra Pradesh were among the low-performing states (as shown in the figure below).

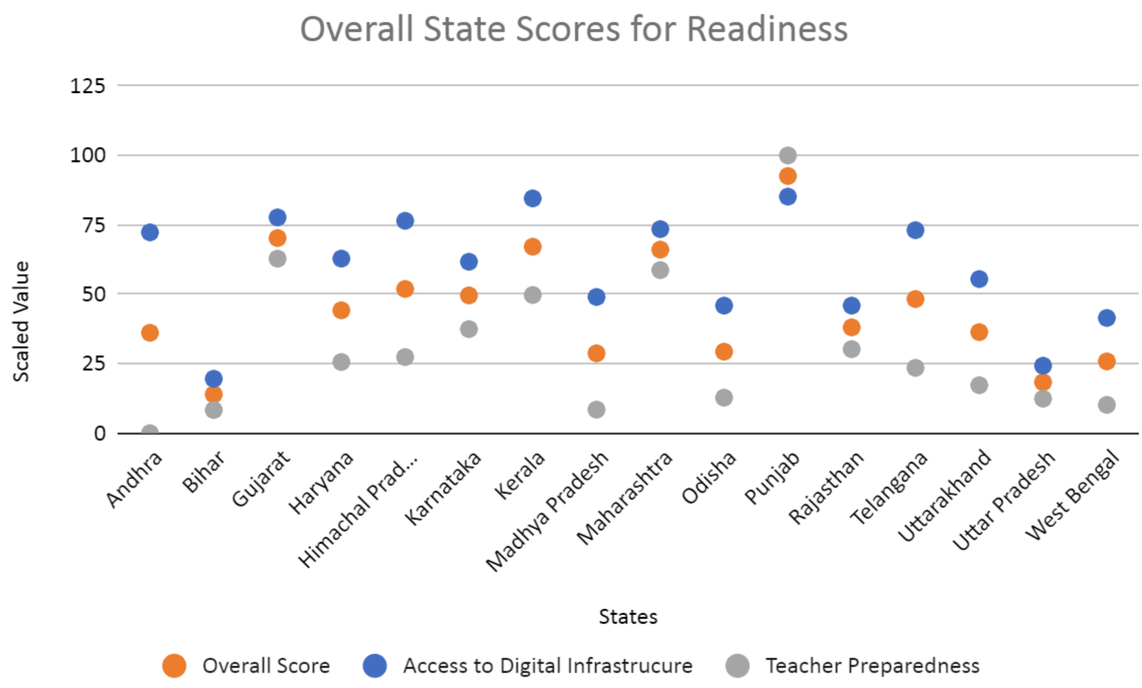

Figure 2: Overall State Scores for Readiness (author's calculations)

5.1.1 Access to Digital Infrastructure

This section analyzes the performance of states for the sub-component 'Access to Digital Infrastructure' in accordance with the Conceptual Framework. These scores are crucial to determine which states were the most readily equipped in terms of infrastructure to enable the successful implementation of EdTech initiatives.

There is a high degree of variation in States' performance on the four domains that make up the 'Access to Digital Infrastructure' component: access to television, access to smartphones, access to the internet, and access to electricity at the household level.

State Scores for 'Access to Digital Infrastructure' Component

Punjab, Kerala, and Gujarat were observed to be the best-performing states for all the four indicators mentioned above. Whereas, Bihar and Uttar Pradesh performed the worst across the four indicators in this component. Andhra Pradesh, Himachal Pradesh, Maharashtra, and Telangana are among the moderately well-performing states across the four indicators, whereas West Bengal, Rajasthan, Odisha, and Madhya Pradesh are among the low-performing states (as shown in Figure 7 below).

The scores were assigned to states by employing the methodology explained in the conceptual framework chapter of this study. The data considered in this analysis has been taken considering the time duration of pandemic and nation-wide lockdowns. The entire data set represents the household level readiness of states for all the indicators. The states for which data is not available for even one of the indicators has been disqualified in this study.

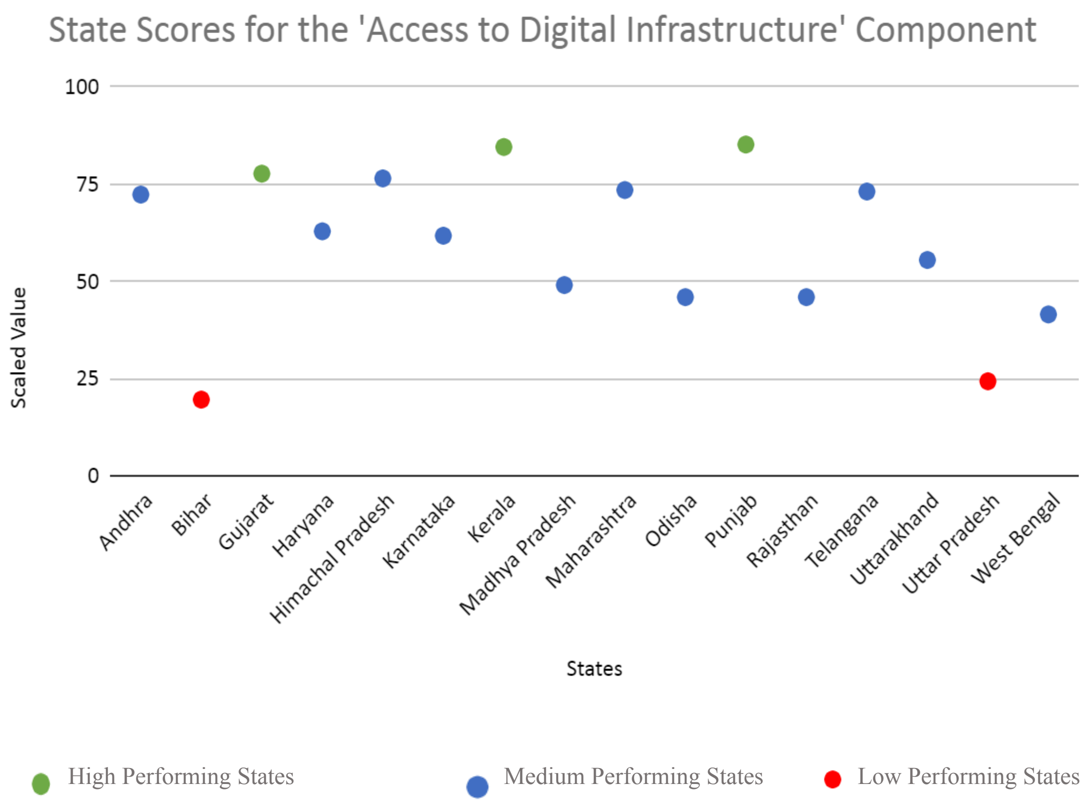

Figure 3: Overall State Scores for the 'Access to Digital Infrastructure' Component (author's calculations).

Access to Television at the Household Level

Andhra Pradesh, Tamil Nadu, and Telangana are the best-performing states, with the highest proportions of households having access to television sets. Jharkhand, Bihar, and Assam are among the worst-performing states. It is observed that states in the Northeast region (Assam, Meghalaya, Manipur, Nagaland) are among the low-performing regions, along with Jammu and Kashmir, Uttar Pradesh, Rajasthan, West Bengal, and Madhya Pradesh. States that perform moderately well on this indicator include Uttarakhand, Karnataka, Gujrat, Himachal Pradesh, Kerala, and Punjab (as shown in figure 2).

The data presented in this study has been sourced from the Annual Status of Education Report 2020 (ASER 2021). This report, published in November 2021, was selected as the primary source due to (i) its survey activities being conducted in September 2020, a period of complete school closures, and (ii) a comprehensive detailing of data regarding television availability at the household level for Indian states.

Due to a lack of available data, the states Goa, Mizoram, Sikkim and Tripura were not included in this analysis.

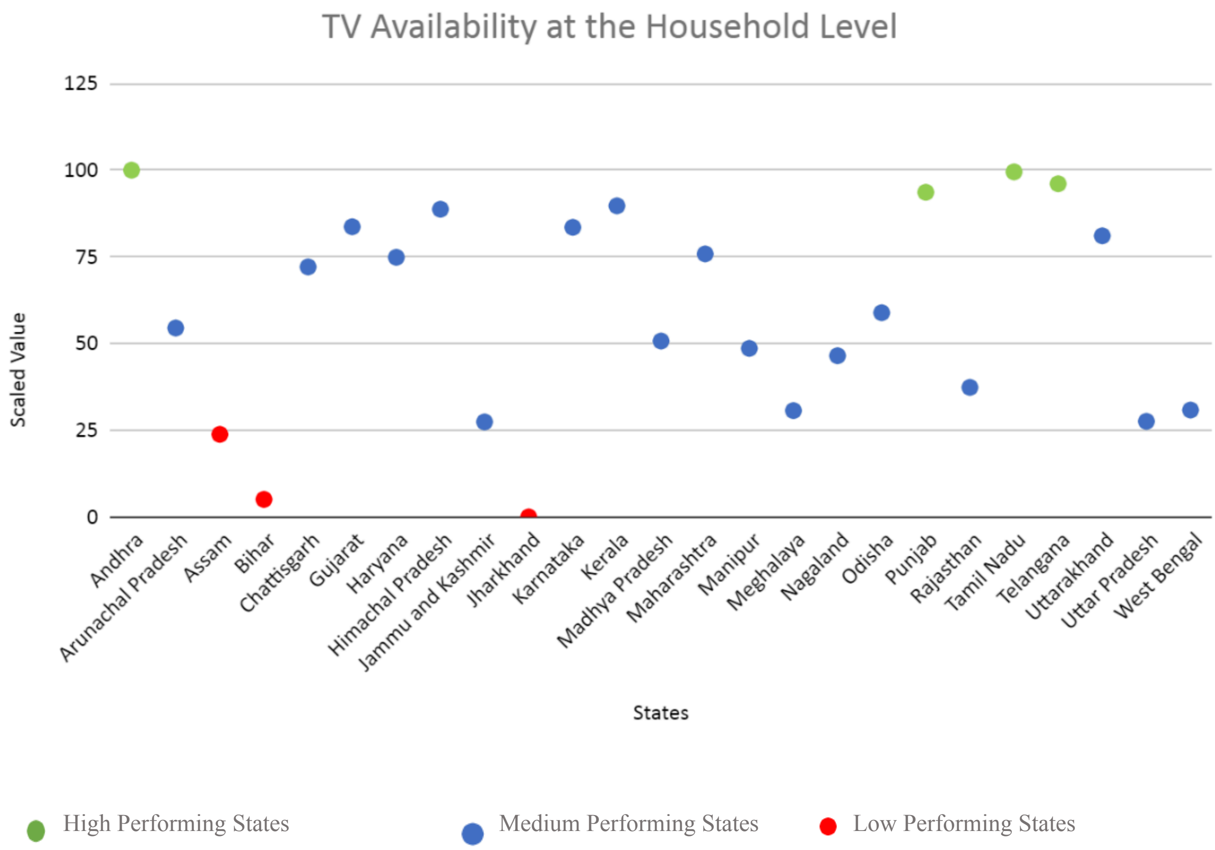

Figure 4: State-Wise Availability of Televisions at the Household Level (ASER 2020).

Access to Smartphones at the Household Level

Kerala, Himachal Pradesh, Manipur, and Nagaland are the best-performing states. Bihar, West Bengal, Uttar Pradesh, and Jharkhand are among the worst-performing states. States from the North East region (Assam, Arunachal Pradesh, Manipur, Meghalaya, Nagaland) perform reasonably well on this indicators (as shown in the figure below). Some low-performing states include Odisha, Tamil Nadu, Rajasthan, and Madhya Pradesh. States that perform moderately well include Maharashtra, Haryana, Gujrat, and Punjab (as shown in figure 5).

The data source for analysis of this indicator is Annual Status of Education Report 2020 (ASER 2021). The report offers household-level data for smartphone availability obtained during September 2020, a period when schools were shut, and people's "only window to the world was their phone" (ASER 2020, p.7). Considering this, assessing smartphone availability at the household level in states with diverse socio-economic profiles is a vital measure of readiness.

Due to a lack of available data, the states Goa, Mizoram, Sikkim and Tripura are not included in this analysis.

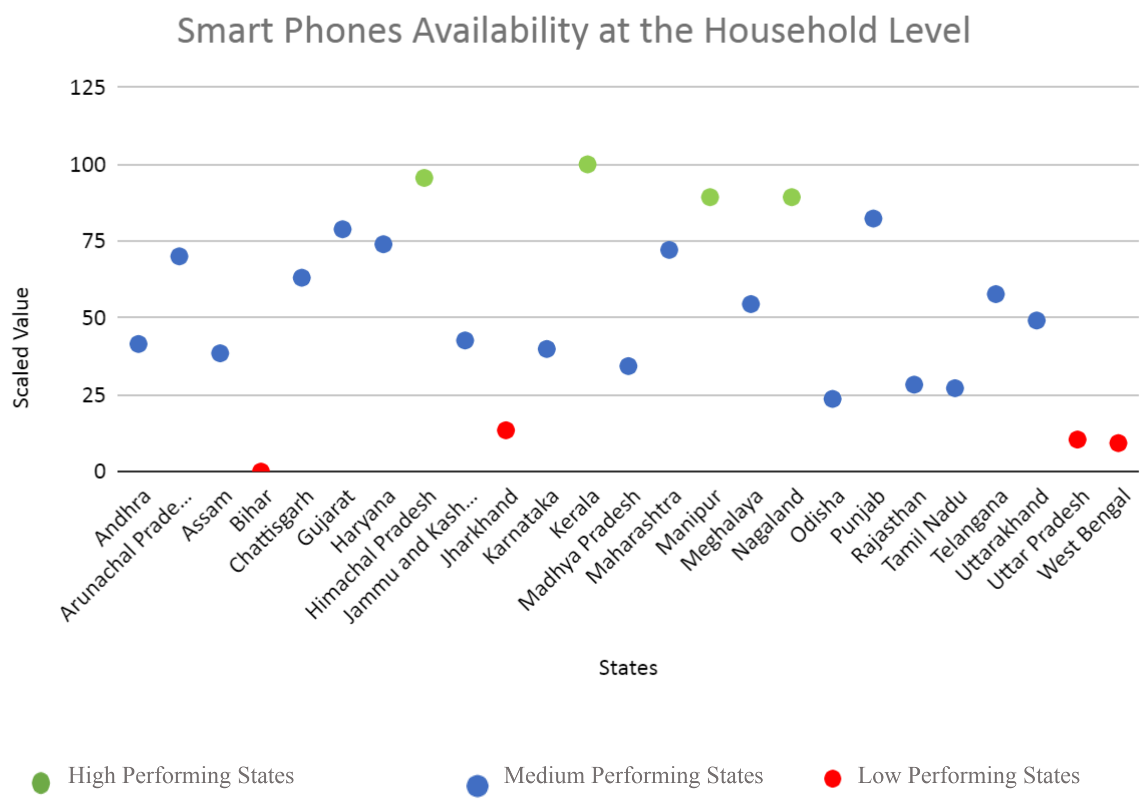

Figure 5: State-wise Availability of Smart Phones at the Household Level (ASER 2020).

<u>Access to the Internet at the Household Level</u>

Delhi, Punjab, and Himachal Pradesh are the best-performing states. Bihar, Jharkhand, Uttarakhand, and Uttar Pradesh are among the worst-performing states. Low-performing states include Assam, Chhattisgarh, Madhya Pradesh, West Bengal, and Odisha. States that performed moderately well include Telangana, Tamil Nadu, Karnataka, Maharashtra, and Kerala (as shown in Figure 6).

Internet was a necessary pre-requisite for the adoption of many digital learning initiatives that were launched during this period. Outside of access to learning content itself, the internet was necessary for student-teacher interactions that occurred through WhatsApp, and messaging applications (as part of medium-tech initiatives described in the literature review). Data for this indicator has been sourced from the Telecom Regulatory Authority of India (TRAI)'s report titled 'The Indian Telecom Services Performance Indicators (April-June 2020)'. The report enumerates the number of internet subscriptions at the household level for each state. The time period for which the figures are obtained (April and June 2020) is significant. Following immediately after the early lockdowns, considering the pace of the pandemic, and the rapid implementation of these initiatives, it is likely to give us an accurate picture of preparedness for the EdTech interventions.

Due to a lack of available data, the states Goa, Mizoram, Sikkim, and Tripura are not included in this analysis.

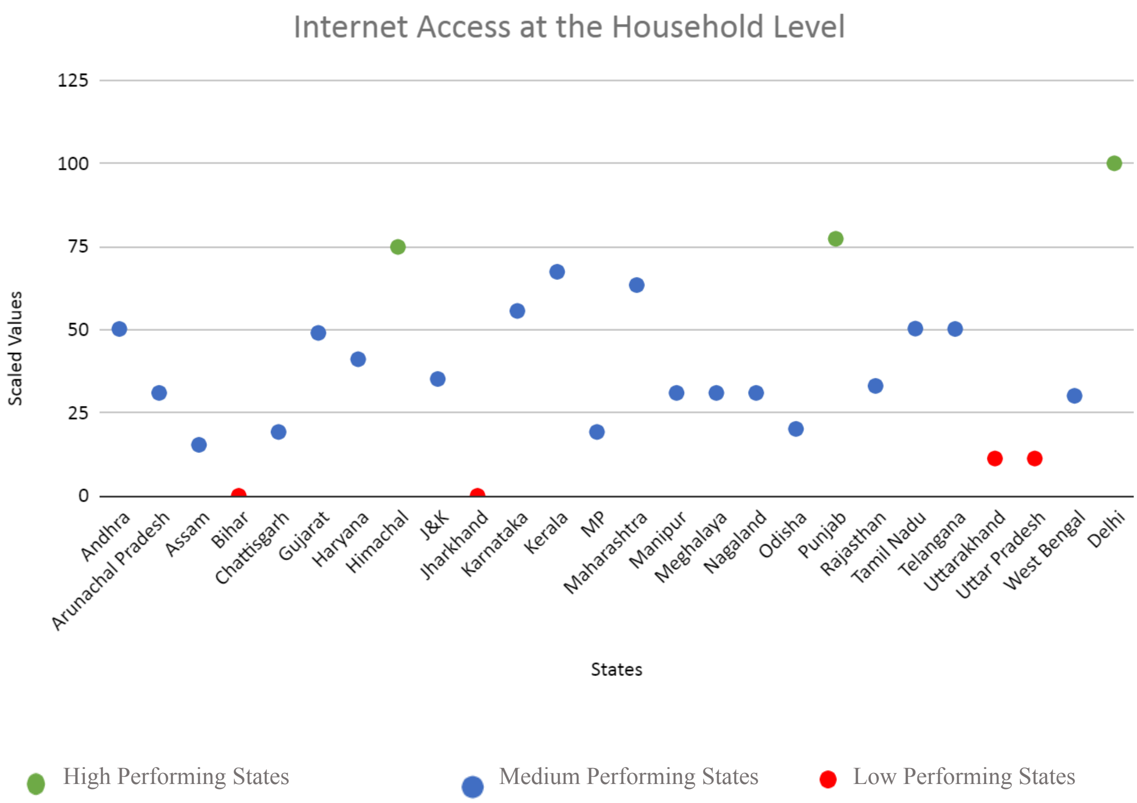

Figure 6: State-wise Access to the Internet at the Household Level (TRAI Report 2020).

Access to Electricity at the Household Level

This indicator is measured for both urban and rural areas within the state. The best-performing states where power outages occured the least in rural areas are Gujarat, Andhra Pradesh, and West Bengal. For Urban areas, the best-performing states are Rajasthan, West Bengal, Chhattisgarh, and Maharashtra. Considering rural areas, the worst-performing states are Himachal Pradesh and Uttar Pradesh. For urban areas, the worst-performing states are Jammu and Kashmir, Arunachal Pradesh, and Nagaland. Low-performing states, where power outages are relatively high in urban areas are Bihar, Haryana, Uttarakhand, and Uttar Pradesh. Moderately-well performing states, where power outages are relatively low in urban areas are Telangana, Meghalaya, Madhya Pradesh, and Gujrat. For rural areas, low-performing states include Karnataka, Haryana, Maharashtra, and Kerala, whereas Telangana, Punjab, and Madhya Pradesh are moderately well-performing states (as shown in figures 7 and 8 below).

Access to electricity is a fundamental necessity for learning to occur through any technological device (including low-tech, medium-tech, and high-tech initiatives). The data for this indicator has been sourced from the Ministry of Power under the Government of India and covers the years 2020-2021. This year is significant for states as they felt the unprecedented brunt of the pandemic suddenly during this period.

Due to a lack of available data, the states Assam, Goa, Jharkhand, Mizoram, Sikkim, Tripura and Manipur are not included in this analysis. Data was also unavailable regarding access to electricity in rural areas for Arunachal Pradesh, Chhattisgarh, Jammu and Kashmir, Meghalaya, Nagaland, and for urban areas in Tamil Nadu.

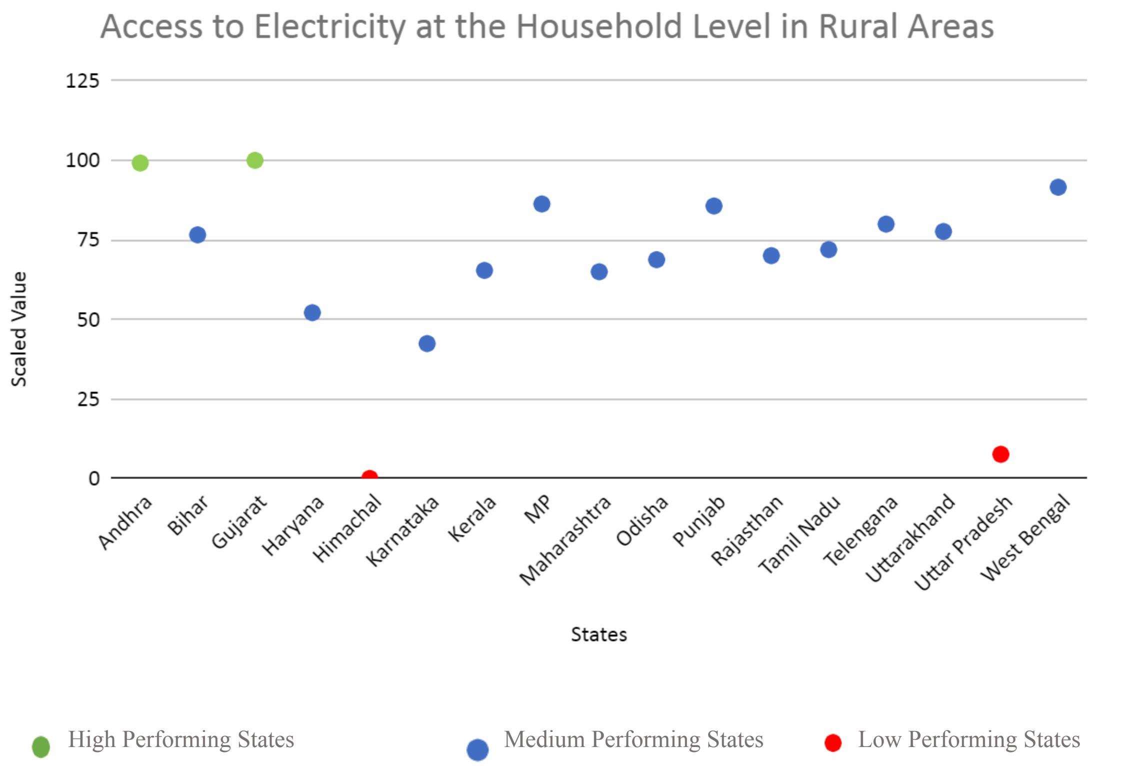

Figure 7: State-wise Access to Electricity at the Household Level in Rural Areas (PFCL, Government of India, 2022).

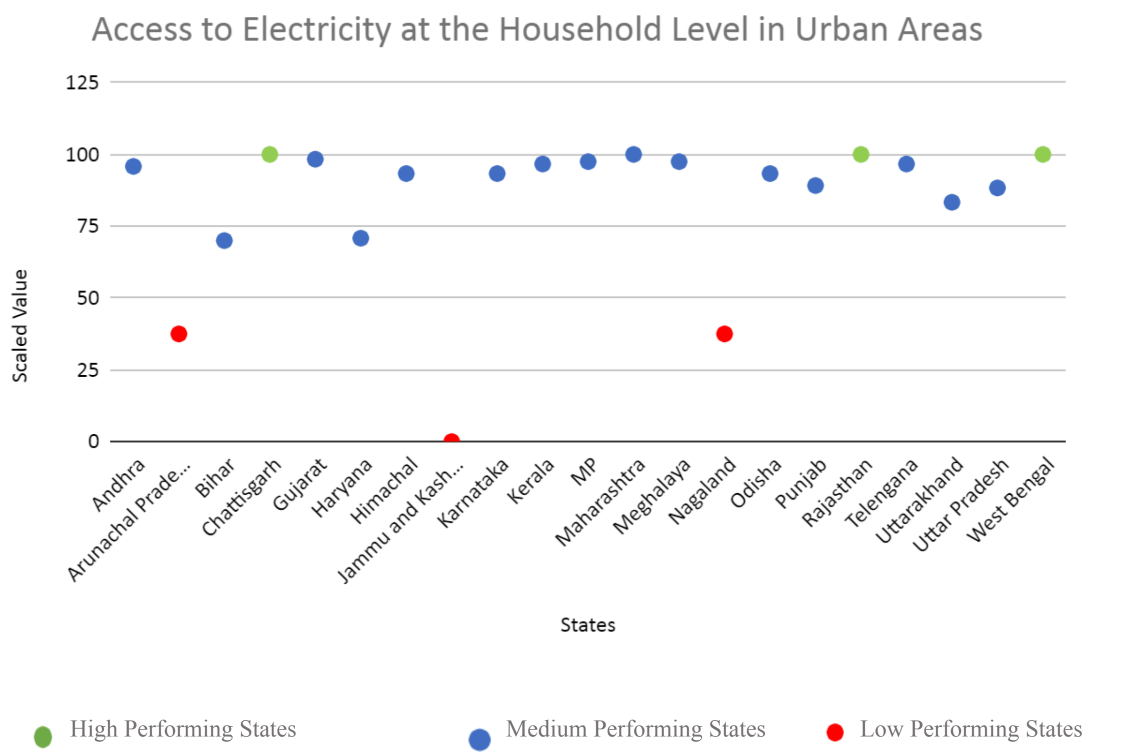

Figure 8: State-wise Access to Electricity at the Household Level in Urban Areas (PFCL, Government of India, 2022)

5.1.2 Teacher Preparedness

Teachers Trained in Computers

Punjab, Gujarat, and Maharashtra are the best-performing states, having the highest percentage of teachers trained in computers. On the other hand, Assam, Andhra Pradesh, and Meghalaya are the worst-performing states with the least number of teachers having received training in computers. Kerala, Karnataka, and Delhi are moderately well-performing states, whereas Arunachal Pradesh, Bihar, Madhya Pradesh, and Jammu & Kashmir are among the low-performing states in the country, having relatively low numbers of teachers trained in computers (as shown in Figure 9 below).

Data from the Unified District Information System for Education (UDISE) for the year 2021 was utilized for this study, a significant year considering the peaks and waves of the pandemic and continued school closures.

Owing to insufficient data availability, the analysis does not include the states of Goa, Mizoram, Sikkim, and Tripura.

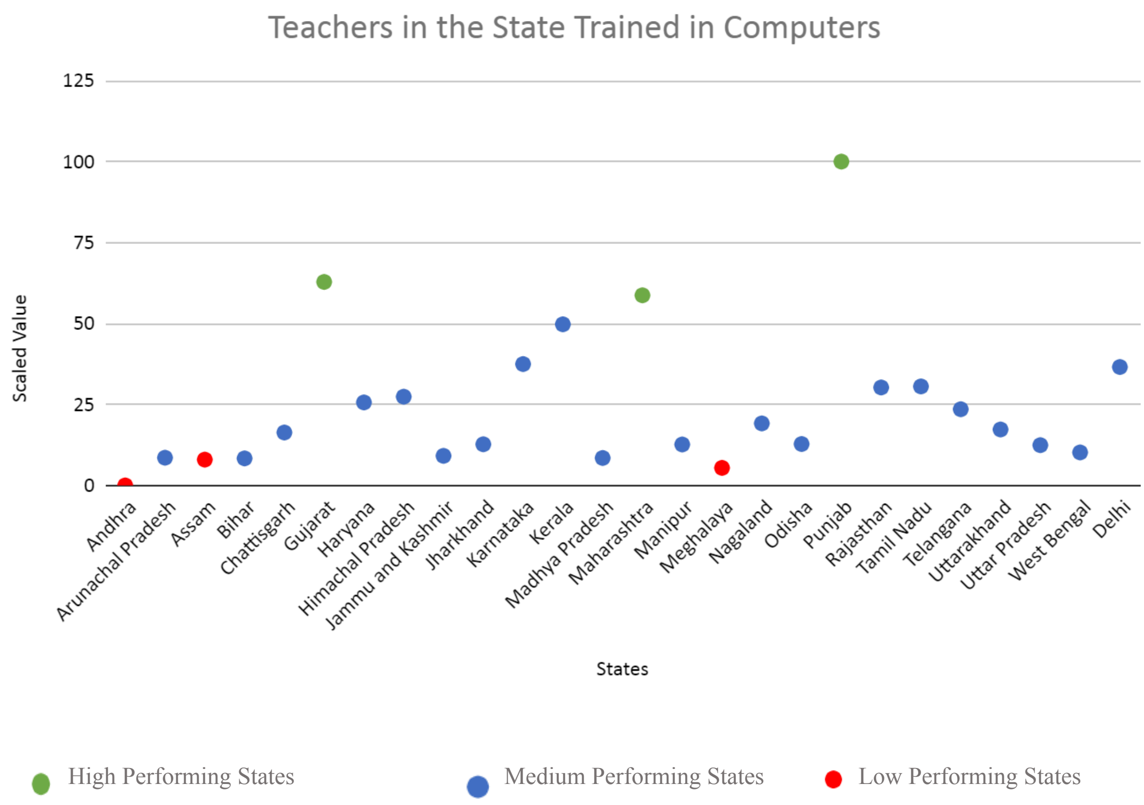

Figure 9: Teachers Trained in Computers in Indian States (UDISE 2021)

5.2 Effectiveness

This section analyses whether children actually engaged with different kinds of technological devices for learning and the impact of the EdTech interventions on learning outcomes of students during COVID-19 pandemic.

Effectiveness Scores

The Effectiveness Scores are assigned to Indian States by analysing overall performance of states in the two sub-components of readiness: Learning through Technology and Learning Outcomes (as defined in the Conceptual Framework). The indicators used to measure these two components include students learning using televisions, students learning using smartphones, and difference in learning outcomes of students from COVID-19 pandemic (signifies widespread adoption of digital learning) to pre-COVID times (signifies learning through traditional chalk and talk model). The overall effectiveness scores were calculated considering the performance of states on all of these indicators.

The overall state scores for the effectiveness component indicate that Punjab, Gujarat and Haryana were the best performing states. Kerala, Himachal Pradesh, and Madhya Pradesh also perform moderately well on this component. On the other hand, Assam, Odisha and Delhi perform the worst. Andhra Pradesh, Tamil Nadu, and Telangana are also among the low-performing states (as shown in the figure below).

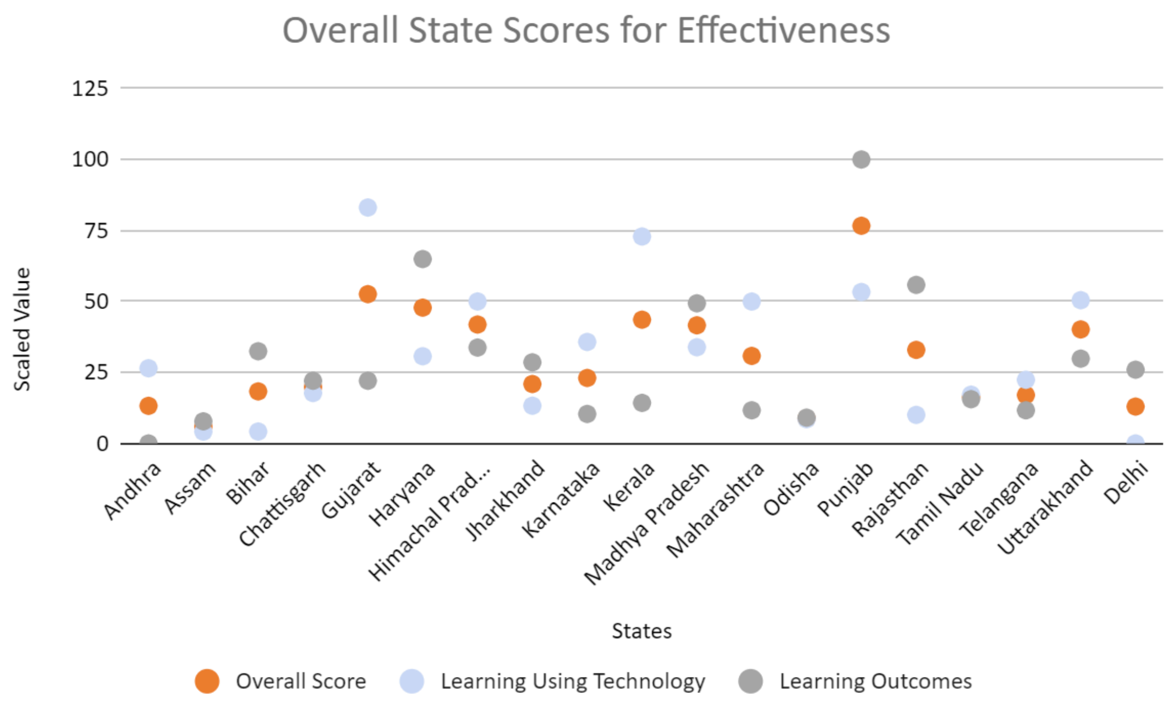

Figure 10: Overall State Scores for Effectiveness (author's calculations).

5.2.1 Learning through Digital Devices

This section analysis the performance of states for the sub-component 'Learning through Digital Devices' in accordance with the Conceptual Framework. The overall state scores for this sub-component are crucial to determine whether students used the available digital resources for learning purposes while learning from home during COVID-19 pandemic.

There is a high degree of variation in States' performance on the two indicators that make up the 'Learning through Technology' sub-component: learning using Television, and learning using smartphones.

The data analysis shows that Gujarat, Kerala, and Uttar Pradesh are the best-performing states, representing more adoption of technology among students for learning through both television and smartphone devices. On the other hand, West Bengal, Assam, and Bihar have shown the worst adoption of technology for learning purpose. Moderately well performing states include Punjab, Uttarakhand, and Himachal Pradesh, while Odisha, Rajasthan, and Jharkhand were among the low-performing states (as shown in the figure below).

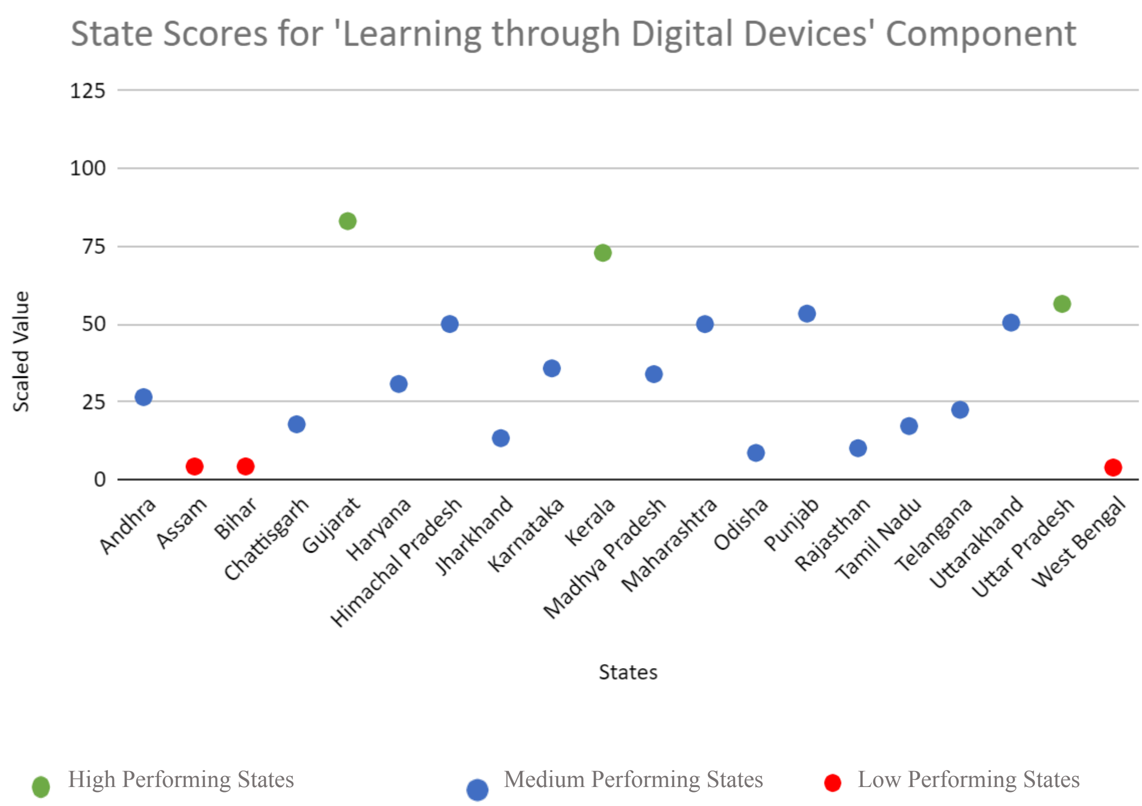

Figure 11: State Score for 'Learning through digital devices' Component (author's calculations).

Students Learning Using Television

Uttar Pradesh, Kerala, and Gujarat were observed to be the best-performing, reporting the highest percentages of enrolled children learning using television. Moderately well-performing states include Uttarakhand, Maharashtra, and Andhra Pradesh. On the other hand, Bihar, Chhattisgarh, and Jharkhand performed the worst on this indicator. Himachal Pradesh, Assam, and Telangana were also low-performers (as shown in Figure 12).

Television was a major component of the government-led effort to maintain learning continuity during the pandemic. However, merely having access to television sets does not reflect student adoption or engagement with the content being broadcasted. This data, sourced from the ASER survey conducted in 2020 aims to understand the proportion of enrolled students who reported learning through television broadcasts.

Due to a lack of available data, the states Arunachal Pradesh, Jammu and Kashmir, Meghalaya, Nagaland, Manipur Sikkim, Tripura are not included in this analysis.

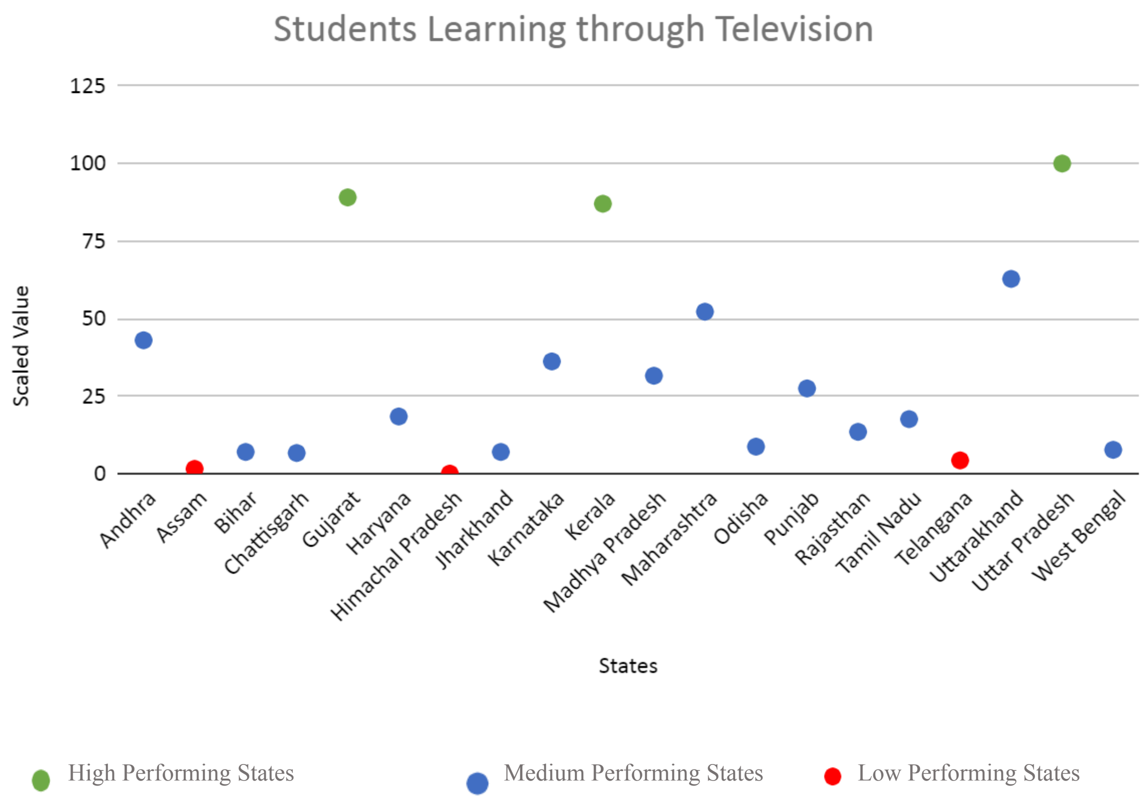

Figure 12: State-wise Distribution of Enrolled Students Learning through Television (ASER 2020).

Students Learning Using Smartphones

Himachal Pradesh, Punjab, and Gujarat were the best-performing, reporting the highest numbers of children learning through smartphones. Other moderately well-performing states include Kerala, Maharashtra, and Haryana. The worst-performing states were Bihar, Rajasthan, and West Bengal, reporting the lowest numbers of students learning through smartphones. Assam, Odisha, and Andhra Pradesh were other low-performing states (as shown in Figure 13).

The ASER report (2021) was used for this analysis. It reveals that among the proportion of households whose children were enrolled in government schools, smartphone ownership went from 29.6% in 2018 to 56.4% by September 2020. For families with children enrolled in private schools, smartphone ownership rose from 49.9% in 2018 to 74.2% in 2020. This rise in ownership, does not, by itself, imply a rise in number of children who actually engaged with the device for learning. The figures for adoption of smartphones for learning vary widely among various Indian states.

Due to a lack of available data, the states Arunachal Pradesh, Jammu and Kashmir, Meghalaya, Nagaland, Manipur Sikkim, Tripura are not included in this analysis.

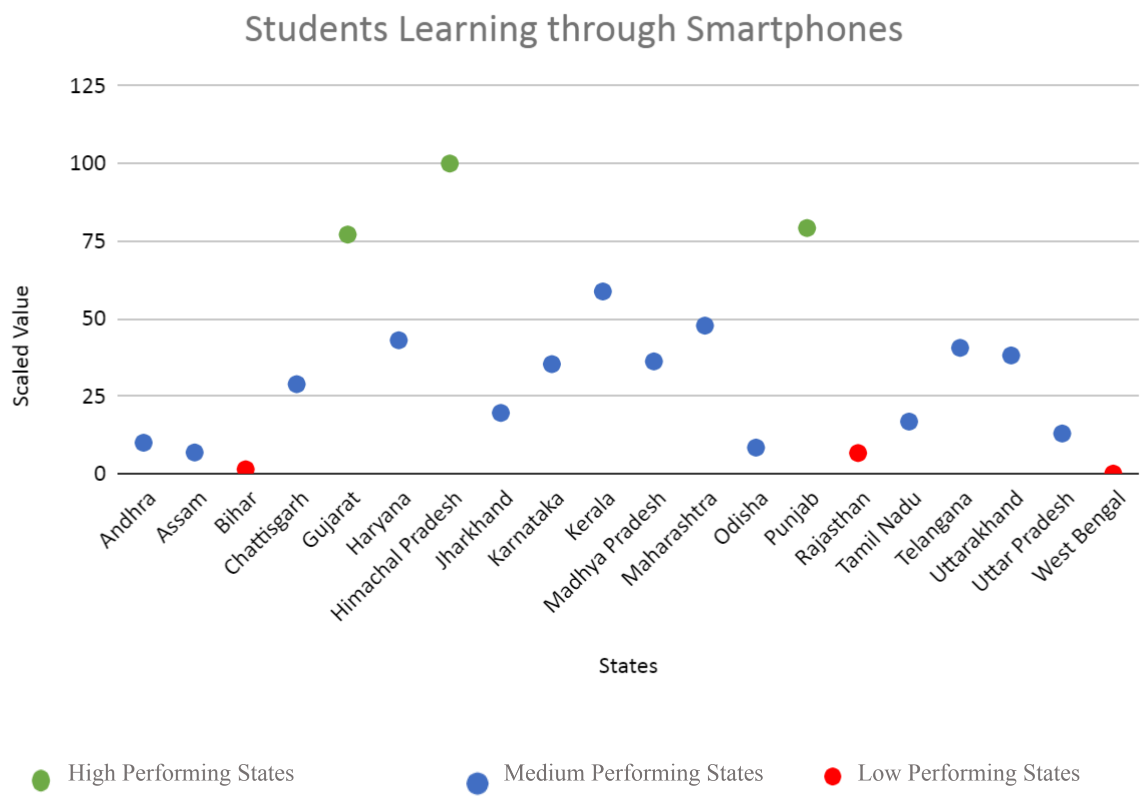

Figure 13: State-wise Distribution of Enrolled Students Learning through Smartphones (ASER 2020).

5.2.2 Learning Outcomes

To analyse the impact of edtech interventions on learning outcomes of the students, performance of Class 10 students in Maths Subject has been taken into consideration. All the students of Class 10 take the Central or State Board Examination as a mandatory exam. Therefore, the author has considered Class 10 Students performance for analysing the difference in performance of students because of rapid adoption of EdTech in the COVID-19 pandemic. The difference between the state-wide scores obtained in NAS 2017 (pre-COVID times when EdTech initiatives were not adopted on a large scale) and the state-wide scores obtained in NAS 2021 (post-the rollout of state-wide large-scale EdTech interventions during COVID-19-induced school closures). The difference between these two was calculated for all states and then scaled to ensure uniformity within the scoring index.

In this delta score for student's performance, the best-performing states were Punjab, Haryana, and Rajasthan, while Madhya Pradesh, Jammu and Kashmir, and Manipur performed moderately well. **The only state which actually recorded improvements in performance of students is Punjab.** The other states such as Haryana and Rajasthan did not see a major dip in student performance post the pandemic. On the other hand, Andhra Pradesh, Assam, and Odisha were the worst-performing states, while Karnataka, Maharashtra, and Telangana were also low-performers.

Data for this analysis was obtained from the National Achievement Survey NAS 2017 and 2021. The delta scores were calculated for all the states to understand the difference in learning levels among students from pre-COVID to during COVID time in the states. This provides a uniform methodology to assess and evaluate the learning outcomes of students across the country. The survey is conducted by the Ministry of Education, Government of India.

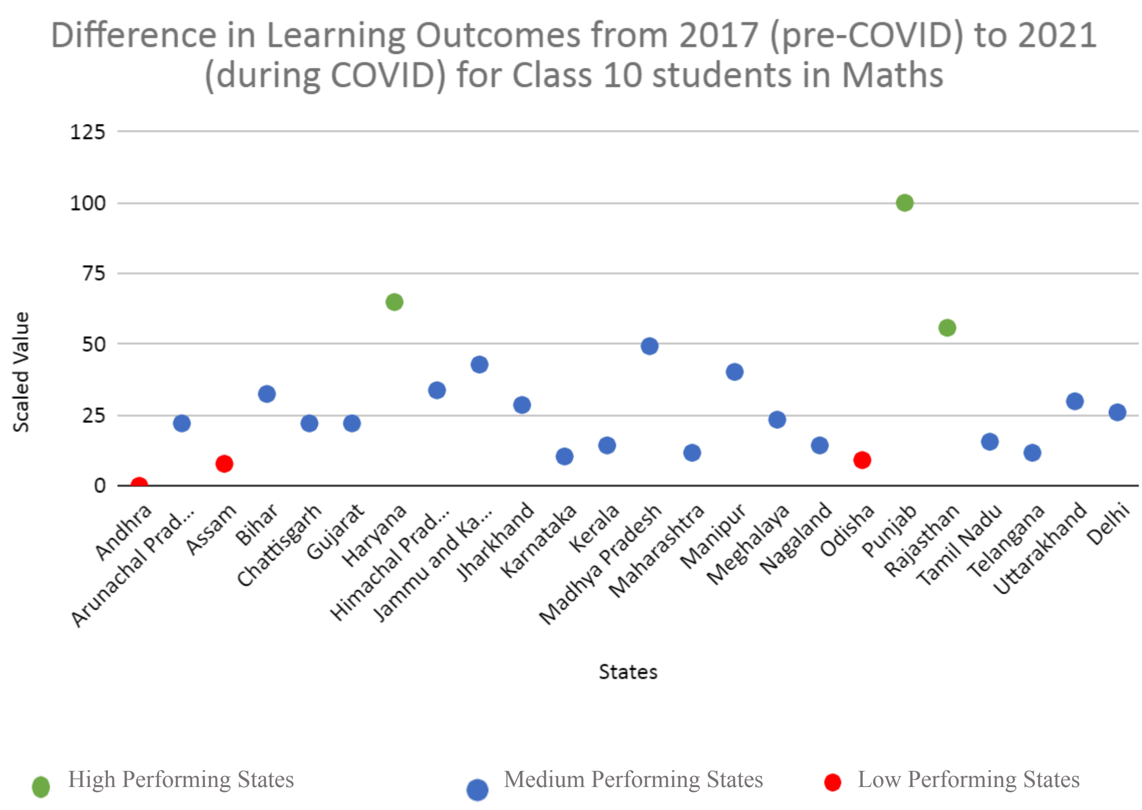

Figure 14: State-wise Distribution of the Difference in Learning Outcomes from 2017 and 2021 for Class 10 students in Maths (NAS 2017; NAS 2021).

5.3 Correlation between Readiness and Effectiveness

To examine the relationship between the effectiveness of an EdTech intervention and the readiness level of a state, a two-variable linear regression analysis was conducted. Here, the dependent variable (effectiveness) is expressed as a linear function of independent variable (readiness). The readiness scores and effectiveness score for all the analysed states were used to understand the correlation between the two variables using regression analysis. This includes data for 14 states that could be considered for the regression owing to insufficient data for other states for some sub-indicators within readiness and effectiveness.

Table 2 reveals the results of a simple linear regression analysis performed to determine how readiness of states to adopt education technology affects its efficacy for learning (measured using Effectiveness Scores). The regression model was found to be statistically significant after the analysis. It can be seen that the R square (R^2) value in the data of this study is 0.500946587. This indicates that 50% of the total variance in effectiveness of the EdTech initiative is explained by the indicators used in level of readiness of that state. This value also indicates that other variables such as Digital Literacy of students and teachers, role of parents etc which are not discussed in this study also contribute to the effectiveness of any Edtech initiative.

Table 3 shows the one-way variance ANOVA analysis results used to analyse the effects of readiness on effectiveness. The coefficient for Readiness ($\beta1$) is statistically significant with a p-value of 0.00462 ($p < 0.05$), indicating that there is a significant relationship between readiness and effectiveness. It can be seen that the regression coefficient is 0.63, and the value of the intercept is 4.625. Thus, the regression equation is obtained as follows:

$$\text{Effectiveness (Y)} = \beta_0 + \beta_1 * \text{Readiness (X)} + \varepsilon$$

Where $\beta0$ is the intercept, $\beta1$ is the coefficient for Readiness (X), and ε is the error term.

$$\text{Effectiveness (Y)} = 4.625 + \text{is } 0.63 * \text{Readiness (X)} + \varepsilon$$

The readiness coefficient ($\beta1$) = 0.63 indicates that, on average, a one-unit increase in readiness of the state is associated with a 0.63 increase in the effectiveness of the EdTech intervention. Thus, there is a positive relationship between the two variables.

Assumptions of linearity, independence of errors, constant variance, and normality of residuals were checked and met in the model. Residual plots showed random scattering around zero, indicating that the model residuals exhibit no systematic pattern.

Thus, states that were better prepared and equipped to handle EdTech interventions tend to perform more effectively. A causal relationship cannot be established as omitted variables include parents' levels of education, health concerns due to COVID, quality and relevance of digital content, levels of digital literacy for students, parents, and teachers, among others.

Regression Statistics	
Multiple R	0.707775802
R Square	0.500946587
Adjusted R Square	0.459358802
Standard Error	13.40994414
Observations	14

Table 2: Regression Statistics

	df	SS	MS	F	Significance F
Regression	1	2166.105	2166.105	12.04552	0.004625
Residual	12	2157.919	179.8266		
Total	13	4324.025			

Table 3: ANOVA results

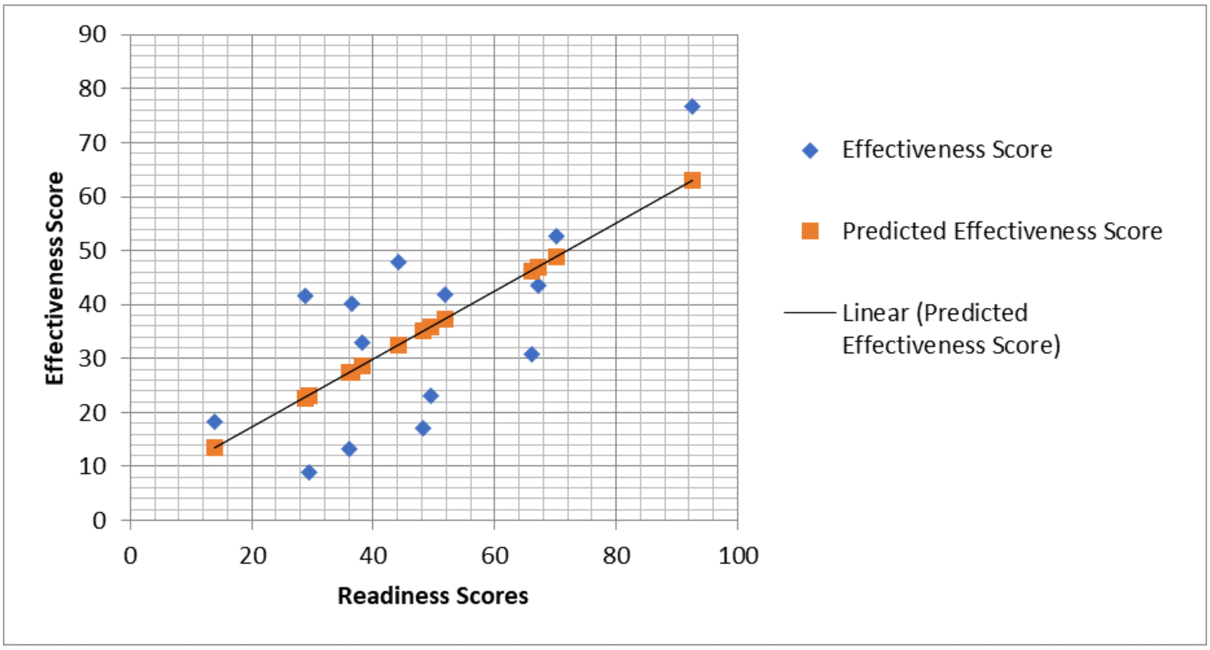

Figure 15: Line of Best Fit between Effectiveness and Readiness

6.0 Summary and Conclusion

The chapter is written with the aim to conclude the report by summarizing the findings of the report and outlining the importance of these findings for further policymaking research. The chapter has been divided into three parts to encapsulate the findings in an orderly manner to comprehend all the meaningful contribution of this study.

The first part provides an overview of the results obtained through the review of empirical evidence obtained through national level surveys. The second part compares the obtained results with the research questions, thus describing the research methodology used to arrive at the results. Finally, the third part provides implications of the research both in terms of limitations of the study and its extension.

6.1 Results

The four key results of the research can be categorized as follows:

1) The conceptual framework tool: Access to Digital Infrastructure, Teacher Preparedness Learning using Technology, and Learning Outcomes were identified as the four indicators to assess readiness and effectiveness respectively. These were further measured using nine sub indicators.

2) An analysis of readiness levels of Indian states for EdTech initiatives launched during the pandemic using the conceptual framework revealed that Indian states did not have the same levels of readiness to be able to implement EdTech interventions. While Punjab, Gujarat, and Karnataka fared well under the readiness component; Bihar, Uttar Pradesh, and West Bengal performed the worst.

3) An analysis of effectiveness of the EdTech initiatives launched during COVID through the conceptual framework also showed that EdTech interventions had widely different outcomes in Indian states. Punjab, Gujarat, and Haryana were the best performing states, while Assam, Odisha and Delhi performed the worst.

4) A strong positive correlation between effectiveness and readiness was discovered by conducting a linear regression. States that were more prepared for adopting the EdTech initiatives showed greater success after their adoption.

The research has made a considerable contribution to the academic literature exploring the readiness levels, effectiveness of EdTech initiatives, and the relationship between the two by propounding an elaborate conceptual framework. The identified indicators characterizing the conceptual framework, and results of the linear regression help to draw conclusions regarding how policymakers must evaluate capacities of a region to formulate effective policies that can aid the transition to digital learning in the context of a crisis such as the COVID-19 pandemic.

Extensive literature exists on barriers in accessing digital technologies, digital learning during the pandemic, teacher preparedness for EdTech, and analysing the efficacy of EdTech interventions in localized contexts. However, no analysis has been conducted for all Indian states, especially in the context of government-led EdTech initiatives during the COVID-19 pandemic. The author also did not come across literature exploring the relationship between the readiness of a state and effectiveness of the EdTech intervention. In this context, the author had to conceptualise, and come up with ways to measure 'readiness' and 'effectiveness.' This ensured that a considerable amount of knowledge, in the form of the conceptual framework, was generated. Furthermore, the linear regression conducted provided insights into the correlation between readiness and effectiveness. The results of the regression speak strongly to factors that policymakers must consider before an EdTech policy can be formulated.

6.2 Research Questions

The report attempted to answer the following research questions:

1. How can we assess the readiness of Indian states to adopt education technology for learning during COVID-19?

2. How can we examine the effectiveness of the ed-tech initiatives taken by governments across states in India during COVID-19?

3. What is the relationship between readiness of Indian States to adopt education technology and effectiveness of the initiatives taken by the Indian state?

The author was able to answer these three questions by following the steps listed below:

1) Formulating the conceptual framework following a rigorous literature review. The literature review aided in identifying gaps in both policies and literature, and narrowing down on indicators that can be used to concretely assess readiness and effectiveness.

2) Using the conceptual framework to explore readiness and effectiveness by drawing on empirical evidence generated thorough national level surveys. This included data from ASER, UDISE, and NAS among others.

3) Testing whether the concepts of readiness and effectiveness are correlated with one another.

With respect to the first two questions, the conceptual framework assisted in the process of collecting empirical evidence. This evidence helped in clear identification of states that were prepared, as compared to states that were not. This comparison was done after the development of an appropriate methodology that allowed scoring on uniform lines.

Lastly, after a conceptual framework along with a scoring methodology had been clearly outlined and employed to assess empirical evidence, a correlation was identified by running a regression on the overall scores obtained for both readiness and effectiveness. A strong positive correlation between readiness and effectiveness was established. States that showed greater readiness were ones were EdTech interventions showed greater effectiveness. This indicates that any EdTech initiative must consider levels of preparedness of teachers, students, and infrastructure before they can be implemented. Further, due to the wide variation in Indian states, any EdTech intervention cannot take a 'one-size fits all' approach. Each Indian state must undertake a specific analysis of its capabilities, and its needs. Thus, future policies in the EdTech domain must be evidence-based.

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Annexure -1: Readiness Scores obtained by Indian States

Readiness Scores			
	Component 1	Component 2	Overall Readiness
Assigned Weights	**0.5**	**0.5**	**1**
Andhra	72.30171688	0	36.15085844
Arunachal Pradesh	NA	8.555769816	NA
Assam	NA	7.967116614	NA
Bihar	19.58705887	8.352785954	13.96992241
Chattisgarh	NA	16.34020095	NA
Gujarat	77.68303307	62.83365472	70.2583439
Haryana	62.86030023	25.62671268	44.24350646
Himachal Pradesh	76.46333716	27.40282148	51.93307932
Jammu and Kashmir	NA	9.134273825	NA
Jharkhand	NA	12.70678981	NA
Karnataka	61.72552134	37.47082107	49.5981712
Kerala	84.53199978	49.75134477	67.14167228
Madhya Pradesh	49.04296968	8.474576271	28.75877298
Maharashtra	73.47239439	58.71308231	66.09273835
Manipur	NA	12.64589465	NA
Meghalaya	NA	5.419669136	NA
Nagaland	NA	19.15152745	NA
Odisha	45.93249192	12.78798336	29.36023764
Punjab	85.17883198	100	92.58941599
Rajasthan	45.93320217	30.25474475	38.09397346
Tamil Nadu	NA	30.56936974	NA
Telangana	73.08758406	23.5258297	48.30670688
Uttarakhand	55.49211938	17.27392672	36.38302305
Uttar Pradesh	24.29826378	12.4327616	18.36551269
West Bengal	41.49250294	10.18978991	25.84114642
Delhi	NA	36.56754288	NA

Table 4: Readiness Scores obtained by States

States	Si1(Availability of TV)	Si2 (Availability of Smartphones)	Si3 (Internet Subscription)	Si4 (Electricity Supply)		Overall - Component 1
				Rural	Urban	
Assigned Weights	**0.125**	**0.125**	**0.125**	**0.0625**	**0.0625**	**0.5**
Andhra	100	41.5313	50.18118568	99.15588694	95.83287671	72.30171688
Arunachal Pradesh	54.4861337	70.0696	30.94651399	NA	37.5	NA
Assam	23.8172920	38.5151	15.33555588	NA	NA	NA
Bihar	5.05709624	0	0	76.58227848	70	19.58705887
Chattisgarh	72.1044045	63.109	19.20568198	NA	100	NA
Gujarat	83.6867863	78.8863	48.99260762	100	98.3328767	77.68303307
Haryana	74.8776509	74.0139	41.07841716	52.10958904	70.8328767	62.86030023
Himachal Pradesh	88.7438825	95.5916	74.85142774	0	93.3328767	76.46333716
J&K	27.4061990	42.6914	35.13552689	NA	0	NA
Jharkhand	0	13.4571	0	NA	NA	NA
Karnataka	83.5236541	39.9072	55.6022612	42.40506329	93.33287671	61.72552134
Kerala	89.7226753	100	67.37208291	65.40072828	96.66575342	84.53199978
Madhya Pradesh	50.7340946	34.3387	19.20568198	86.28680423	97.5	49.04296968
Maharashtra	75.8564437	72.1578	63.38599797	64.97867175	100	73.47239439
Manipur	48.6133768	89.3271	30.94651399	NA	NA	NA
Meghalaya	30.6688417	54.5244	30.94651399	NA	97.5	NA
Nagaland	46.4926590	89.3271	30.94651399	NA	37.5	NA
Odisha	58.8907014	23.6659	20.11885781	68.77614011	93.3328767	45.93249192
Punjab	93.6378466	82.3666	77.30105812	85.65389284	89.1657534	85.17883198
Rajasthan	37.3572593	28.3063	33.04826786	70.04196289	100	45.93320217
Tamil Nadu	99.5106035	27.1462	50.28264966	71.94069707	NA	NA
Telangana	96.0848287	57.7726	50.18118568	79.95769031	96.66575342	73.08758406
Uttarakhand	81.0766721	49.1879	11.21901725	77.6368996	83.3328767	55.49211938
Uttar Pradesh	27.5693311	10.4408	11.21901725	7.594936709	88.3328767	24.29826378
West Bengal	30.8319739	9.28074	30.07682273	91.56095023	100	41.49250294
Delhi	NA	NA	100	NA	NA	#VALUE!

Table 5: Component 1 (Access to Digital Infrastructure) Scores obtained by States

Indian States	Si1 (Teachers trained in computers)
Andhra	0
Arunachal Pradesh	8.555769816
Assam	7.967116614
Bihar	8.352785954
Chattisgarh	16.34020095
Gujarat	62.83365472
Haryana	25.62671268
Himachal Pradesh	27.40282148
Jammu and Kashmir	9.134273825
Jharkhand	12.70678981
Karnataka	37.47082107
Kerala	49.75134477
Madhya Pradesh	8.474576271
Maharashtra	58.71308231
Manipur	12.64589465
Meghalaya	5.419669136
Nagaland	19.15152745
Odisha	12.78798336
Punjab	100
Rajasthan	30.25474475
Tamil Nadu	30.56936974
Telangana	23.5258297
Uttarakhand	17.27392672
Uttar Pradesh	12.4327616
West Bengal	10.18978991
Delhi	36.56754288

Table 6: Component 2 (Teacher Preparedness) Scores obtained by States

Annexure -2: Effectiveness Scores obtained by Indian States

	Component 3	Component 4	Overall Effectiveness
Assigned Weights	**0.5**	**0.5**	**1**
States			
Andhra	26.48422397	0	13.24211198
Arunachal Pradesh	NA	22.07792208	NA
Assam	4.177008998	7.792207792	5.984608395
Bihar	4.197594215	32.46753247	18.33256334
Chattisgarh	17.75072197	22.07792208	19.91432203
Gujarat	83.0882002	22.07792208	52.58306114
Haryana	30.71851357	64.93506494	47.82678925
Himachal Pradesh	50	33.76623377	41.88311688
Jammu and Kashmir	NA	42.85714286	NA
Jharkhand	13.28850331	28.57142857	20.92996594
Karnataka	35.74607986	10.38961039	23.06784512
Kerala	72.88598773	14.28571429	43.58585101
Madhya Pradesh	33.87938853	49.35064935	41.61501894
Maharashtra	49.97285138	11.68831169	30.83058153
Manipur	NA	40.25974026	NA
Meghalaya	NA	23.37662338	NA
Nagaland	NA	14.28571429	NA
Odisha	8.547340032	9.090909091	8.819124561
Punjab	53.33510346	100	76.66755173
Rajasthan	10.06229266	55.84415584	32.95322425
Tamil Nadu	17.1800043	15.58441558	16.38220994
Telangana	22.41282608	11.68831169	17.05056889
Uttarakhand	50.45526146	29.87012987	40.16269567
Uttar Pradesh	56.46853147	NA	NA
West Bengal	3.839590444	NA	NA
Delhi	0	25.97402597	12.98701299

Table 7: Effectiveness Scores obtained by States

Component 3: Learning through Technology			
States	Si1 (Students learning using TV)	Si2 (Students learning using Smartphones)	Overall Component 3
Assigned Weights	**0.25**	**0.25**	**0.5**
Andhra	43.00341297	9.965034965	26.48422397
Arunachal Pradesh	NA	NA	NA
Assam	1.535836177	6.818181818	4.177008998
Bihar	6.996587031	1.398601399	4.197594215
Chattisgarh	6.655290102	28.84615385	17.75072197
Gujarat	89.07849829	77.0979021	83.0882002
Haryana	18.43003413	43.00699301	30.71851357
Himachal Pradesh	0	100	50
Jammu and Kashmir	NA	NA	NA
Jharkhand	6.996587031	19.58041958	13.28850331
Karnataka	36.1774744	35.31468531	35.74607986
Kerala	87.03071672	58.74125874	72.88598773
Madhya Pradesh	31.56996587	36.18881119	33.87938853
Maharashtra	52.21843003	47.72727273	49.97285138
Manipur	NA	NA	NA
Meghalaya	NA	NA	NA
Nagaland	NA	NA	NA
Odisha	8.703071672	8.391608392	8.547340032
Punjab	27.47440273	79.1958042	53.33510346
Rajasthan	13.48122867	6.643356643	10.06229266
Tamil Nadu	17.57679181	16.78321678	17.1800043
Telangana	4.266211604	40.55944056	22.41282608
Uttarakhand	62.79863481	38.11188811	50.45526146
Uttar Pradesh	100	12.93706294	56.46853147
West Bengal	7.679180887	0	3.839590444
Delhi			0

Table 8: Component 3 (Learning through Technology) Scores obtained by States

States	Si1 (Class 10 Maths)
Assigned Weights	**0.5**
Andhra	0
Arunachal Pradesh	22.07792208
Assam	7.792207792
Bihar	32.46753247
Chattisgarh	22.07792208
Gujarat	22.07792208
Haryana	64.93506494
Himachal Pradesh	33.76623377
Jammu and Kashmir	42.85714286
Jharkhand	28.57142857
Karnataka	10.38961039
Kerala	14.28571429
Madhya Pradesh	49.35064935
Maharashtra	11.68831169
Manipur	40.25974026
Meghalaya	23.37662338
Nagaland	14.28571429
Odisha	9.090909091
Punjab	100
Rajasthan	55.84415584
Tamil Nadu	15.58441558
Telangana	11.68831169
Uttarakhand	29.87012987
Uttar Pradesh	NA
West Bengal	NA
Delhi	25.97402597

Table 9: Component 4 (Learning Outcomes) Scores obtained by States