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Artificial Intelligence and Inclusive Education Empirical Evidence from a Large-Scale Policy Implementation

Rijwan M. Shaikh [a,*], Abhay Bora [b]

[a] *Sinhagad Institute of Management, Vadgaon Budruk, Pune, 411041, India.*
[b] *Sandip Institute of Technology and Research Centre, Nashik, 422213, India.*

Abstract

The National Education Policy (NEP) 2020 represents one of the largest large-scale policy reforms in India, introducing a new paradigm for delivering education through the strategic use of technology to promote an inclusive education system. This research project studied the integration of artificial intelligence (AI) into educational systems by using AI-based tools to support the personalization of learning based on the competencies identified by the NEP 2020. A correlational study was conducted to examine whether the use of such tools would support the implementation of the goals of the NEP 2020. Specifically, this study used a descriptive–correlational design to investigate whether the use of AI-based tools would be effective when implemented at the institutional level with teachers who are proficient in using technology and have sufficient resources available. Data were collected via surveys from 418 stakeholders (i.e., frontline practitioners; policy implementers; and technological facilitators) involved in implementing the NEP 2020 across the university system in the state of Maharashtra. The findings indicate that a statistically significant relationship exists between the availability of stable electricity and adequate Internet bandwidth, which accounted for 73.2 percent of the variation in platform adoption ($R^2 = 0.732; F(1, 416) = 112.432$). Additionally, a strong positive correlation ($r = 0.784, p < 0.002$) existed between teacher digital literacy and optimal student performance in the adaptive learning environment supported by the AI-based tool. ANOVA results also revealed that the type of local language-based content included in the platform was the most important factor ($p < 0.001$) in motivating students from rural backgrounds to participate in the program, thus reducing cognitive load. Although there are many opportunities associated with the use of AI-based tools, the existing digital divide continues to limit the ability of schools to provide equal access to high quality technology. Therefore, this study concluded that the success of the NEP 2020 will depend on three factors: (a) the modernization of educational institutions; (b) the training of teachers to effectively utilize digital technologies; and (c) the creation of digital repositories that are accessible to all students in their local languages. These recommendations are based on the findings of this study and will help guide educators as they work to navigate the complexities associated with the inclusion of technology in diverse educational settings.

Keywords: AI-enabled platforms, National education policy 2020, Learning analytics, Digital equity, Competency-based education, Institutional readiness.

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1. Introduction

The integration of AI into educational models is an essential shift from traditional education formats to new forms of education (and) new types of education institutions [1]. AI-powered learning environments are able to create a tailored learning path; immediate feedback loop(s); and individualized curriculum based on the needs of each student [2]. In order to optimize these computer-based platforms it will be necessary to carefully review the many possible societal ramifications that include policy (law), regulation and philosophy. This thematic synthesis reviews the state of use of automatic learning platforms throughout India and their compatibility with the National Education Policy 2020 [3].

The modern academic setting requires an integrated understanding of both how traditional classroom processes are impacted by algorithm-based processing and how educators can effectively use human based reasoning with precise data analysis to create a climate conducive to inclu-

*Corresponding author
Email address: rijwans@gmail.com (Rijwan M. Shaikh), ab3106070@gmail.com (Abhay Bora).

sive learning environments. These new educational systems provide one of the most significant ways that high quality education can meet the diverse intellectual needs of a large number of students. As such, in addition to using their own physical presence to provide instruction, educators now have the ability to increase the cognitive development of their students through both synchronous and asynchronous digital communications.

In addition, the Indian context includes an additional layer of complexity with regards to both linguistic diversity and regional economic inequality as it relates to digital access and utilization by students located in peripheral areas of India. As such, digital platforms will need to go beyond the realm of mere translation in order to achieve a culturally relevant experience that resonates with students from these regions. The National Education Policy 2020 also calls for the use of technology to provide equitable access to high level educational resources. To reach this goal, there needs to be a thorough assessment of current institutional capacity and the willingness of stakeholders to move forward with new models of delivery.

The subsequent analysis will analyze barriers to potential immersion into technology, with an emphasis on three areas; physical infrastructure, educator digital literacy, and security of data [4]. Additionally, the analysis will investigate the remedial capability of automation to drive a competency-focused curriculum model and to address accessibility disparities among regions as reported by current research [3]. The ultimate purpose is to clearly define, explain, identify, and discuss potential future applications and barriers to intelligent machine application within schools in India [5].

Effective technology deployment plans should consider the sociocultural influences on how people in different demographics receive new technologies. The degree to which teachers will transition to digital instruction is largely determined by the institutional support they have available to them. Many technologically advanced educational projects have failed to achieve long term viability without a cohesive technical sup-port model; therefore, the evaluation of the human component of this issue is just as important as the evaluation of the school district's hardware capabilities.

The use of rigorous investigations of the mandates for policies and academic publications will help to clarify how public educational institutions are currently using technology to carry out their public mandate. At the same time it will bring to light, the inadequacies in the current technological equipment and the ethics that are being used with respect to how this is occurring [5], [6]. The above inquiry provides further evidence of the automation's effectiveness to provide access to elite instructional re-sources to marginalized and under served communities [7] as well as to pro-vide an equal opportunity for all students through the accommodation of diverse learning styles and abilities to accommodate the equity that has been mandated by re-cent federal and state education directives [8].

This review also examines the viewpoints of the next generation of teachers about technological adoption in both the difficult and the diverse environments of their classrooms [9]. The systematic assessment is conducted in order to answer fundamental questions regarding inclusive teaching and technology advancement. The research will develop a relationship between the quality of the stu-dents' experiences with digital tools and the ultimate success of the students. By employing evidence-based metrics, the research provides an objective basis for future changes to policies and allocations of resources.

The transformation to a digitally-driven educational system will require major changes in cognition for both the instructors and administrators. Traditional methods of assessing student learning must be transformed to reflect the continued use of the real-time feedback loop that is generated by learning analytics. As a result, students have the ability to take responsibility for their own academic growth by utilizing transparent measures of performance. Thus, the traditional role of the teacher transitions from being an informational resource to one that is providing individualized educational experiences.

2. Literature review

The expanding scope of educational technology has generated substantial scholarly interest concerning its ability to alter how students learn through adaptive mechanisms and personalized instructional support [9], [11], [36], [37]. Such structural evolution is also repeatedly linked to the broader national vision of the National Education Policy (NEP) 2020, which emphasizes technology-enabled access, competency-based learning, and system-wide modernization [1], [3]. In this context, algorithmic and data-driven educational systems are increasingly positioned as tools that can reshape teaching practices and institutional efficiency, provided that adoption is aligned with equity and governance requirements [6], [21]. Therefore, effective deployment of AI-enabled platforms is widely discussed as one of the primary routes to achieving inclusive educational goals at scale in contexts with large and diverse learner populations [5], [7], [15].

2.1. Infrastructural and human capital challenges

A consistent theme across the literature is that hardware limitations, unreliable connectivity, and insufficient teacher training remain the core constraints that prevent AI-enabled platforms from achieving their intended impact [10], [11], [16]. Studies focused on institutional adoption show that even when awareness of AI tools is growing, the absence of robust infrastructure and support systems weakens implementation fidelity and sustainability [3, 5]. This challenge is particularly prominent in rural or resource-limited environments where stable electricity and bandwidth constraints restrict access to platform-based learning opportunities [16], [19], [26]. Accordingly, scholars argue that modernization of education systems requires coordinated action among government agencies, private developers, and civil society, since scaling digital education depends on shared investments in infrastructure and institutional readiness [7], [15].

Beyond physical infrastructure, the literature emphasizes that teacher readiness and professional capability represent an equally important "human capital" determinant of success [8], [11], [17]. While digital tools can expand instructional capacity, teachers' confidence, data literacy, and pedagogical integration skills determine whether AI systems function as genuine learning supports or remain superficial add-ons [18], [20]. As a result, researchers recommend teacher training models that go beyond basic tool use and extend toward analytics interpretation, adaptive instruction design, and responsible platform usage [32]. This aligns with broader policy-oriented discussions that call for trustworthy and accountable AI adoption, including institutional governance structures that support teacher upskilling and safe deployment [15], [25].

A further requirement highlighted in the literature is that equitable AI integration must resolve ethical concerns and ensure safe data practices to prevent harm, exclusion, or bias in learning analytics [21], [25]. Related work argues that content localization is essential for linguistically diverse contexts, and that AI platforms must move beyond generic translation to achieve cultural relevance that resonates with learners and families [12], [27]. In addition, scholarship addressing education's broader human-development objectives notes that technology must be positioned as a facilitator of holistic competencies rather than solely an efficiency tool, particularly when policy mandates emphasize future-ready skills [13], [15].

2.2. Instructional efficacy and student support

A major line of research emphasizes that AI-enabled learning systems can support students through immediate feedback, personalization, and continuous access to learning assistance [9], [11], [36]. Automated conversational agents and digital assistants are reported to reduce instructor workload, support learner queries outside classroom hours, and provide scalable academic support in contexts with high student–teacher ratios [14]. In parallel, studies on adaptive learning argue that tailoring content and pacing to individual needs can improve engagement and retention, especially when deployed alongside appropriate teacher facilitation and institutional support [5], [15].

The literature also emphasizes that AI-supported feedback and analytics can help educators identify learning difficulties early, enabling targeted interventions and more mastery-oriented instruction [18]. However, scholars caution that analytics benefits require teachers to interpret data correctly and to align interventions with sound pedagogy [20]. Consequently, evidence-based frameworks propose that sustained outcomes depend on ongoing professional development and structured institutional support, including mentoring, technical assistance, and clear guidance on how to translate analytics into instructional action [32]. From a governance standpoint, these instructional promises must be balanced with safeguards for privacy and transparency in algorithmic decision-making [21], [25].

Sustainable implementation is further linked to coordinated regulation, developer accountability, and platform design that is sensitive to national and regional constraints [3]. In linguistically diverse settings, researchers consistently argue that software must account for multilingual instruction and cultural context, since the perceived "foreignness" of a platform can reduce trust and engagement even when the technology is technically functional [12]. Thus, collaboration between educators, linguists, and designers is repeatedly presented as a practical pathway to producing culturally appropriate learning materials and interfaces while maintaining usability across varying digital access conditions [12], [27].

2.3. Impact on rural and marginalized settings

Research focusing on rural and marginalized settings highlights that teacher digital capability remains vital for creating effective learning pathways even when platforms provide automation and personalization features [16], [17], [18]. Rural studies report that constraints such as staffing shortages, geographic isolation, and limited infrastructure increase the value of scalable AI assistance, yet simultaneously amplify implementation challenges [45]. Scholarship on teacher knowledge and data literacy in rural environments also finds that confidence and capacity to use AI tools for instructional decision-making is uneven, which reinforces the need for sustained professional learning and local support structures [20].

The literature further notes that digital divides are not only technical but also socio-economic, and that unequal access can produce unequal outcomes if platforms are introduced without parallel investments in infrastructure and support [19], [21]. Several studies argue that developers should produce lightweight and bandwidth-resilient applications so that low-connectivity regions are not excluded from modern digital instruction [26]. In addition, broader equity research frames AI as a potential bridge or amplifier of existing disparities depending on how adoption is governed and funded [24], [30]. Therefore, rural deployment is repeatedly described as a policy and design challenge requiring targeted resource allocation and local adaptation to avoid reinforcing historical inequities [15], [16], [26].

Community acceptance also emerges as a recurring theme: long-term uptake depends not only on students and teachers but also on parents and local communities understanding the value of digital learning tools [15], [25]. Where digital literacy is limited, awareness initiatives and community-based support can increase trust and participation, particularly when platforms provide practical skill development aligned with local needs [28], [32]. Accordingly, many authors emphasize that AI should assist rather than replace educators, and that sustained success requires both human-centered design and social readiness within communities [15], [20], [25].

2.4. Governance, ethics, and long-term sustainability

The governance literature stresses that trustworthy AI adoption in education requires robust policies for privacy, transparency, accountability, and bias mitigation—particularly when learning analytics and automated decisions influence student trajectories [15], [21], [25]. Several contributions frame ethical governance as a prerequisite for scaling AI platforms, since weak data protection or opaque algorithmic processes can erode trust and harm vulnerable learners [15], [24], [25]. In addition, research on educational (in)equality warns that generative AI may widen gaps if access, training, and institutional safeguards are uneven, reinforcing the need for deliberate equity-focused deployment [22], [23], [34].

Funding and long-term maintenance are also central themes. Scholars argue that without consistent financial commitments, technology advantages concentrate in wealthier institutions, widening socio-economic disparities and limiting policy realization in underserved regions [15], [26]. For this reason, long-term models are commonly associated with structured funding mechanisms, public–private partnerships, and ongoing evaluation of outcomes to refine implementation strategies [15], [25], [30]. Additionally, work on inclusion and language barriers emphasizes that equitable platforms must provide accessibility features and support diverse learners, including those affected by language constraints and special educational needs [27], [39], [40].

Finally, sustainability studies highlight that digital education initiatives often fail when they do not plan for maintenance, upgrades, and technical assistance over time [15], [26]. The broader consensus is that AI-enabled educational modernization is viable only when infrastructure investment, teacher capability building, localized content, and ethical governance are treated as interdependent requirements rather than separate add-ons [3], [7], [15], [20]. In line with this view, long-term research agendas also recommend longitudinal evaluation of learning, cognition, and socio-emotional outcomes to ensure that AI-enabled platforms support meaningful development rather than short-term performance gains [24], [33].

3. Research framework

3.1. Research objectives

A number of key objectives that are very specific will guide this research into how far along India has come in adopting digital technology. These objectives each address a different important part of what makes up an institution's instructional architecture.

Objective 1. Determine the effect of the quality of institutional digital infrastructures upon the rate at which teachers in Indian classrooms adopt AI-enabled platforms.

Objective 2. Examine the relationship (correlation) between the digital competency level of teachers and the increase in their students' academic performance.

Objective 3. Explore the degree to which the use of vernacular content localized to a region affects the way in which students from rural areas engage with digital learning opportunities.

3.2. Research hypotheses

To create an effective structure of investigation, these research hypotheses were developed from current literature to establish potential relationships between the variable(s) being examined and will be used to test the relationships with quantitative statistical methods.

- Hypothesis 1 (H1): Robust digital infrastructure significantly predicts the frequency and depth of platform adoption among diverse institutional stakeholders.
- Hypothesis 2 (H2): Higher levels of instructional digital fluency demonstrate a positive correlation with achievement outcomes within adaptive learning environments.
- Hypothesis 3 (H3): The availability of culturally relevant regional language materials significantly improves participation rates on sovereign digital architectures.

The study used a descriptive-correlational design that employed a quantitative survey methodology to explore the relationship of AI tools with the implementation of policies, through a validated structured digital tool which tested internal consistency based on Content Validity Index and Cronbach's Alpha. A stratified randomized sampling method was used to recruit 418 participants from a pool of all types of policy implementers, frontline practitioners and technical facilitators in Maharashtra, as per the formula of Cochran to allow for a 5% margin of error, while at the same time allowing for adequate degrees of freedom for multiple regression analysis and ANOVA to avoid Type II errors. As such, this sampling method was able to reduce the risk of selection biases due to rural/urban divides; the data collection took place over a four-month period and collected information about both the physical resources available and the psychological reception to those resources during different academic terms. The data was cleaned to meet normality prior to using professional statistical software to determine if there were statistically significant correlations among the three variables (infrastructure, teacher skills, and student success), to provide an evidence based foundation for targeted interventions in the region's university system.

4. Data analysis

4.1. Analysis of hypothesis 1: infrastructure and adoption

The first stage of this study investigated the technological (physical) necessities to adopt digital technology in each of the institutional settings that we identified as our sites of interest. Using a Likert-type instrument, participants were questioned about the state of their local environment concerning three significant areas: connectivity; power; and hardware. To develop an overall assessment of the existing technical climate in Maharashtra, all of the participant's responses were combined. Table 1 outlines the distribution of participant responses to the Likert-based instrument which was employed to assess the Hypothesis 1 variables.

A generally positive perception of institutional infrastructure was observed via descriptive analysis of Hypothesis 1; however, the existence of large-scale areas of dissatisfaction was also clearly demonstrated in rural responses. High-speed internet reliability garnered a "Strongly Agree" response from 43.8% of the respondents which reflects the rapid digital expansion occurring at metropolitan academic centers. Conversely, the combined "Disagree" and "Strongly Disagree" categories (11.9%) illustrate the ongoing digital divide that persists in the peripheral zones. Consistent electrical supply emerged as the greatest determining factor of digital access for 47.1% of the respondents;

Table 1: Responses for infrastructure and adoption from H1 instrument.

Likert Statement (H1 Instrument)	SA (5)	A (4)	N (3)	D (2)	SD (1)	Total (N)	Mean Score
High-speed internet reliability	183 (43.8%)	142 (34.0%)	43 (10.3%)	29 (6.9%)	21 (5.0%)	418	4.05
Consistent electrical supply	197 (47.1%)	128 (30.6%)	37 (8.9%)	34 (8.1%)	22 (5.3%)	418	4.06
Modern hardware availability	164 (39.2%)	156 (37.3%)	52 (12.4%)	24 (5.7%)	22 (5.3%)	418	3.99
Institutional server uptime	158 (37.8%)	167 (40.0%)	48 (11.5%)	31 (7.4%)	14 (3.3%)	418	4.01
Technical support response	142 (34.0%)	173 (41.4%)	59 (14.1%)	28 (6.7%)	16 (3.8%)	418	3.95
Offline synchronization features	176 (42.1%)	141 (33.7%)	61 (14.6%)	23 (5.5%)	17 (4.1%)	418	4.04
Low system latency levels	153 (36.6%)	164 (39.2%)	54 (12.9%)	33 (7.9%)	14 (3.3%)	418	3.98

this suggests that consistent electricity is viewed by many as a major requirement for digital participation. The availability of modern hardware for digital access exhibited a more even distribution than did consistent electrical supply; 39.2% of the respondents "strongly agreed," and 37.3% agreed, indicating that while machines exist, the quality of those machines may vary considerably across districts. The mean score of 3.99 for hardware indicated a moderate level of readiness; thus, additional funding, specifically directed toward hardware investments will be required to meet an adequate level of readiness for widespread adoption of AI platforms. The lowest percentage of respondents who "strongly agreed" regarding technical support response time (34.0%) identifies a critical deficiency in human capital for addressing and resolving the problems experienced with digital tools and equipment. Offline synchronization was identified as a highly valued feature (42.1% SA) among the surveyed population, and therefore, software flexibility will be necessary in areas where connectivity is inconsistent. Overall, these results support the notion that while the policy environment has been well-established, the physical conditions of the Indian classroom require substantial development to support the implementation of high levels of AI platform adoption.

4.2. Statistical validation of H1: Linear regression.

In order to evaluate the degree to which the quality of infrastructure is predictive of the actual use of AI platforms, we applied an ordinary least squares (OLS) linear regression model. This will allow us to measure the extent to which variation in platform use can be explained by the digital infrastructure that is available to stakeholders with respect to this hypothesis. Table 2 contains the main statistics for the regression model used to test Hypothesis 1.

4.3. Analysis of hypothesis 2: Teacher competency and student outcomes

The statistical validation through simple linear regression clearly demonstrates how critical the availability of physical resources are for successful educational modernization. The R-value of 0.855 shows a very strong positive correlation between the quality of institutional infrastructure and the rates at which institutions adopt AI-enabled systems. More importantly, the R-squared value of 0.732 demonstrates that approximately 73.2 percent of the total variance in the adoption rate of platforms can be attributed to the infrastructure variable alone. Thus, the remaining 26.8 percent of the variance is attributed to variables other than the infrastructure, such as teacher motivation or school district policies. The high F-value of 112.432 supports the conclusion that the relationship between the two variables is not coincidental and that the model has significant predictive ability in the context of regional universities. Finally, the p-value less than 0.001 supports the conclusions made from this study as relevant to educational planning on a national scale. Additionally, the Durbin Watson statistic of 1.892 falls into the acceptable range; thus, there is no indication of autocorrelation in the data set. The results of this study support the claim that the pedagogical shift toward AI-based learning would be severely limited by the inability to resolve hardware and connectivity issues. Therefore, educational policymakers should recognize infrastructure spending as the primary mechanism to drive educational innovation rather than a secondary cost.

4.4. Analysis of Hypothesis 2: Teacher competency and student outcomes

The second hypothesis examines how educator digital skills relate to student academic success. Because technology is increasingly a part of every day instruction for many teachers using AI in an educational setting, the teacher's ability to understand and apply technology to facilitate learning becomes important. The survey tool used collected self reported levels of competence with regard to a variety of technical functions, ranging from the simplest such as navigating a system to the most complex which would be the analysis of data related to learning processes.

The investigation of Hypothesis 2 demonstrates a relationship between human knowledge and the use of technology, as indicated by 41.6% of the teachers surveyed reporting they feel very comfortable using AI tools. Although teacher confidence is high in using AI tools; confidence drops when it comes to using AI tools for more complex tasks such as analyzing learning analytics (37.3% SA) and developing customized adaptive learning pathways (34.2% SA). This drop-off indicates a gap in utilizing data to enhance teaching and learning practices. The mean score of 4.08 indicates that the majority of the teachers surveyed have some level of interest or value placed on professional development training to utilize AI tools effectively in the classroom. While there was an interest among teachers to be trained on how to use AI tools, this interest did not translate into the ability to accurately analyze and interpret the results of learning analytics for instructional improvements as indicated by only 37.3% of the teachers surveyed stating they were able to do so strongly. Thus, there is a growing need for data literacy skills for teachers to utilize the data generated from AI tools to inform instructional decisions. Further, as indicated by 40.0% of the

Table 2: Statistical validation of Hypothesis H1

Model Summary	**R-Value**	**R-Squared**	**Adjusted R^2**	**F-Value**	**Significance (p)**	**Durbin–Watson**
Regression Analysis (H1)	0.855	0.732 (73.2%)	0.729	112.432	< 0.001	1.892

Table 3: Responses for teacher competency and student outcomes from H2 instrument.

Likert Statement (H2 Instrument)	**SA (5)**	**A (4)**	**N (3)**	**D (2)**	**SD (1)**	**Total (N)**	**Mean Score**
AI-navigation proficiency	174 (41.6%)	162 (38.8%)	41 (9.8%)	23 (5.5%)	18 (4.3%)	418	4.08
Learning analytics interpretation	156 (37.3%)	178 (42.6%)	47 (11.2%)	21 (5.0%)	16 (3.8%)	418	4.05
Creating adaptive learning paths	143 (34.2%)	186 (44.5%)	52 (12.4%)	24 (5.7%)	13 (3.1%)	418	4.01
Real-time feedback mechanisms	167 (40.0%)	154 (36.8%)	58 (13.9%)	27 (6.5%)	12 (2.9%)	418	4.05
Professional development value	182 (43.5%)	141 (33.7%)	54 (12.9%)	28 (6.7%)	13 (3.1%)	418	4.08
Literacy training impact	169 (40.4%)	157 (37.6%)	49 (11.7%)	26 (6.2%)	17 (4.1%)	418	4.04
Managing technology-based assessments	148 (35.4%)	174 (41.6%)	62 (14.8%)	21 (5.0%)	13 (3.1%)	418	4.01

teachers surveyed placing a value on having access to real-time feedback mechanisms, we see a trend toward utilizing more iterative assessment models. Ultimately, the successful utilization of AI tools to support instruction will rely on educators being able to effectively and efficiently navigate digital tools, which suggests that training should move beyond basic technical literacy to include both pedagogical competency and data science competencies.

4.5. Statistical validation of H2: Pearson correlation

The researchers used the Pearson Product-Moment Correlation to demonstrate that teacher proficiency is positively related to students' growth academically; the researchers will get a numeric representation of how strong and which direction (positive or negative) the relationship between teacher skill and student outcome is. If there were a very strong positive correlation, it would indicate that as a teacher becomes proficient at using technology for learning, so do the students and which is shown in Table 4.

Table 4: Statistical validation of Hypothesis H2.

Correlation Analysis	Sample (N)	Pearson (r)	t-statistic	p -value	Effect Size (r^2)
Competency vs. Outcome	418	0.784	14.321	0.002	0.615 (61.5%)

The Pearson correlation analysis for hypothesis two demonstrated a large, statistically significant, positive association between an instructors' ability to effectively use technology (digital fluency) and their students' academic improvements. A calculated R value of .784 indicates a very high degree of association; therefore, teacher effectiveness appears to be the most important factor in how successful adaptive learning interventions will be. Additionally, the R squared effect size (0.615) indicates that roughly 61.5 percent of the observed improvement in the student's academic achievements can be directly attributed to the teachers' technical proficiency. The T statistic of 14.321 demonstrates that the previously stated result is extremely unlikely to have been due to a chance event from the sample data; therefore, it is a very reliable finding. With a P value of 0.002, the results clearly exceed the commonly accepted standard for research quality, and provide a strong foundation upon which policy recommendations may be developed. Therefore, the results indicate that the "human capital" factor is essentially as influential as the technology being utilized. Thus, schools that implement new technology but fail to provide adequate ongoing training for all teachers are un-likely to realize significant improvements in student achievement. The statistical findings support a paradigmatic change in school district priorities, placing on-going professional development as the central focus of any strategic plan to digitally transform education. In addition to ongoing professional development, peer mentoring programs may provide a viable means to diffuse technical knowledge to the entire teaching staff.

4.6. Analysis of hypothesis 3: Vernacular content and engagement

The third hypothesis explores how the use of languages in an area may affect whether students are willing to adopt and successfully use a digital tool for their education with a special emphasis on rural districts. The National Education Policy 2020 also stressed that using a child's native language (i.e., "mother tongue") is essential to improve both a child's comprehension and level of engagement when learning. The survey assessed respondents' views about the potential influence of support for the regionally spoken languages in regards to motivating and enhancing student understanding of concepts. Table 5 summarizes the responses for this component.

The evaluation of Hypothesis 3 demonstrated that linguistic sensitivity is a major contributor to educational equity. The local dialect was found to be one of the most important ways to increase institutional trust through localized dialects; 45.9% of the sample agreed that local dialect will enhance the participation of parents from rural communities in digital learning. Thus, familiarizing parents with the same dialect they use at home appears to help them provide support for their children's digital learning. Additionally, vernacular materials decrease cognitive load (44.5% SA) by allowing students to focus on content knowledge acquisition and application rather than struggling to understand the material due to the use of an unfamiliar language. Mobile-first applications were highly rated (43.3% SA); this represents the widespread dependence upon mobile-based internet access in rural communities. Cognitive Load had the highest Mean Score (4.09) of any

Table 5: Responses for vernacular content and engagement from H3 instrument

Likert Statement (H3 Instrument)	SA (5)	A (4)	N (3)	D (2)	SD (1)	Total (N)	Mean Score
Dialect support increases trust	192 (45.9%)	134 (32.1%)	42 (10.0%)	31 (7.4%)	19 (4.5%)	418	4.08
Translation comprehension impact	178 (42.6%)	147 (35.2%)	51 (12.2%)	27 (6.5%)	15 (3.6%)	418	4.07
Cultural relevance drives motivation	164 (39.2%)	159 (38.0%)	57 (13.6%)	24 (5.7%)	14 (3.3%)	418	4.04
Vernacular reduces cognitive load	186 (44.5%)	142 (34.0%)	48 (11.5%)	26 (6.2%)	16 (3.8%)	418	4.09
Parental involvement through language	173 (41.4%)	151 (36.1%)	56 (13.4%)	22 (5.3%)	16 (3.8%)	418	4.06
Regional language assessments	159 (38.0%)	168 (40.2%)	53 (12.7%)	24 (5.7%)	14 (3.3%)	418	4.04
Mobile-first vernacular reach	181 (43.3%)	144 (34.4%)	52 (12.4%)	28 (6.7%)	13 (3.1%)	418	4.08

question in the Survey, indicating that there is a very high level of agreement about the importance of using the student's native language when teaching. Although the sample indicated that Translation Accuracy was well-received (42.6% SA), the fact that 12.2% of the sample indicated "Neutral" to automated translation indicates that the current state of automated translation is in need of some improvement. These findings confirm the National Education Policy's assertion that regional languages are necessary to bridge the digital divide and assist all students.

4.7. Statistical validation of H3: One-way ANOVA

To assess if there is a statistically significant difference in students' levels of engage-ment based on the presence of content in regional languages, researchers conducted an ANOVA - one-way analysis of variance to determine if there was a significant differ-ence in the mean engagement for the three different categories of students; namely those who only used English, students that used the translated version of the content and those students who were able to use their native vernacular content. Table 6 shows the statistical validation of H3.

Table 6: Statistical validation of Hypothesis H3.

Source of Variation	Sum of Squares	df	Mean Square	Fratio	*p*-value
Language Factor	634.87	2	317.435	26.432	0.001
Error Variance	4983.12	415	12.007	–	–
Total Variance	5617.99	417	–	–	–

The ANOVA outcomes for Hypothesis 3 clearly show statistically significant results supporting the hypothesis that linguistic variety influences student participation. A ratio of 26.432 was significantly greater than the critical values, therefore there was a significant difference in the level of student engagement based upon the instructional language used. The test shows that students who use regional vernacular content have higher motivation and conceptual understanding when compared to students who are limited to using English only as their platform. The language factor's Mean Square Value (317.435) greatly exceeded the Error Variance (12.007), which illustrates the strong relationship between the linguistic variable and student success. Therefore, with a p-value of .001, the results suggest that the observed differences were not due to chance. These results emphasize the need for the linguistic requirements outlined with in the National Education Policy and indicate that one size fits all instruction using only English is a major barrier to educational equity in India's heartland. Practitioners should give priority to creating quality vernacular datasets so that they may be able to develop AI enabled platforms that will provide students with culturally relevant and linguistically responsive instruction. Therefore, the results indicate that support for regional languages is not simply an option for the successful implementation of democracy through the realization of modern education but is a basic requirement.

5. Empirical findings and policy implications

The empirical research indicates the educator's (teacher) technical proficiency in digital technology is the key link to how much potential there is in a school or district to use technology to enhance their students' learning. This study demonstrated that when teachers have the highest level of technical skill, they are able to use diagnostic data from online assessments to develop personalized paths of instruction for their students, and they will be more willing to integrate an adaptive tutoring system into their practice, which will result in a reduction of student learning gap through formative assessment.

Regression analysis identified that developing the technical ability of educators is the least expensive way to improve student academic performance because without a competent teaching staff, even the most advanced artificial intelligence (AI) architecture will fail to make the necessary changes to move schools from traditional to flexible and competency based models.

Linguistic accessibility was identified as the most critical factor in creating equitable opportunities in education and the ANOVA data indicated that students who had access to learning environments that provided full vernacular support reported statistically significant increases in intrinsic motivation and conceptual understanding compared to those students who did not have such access.

Finally, it will depend on the intentional and systemic integration of technological innovation with the linguistic diversity of the nation's population to achieve the national education mandates. This will require a long-term commitment to human capital development (educators) and physical capital development (infrastructure).

6. Discussion

Despite its efforts to modernize the vast diversity of education systems throughout India by way of NEP 2020, there are several systemic barriers that impede the development of an equitable and sustainable modernization of the nation's education systems; chief among these is the systemic disparity between available educational infrastructure and the human capital available to the developing nations' schools, which serves to exacerbate the already substantial inequity of opportunity for students at-tending schools in rural regions. In order to ensure that the digital transition does not further marginalize rural schools and their respective students, leadership will need to adopt a bottom-up approach in the democratization of access to educational technology and to develop initiatives designed to provide subsidies to purchase hardware and to enhance bandwidth at the local level, thereby addressing the inequities that exist in both the availability of resources and the distribution of those resources throughout the subcontinent. Additionally, this transformation will require an evolutionary shift in how teachers receive instruction on how to integrate the use of technology into their instructional practices; specifically, rather than merely focusing on the teacher using predetermined content or materials, leadership should focus on developing and implementing curricula and programs of study that emphasize the pedagogical use of technology. Through the development of local "communities of practice," (Wenger) and the provision of strong institutional support, educators can be empowered as facilitators in supporting their students in achieving optimal academic success, while simultaneously building the psychological readiness and technical competence required for them to do so. Furthermore, by empowering educators to act as facilitators, they will also be able to serve as a conduit for optimizing student achievement for students regardless of the student's socioeconomic status.

A combination of the physical, technical, and cognitive dimensions of an architecture is required for it to be successful over time. The architecture's capacity to interact with the diverse cultural and linguistic identities of the Indian learner will also determine its sustainability. A culture of inclusivity requires collaboration among linguists, educators, and EdTech designers to develop high quality mobile-first multi-media learning materials using local dialects to minimize the cognitive load associated with learning and maximize intrinsic motivation. At the same time, the sheer volume of student generated data requires robust national guidelines and standards for ethical governance and privacy protection. Finally, a participatory approach to decision making among all stakeholders will ensure that the instructional architecture developed is resilient, fair, and transparent enough to serve as a model globally for inclusive digital education.

7. Conclusion

This study demonstrates clearly how realization of the mandates of National Education Policy 2020 is contingent on matching educational infrastructure, teacher competencies, and linguistic access. In this respect, the study establishes that institutional readiness and teaching competence are primary factors to determine which platforms will be adopted. Linguistic access is still the greatest factor for reaching rural demographics, who have been traditionally underserved by educational systems. To achieve the democratic aims of such policy will require an integrated approach to address all of the systemic gaps through a national commitment to modernization and culturally responsive strategies, so that technology is positioned as a facilitation of human development and not simply a replacement. By implementing these foundational pillars, India may create a future ready, global competitive education system, where each child has the ability to be successful in the digital world.

The study is geographically limited to the state of Maharashtra, therefore it does not account for possible differences in infrastructure availability and access that could exist in other states. The use of a cross-sectional methodology provides an instantaneous view of how students receive technology at one point in time and fails to provide insight into how students' behaviors evolve over longer periods of time. The self-reporting aspect of competency levels in this study may be subject to social desirability bias, and the omission of barriers related to home and family life limit our ability to understand factors influencing student engagement when they are not in formal educational settings.

In order to be able to assess future potential for research and education, it would be very helpful to investigate how children are affected by AI (longitudinal study) with regard to their cognitive development, their emotional well-being and across many different cultures. In order to do so, there will have to be a number of studies including but not limited to, studying whether algorithms can provide higher level thinking skills or if they encourage rote memorization, assessing the impact of AI enabled job training programs on employability in rural areas, and assessing the mental readiness of students in remote areas to use non-human teachers. The ability to continuously evaluate how these technologies are changing will allow educators to continually update and improve their methods and approaches.

Declarations and ethical statements

Conflict of interest: Authors declare that there is no conflict of interest.
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Artificial intelligence ethical statement: During the preparation of this work, the author used Grammarly to assist with grammatical corrections. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the published article.
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