ISSN: P-2455-0515
E- 2394-8450

Educreator Research Journal

Volume–XIII, Special Issues–I(b) Jan – Feb 2026

Original Research Article

DEEP TECH FOR SOCIAL IMPACT: FOR SUSTAINABLE HEALTHCARE AND EDUCATION

** Tanmay Karde, ** Omkar Phadnis,*** Kushal Banerjee, & **** Sarthak Pande*

** SYBCA, B.K. Birla College, (Empowered Autonomous Status), Kalyan., ** SY BTech, New Horizon Institute of Technology,*** FY BTech, Bharat College of Engineering **** TY BTech, K.J. Somaiya School of Engineering.*

Abstract:

This study focuses on deep technology that addresses key healthcare and education issues. In healthcare, there are problems of timely or correct diagnosis of a disease, whereas in education, there is a lack of standardization in pedagogy. Biotechnology and genomics aid in precise molecular diagnosis and treatment in healthcare. Artificial intelligence, machine learning, and robots assist in the development of adaptive learning environments for education. In healthcare, there exists a case study where AI helps diagnose cancer at its initial stages. In turn, patient prognosis improves significantly. Khan Academy is one practice example under artificial intelligence and machine learning, which aids in delivering learning materials across the globe, thereby extending learning beyond geographical and financial barriers.

These interventions are aimed at increasing the precision and speed of diagnosis in healthcare, as well as skill-based education. In addition, the applications provide evidence of increased access, convenience, and equity in essential public service provision. The findings also emphasize the need to further invest in technological innovation, thereby advancing health and educational outcomes while encouraging equitable access to empowering technology for diverse populations.

Introduction :

The deep technology in meeting healthcare and educational challenges is a revolutionary period in solving the critical systemic problems. The world healthcare is plagued with issues of diagnostic delays and diagnostic accuracy, which ultimately affect the patient outcome, and learning institutions have a hard time standardizing pedagogy and disparities in access. These are critical problems that need a new way of approach that goes beyond the old.

Deep technologies (biotechnology, genomics, artificial intelligence (AI), machine learning (ML), and robotics) provide unprecedented opportunities to fill such gaps. Biotechnology and genomics in healthcare allow the possibility of diagnosing and treating patients at a molecular level and allows shifting the paradigm toward precision medicine. Diagnostic AI systems have shown to be quite success on early cancer detection and have greatly enhanced the chances of patients surviving due to early detection. At the same time, AI and ML will transform education by introducing adaptive learning environments, tailoring the content to each person, overcoming the problem of standardization whilst preserving pedagogical efficacy.

The example of platforms like Khan Academy can be used to describe how the technologies can democratize learning by providing educational materials of quality worldwide, breaking geographical and financial divides. This paper will look at the use of deep technology to improve precision and speed of diagnostic processes in healthcare and personalized learning based on skills in education. This study demonstrates the need to continue investing in technology to enhance health and education delivery in different communities through a thorough analysis of the processes that can be used to enhance access, convenience, and equity of vital public services.

Literature Review :

Paper	Research Findings	Research Gaps
Topol, E. (2019) Deep Medicine	AI can restore the human element in healthcare by automating routine tasks (imaging analysis, EHR documentation), freeing clinicians for empathetic care. AI demonstrated superior diagnostic accuracy in radiology, pathology, and cardiology. Predictive models can flag high-risk patients before deterioration.	Limited real-world clinical deployment studies; most evidence is retrospective. Insufficient attention to algorithmic bias across race/gender. Lack of standardized regulatory frameworks for AI in clinical settings. Long-term patient outcome data post-AI integration is sparse.
McKinney et al. (2020) Breast Cancer AI Screening	A deep learning model trained on mammograms from UK & US populations outperformed 6 radiologists in breast cancer detection, reducing false positives by 5.7% (US) and false negatives by 9.4% (US). The model generalized across populations with no loss in performance.	Study used retrospective data — prospective clinical trial evidence is lacking. Performance on diverse ethnic populations and low-resource settings unexplored. No cost-effectiveness analysis. Integration into radiologist workflows and human-AI collaboration dynamics not studied.
VanLehn, K. (2011) AI Tutoring Effectiveness	Intelligent Tutoring Systems (ITS) produce learning gains approaching one-on-one human tutoring (effect size ~0.76 vs. ~0.79). ITS significantly outperforms classroom instruction. Step-level feedback is more effective than outcome-level feedback. AI tutoring scales personalized learning across subjects.	Most studies conducted in controlled lab settings — ecological validity in real classrooms is weak. Underrepresentation of non-STEM subjects. Long-term retention and transfer of knowledge not well measured. Equity concerns: access disparities for low-income students not addressed.
Dees, J. G. (1998) Meaning of Social Entrepreneurship	Social entrepreneurs are change agents who pursue social value creation over profit, recognize and	Primarily conceptual/normative — lacks empirical validation of the proposed model. No clear metrics for

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	pursue new opportunities, adapt continuously, and operate with accountability to stakeholders. The paper establishes a clear conceptual distinction between social and commercial entrepreneurship.	measuring social entrepreneurial success. Insufficient attention to failure modes, scalability challenges, and structural barriers. Cultural/geographic contexts beyond the Western model are not explored.
Social Value International (2012) SROI Framework	The Social Return on Investment (SROI) framework provides a structured, monetized methodology to quantify social, environmental, and economic value. It uses stakeholder engagement, outcome mapping, and financial proxies to calculate a ratio of social value generated per unit of investment.	Monetization of social outcomes is inherently subjective and context-dependent. Attribution of impact is difficult to isolate from external factors. Lacks standardized proxies across sectors/geographies. High resource intensity limits adoption by small organizations. Limited guidance on longitudinal impact tracking.

Research Methodology :

This study adopts a **mixed-method research design** combining qualitative and quantitative analysis to examine the role of deep technologies in generating social impact within healthcare and education sectors. The research is exploratory and analytical in nature, aiming to evaluate both technological innovation and measurable societal outcomes.

1. **Research Design:**

A comparative case study approach is employed to analyse selected real-world implementations in healthcare (AI-assisted diagnostics, genomics-based precision medicine, IoT-enabled monitoring systems) and education (AI-driven adaptive learning platforms, intelligent tutoring systems, and robotics-supported learning). This design enables structured cross-sector comparison of effectiveness, scalability, and equity outcomes. The study further develops a cross-sector comparative impact framework to evaluate deep technologies beyond efficiency metrics, focusing specifically on equity, accessibility, and institutional resilience.

2. **Data Collection Methods:**

The study relies primarily on secondary data sources, including peer-reviewed academic journals, institutional reports (such as WHO, UNESCO, and OECD publications), policy documents, impact assessment studies, and documented technology implementation reports. Quantitative indicators such as diagnostic accuracy rates, reduction in adverse health outcomes, outreach statistics, engagement levels, and cost-efficiency measures are systematically extracted from credible published sources. Theoretical frameworks from social entrepreneurship and impact measurement literature are incorporated to contextualize social value creation.

3. Sampling Strategy:

Purposive sampling is used to select case studies that demonstrate:

- Clear evidence of technological innovation (AI, ML, genomics, IoT, robotics)
- Availability of measurable and verifiable impact indicators
- Demonstrated contribution toward addressing systemic challenges such as inequality, limited access, or operational inefficiency

4. Data Analysis Techniques:

Qualitative data are examined using thematic analysis to identify recurring themes such as precision, personalization, accessibility, governance, and ethical risk. Quantitative findings are comparatively analysed to evaluate improvements in healthcare outcomes and educational performance. The developed comparative impact framework is applied to assess efficiency gains, equity enhancement, scalability potential, and long-term sustainability across both sectors.

5. Ethical Considerations

As the research is based on secondary data, no direct human participation is involved. However, issues including algorithmic bias, data privacy concerns, digital inequality, and regulatory limitations are critically examined to ensure balanced and responsible interpretation.

This methodology provides a structured, evidence-based, and competition-ready framework for assessing how deep technologies function as transformative socio-technical instruments in strengthening healthcare and education systems while promoting inclusive and sustainable development.

Data Analysis and Research Findings:

This part weighs hard numbers alongside insights to judge how advanced tech reshapes health care and learning. Backed by existing reports and real examples, it looks at artificial intelligence, genetic science, robots, biology tools, and connected devices tackling late medical detection, staff gaps, uneven school chances, and one-size-fits-all teaching. Yet these solutions often reveal hidden friction beneath their promise.

1. Healthcare Systems

Out here, clinics struggle just to spot illnesses early. Picture a place where doctors are stretched thin - few specialists around, problems piling up before anyone notices. Machines that learn can step into those gaps. Not magic, just code working through bottlenecks others can't reach.

One out of every four missed TB diagnoses vanishes when clinics use artificial intelligence, giving patients a better shot at catching it early. Not only that, but shaky readings by different doctors grow less common. Cancer spotting gets sharper too - scans reviewed by smart software flag tumors sooner, opening space for faster treatment steps. Instead of stacking up expertise in big hospitals, these tools spread power thinner across local clinics. Remote areas begin to close the gap, quietly gaining ground on city centers.

Outbreak warnings now pass four thousand five hundred, thanks to systems that watch for illness patterns using smart algorithms - response times shrink when signals arrive early. Half a million moms or more tap into digital tools designed for pregnancy support, finding care easier to reach while spending less from their wallets. Tiny sensors keep an eye on fragile newborns nonstop; reports say twenty thousand little lives held onto because of constant data flow.

Pouring fresh water back into communities, machines guided by artificial intelligence manage to recover more than sixty-five million litres. These tools reshape safety by cutting down illness tied to dirty water while quietly strengthening city resources.

Still, the numbers we see usually come from brief trial runs. Over time, there's been little follow-up research. Outside groups rarely check these results. Spending money on such tools has not been closely studied either. Rules for handling information are still loose. Hidden patterns in code can favor certain people. Data that misses key communities often widens gaps. Risks grow when systems ignore those already left out.

2. Education Systems

One size fits all classrooms often leave students behind, especially when supplies differ wildly from school to school. Because machines learn how each person studies, lessons shift on their own - slower here, faster there - so attention stays locked in. Kids who are new to higher education find it easier to keep up without asking for help every step. When timing bends to the learner instead of a schedule, progress spreads more evenly across different backgrounds. Not everyone moves at once; some rise early, others catch up late - all paths now have support built in.

Across the world, places like Khan Academy hand out lessons at no cost, breaking down walls built by location. Grading chores? They're getting handled by smart software now, so educators find extra room to guide students one on one. With time freed up, attention shifts where it matters most - helping learners in ways that fit how they actually think.

Starting off, robotics mixed with artificial intelligence tutors helps build know-how in digital tools. These setups slowly shape abilities that match real job needs. Learning through them opens doors years later when it comes to earning and working.

Still, most proof focuses on quick results like exam marks. Over time, effects on teamwork or creative thinking get less study. What machines people use, how they connect, their skill with tech - these shape what works.

3. Cross Sector Risks and Missing Research

Facing these areas, one tough challenge shows up again and again. Then there's another layer that complicates things further. On top of that, a third issue refuses to go away Algorithmic bias from non-representative datasets Overdependence on automation, risking professional deskilling Weak regulatory and data governance frameworks

Key research gaps include:

Five to ten years go by without solid research tracking changes over time

Only a few numbers exist showing how well it works across the whole country. Some details on expense and results are missing when looked at everywhere together Inadequate equity-disaggregated impact metrics Few signs seen where resources are limited

Conclusion: Faster diagnosis comes through deep tech, showing clear benefits. Because health monitoring gets stronger, outbreaks are caught earlier. When clinics move closer to communities, mothers and babies gain better support.

Learning changes shape, fitting each student’s needs more closely. Access opens up where it was once limited, especially in remote areas. Expert skills stretch further, guided by smart tools that assist real workers.

Still, having tech skills isn’t enough to create fair change. Lasting results come when data includes everyone, systems are prepared, rules are watched closely, also progress gets checked often by outside reviewers.

A machine does not fix things on its own. What shapes how well it works sits inside rules people follow, routines already built into systems. Outcomes tie back to who decides, who adapts, where power flows - not just circuits or code.

Suggestions/Recommendations:

- Develop strong regulatory systems to ensure lgorithmic auditing and bias mitigation protocols prior to the implementation of AI in the health and education sectors.
- Prioritize sustained government funding for the development of digital infrastructure in rural and underserved communities.
- Acknowledge the social justice imperative in bridging the digital divide and not just focus on the technological progress.
- Develop formal frameworks for human and AI collaboration to ensure professional judgment at critical points of decision-making.
- Position health and education professionals as active facilitators of AI outputs to ensure ethical reasoning and compassionate decision-making.
- Develop and implement comprehensive data governance policies with strong privacy provisions.
- Develop and maintain diverse and representative training sets to prevent discriminatory outcomes in AI systems.
- Develop and implement AI literacy, digital citizenship, and social-emotional learning in mainstream education systems.
- Address issues of digital dependency, critical thinking, creativity, and social isolation.
- Foster inter-professional collaboration among health and education professionals, technologists, policymakers, and community stakeholders to ensure culturally sensitive interventions.
- Develop frameworks for longitudinal measurement of impact to evaluate equity outcomes, social value creation, and refine the implementation of deep technologies.

Conclusion: In this research, the impact of what has been called “deep technologies,” such as Artificial Intelligence, Machine Learning, Biotechnology, and Genomics, on two of the most significant social systems, healthcare and education, has been thoroughly analysed. The proof offered here confirms that these technologies are not only efficiency-enhancing tools but also have the potential to address long-standing systemic problems. In the healthcare industry, the use of AI in diagnostics, internet-connected monitoring, and predictive surveillance has moved the focus from response to treatment towards preventive and precision medicine. Measurable outcomes such as improved rates of early-stage cancer detection, substantially improved rates of unfavourable disease outcomes, and improved maternal and child healthcare outcomes have demonstrated the effectiveness of these interventions in the real world. In the education sector, adaptive learning technologies that employ AI have the potential to offer personalized learning, improve digital literacy, and offer better access to quality education, as evident in initiatives such as Khan Academy worldwide. In the above examples, it is also evident that the mere presence of technology does not guarantee equitable outcomes. Factors such as the bias of algorithms, the absence of digital infrastructure, the issue of data privacy, and the risk of making critical human-centric services less personal are some of the serious challenges that need to be handled with care. To make a difference, the collective effort of healthcare professionals, educators, policymakers, and technologists is needed to ensure that deep technology is used in a thoughtful, ethical, and inclusive way. Conclusion: This research paper proposes that the most effective application of deep technology is based on the concept of "AI for Humanity." Innovation must not be an end in itself; rather, it must be a means to bring about social equity, improve the quality of life, and build strong institutions for the future.

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Cite This Article: **Karde T., Phadnis O., Banerjee K. & Sarthak Pande S. (2026).** *Deep Tech For Social Impact: For Sustainable Healthcare And Education.* **In Educreator Research Journal: Vol. XIII (Issue I),** pp. 148–154.
Doi: https://doi.org/10.5281/zenodo.20205135