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Abstract:

Generative AI (GenAI) artefacts might transform education for marginalized rural communities in developing countries, facing formidable challenges and a persistent digital divide. In this research, we conduct a mixed-method study, where first, we employ in-depth interviews of marginalized rural communities from the mountain and plain areas to understand enablers of GenAI artefacts usage in rural educational settings. Then, we employ the decision-making method, i.e., Grey DEMATEL, to find the causal linkages among enablers. Drawing on a socio-technical theoretical lens, our study explains the enablers responsible for facilitating GenAI artefact usage. One key finding of our study is that among the top five enablers, it is the "policy initiatives at the government level" that drive the other four enablers: "GenAI training for rural teachers and students," "GenAI awareness among rural communities," "GenAI training programs for rural families," and "leadership commitment at school level." In addition, we developed an empirical framework to illustrate the most influential relationships among the enablers. Our novel research advances the understanding of socio-technical theory and contributes to the IS literature by uncovering the enablers of GenAI artefacts. Our study also offers practical implications for relevant stakeholders to leverage the potential of GenAI artefacts in supporting rural education.

Keywords: Generative AI, Rural, Education, Digital Divide, Interviews, Socio-technical Theory.

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This manuscript underwent [editorial/peer] review. It was received xx/xx/20xx and was with the authors for XX months for XX revisions. [firstname lastname] served as Associate Editor.] **or** The Associate Editor chose to remain anonymous.]

1 Introduction

The recent advancements and breakthroughs in machine learning (ML) have led to the development of more sophisticated technologies for digital content creation, such as generative AI (GenAI) platforms (Baidoo-Anu & Ansah, 2023). While most AI systems possess predictive capabilities, such as classifiers discerning between images, GenAI systems can craft entirely new images, texts, videos, and other multimedia content. This innovation in technological creativity represents a game-changing advancement (Gartner, 2023). GenAI is unique in its data generation capability, enabling it to create new information instead of merely analyzing pre-existing data. It captures the complexities of human language patterns and can be used for intricate tasks such as summarising text, translating languages, and building dialogue systems (Ooi et al., 2023). Since the advent of ChatGPT 3.0 in November 2022, people have become aware of the vast potential of GenAI and large language models (LLMs) (Pan et al., 2023). In recent years, significant and swift progress has been made in GenAI, such as ChatGPT, GPT-4, BARD, and Claude (Ooi et al., 2023; Dwivedi et al., 2023; Sætra, 2023). These rapid developments have prompted researchers to study the role of GenAI in various areas such as e-government, marketing, human resources, healthcare, manufacturing, tourism, supply chain, academics, and others (Gartner, 2023; Dwivedi et al., 2023; Kshetri et al., 2024; Wamba et al., 2023; Shin & Kang, 2023; Peres et al., 2023; Koc et al., 2023).

GenAI platforms might help enhance educational and learning experiences at all levels, including primary, secondary, higher education, and professional development (Kasneci et al., 2023). These platforms are gaining attention in the education sector for their vast array of potential applications, such as creative writing, asynchronous learning, critical analysis of academic works, personalized and individualized support, interactive learning, adaptive learning, and others (Baidoo-Anu & Ansah, 2023; Ahmad et al., 2023). Notably, GenAI benefits are likely to be more pronounced in the case of rural and marginalized communities of a developing country, such as India. For example, despite the substantial strides taken to enhance the educational system in India, several rural education challenges persist, such as weak socio-economic conditions, lack of good schooling, lack of educational resources, and other infrastructure, creating an unconducive learning environment (Cry, 2024). By bridging the digital divide, GenAI platforms might offer innovative solutions to these challenges, accelerating progress toward attaining the United Nations (UN) Sustainable Development Goal (SDG) 4, which ensure inclusive and equitable quality education and promote lifelong learning opportunities for all (Watson et al., 2021; UNESCO, 2023; Schoormann et al., 2023; Saba et al., 2024; Dwivedi et al., 2023). Specifically, GenAI's potential to generate adaptive learning material to support students from under-resourced rural schools to technically advanced urban institutions aligns with the educational equity vision underpinning UN SDG 4.

The rapid proliferation of GenAI platforms has exponentially accelerated data generation and processing, thereby concentrating AI deployment in the Global North (UNESCO, 2023). This impact can be noticed in the GenAI global market size, which is projected to reach 36.06 billion USD in 2024 and is expected to reach a market volume of 356.10 billion USD by 2030 (Statista, 2024). The possibility of creating and running their own GenAI models seems far-fetched for most firms and countries, particularly in the Global South. Therefore, most firms adapt customized GenAI solutions for their business needs, contributing to GenAI market growth. For example, India's GenAI market is expected to surpass 6.28 billion USD by 2030 from 0.64 billion USD in 2024 (Statista, 2024). The potential benefits of GenAI have primarily been explored and realized in developed regions. In contrast, there has been a lack of focus on exploring and realizing GenAI's potential to address the challenges of developing regions, for example, GenAI's ability to compensate for insufficiencies in infrastructure, technological access, and other challenges (Mannuru et al., 2023). We address this research gap in the context of rural education in developing regions. In this research, we aim to study the following research question*: **"How can we leverage GenAI artefacts to address education-related challenges faced by rural and marginalized communities?"***

In this study, we define GenAI artefacts as a contextual refinement of the broader concept of information systems (IS) artefacts, which are dynamic, mediating structures that influence and are influenced by organizational and institutional practices (Orlikowski & Iacono, 2001; Livari, 2017). In addition, Lee et al. (2015) describe an IS artefact as a system 'consisting of subsystems that are (1) a technology artefact, (2) an information artefact and (3) a social artefact, where the whole (the IS artefact) is greater than the sum of its parts (the three constituent artefacts as subsystems)' (p. 6).

The potential of GenAI artefacts in education, particularly in higher education (Rudolph et al., 2023; Lim et al., 2023; Yusuf et al., 2024), and their use in research work has been discussed in past studies (Pan et al., 2023; Susarla et al., 2023; Niszczota & Conway, 2023; Fui-Hoon Nah et al., 2023). In addition, few researchers have studied the impact of GenAI artefacts like ChatGPT and other LLM artefacts in school educational settings (Baidoo-Anu & Ansah, 2023; Tlili et al., 2023; Yan et al., 2024; Murugesan & Cherukuri, 2023). However, to our understanding, no work has focused on the role of GenAI artefacts in rural educational settings, particularly for marginalized communities in developing countries.

In this research, we pursue the following research objectives:

RO1: To explore the role of GenAI artefacts in addressing rural education challenges in a developing country context.

RO2: To identify the enablers of GenAI artefacts' use and adoption for education by marginalized rural communities.

RO3: To analyze the cause-effect linkages among the GenAI enablers for deeper insights into rural education in developing countries.

In this study, we consider India as a suitable setting for our research due to the following reasons: first, it provides a developing country setting with a projected population of more than 1.43 billion, the most significant population of whom, i.e., over 909 million, live in rural regions (World Bank, 2023). Second, according to the report 2021-22 (UDISE, 2023), out of a total of 14.68 lakh schools in India, rural India is home to approximately 12.34 lakh schools, highlighting the significant concentration (82.9%) of schools in rural areas. Finally, education in rural India has several formidable challenges, including a lack of infrastructure, poor socio-economic conditions, inadequate resources, less experienced teachers, poor quality education, and other issues (ASER, 2023).

We employed a mixed-method approach to study the research objectives, combining in-depth interviews (qualitative method) and the grey DEMATEL technique (quantitative method). In-depth interviews helped us to achieve a comprehensive and profound understanding of the enablers responsible for facilitating GenAI usage in rural education, whereas the multi-criteria decision-making (MCDM) technique, grey DEMATEL, is appropriate for finding causal relationships among GenAI enablers. In addition, our study offers profound insights into the phenomena by understanding enablers through the lens of socio-technical theory (STT) for contemporary GenAI in educational settings. Consequently, our research provides valuable insights for multiple stakeholders, such as scholars, practitioners, and policymakers, on the key aspects of GenAI enablers for rural education in developing countries.

Following the introduction, the remaining paper is organized as follows. Section 2 reviews the literature to identify GenAI enablers for rural education in developing countries and underscores the research gap of this study. Section 3 presents the methodology, which includes a mixed-method approach. Section 4 represents the results and analysis. Section 5 provides a discussion of the findings. In Section 6, theoretical and practical implications are provided. Section 7 provides the conclusion, and finally, Section 8 presents the limitations and future research directions.

2 Literature Review

2.1 Overview of GenAI

GenAI refers to a technological paradigm leveraging the capabilities of ML and deep learning (DL) models to generate new data samples that mimic the characteristics of existing massive training datasets (Lim et al., 2023; Laine et al., 2025). It is driven by complex, multifaceted prompts formulated in natural languages, specific instructions, or open-ended questions used to translate texts, generate images, video, and audio, and create synthetic data (Susarla et al., 2023; Ali et al., 2024). The evolution of GenAI reflects a significant leap from early computational models like the Turing test for assessing AI intelligence to modern neural architectures (Kaplan & Haenlein, 2024). GenAI includes a variety of techniques like Generative Adversarial Networks, Generative Pre-trained Transformers (GPT), Generative Diffusion Models, Geometric DL, and Variational Autoencoder (Laine et al., 2025).

LLMs represent a step forward in natural language processing and serve as a lingua franca among GenAI research subfields (Alier et al., 2024). These pre-trained models utilize neural network architectures like transformers (Benbya et al., 2024) to capture long-range dependencies and effectively model global context. LLMs can perform zero-shot learning, providing direct answers, or one-shot/multishot learning (Kojima et al., 2022). Prominent examples of LLMs include BERT, T5, and the GPT family, such as GPT3 and GPT4 (Delen et al., 2024). ChatGPT is a widely recognized LLM that uses generative and conversational AI to produce human-like text in response to diverse inputs (Dwivedi et al., 2023). Specifically, ChatGPT is built upon the GPT-3.5-Turbo architecture, a 175 billion-parameter model capable of processing 4,096 tokens (approximately 2,500 words) of context (Alier et al., 2024). Recently, Deepseek has disrupted the GenAI chatbots with the latest model, R1-Zero, outperforming GPT-4o and Claude-3.5-Sonnet (Guo et al., 2025). DeepSeek-R1 is a reasoning model developed using a multi-stage training pipeline incorporating reinforcement learning and supervised fine-tuning (SFT). The model is based on DeepSeek-V3-Base and is trained with a small amount of cold-start data. With 37 billion activated parameters and 671 billion total parameters, it represents a significant advancement in generative and reasoning capabilities, redefining the state-of-the-art in GenAI (Guo et al., 2025).

Recent studies show GenAI's profound applications spanning diverse domains like e-government services, education, marketing, human resources, finance, art, entertainment, healthcare, manufacturing, tourism, service industries, and others (Dwivedi et al., 2023; Wamba et al., 2023; Shin & Kang, 2023; Carayannis et al., 2024). Specifically, GenAI has revolutionized the content creation writing by collating with recent ML and DL algorithms and exploring new creative artistic horizons (Feuerriegel et al., 2024). In healthcare, GenAI has demonstrated tremendous potential in precision medicine, drug discovery, and personalized treatment plans. It also facilitates the identification of patterns in complex datasets, which leads to targeted therapies for complex diseases (Gartner, 2023; Chan & Hu, 2023). In the business domain, GenAI toolkits, such as ChatGPT, transform customer service by providing real-time, personalized interactions (Lim et al., 2023). GenAI leverages natural language processing, predictive analytics, and algorithmic trading, enabling enhanced customer experiences, optimized investment portfolios, and churning out more profits for businesses (Korzynski et al., 2023; Forner & Ozcan, 2023).

While GenAI has emerged as a transformative tool in educational settings, it presents significant challenges that require careful deliberation. GenAI artefacts, including LLMs like ChatGPT, have been increasingly integrated into higher education and scholarly work, demonstrating their potential to enhance learning and research (Pan et al., 2023; Rudolph et al., 2023; Lim et al., 2023; Susarla et al., 2023). Moreover, these models summarise complex academic content, making scholarly knowledge more accessible to students and researchers (Castillo-González et al., 2022). For instance, ChatGPT can distil intricate research into concise summaries, enabling students to engage with advanced material more effectively, while its ability to generate tailored educational content supports personalized learning, improving student engagement and comprehension (Baidoo-Anu & Ansah, 2023). These capabilities are particularly valuable in resource-limited settings (Zhai, 2022). Despite its potential, GenAI has certain limitations, such as hallucinations, factual inaccuracies, algorithmic bias, and others (Yan et al., 2024). These platforms may generate factually inaccurate text, often hallucinating, pose risks to their reliability, and potentially mislead educators and students (Yan et al., 2024; Bang et al., 2023; Sadeghpour et al., 2025). Additionally, algorithmic bias from training data can also produce inequitable content, while repetition and unintentional plagiarism raise concerns about originality (Bang et al., 2023; Ng et al., 2021). Ethical issues, including transparency gaps and privacy risks, further complicate its use, alongside challenges to traditional assessment methods as AI-augmented cognition blurs evaluation lines (Augenstein et al., 2024; Stokel-Walker & Van Noorden, 2023). Nevertheless, ChatGPT's potential in underserved rural contexts is promising yet understudied, where it could address resource shortages and teacher deficits by providing scalable, localized solutions (Baidoo-Anu & Ansah, 2023; Zhai, 2022; Pan et al., 2023). Thus, our study delves deeper into the GenAI enablers for rural education in developing countries to bridge the educational gap. Furthermore, the risks associated with the use of GenAI, such as hallucination, algorithmic bias, privacy concerns, and challenges in assessment, tend to be amplified in rural school settings due to lower levels of digital literacy, lack of awareness, limited access to reliable technological infrastructure, and ubiquitous language barriers. In addition, the absence of sustained technical support and capacity-building programs exacerbates students' and teachers' vulnerability to misinformation and misuse. Solutions that build trust (robust privacy and security), promote inclusiveness (localized language support) (Rao & Dixit, 2022), and empower rural teachers and students (providing comprehensive training) need to be put in place to mitigate risk and enable teachers and students to participate in GenAI-enabled education.

2.2 GenAI in Education

GenAI has shown tremendous potential in reforming education by offering advanced text-generation capabilities and problem-solving skills, significantly enhancing learning experiences and knowledge gaining (Dwivedi et al., 2023). GenAI tools like ChatGPT have assisted students with reading, writing, information analysis, and research skills, but cannot fully replace human interaction in learning (Shoufan, 2023). In higher education, the GenAI tools have assisted student learning, fostered personalization and timely feedback, enhanced engagement, and delivered targeted support (Liu et al., 2023; Van Dis et al., 2023). These models are employed for lesson planning, interactive chat-based teacher training, and student assessment (Ahmad et al., 2023). Few models, like DALL-E and Stable Diffusion, can support teaching technical and artistic concepts (Dehouche & Dehouche, 2023). GenAI's potential to enhance student learning is significant, like ChatGPT, and it can assist students, especially non-native speakers, with brainstorming and writing feedback (Atlas, 2023). However, the adoption of GenAI in school education, particularly in rural settings, remains understudied (see Table 1).

Table 1. Existing Research into the Use and Adoption of GenAI Artefacts in School Educational Settings

Author	**Methodology**	**Qualitative**	**Survey**	**Quanti-tative**	**Mixed method**	**Rural research settings**	**Theoretical lens**	**Country settings**	**Time frame of study**
Kasneci et al., 2023	Commentary paper	×	×	×	×	×	Educational theory	Study Context	×
Chiu, 2023	Survey	✓	✓	×	×	×	×	China	×
Su et al., 2023	PRISMA - review	×	×	×	×	×	× (Knowledge and theory of mind skills Assessment)	×	×
Liu et al., 2023	Commentary paper	×	×	×	×	×	×	China	×
Han et al., 2024	Interviews	✓	×	×	×	×	×	USA	April 2023
Tlili et al., 2023	Qualitative case study approach	✓	×	×	✓	×	Social exchange theory	China	×
Maulidati & Abbott, 2024	Semi-structured interviews	✓	×	×	×	×	(Postpheno-menology)	Indonesia	×
Hönigsberg et al., 2025	Case study	✓	×	×	×	×	Technology-mediated learning theory	France	2023-24
Rudolph et al., 2023	Commentary paper - review	✓	×	×	×	×	×	×	×
Our Study	**In-depth Interview + MCDM**	✓	×	✓	✓	✓	**Socio-technical theory (STT)**	**Developing country (India)**	**2023-24**

The adoption of GenAI in education presents several challenges, including copyright concerns, algorithmic bias, misinformation and disinformation, excessive reliance, lack of teacher expertise, difficulty distinguishing AI-generated content, cost considerations, data privacy issues, and sustainability (Dwivedi et al., 2023). While ChatGPT may have limitations in certain areas, such as stoichiometry, its overall utility in supporting student learning is undeniable (Ahmad et al., 2023). International regulatory bodies have addressed potential benefits and concerns surrounding GenAI in education. For example, UNESCO (2023) provides a global guidance framework for multiple stakeholders like governments, AI systems and services providers, institutional users, and individual users. In addition, UNESCO (2024a) has provided an AI competency framework for teachers, which outlines fifteen competencies across five dimensions and has been categorized into three progression levels: acquire, deepen, and create. In addition, UNESCO (2024b) also provided an AI competency framework for students, which outlines twelve competencies across four domains and has been categorized into three progression levels: understand, apply, and create.

Extant literature shows that GenAI studies challenges and limitations in school education have been sparsely studied (Kasneci et al., 2023; Chiu, 2023; Su et al., 2023; Liu et al., 2023; Han et al., 2024). Chiu (2023) investigated how GenAI changes school education from teachers' and leaders' perspectives, focusing on student learning, teaching, assessment, and administration. Liu et al. (2023) proposed a conceptual framework incorporating stakeholders such as administrators, developers, teachers, and students involved in applying GenAI in schools. Han et al. (2024) further highlight the potential benefits of GenAI in creating adaptable teaching resources, fostering creative thinking, and delivering personalized feedback to students. However, concerns persist regarding authorship, student autonomy, and the risks of bias or misinformation in AI-generated content. However, a notable gap in the literature concerning its usage in rural educational settings remains. Thus, the novelty of our study lies in exploring the enablers responsible for facilitating the use of GenAI artefacts to improve the quality of education among rural schools. Table T1 (see supplementary sheet) lists 9 GenAI enablers for rural educational settings in developing countries, identified through a comprehensive literature review.

2.3 GenAI in Rural Educational Settings Through the Lens of Socio-technical Theory (STT)

GenAI enablers in rural educational settings should not be viewed solely through a technological lens. Instead, GenAI enablers should be viewed through a socio-technical lens, as how marginalized people engage with GenAI artefacts is especially important. Therefore, we utilized STT (Bostrom & Heinen, 1977) as a theoretical lens to classify and better understand the GenAI artefacts enablers in rural educational settings, especially in the context of developing countries.

According to STT, an IS consists of a technical subsystem, which integrates the processes, tasks, and technological elements required for its operation, and a social subsystem, dealing with the organizational structure, workforce, and their competencies, attitudes, and interpersonal dynamics (Bostrom & Heinen, 1977), refer in Figure 1.

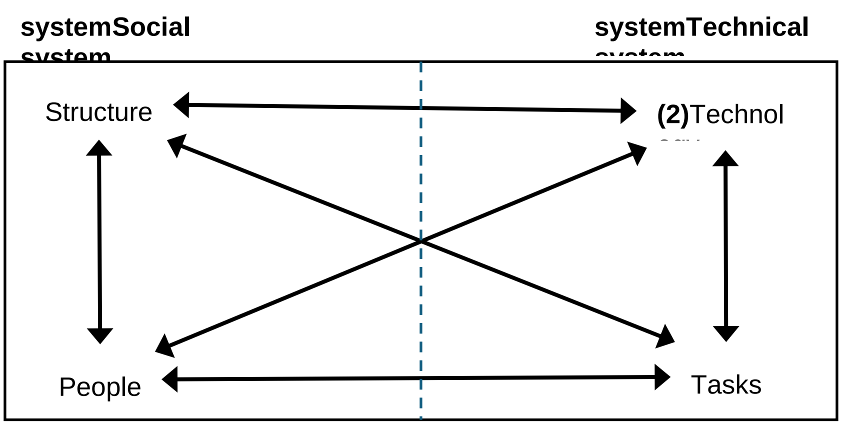


Figure 1. STT Framework (Adapted from Bostrom and Heinen (1977))

Through the theoretical lens of STT, on the one side, people in the social subsystem of an IS are defined as individuals or groups within the organizational context who "have a vested interest or can define requirements for the organization", such as employees, managers, users, customers, subcontractors, and suppliers (Srivastava & Dixit, 2023). On the other hand, the social system's structure is characterized by institutional frameworks, like formal work organization, communication, and authority hierarchies, as well as overarching values, norms, role expectations, and behavioral norms (Oesterreich & Teuteberg, 2019). The technology component within the technical subsystem incorporates the necessary software and hardware, along with the infrastructure, methods, and tools needed to support the implementation process. The second component of the technical subsystem comprises the tasks that fulfill organizational goals, objectives, and stakeholder requirements (Oesterreich & Teuteberg, 2019). Given the assumption that both subsystems interact, joint optimization is fundamental for addressing the issues of IS adoption (Bostrom & Heinen, 1977).

Previous studies have validated STT in diverse contexts, including IT, AI adoption, and big data practices (Oesterreich & Teuteberg, 2019; Srivastava & Dixit, 2023; Kus et al., 2022). Oesterreich and Teuteberg (2019) used STT to examine the barriers to Building Information Modelling adoption within the Architecture, Engineering, and Construction industry, viewing it as an Inter-Organizational IS and emphasizing the interplay between technical and social subsystems. Further, Kus et al. (2022) employ STT to analyze the challenges and varying adoption rates of AI in healthcare between Germany and China, emphasizing the interplay between social and technical subsystems within national healthcare sectors. Further, Srivastava and Dixit (2023) employed STT to investigate the factors influencing the post-adoption utilization of AI and big data technologies within the specific context of developing nations. Through the theoretical lens of STT, we attempt to deepen our understanding to uncover the enablers of GenAI artefact usage among marginalized rural users for educational settings.

3 Research Methodology

This study employs a mixed-methods approach, incorporating in-depth interviews and MCDM methods, like the DEMATEL technique, to determine GenAI enablers for rural education in developing countries. The mixed-method approach integrates qualitative and quantitative techniques within a single research inquiry and has profound insights through rich narratives and a comprehensive understanding of extensive datasets (Venkatesh et al., 2013). This approach is deemed suitable for our study for several reasons: identifying the GenAI enablers for rural education in developing countries is a multifaceted and complex phenomenon that may not be adequately captured by a single method alone. A mixed-method approach utilizes two or more methods to discern diverse perspectives on the same phenomenon, which renders additional insights and enhances the validity of results through triangulation from various evidence sources (Ye et al., 2021). Figure 2 illustrates the research framework employed in this study.

In this study, an in-depth interview is the crucial element of the mixed-methods research. Our study conducted an in-depth interview to uncover the key GenAI enablers for rural educational settings in developing countries, particularly India. The significant benefit of in-depth interviews is that they provide far more detailed information and deep insights than other data collection methods, such as surveys (Boyce & Neale, 2006). Subsequently, Grey-DEMATEL is used to find the causal relationship among the identified factors (Govindan, 2022). Our study employs Grey-DEMATEL to complement the in-depth interview findings, validate the narrative findings, and triangulate the explored GenAI enablers for rural educational settings in developing countries. The mixed-method approach provides a more detailed and precise depiction of incorporating GenAI artefacts in rural educational settings. These include uncovering novel enablers, evaluating the prominence among the enablers, and providing the causal relationship between the enablers still scarce in the extant literature.

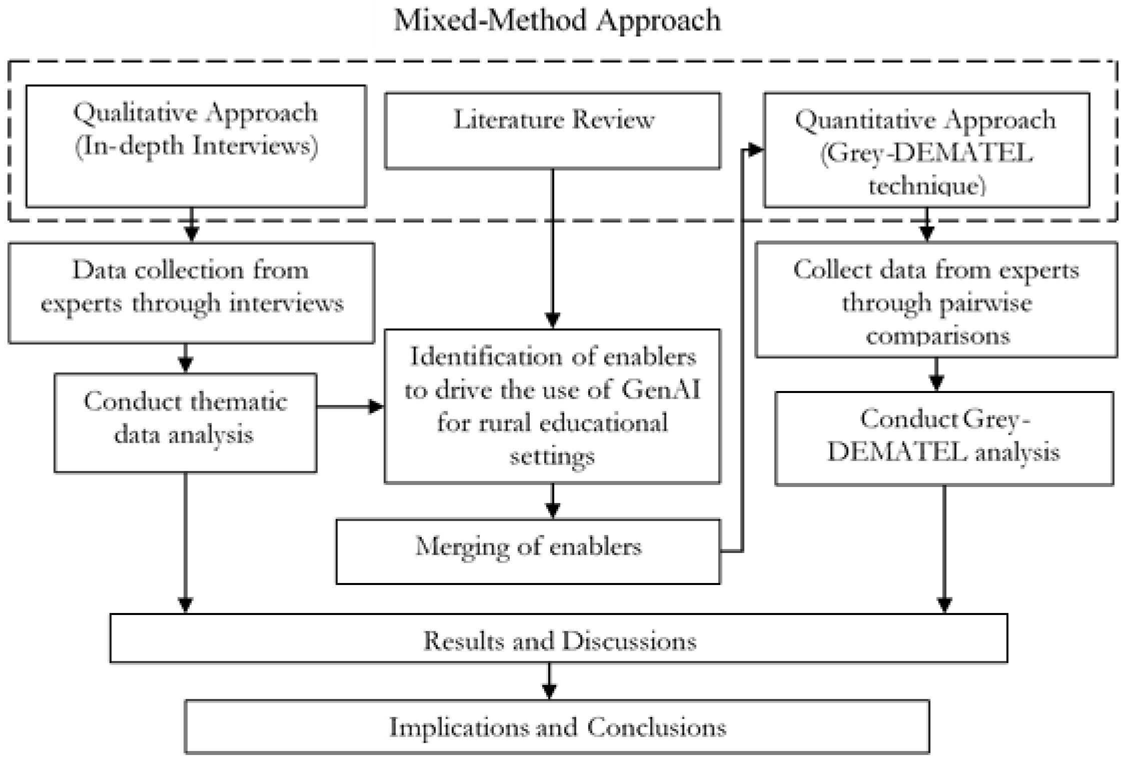


Figure 2. Research Framework (Author's own)

3.1 Data Collection and Respondent Selection

In this study, twelve respondents from diverse backgrounds were inducted to gain deep insights and improve the understanding of GenAI enablers for rural education in developing countries. The decision to include twelve respondents in this study was guided by principles of thematic saturation in qualitative research, wherein data collection continues until no new themes or insights emerge and no further change in the codebook (Guest et al., 2006). Prior studies in similar exploratory, interview-based research have demonstrated that data saturation is often achieved within six to twelve participants, particularly when the participant group is relatively homogenous concerning the research topic (Braun & Clarke, 2021; Constantinou et al., 2017; Guest et al., 2006). Moreover, we continuously assessed data saturation during the data collection process. No substantially new themes emerged by the seventh interview, confirming the saturation point, which affirms that the sample size was adequate for the depth and scope of this exploratory qualitative inquiry (Braun & Clarke, 2021).

The demographic profile of the participants is shown in Table T2 (see supplementary sheet). While India is characterized by profound socio-cultural diversity, this study focuses on a specific rural educational context within a delineated geographic and linguistic region. The data collection phase was held from November 2023 to April 2024 in Uttarakhand, India's mountain and plain regions. Uttarakhand was chosen as an ideal setting due to its geographical location in the Himalayan Mountain ranges and socio-economic characteristics, which provide a representative context for understanding the challenges of integrating GenAI into rural education (Government of Uttarakhand, n.d.). The state encompasses remote mountainous regions. Even within the plain areas, some parts are relatively less accessible plains, offering a diverse perspective on digital adoption and infrastructural constraints. We employed purposive sampling for respondent selection. In addition, a chain referral was also used to include more respondents for our research (Iong & Phillips, 2023). This technique is prone to homophily bias, where participants may nominate peers with similar backgrounds (Platt et al., 2015). To address this issue, participants were included in the study only if they enhanced diversity in at least one aspect, such as role, experience, gender, or location (Iong & Phillips, 2023). Consequently, exclusion criteria were employed to prevent network bias and ensure that referred individuals genuinely belong to the target population. Exclusion criteria included under investigation are: (i) lack of direct engagement with the digital platforms, (ii) duplicate nominations, and (iii) referrals that did not extend diversity. In addition, to ensure sample heterogeneity, only one respondent was accepted from each referrer. This screening procedure safeguards against any single group exerting disproportionate influence on our respondents' dataset. Individuals and organizations were guaranteed confidentiality and anonymity to maintain our study's ethical code of conduct. We used purposive and chain-referral sampling to align with our study's exploratory and context-specific nature, which sought to understand the nuanced experiences and perceptions of individuals engaging with rural educational settings. This localized approach ensured contextual coherence while capturing meaningful variation across socio-economic status, gender, educational background, and levels of digital literacy. Further, purposive sampling enables the intended selection of participants with rich and first-hand expertise relevant to the research objective. This approach facilitates the collection of contextually pertinent and analytically rich data, aligning with the qualitative emphasis on depth over breadth (Iong & Phillips, 2023).

The data was analyzed using a thematic analysis technique, which enables the identification of patterns within large, intricate data sets. Using the Gioia method (Gioia et al., 2013), we conducted thematic content analysis to identify the enablers responsible for facilitating the use of GenAI artefacts to improve the quality of education among rural schools. The thematic analysis was executed by a panel of three members, consisting of one professor and two research scholars, who extracted themes from the interview responses and categorized them accordingly. Subsequently, as exemplified by Sjodin et al. (2021), we employed a three-stage approach (see Table 2) and aggregated dimensions were generated to represent a higher level of coding abstraction.

3.2 In-depth Interviews

An in-depth interview is a qualitative approach that requires intensive individual interviews with respondents to delve into their perspectives on a specific idea, program, or context (Boyce & Neale, 2006). This approach is highly diverse, intricate, and nuanced, and thematic analysis is regarded as a fundamental method for qualitative analysis (Braun & Clarke, 2006). In this study, we employ thematic analysis to identify, analyze, and report themes, transcribing the collected data to gain valuable insights into GenAI usage in rural educational settings in developing countries. In this study, we obtained data by interviewing twelve experts from diverse backgrounds, such as teachers, professionals, and government executives looking after rural educational activities, encompassing theoretical insights and real-world applications within the industry and academia. The participants were carefully chosen to ensure a representative sample, capturing various experiences and viewpoints.

The respondents were interviewed using open-ended questions with the help of an interview guide (as provided in the supplementary sheet). For example, respondents were encouraged to contemplate questions such as: What are the challenges in the rural education systems? How can GenAI facilitate the rural education system? Further questions were used to clarify points and obtain additional details, enabling a more in-depth exploration of this study. The interview schedule was meticulously planned and executed, allowing for detailed and nuanced discussions. Each interview lasted 60-120 minutes and was conducted in person at their respective offices or via telephonic conversations. Each interview was recorded and transcribed, and these transcripts served as the basis for the data analysis. All the interviews were conducted in English and Hindi to gain better insights. Next, aggregate dimensions were established by classifying the factors through zero-order and first-order codes (see Table 2). Finally, we triangulated our data using different methodological techniques (Ye et al., 2021). The operational definitions of GenAI artefact enablers are mentioned in Table 3.

Table 2. Classification of zero-order, first-order, and second-order codes

Zero-order codes (Excerpts from in-depth interviews)	First-order themes	Second-order (Aggregate dimensions: Enablers)
• Arranging money for the Internet is difficult • Poor socio-economic conditions • The cost of internet data is high • Data needs to be affordable • Price of data needs to be low	Monetary issues High Cost Affordability concern Low price	Affordable Internet data
• Poor network quality in remote areas • Weak networks create discouragement • For better network need to pay more • Network needs to be affordable	Better network costs more High cost for better network Affordability concern	Affordable telecommunication network

• Providing affordable devices for the underserved communities • High upfront costs of devices • Affordable devices need to be access GenAI artefacts • Subsidized devices fosters community participation	Device cost is prohibitively high Rural users cannot afford Lower income Cost barrier	Providing subsidized devices among lower-income groups
• Equal access to technology regardless of socio-economic background • A common space to learn under supervision • Collaborative learning environment • Ease of accessibility will be through labs • Shared resource environment	Poor economic conditions can't afford devices Enable familiarity with technology Ensuring basic digital knowledge	Availability of computer labs in schools
• Don't know about the present trend in technology • Less understanding of digital landscapes • Lower level of literacy • Lack of exposure to digital things due to geographical isolation	Not aware of digital things No idea about digital landscapes	GenAI awareness among rural communities
• To better understand the responsible and ethical implications (such as bias, privacy, misinformation and others) of GenAI artefacts • Training required to leverage the potential of GenAI • To Equip with prompt skills for better results • Lack of digital literacy	Knowledge dissemination of GenAI Capacity building	GenAI training for rural teachers and students
• Ensuring to address local challenges, i.e., education, agriculture, healthcare, and others • To Develop a basic idea about GenAI • Equipping rural citizens with essential GenAI skills • Enabling rural families to guide their children safely	Understanding of GenAI Promoting digital skills	GenAI training programs for rural families
• Gaining knowledge through family, friends and relatives • Developing GenAI knowledge through community outreach initiatives • Utilizing GenAI knowledge through peers	Receiving GenAI knowledge through peers Sharing of GenAI knowledge through community outreach	Social Influence of GenAI artefacts
• Identifying lag or error to avoid technical glitches • Updating software and antivirus tools to protect from malware or cyberattacks • Ensuring technical support • Maintenance of devices to ensure seamless user experience	Ensuring Support Maintenance activities	Technical support and maintenance of computer devices for using GenAI artefacts
• Reducing the learning curve through simple and intuitive interfaces • Ease of use • Technological self-efficacy • Reducing dependence on external assistance • Empowering rural users to thrive and explore more without anxiety	Simple and easy to use Satisfaction Foster confidence	GenAI artefacts' ease of use
• Removing language barriers • Easily understandable language • Enhancing learning experience through local language • Lower the intimidation factor among rural users	Localized language support Language barrier	Localized language support in GenAI artefacts
• Expanding infrastructure to rural areas • Funding for training programs • Providing resources to underserved communities • Seeking collaboration to secure funding • Ensuring funds for smooth operations • Investment in capacity building	Funding technological capabilities Investment to encourage GenAI usage	Financial Support for GenAI initiatives, i.e., Public & private enterprises
• Building Trust towards GenAI artefact usage • Awareness regarding ethical usage • Awareness regarding responsible usage • Required regulation to mitigate biases	Data security Data privacy Regulations for GenAI	Data Privacy and Security Regulations for

• Safeguarding data security and privacy of rural users		GenAI
• Establish a clear vision • Setting goals and allocating resources • Advocating for infrastructure development • Encouraging inclusivity and equity • Ensuring the ethical use of GenAI • Strategic implementation	Facilitate funding Creating conducive environment Encouraging stakeholders	Leadership commitment at the school level

Table 3. Operational Definitions and STT Impact Level of GenAI Artefacts Enablers

Enabler Code	STT Impact Level	Enablers (GenAI artefacts)	Descriptions	References
E1	Structure	Affordable Internet data	It refers to the requirement of affordable internet data plans among rural communities to effectively leverage GenAI artefacts to transform the learning experience.	Experts Opinion
E2	Structure	Affordable telecommunication network (4G/5G)	It refers to providing cost-effective network quality for rural stakeholders to access the Internet to improve the educational experience through seamless GenAI access.	Experts Opinion
E3	People	Providing subsidized devices among lower-income groups	It refers to providing subsidized digital devices to economically disadvantaged students and their families, enabling them to access the GenAI artefacts in their respective residences for 24*7 accessibility, which in turn bridges the digital divide among rural communities.	Experts Opinion (In-depth Interview)
E4	Structure	Availability of computer labs in schools	It refers to providing digital devices such as PCs, smartphones, and laptops at rural schools, ensuring they have reliable access to educational software, internet resources, and other digital tools necessary for GenAI usage.	Adapted from Education.Gov.in, 2020
E5	People	GenAI awareness among rural communities	It involves disseminating knowledge through (Wall painting/radio/posters/ newspapers/ text messages/ social media) regarding the usage of GenAI among rural stakeholders.	Experts Opinion
E6	People	GenAI training for rural teachers and students	It refers to the process of educating and developing the skills of teachers and students with the help of NGO/ Self-help groups /CSR to make them understand and work with GenAI artefacts effectively.	Adapted from Kasneci et al., 2023; Liu et al., 2023
E7	People	GenAI training programs for rural families	It refers to imparting digital literacy among rural families to achieve technological self-efficacy and be competent enough to leverage GenAI.	Adapted Chiu et al., 2023
E8	People	Social influence of GenAI artefacts	It refers to how people become more aware of and inclined to use GenAI artefacts when they are being made familiar with and influenced by family members or through social networks.	Experts Opinion
E9	Task	Technical support and maintenance of computer devices for	It refers to the comprehensive IT support to ensure effective computer deployment and maintenance for addressing rural challenges,	Adapted from Mannuru et al.,

		using GenAI artefacts	such as limited access to resources and technical expertise.	2023
E10	Technology	GenAI artefacts' ease of use	It refers that GenAI artefacts must be simple and intuitive for all stakeholders to operate seamlessly and effortlessly.	Adapted from Wael Al-khatib et al., 2023; Gupta et al., 2024
E11	Technology	Localized language support in GenAI artefacts	It refers to providing a multilingual localized interface designed to operate in diverse regional languages, making GenAI artefacts more accessible to diverse populations.	Baidoo-Anu & Ansah, 2023
E12	Task	Financial support for GenAI initiatives	It refers to creating a cooperative environment that combines the unique capabilities of the public and private sectors, including private firms, NGOs, and other entities, to effectively implement and utilize GenAI in classrooms in rural settings.	Alier, 2024
E13	Structure	Data privacy and security regulations for GenAI	Data privacy ensures that users' data are handled carefully to protect individuals' privacy rights & data security ensures that sensitive information remains confidential and integral while protecting from unauthorized access, breaches, and misuse.	Dwivedi et al., 2023; Kasneci et al., 2023; Ali et al., 2024
E14	People	Leadership commitment at the school level	Leadership can enable a visionary and supportive GenAI environment by developing a clear strategy and creating a continuous learning environment that aligns with educational goals.	Experts Opinion
E15	Structure	Policy initiatives at the government level	It refers to introducing regulations ensuring GenAI tools used in education are unbiased, secure, and aligned with ethical standards while ensuring that students in remote areas receive the same quality of education as their urban counterparts.	Ooi et al., 2023; Dwivedi et al., 2023

3.3 Grey-DEMATEL Technique

In real-world situations, the inherent bias and ambiguity in the results are due to incomplete data and subjective human evaluations (Cui et al., 2019). Grey systems theory helps mitigate problems from incomplete information and human judgments in uncertain situations (Koley et al., 2025). Unlike other systems, the grey system's strength lies in its ability to produce possible outcomes using a small data set or when factors are substantially varied (Govindan, 2022). For example, prioritizing factors in a decision-making problem can be represented as linguistic variables expressed as numerical intervals that encompass uncertain information (Koley et al., 2025). While MCDM methods like AHP (Gupta et al., 2017), TOPSIS, or ANP effectively rank or prioritize alternatives, grey-DEMATEL uniquely prioritizes and provides causal relationships among enablers, distinguishing between cause-and-effect groups. Moreover, integrating grey systems theory allows DEMATEL to handle uncertainty and ambiguity in expert judgments (Govindan, 2022), which is particularly valuable in complex and data-scarce environments. Unlike other MCDM methods, grey-DEMATEL can address ambiguity and incomplete information, allowing for more nuanced and accurate assessments (Koley et al., 2025).

This MCDM approach effectively calculates the intricate interrelationship among complex factors and classifies all enablers into cause-and-effect groups by analyzing the visual relationships between levels within the system (Govindan, 2022; Kumar & Dixit, 2018). The DEMATEL technique seeks to determine the interrelationships between the elements of the systems through a causal interrelationship diagram. For example, previous studies utilized grey-DEMATEL in various sectors, including airlines, green business, ride-hailing services, and others (Chand et al., 2023; Cui et al., 2019; Koley et al., 2025). Our study employed grey theory jointly with the traditional DEMATEL process to effectively analyze the GenAI enablers for rural education in developing countries. The computational steps for applying the grey-DEMATEL technique are presented in the supplementary sheet (Page no. 4).

4 Result and Analysis

The enablers were uncovered through a literature review, and further, through in-depth interviews, a few novel enablers were explored. The enablers revealed through interviews are summarized in Table T3 (see supplementary sheet). The combined list of enablers identified through the literature review and uncovered through interviews is provided in Table 3. Aggregate dimensions were established by classifying the factors through zero-order and first-order codes. For example, the zero-order code from the interview excerpts, such as "The cost of internet data is high," is assigned to aggregated dimensions as "Affordable Internet data." Based on the STT framework (refer to section 3), we categorized the enablers based on their shared characteristic and according to the STT impact level (i.e., structure dimension, people dimension, technology dimension, and task dimension), thereby improving the understanding of GenAI enablers in rural educational settings. In line with the example above, the enabler "Affordable Internet data" is assigned to the 'structure' dimension of the STT framework, as it has relevance with structure and can be achieved through regulatory measures or government policies (Oesterreich & Teuteberg, 2019).

The identified enablers have been described separately under different subsystems (dimensions), as shown in Table 3. A significant benefit of using STT as a theoretical lens is its emphasis on the interplay and dynamic relationships across the two subsystems, i.e., social and technical subsystems. Thus, we provide insightful explanations from the IS domain, fostering a deeper understanding of the enablers and addressing the contemporary issues of the non-availability of GenAI artefacts in rural educational settings in developing countries such as India. Enablers of GenAI artefacts are grouped according to STT dimensions based on similar characteristics, as illustrated in Figure 3. Further, throughout this paper, we will refer to the respondents as R1, R2, etc.

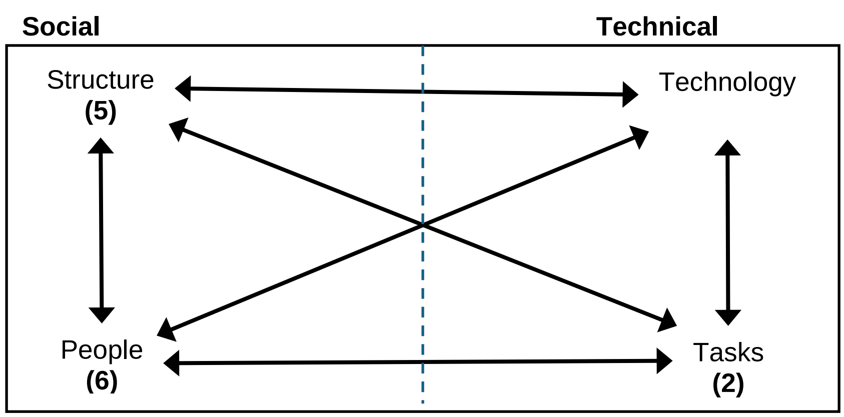


Figure 3. Enablers of GenAI Artefacts Grouped According to STT Dimensions Based on Similar Characteristics (Adapted from Bostrom and Heinen (1977))

4.1 Socio-Technical System

4.1.1 Social Subsystem (Structure Dimension)

Concerning the structural dimension of GenAI enablers, the enablers categorized within this group, based on their attributes, include affordable Internet data (E1), affordable telecommunication network (E2), availability of computer labs in schools (E4), data privacy and security regulations for GenAI (E13) and policy initiatives at the government level (E15). Our respondents elucidated how affordable internet data can overcome the barrier of costly subscriptions to internet plans. Rural communities in developing countries typically experience higher poverty rates, limiting families' ability to afford internet data. With limited income, purchasing internet data plans may not be a priority, as basic needs like food and shelter take precedence. In this regard, one of the school teachers commented: *"I work in a rural school in a mountain area as a middle school teacher […]. The socio-economic conditions of most of the students' families are in very poor financial conditions. Even where internet network access exists, the cost of internet data plans can be prohibitively high for them to afford as these families barely make ends meet due to their poor socio-economic conditions" (R1).* Further, our respondents have underscored that an affordable quality network is essential in rural areas, where income is seasonal or irregular, and households may not have the financial stability to commit to regular internet expenditures. This instability of financial resources makes it challenging to consistently afford better network (i.e., 3G/4G/5G) quality. For example, an NGO worker stated: *"In rural areas, even if the better internet network coverage is available, the cost is prohibitively high per their financial conditions. An affordable quality network will ensure that rural teachers and students can access these tools without financial hindrances. It ensures that cost barriers do not exclude marginalized groups, such as low-income families, from accessing better internet networks for GenAI-enabled education" (R10).*

Due to the poor socio-economic background of rural students, they lack personal devices or internet access at home. Our respondent (Deputy Asst. Superintendent) has highlighted*: "The availability of computer labs in rural schools is essential for the effective use of GenAI in education among rural teachers and students. Due to their poor socio-economic conditions, rural students hardly have any digital devices at home, which makes them unfamiliar with digital efficacies and the potential of GenAI. A well-equipped computer lab ensures equal learning opportunities for all students, regardless of socio-economic conditions" (R4).*

Data security and privacy emerged as the most frequently highlighted themes across studies examining the implementation and use of GenAI in educational settings. Earlier scholars have raised concerns about the technological challenges of data security and privacy issues in using GenAI in educational settings (Dwivedi et al., 2023; Kasneci et al., 2023; Ali et al., 2024). One of the respondents (IT officer) emphasized: *"In rural areas, where digital literacy is limited, the risk of data breaches, cyber-attacks, and unauthorized access of users' (i.e., teachers and students) and institutional data is heightened. Data security and privacy measures are essential for gaining the trust of teachers, students, and policymakers in rural areas, particularly in communities where scepticism toward digital technologies may exist due to limited exposure or awareness. This measure safeguards students and institutions from possible harm, such as identity theft or unauthorized data sharing" (R7).*

Our respondents (Private organization executives) brought attention to the fact that policy initiatives are indispensable for the successful use and adoption of GenAI in rural educational settings: *"Better policy initiatives can advocate the allocation of funding, infrastructure, and resources to underserved communities, ensuring that all students, regardless of their socio-economic conditions can benefit from GenAI-driven educational tools. Policy initiatives provide the regulatory, financial, and ethical frameworks to address challenges of rural settings, ensuring equitable access and fostering an enabling environment for inclusion of marginalized communities" (R11).*

4.1.2 Social Subsystem (People Dimension)

The GenAI enablers assigned to the people dimension relate to human factors such as knowledge, awareness, training, behaviour, and skills. The enablers, organized into this group according to their traits, are providing subsidized devices among lower-income groups (E3), GenAI awareness among rural communities (E5), GenAI training for rural teachers and students (E6), GenAI training programs for rural families (E7), social influence of GenAI artefacts (E8) and leadership commitment at the school level (E14). Our respondents (Deputy Asst. Superintendent) revealed that providing subsidized devices among lower-income groups is crucial due to their appalling socio-economic conditions*: "Individuals in rural regions typically confront a scarcity of financial resources, often living below the poverty line, which hinders them from affording digital devices for their children's education. To reduce the educational divide and promote equitable learning opportunities, governments must implement subsidy programs that provide rural users with equal access to digital devices, thereby improving educational outcomes in the contemporary AI era" (R9).*

In addition, the lack of awareness of GenAI among teachers and students in rural areas can be attributed to the absence of prior exposure and access to digital devices, poor socio-economic conditions, lower literacy levels, and insufficient teacher training (Fourie & Krauss, 2011). As one of the respondents (teacher) commented: *"Rural students, due to their poor socio-economic and socio-cultural conditions, spend most of their time on household chores and labour-intensive activities after school, specifically more on harvesting periods […] limiting their exposure to educational resources. Rural communities frequently grapple with socio-economic challenges, such as poverty and resource scarcity, which prioritize immediate needs over technological know-how. The targeted initiatives to promote the awareness of GenAI literacy in rural schools can contribute to filling this knowledge gap" (R2).*

GenAI training is essential among rural teachers and students to leverage the potential of GenAI-driven educational tools. It empowers rural educators with the skills to integrate AI into their teaching, enhances student engagement and learning outcomes, and promotes equity and inclusiveness. One of our respondents (Training Officer) commented: *"Rural teachers and students often lack exposure to advanced technologies like GenAI. Training equips them with the skills to operate GenAI tools and the knowledge to integrate these tools effectively into their teaching and pedagogical practices. Training ensures marginalized communities have the necessary skills to participate in the digital era and access quality education" (R8).*

Our interview findings uncovered that the social influence of GenAI artefacts by families, peers, and others is crucial in shaping trust and enabling effective GenAI usage among communities. Our respondent (rural school teacher) exemplified: *"I became aware of GenAI tools such as ChatGPT and Meta AI in WhatsApp through my daughter. She told me how to use these tools to get information about any topic […]. I have shared this information with my other colleagues, and now they are aware of it and are using it for a few of their teaching tasks. This hands-on, peer-to-peer guidance is often more apt and easier to understand GenAI artefacts" (R5).*

One of our respondents (teacher) highlighted that*: "the key enablers to introduce new initiatives, schemes, technologies, a strong commitment is required […] leaders such as principals, heads, and officials are often reluctant to induct new things at schools […]. Leaders need to support their subordinates at school and drive capacity building programs, securing funding and partnerships to provide the necessary resources" (R3).*

4.1.3 Technical Subsystem (Technology Dimension)

Concerning the GenAI enablers of technology dimension pertains to the technical components of a system, including hardware, software, and other IT artefacts. The enablers identified in this group include GenAI artefacts' ease of use (E10) and Localized language support in GenAI artefacts (E11). Our respondent (IT officer) suggested that the ease of use of GenAI artefacts may encourage widespread adoption among rural citizens, where technological apprehension is commonly linked to its complexities: "*Simple and intuitive interfaces ensure that technology is usable even to first-time or inexperienced users*" *(R7)*. Unsurprisingly, our respondent (teacher) underscored the importance of incorporating localized language support into the interfaces of GenAI artefacts: "*In developing countries, digital literacy is often limited in rural areas due to poor socio-economic conditions. In addition, the lack of proficiency in global languages, such as English, creates linguistic barriers for teachers and students. Localized language support is critical in addressing this issue by fostering greater inclusivity and accessibility*" *(R3)*.

4.1.4 Technical Subsystem (Task Dimension)

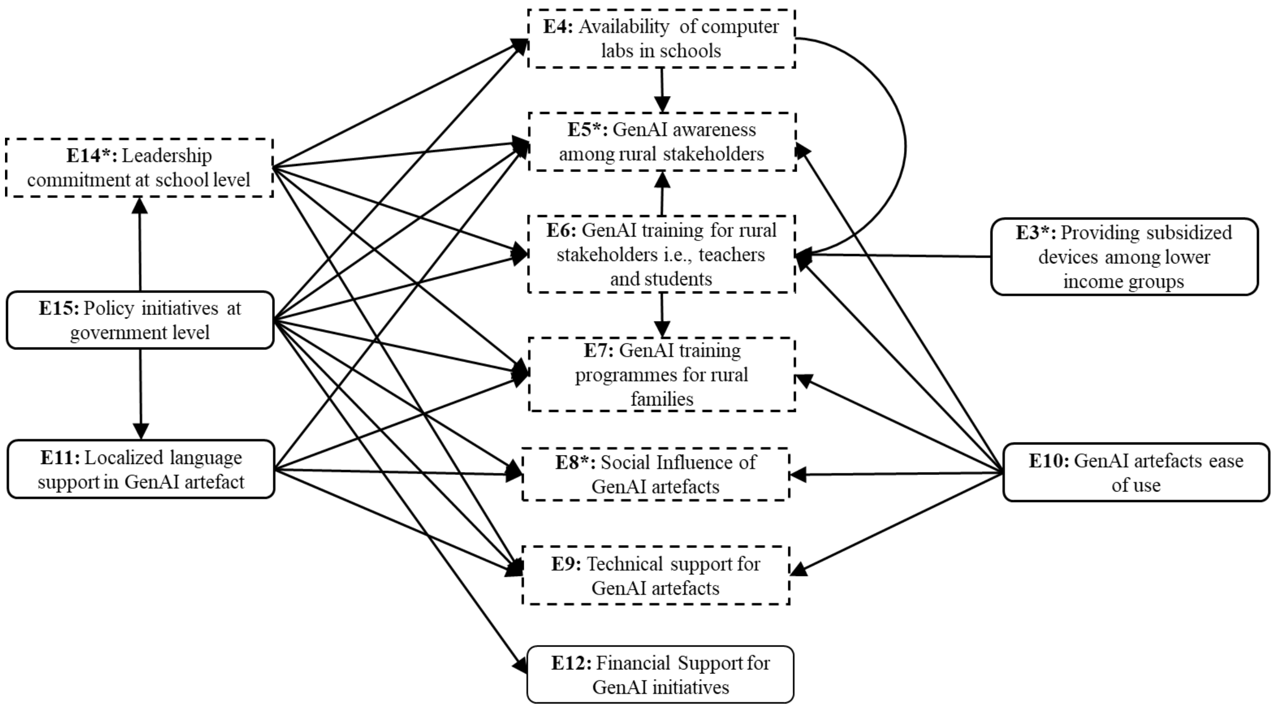
The task dimension within the technical subsystem focuses on achieving organizational goals, purposes, and stakeholder expectations. Thus, task-related enablers facilitate organizations using the GenAI artefact to achieve their goals. The enablers in this dimension are technical support and maintenance of computer devices for using GenAI artefacts(E9) and financial support for GenAI initiatives (E12). Our respondent (executive) informed us that the technical support and maintenance of computer devices for using GenAI artefacts are critical to overcoming infrastructure limitations: "*Owing to limited exposure to digital technologies, rural teachers often lack the necessary technical competencies to troubleshoot device-related issues. Ensuring the regular upkeep of essential digital tools and devices, including computers and internet connections, is crucial for their sustained functionality and uninterrupted learning experiences*" *(R12)*. Additionally, one of the respondents (Deputy Superintendent) indicated that: *"GenAI artefacts necessitate substantial financial investment to address numerous infrastructural, technological, and human resource challenges in resource-constrained environments. Beyond initial deployment of IT artefacts, it further necessitates technical support, training and capacity-building initiatives, and infrastructural maintenance to ensure the longevity and functionality of these tools*" (R6).

The results obtained through a quantitative approach, i.e., the grey DEMATEL technique, serve as a supplementary reinforcement to the qualitative findings for this study and are mentioned below.

4.2 Results of the Grey-DEMATEL Method

This study utilized the Grey-DEMATEL technique to find prominence (i.e., ranking among the enablers) and causal interrelationships among the enablers responsible for facilitating the use of GenAI for rural educational settings in developing countries. The enablers are prioritized according to the prominence values as follows: E15 > E6 > E5 > E7 > E14 > E8 > E12 > E10 > E9 > E11 > E4 > E3 > E13 > E1 > E2 (as shown in Table T8, Supplementary sheet). Based on positive relation values, eight enablers, namely E1, E2, E3, E10, E11, E12, E13, and E15, have been categorized under the cause group. Likewise, based on negative relation values, seven enablers, such as E4, E5, E6, E7, E8, E9, and E14, have been categorized under the effect group. In this study, we have also developed the empirical framework depicted as a diagraph, as shown in Figure 4.

4.2.1 An Empirical Framework Based on Grey-DEMATEL Digraph Map



Notes: The solid line represents cause factors, and the dotted line represents effect factors.
* highlights the novel factors explored through In-depth interviews.

Figure 4. Empirical Framework of Interrelationships Among GenAI Enablers in Rural Educational Settings (Considering Threshold Value = 0.13)

Our analysis revealed that a few identified enablers consistently reinforce existing findings and theories in using GenAI artefacts in educational settings. In this study, an empirical framework is also developed to illustrate the relationships that have emerged between the enablers, as depicted in Figure 4. For analytical clarity, only inter-relationships surpassing the 0.13 threshold were retained, filtering out less effective associations to ensure that our focus remains on the most influential relationships among enablers. It is evident from the framework that enablers interact both within cause and across effect enablers.

Based on the diagraph map, the most significant enabler is the policy initiatives at the government level, which belongs to the cause factor and influences nine enablers within the cause-and-effect enablers. Also, as per the prominence values, it is ranked as the topmost enabler, which indicates its importance among other enablers in the system. Further, the enablers, such as leadership commitment at the school level and GenAI artefact ease of use, influence five enablers each. Our research also suggests that GenAI awareness among rural stakeholders, GenAI training for rural stakeholders, and technical support and maintenance of computer devices for using GenAI artefacts are the most significant enablers that belong to the effect group and are heavily influenced by other enablers in the system. One important aspect to highlight is that enablers, such as leadership commitment at the school level, have the most significant impact and influence on other enablers within the system. The research findings are further discussed in the next section to gain deeper insight into using GenAI artefacts in rural education in developing country contexts.

As mentioned above in the results section, enablers such as “providing subsidized devices among lower-income groups (E3)”, “GenAI artefacts’ ease of use (E10)”, “localized language support in GenAI artefacts (E11)”, “financial Support for GenAI Initiatives (E12)”, and “Policy initiatives at the government level (E15)”, belongs to the cause group and needs to be accorded precedence. For GenAI implementation in rural educational settings, enablers such as GenAI artefacts’ ease of use and localized language support are platform-driven. They are relatively more feasible in the short term, given their dependence on technological development and innovation rather than extensive institutional reform. These measures can be integrated into digital ecosystems with comparatively lower administrative overhead. These enablers are technically feasible to implement through platform modifications, software updates, or app-level features without requiring large-scale physical investment (Gupta et al., 2024). Conversely, enablers such as providing subsidized devices among lower-income groups, financial support for GenAI initiatives, and policy initiatives at the government level require significant resource commitments, interdepartmental coordination, and policy-level decision-making, which may extend implementation timelines. While these remain critical for long-term systemic policy-level engagement, their feasibility in the immediate context is relatively constrained due to high investment and policies at the central or state level.

Likewise, enablers such as “availability of computer labs in schools (E4)”, “GenAI awareness among rural communities (E5)”, “GenAI training for rural teachers and students (E6)”, “GenAI training programs for rural families (E7)”, “social influence of GenAI artefacts (E8)”, “technical support for GenAI artefacts (E9)”, “leadership commitment at the school (level E14)” have been categorized under the effect group and are positioned for intervention after addressing enablers in the cause group. Enablers such as GenAI awareness among rural communities and the social influence of GenAI artefacts are more immediately actionable due to their lower dependence on infrastructural investments, with community-based outreach and low-cost digital campaigns. Similarly, leadership commitment at the school level emerges as a critical yet operationally feasible enabler, primarily driven by local administrative will and requiring comparatively minimal financial or infrastructural investment. Moreover, the presence of CSR initiatives and NGOs may augment the practical feasibility of implementing these enablers. In contrast, enablers such as the availability of computer labs in schools, technical support for GenAI artefacts, and training programs for teachers, students, and families, while essential for long-term impact, present more significant feasibility challenges in the short term due to the need for physical infrastructure, skilled personnel, and continuous funding. Its feasibility is context-dependent and relies heavily on financial investment, institutional backing, and regional support mechanisms (CSR, NGOs, state policy, and local infrastructure) (Liu et al., 2023). Therefore, the prioritization of enablers, grounded in implementation feasibility, is intended to enhance the practical applicability of the empirical framework within real-world rural educational contexts. In addition, the enablers were classified according to their practical feasibility based on short-term and long-term implementation, as determined through experts’ assessment, as mentioned in Table 4.

Table 4. Practical Feasibility of Enablers Based on Short-term and Long-term Implementation

Enabler Code	**Enablers (GenAI artefacts)**	**Short-term (Organizationally implementable) / Long-term (Policy-dependent/ Systemic)**
E1	Affordable Internet data	Policy-dependent/ Systemic
E2	Affordable telecommunication network (4G/5G)	Policy-dependent/ Systemic
E3	Providing subsidized devices among lower-income groups	Policy-dependent/ Systemic
E4	Availability of computer labs in schools	Policy-dependent/ Systemic
E5	GenAI awareness among rural communities	Organizationally implementable
E6	GenAI training for rural teachers and students	Policy-dependent/ Systemic
E7	GenAI training programs for rural families	Policy-dependent/ Systemic
E8	Social influence of GenAI artefacts	Organizationally implementable
E9	Technical support and maintenance of computer devices for using GenAI artefacts	Policy-dependent/ Systemic

E10	GenAI artefacts' ease of use	Organizationally implementable
E11	Localized language support in GenAI artefacts	Organizationally implementable
E12	Financial support for GenAI initiatives	Policy-dependent/ Systemic
E13	Data privacy and security regulations for GenAI	Policy-dependent/ Systemic
E14	Leadership commitment at the school level	Organizationally implementable
E15	Policy initiatives at the government level	Policy-dependent/ Systemic

5 Discussion

Our research identifies fifteen enablers responsible for GenAI artefact usage in rural educational settings in developing countries such as India. Through the literature review, we identified nine enablers and uncovered six novel enablers through in-depth interviews. Our study utilizes the STT theoretical lens to understand enablers responsible for GenAI artefact usage among marginalized rural users. Further, to supplement our findings, all enablers were analyzed using a grey-DEMATEL technique to determine the prominence and causal inter-relationship among the enablers responsible for using GenAI artefacts in rural educational settings.

5.1 Social System

As for the structural dimensions, out of five enablers, four belong to the cause group factors named *affordable Internet data, affordable telecommunication network, data privacy and security regulations* for *GenAI,* and *policy initiatives at the government level*. Further, the *availability of computer labs in schools* belongs to the effect group enabler. In the causal relationship diagram (see Figure F1 and Table T8 supplementary sheet), according to the ranking obtained, *policy initiative at the government level* (E15) is the most critical enabler that can drive the GenAI artefact usage in rural educational settings. Across the globe, governments are actively working on developing comprehensive policies and initiatives to regulate and effectively incorporate GenAI into educational settings. Policy initiatives in educational settings emphasize the need to strike a proper balance between leveraging the benefits of GenAI and addressing the associated risks, such as bias, misuse, and others. Our findings align with and support the report by UNESCO (2023), which proposes key steps, presenting frameworks and concrete examples for governments to use GenAI in education.

Concurring with the Education.Gov.in (2020), our findings emphasize the *availability of computer labs in schools* (E4) in a resource-constrained environment. Due to a low socio-economic background, rural students may not possess or access personal digital devices. In this regard, computer labs serve as a shared space where students can have hands-on learning experiences using GenAI artefacts, ensuring equitable access to technology and opportunities under the supervision of their teachers. This finding aligns with the existing literature (Wael Al-khatib, 2023; Gupta et al., 2024). Challenges in the availability of computer labs in rural schools primarily stem from financial and logistical constraints. However, facilitative conditions may arise through cooperative structures such as public-private partnerships, NGO's, and shared use of community facilities. Concurring with Ooi et al. (2023) and Dwivedi et al. (2023), our findings highlight that *data privacy and security regulations for GenAI* (E13) emerge as key GenAI enablers for rural education in developing countries. They build trust, protect sensitive information, and ensure ethical and responsible data usage. This enabler belongs to the cause group, indicating it can influence other enablers. Data privacy and security regulations for GenAI artefacts confront challenges due to the absence of comprehensive legal frameworks specific to GenAI usage in rural contexts and limited user awareness of digital rights, also noted in the context of other IT artifacts (Mandari et al., 2017). However, facilitators include national data protection policies, global best practices, and the potential for localized regulatory guidelines that safeguard user data while enabling responsible AI adoption.

Concerning the affordability aspects of using GenAI artefacts among rural communities, through a qualitative approach, our findings reveal three novel enablers, namely *affordable Internet data* (E1), *affordable telecommunication network* (E2), and *providing subsidized devices among lower-income groups* (E3). Further, through the quantitative method, our findings complement that these enablers belong to the cause group, i.e., they can influence other enablers. In developing nations, rural populations are predominantly from lower socio-economic backgrounds, which limits their access to Internet data. In essence, *affordable Internet data* allows such individuals to tap into the transformative potential of GenAI in educational settings. Likewise, *affordable telecommunication networks* enable rural schools or individuals to have better access and leverage the full potential of GenAI by providing reliable, fast, and cost-effective Internet access. In developing countries, rural communities experience elevated levels of poverty, which can significantly hinder the ability of families to afford educational devices for their children. The government and relevant stakeholders must provide affordable data, networks, and *subsidized devices for rural communities*. It can democratize access to GenAI in an educational context, leading to enhanced learning, increased engagement, and better future opportunities. These findings underscore the need for government-led digital inclusion schemes such as affordable data plans, better network quality, and subsidized devices for rural communities, ensuring equal access and opportunities to digital resources and addressing socio-economic obstacles.

As per the ranking, the second most vital enabler is *GenAI training for rural teachers and students* (E6) for using GenAI in rural education in developing countries. Providing targeted training for teachers and students is imperative to foster the usage of GenAI artefacts in rural settings. Equipping teachers with the skills to craft precise and effective prompts can better harness the capabilities of GenAI artefacts. This would enable more accurate and valuable outputs, such as generating lesson plans, simulations, quizzes, and creative content while understanding ethical and responsible considerations (Kasneci et al., 2023; Alier et al., 2024). Also, *GenAI training programs for rural families* (E7) would play a significant role in children's education, often supplementing school learning with home-based support (Chiu, 2023). Through the in-depth interviews, our study reveals three novel enablers, namely, *GenAI awareness among rural communities* (E5), *social influence of GenAI artefacts* (E8), and *leadership commitment at the school level* (E14), which have been further classified under the effect group through the grey-DEMATEL technique. Our findings uncover the significance of disseminating *GenAI awareness among rural teachers and students* (the third most crucial enabler) to enhance educational quality and prepare rural communities for a technology-driven future. GenAI awareness among rural teachers and students is hindered by limited exposure to emerging technologies in rural curricula and a lack of orientation programs. However, facilitators include community outreach programs, tie-ups with private organizations (i.e., CSR initiatives), and partnerships with educational NGOs to promote foundational understanding.

Further, the *social influence of GenAI artefacts* is a critical enabler among the rural populace. Due to socio-cultural factors, rural populations often exhibit limited awareness and resistance toward engaging with digital ecosystems. In this regard, social endorsement and peer influence help establish trust and foster knowledge of GenAI artefacts among rural communities. Our findings uncover that *leadership commitment at the school level* can play a vital role in establishing a clear vision and well-defined strategy, encouraging staff to embrace digital advancements, advocating for resources, and securing funding to ensure the school has all the resources for GenAI usage. Rural schools often face challenges related to geographic isolation, limited digital experience, and limited infrastructure. Thus, leadership commitment is crucial for overcoming these challenges and improving the quality of education by unlocking the benefits of GenAI artefacts.

5.2 Technical System

Our study reveals that *financial support for GenAI initiatives* through various agencies (E12), such as public and private organizations, NGOs, and others, can significantly expedite the use and adoption of GenAI artefacts in rural schools while complementing governmental initiatives. This support can be directed towards funding critical infrastructure upgrades and providing resources for training and capacity-building programs. Funding in these aspects ensures that teachers and students in rural areas have the same teaching and learning opportunities as urban regions. Our findings align with the existing research (Alier et al., 2024). Financial support for GenAI initiatives confronts challenges such as limited budget allocations and a lack of targeted funding mechanisms for emerging technologies. However, facilitators include potential funding through CSR initiatives and multi-stakeholder partnerships to bridge digital divides in underserved communities. Next, *technical support and maintenance of computer devices for using GenAI artefacts* (E9) is a crucial enabler for rural education in developing countries. Regular maintenance and readily available technical assistance can ensure the smooth functioning of GenAI artefacts, enhancing their usability and sustainability in rural settings (Mannuru et al., 2023). The shortage of trained personnel in rural areas and limited infrastructure for ongoing maintenance and troubleshooting constrain technical support for GenAI artefacts. However, facilitators include capacity-building programs and collaborations with local ICT centers to provide sustained technical assistance.

Further, the results show that *localized language support in GenAI artefacts* (E11) emerges as an influential GenAI enabler for rural education in developing countries. In rural regions, teachers and students often lack proficiency in English, which is primarily used in GenAI artefacts. GenAI artefacts can integrate localized languages to make educational resources accessible among rural teachers and students, thus bridging the language barrier. The findings from the respondents support the existing research (Baidoo-Anu & Ansah, 2023). Localized language support in GenAI artefacts presents challenges, such as the limited availability of high-quality regional language datasets and the technical difficulty of accommodating diverse dialects. However, facilitators include growing government-led language digitization initiatives, which enhance feasibility in rural contexts. Another key study finding indicates that GenAI artefacts' ease of use is critical in facilitating adoption, particularly within resource-constrained rural contexts. Often, in rural areas, teachers and students may have limited exposure to or experience with digital tools. GenAI artefacts should have intuitive interfaces and simple functions so students and teachers can easily understand, allowing them to focus on learning. The major challenge of GenAI artefacts' ease of use is low digital literacy levels among rural communities and the lack of intuitive interfaces tailored to rural users. However, facilitators include advances in user-centred design, voice-based inputs, and visual interfaces, which can significantly improve accessibility among rural populations with low digital literacy levels.

6 Theoretical Contributions and Practical Implications

6.1 Theoretical Contributions

Our study contributes to IS literature by addressing a crucial gap in understanding how contextual factors shape the use of GenAI artefacts among marginalized rural communities in educational settings in a developing country context. In addition, we contribute to the digital divide literature (van Dijk, 2020) by highlighting the socio-economic and technical enablers that facilitate the use of GenAI artefacts in rural educational settings. These findings highlight the role of key enablers in narrowing the pervasive digital divide in developing countries. Further, our study contributes to GenAI literature by demonstrating that enablers in rural educational settings are not only confined to infrastructure or cognitive dimensions. Instead, they are shaped by the socio-economic aspects. Thus, this study broadens the knowledge of GenAI literature in education through deepening our understanding of enablers in GenAI artefact usage among marginalized rural communities.

Following Bostrom and Heinen's (1977) STT's premise that effectiveness arises from the joint optimization of social and technical systems, our findings underscore that the use of GenAI artefacts among marginalized rural communities emerges from the interplay between technical and social systems, rather than from either domain alone. Thus, through the STT theoretical lens, we identify and theorize the enablers that facilitate the use of GenAI artefacts in rural educational settings and make several significant contributions.

First, our study contributes to the extant IS literature by uncovering six novel enablers that can facilitate the use of GenAI in rural educational settings. Enablers such as "*affordable Internet data*", "*affordable telecommunication network*", and "*providing subsidized devices among marginalized communities*" further the body of knowledge by shifting attention from mere infrastructure availability to the economic feasibility of resources in rural educational settings. While prior studies stressed connectivity or device access (Sætra, 2023; Ali et al., 2024; Baidoo-Anu & Ansah, 2023; Jin et al., 2023), our findings show that affordability is the decisive factor that shapes GenAI usage among marginalized communities. This highlights that access must be theorised not only in technical or infrastructural terms but also in relation to affordability aspects faced by marginalised communities. In doing so, the study contributes to digital divide literature by highlighting socio-economic perspectives by positioning cost structures as central to equitable technology adoption. In our research, we refer to "technology adoption as the acquisition or purchase and potential use" (Sringeswara et al., 2025) of GenAI artefacts. Further, our study identified enablers such as *"GenAI awareness among rural communities"* and *"social influence of GenAI artefacts"* that extend the body of IS literature by theorizing and offering a more nuanced understanding of these enablers in digitally marginalized rural communities. Lastly, our novel findings contribute that *"leadership commitment at the school level,"* not only legitimizes GenAI use but also mobilizes resources, sets norms, and fosters sustained usage of GenAI artefacts.

Second, our research also contributes by framing a novel empirical framework for analysing the most influential enablers and their interrelationships for the use of GenAI artefacts in rural educational settings.

While interviews provide contextualized and nuanced insights into participants' lived experiences, MCDM techniques enable the structured prioritization of these insights into measurable decision criteria. In addition to prioritization, our study establishes causal interrelationships among the enablers that facilitate the use of GenAI artefacts in rural educational settings in the context of developing countries in the Global South.

6.2 Practical Implications

Our study offers valuable insights for policymakers, private agencies, and other stakeholders (including NGOs, top-level leadership at school, and local administrative bodies) looking into GenAI artefacts for inclusive education among marginalized rural communities.

First, this research offers valuable insights to policymakers by providing a comprehensive list of fifteen GenAI enablers to strategically narrow the digital divide between urban and rural students. They can work with local administrative bodies and private agencies to facilitate key enablers such as affordable internet data, affordable network quality, and subsidized digital devices among underserved communities in rural educational settings. Further, our findings suggest that these government agencies need to implement robust data security and privacy measures to mitigate cyber fraud, algorithmic bias, misinformation and disinformation, unfairness, discrimination, and the misuse of GenAI artefacts in rural educational settings.

Second, our study provides actionable items for policymakers to design tailored intervention initiatives to mitigate cost, access, and educational disparities impeding GenAI artefacts usage. These initiatives can better address the concerns among marginalized communities, thereby potentially enhancing digital inclusion initiatives. Considering this, developing countries like India have already undertaken significant measures, including the Digital India mission and state-sponsored laptop distribution programs targeting marginalized ones (Sringeswara et al., 2025). Our research suggests that a well-informed and coordinated effort between government policymakers and key stakeholders can substantially facilitate the use of GenAI in developing countries.

Third, NGOs and local administrative bodies can spearhead extensive awareness and training programs to acquaint rural communities with GenAI artefacts, fostering better learning and teaching experiences among students and teachers, respectively. Further, the findings suggest actionable paths for policy initiatives and institutional support. Governments and other stakeholders should view GenAI artefacts not as a standalone innovation but as part of an integrated rural educational strategy, i.e., embedding it within teacher training curricula and partnering with private agencies to provide technical support and training. Such alignment can ensure scalability, sustainability, and equity in the deployment of GenAI artefacts in rural educational settings.

Fourth, it is imperative that top-level leadership at school allocate sufficient resources for computer laboratories, thereby enabling the integration of GenAI artefacts to improve learning outcomes among marginalized groups. Henceforth, our study suggests that all stakeholders need to work in synchronization to leverage GenAI artefacts to bridge the digital divide and drive progress towards aligning with UN SDG 4, ensuring quality education among rural marginalized communities for better inclusivity.

7 Conclusions

In the contemporary AI era, GenAI has attained considerable global cognizance in various fields, and the education sector is no exception. This study uncovers key enablers for using GenAI artefacts in rural educational settings in developing countries, particularly rural India. Our research identified fifteen key GenAI enablers for rural education in developing countries through an extensive literature review and in-depth interviews with respondents. Next, we employed a mixed-method approach to understand the novel enablers comprehensively. Drawing insights through the STT lens, this study enables a more nuanced analysis by guiding research away from both the overvaluation of technology, known as ‘technological fetishism’, and the sociocentric bias that often overlooks the influence of technological systems (Risius et al., 2024). Moreover, analysing the interactions between social and technical factors enhances our understanding of how GenAI artefacts can be leveraged among marginalized rural users. This contributes to narrowing the digital divide and improving educational quality in rural school settings, enhancing the understanding of the STT lens.

Further, the findings revealed that enablers such as “policy initiatives at the government level,” “financial support for GenAI initiatives,” “data privacy and security regulations for GenAI,” “GenAI artefacts’ ease of use,” and “localized language support in GenAI artefacts” are having high importance in facilitating GenAI in rural educational settings. These five causal groups of enablers belong to both the social and technical components, exerting a direct influence on the overall system. The decision-makers need to emphasize the causal group enablers more to improve education quality in rural settings. Finally, our research findings would benefit decision-makers and other relevant stakeholders involved in rural educational systems.

8 Research Limitations and Future Research Directions

Despite the significant outcomes of this study, our study also has certain limitations. First, this study is based on experts’ opinions, which are subjective in nature and selected using the convenience sampling method, which could introduce some bias into the developed model. Second, data was collected from a single state, Uttarakhand (India), restricting the generalisation of the findings. Therefore, future researchers could confirm the proposed research model using a different cohort of experts, potentially from various regions of India or other developing nations. Third, we have outlined fifteen enablers in this study; however, future researchers could consider adding or dropping them while delving into other contextual enablers. Additionally, the proposed model has not undergone empirical testing in this study, allowing researchers to collect data and validate the model statistically through the structural equation modeling technique. Finally, future researchers can utilize other MCDM methods like the fuzzy-analytic hierarchy process, fuzzy-DEMATEL, and other qualitative methods, such as fuzzy set qualitative comparative analysis to determine the importance of the GenAI artefacts enablers in rural educational settings.

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Declaration of AI

While preparing this work, the authors used Grammarly to check spelling and grammar, restructure sentences, and enforce style guidelines. Then, the authors reviewed and edited the content as needed, taking full responsibility for the publication’s content.

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Appendix A: Unveiling Enablers to the Use of Generative AI Artefacts in Rural Educational Settings: A Socio-Technical Perspective

Table A1. Literature Review Driven GenAI Enablers for Rural Educational Settings in Developing Countries

Enabler code	Enablers	Description of enablers	References
E4	Availability of computer labs in schools	It refers to providing digital devices such as PCs, smartphones, and laptops at rural schools, ensuring they have reliable access to educational software, internet resources, and other digital tools necessary for GenAI usage.	Adapted from NEP, 2020
E6	GenAI training for rural teachers and students	It refers to the process of educating and developing the skills of teachers and students with the help of NGO/ Self-help groups/ CSR to make them understand and work with GenAI platforms effectively.	Adapted from Kasneci et al., 2023, Liu et al., 2023
E7	GenAI training programs for rural families	It refers to imparting digital literacy among rural families to achieve technological self-efficacy and be competent enough to leverage GenAI.	Adapted Chiu et al., 2023
E9	Technical support and maintenance of computer devices for using GenAI platforms	It refers to the comprehensive IT support to ensure effective computer deployment and maintenance for addressing rural challenges, such as limited access to resources and technical expertise.	Adapted from Mannuru et al., 2023
E10	GenAI platforms' ease of use	It refers that GenAI platforms must be simple and intuitive for all stakeholders to operate seamlessly and effortlessly.	Adapted from Wael Al-khatib et al., 2023; Gupta et al., 2024
E11	Localized language support in GenAI platforms	It refers to providing a multilingual localized interface designed to operate in diverse regional languages, making GenAI platforms more accessible to diverse populations.	Baidoo-Anu & Ansah, 2023
E12	Financial Support for GenAI Initiatives	It refers to creating a cooperative environment that combines the unique capabilities of the public and private sectors, including private firms, NGOs, and other entities, to effectively implement and utilize GenAI in classrooms in rural settings.	Alier, 2024
E13	Data Privacy and Security Regulations for GenAI	Data privacy ensures that users' data are handled carefully to protect individuals' privacy rights & data security ensures that sensitive information remains confidential and integral while protecting from unauthorized access, breaches, and misuse.	Dwivedi et al., 2023; Kasneci et al., 2023; Ali et al., 2024
E15	Policy initiatives at the government level	It refers to introduce regulations ensuring GenAI tools used in education are unbiased, secure, and aligned with ethical standards while ensuring that students in remote areas receive the same quality of education as their urban counterparts.	Ooi et al., 2023; Dwivedi et al., 2023

Table A2. Demographic Profile of Respondents
(Working in Various Organizations: Central govt./State govt./Private Enterprise/NGO)

Respondent	Age	Job designation	Work exp. (years)	Gender	Educational Qualification	Background
R1	38	Teacher	12	Male	Graduate	Mountain Region (Rural)
R2	39	Teacher	11	Female	Postgraduate	Plain region (Rural)
R3	51	Teacher	25	Male	Graduate	Mountain Region (Rural)
R4	34	Teacher	8	Male	Graduate	Mountain Region (Rural)
R5	32	Teacher	03	Female	Postgraduate	Plain region (Rural)
R6	45	Deputy Superintendent (education dept.)	10	Female	Postgraduate	Responsible for the initiatives in the education department
R7	38	IT officer (Specialist)	9	Male	Graduate	For IT-related tasks at the state government

		(education dept.)				
R8	38	Training Officer (education dept.)	5	Male	Graduate	Responsible for the overall development of the teachers
R9	39	Deputy Asst. Superintendent (education dept.)	8	Male	Postgraduate	Responsible for the overall development of the schools (for rural regions)
R10	30	NGO staff	7	Female	Graduate	Assisting government and other agencies in driving the initiatives in rural settings
R11	36	Executive	10	Female	Postgraduate	Officers from private organizations that provide the technical platform to the government for assessment, attendance, accreditation, and other administrative tasks
R12	40	Executive	12	Male	Graduate	

Table A3. Interview-driven GenAI Enablers

Enabler code	**Enablers**	**Description of the enabler**	**References**
E1	Affordable Internet data	It refers to the requirement of affordable internet data plans among rural communities to effectively leverage GenAI platforms to transform the learning experience.	Experts opinion
E2	Affordable telecommunication network	It refers to providing cost-effective network quality (3G/4G/5G) for rural stakeholders to access the Internet to improve the educational experience through seamless GenAI access.	Experts opinion
E3	Providing subsidised devices among lower-income groups	It refers to providing subsidized digital devices to economically disadvantaged students and their families, enabling them to access the GenAI platforms in their respective residences for 24*7 accessibility, which in turn bridges the digital divide among rural communities.	Experts opinion
E5	GenAI awareness among rural communities	It involves disseminating knowledge through (Wall painting/radio/posters/ newspapers/ text messages/ social media) regarding the usage of GenAI among rural stakeholders.	Experts opinion
E8	Social Influence of GenAI artefacts	It refers to how people become more aware of and inclined to use GenAI platforms when they are being made familiar with and influenced by family members or through social networks.	Experts opinion
E14	Leadership commitment at the school level	Leadership can enable a visionary and supportive GenAI environment by developing a clear strategy and creating a culture of continuous learning that aligns with educational goals.	Experts opinion

Appendix B: The Computational Steps Involved in the Grey-DEMATEL Process

Step 1: The direct initial matrix is constructed from experts' evaluation; $'K'$ denotes the number of decision-makers to provide ratings on $'n'$ identified enablers using the grey linguistic scale in mentioned below.

Linguistics Expression	Grey Scale Range	Normal Value
No influence (NI)	[0.0, 0.1]	0
Very low influence (VLI)	[0.1, 0.3]	1
Low influence (LI)	[0.2, 0.5]	2
Medium influence (MI)	[0.4, 0.7]	3
High influence (HI)	[0.6, 0.9]	4
Very high influence (VHI)	[0.9, 1.0]	5

Step 2: The description of the grey number is given below:

$$\otimes G_{ij}^{k} = (\underline{\otimes} G_{ij}^{k}, \overline{\otimes} G_{ij}^{k}) \tag{1}$$

$\otimes G_{ij}^{k}$ denotes the grey number, and $\overline{\otimes} G_{ij}^{k}$ and $\underline{\otimes} G_{ij}^{k}$ represent the upper and lower value of a particular grey number, respectively (Julong, 1989), where $1 \leq k \leq K; 1 \leq i \leq n; 1 \leq j \leq n$. We follow the notation for experts as $[\otimes G_{ij}^{1}], [\otimes G_{ij}^{2}] \ldots . [\otimes G_{ij}^{K}]$.

Step 3: Calculate the average grey relation matrix $[\otimes \tilde{G}_{ij}]$ by aggregating the grey relationship matrix determined earlier as

$$\otimes \tilde{G}_{ij} = \left(\frac{\sum_k \underline{\otimes} G_{ij}^{k}}{K}, \frac{\sum_k \overline{\otimes} G_{ij}^{k}}{K} \right) \tag{2}$$

Step 4:

a. Calculate the crisp number by utilizing an average grey value from Step 2 and applying the following equations:

$$\underline{\otimes} \bar{G}_{ij} = (\underline{\otimes} \tilde{G}_{ij} - \min_j \underline{\otimes} \tilde{G}_{ij}) / \Delta_{min}^{max} \tag{3}$$

$$\overline{\otimes} \bar{G}_{ij} = (\overline{\otimes} \tilde{G}_{ij} - \min_j \overline{\otimes} \tilde{G}_{ij}) / \Delta_{min}^{max} \tag{4}$$

where $\overline{\otimes} \bar{G}_{ij}$ and $\underline{\otimes} \bar{G}_{ij}$ represent the normalized upper and lower limits of a given grey number.

$$\Delta_{min}^{max} = \max_j \overline{\otimes} \tilde{G}_{ij} - \min_j \underline{\otimes} \tilde{G}_{ij} \tag{5}$$

b. Then, calculate the total normalized crisp value using

$$\tau_{ij} = \frac{(\underline{\otimes}\bar{G}_{ij}\,(1 - \underline{\otimes}\bar{G}_{ij})) + (\bar{\otimes}\bar{G}_{ij} \times \bar{\otimes}\bar{G}_{ij})}{(1 - \underline{\otimes}\bar{G}_{ij} + \bar{\otimes}\bar{G}_{ij})} \tag{6}$$

c. Now, we compute the final crisp value,

$$\tau^*_{ij} = (\min_j \underline{\otimes}\,\tilde{G}_{ij} + (\tau_{ij} \times \Delta^{max}_{min})) \tag{7}$$

and the matrix T = $[\tau^*_{ij}]$ (8)

Step 5: We calculate the normalized crisp relation matrix A using the normalization factor B,

$$B = \frac{1}{\max_{1 \le i \le n} \sum_{j=1}^{n} \tau^*_{ij}} \tag{9}$$

A = $T \times B$ (10)

Each element in matrix A falls between 0 and 1.

Step 6: We compute the total relation matrix "Q" by using Eq. (11)

$$Q = A \times (I - A)^{-1} \tag{11}$$

Where I represent an identity matrix.

Step 7: Now we calculate the sum of row and column followed by prominence and net effects as follows:

a. To determine the cause and effect parameters, we compute the sum of row and column (r_i and c_i) by the following expressions as mentioned below:

$r_i = \left[\sum_{j=1}^{n} q_{ij}\right] \forall i$, and (12)

$$c_j = \left[\sum_{i=1}^{n} q_{ij}\right] \forall j \tag{13}$$

While q_{ij} represents the elements in the total relation matrix, Q

b. Then, we calculate the prominence and relation (net effect) as mentioned below:

$$Y_i = [r_i + c_j]\ \forall i = j \tag{14}$$

$$Z_i = [r_i - c_j]\ \forall i = j \tag{15}$$

where Y_i and Z_i denote the prominence and net effect among the factors. If Z_i becomes positive, the enabler is likely to be a "cause" enabler, i.e., the factors influenced other factors rather than being influenced by them. If Z_i becomes negative, it is taken as an "effect" enabler, i.e., others influence the enabler.

Step 8: Set up a causal diagram. A causal diagram is created utilizing the values obtained from Eqs. (14) and (15) and is shown in Figure F1.

- Table T7 (see supplementary sheet) depicts the total relationship matrix (Q) for GenAI enablers in rural educational settings. In the Table, T7 (r + c) values describe 'prominence,' and (r - c) values represent 'relation.' To plot causal interrelationships, the r + c (prominence) values are placed on the horizontal axis, while the r - c (relation) values are placed on the vertical axis. Enablers with positive (r - c) values positioned above the x-axis, which means these enablers exert influence on other enablers and are called the 'causal group'. However, enablers with negative (r – c) values positioned below the x-axis are influenced by other enablers in the systems and referred as the 'effect group'.

Table T4 depicts the pairwise comparison of enablers taken from an expert (for example shown expert 1). Subsequently, the computational steps outlined above led to the establishment of Tables T4, T5, T6, T7, and T8.

Table B1. Pairwise Comparisons of Enablers (e.g., For Expert 1)

Enabler Code	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15
E1	0	0	3	2	2	2	2	2	3	4	3	3	2	1	3
E2	4	0	2	2	2	2	3	2	3	4	3	3	2	1	3
E3	1	1	0	3	3	4	3	3	3	3	3	2	2	2	3
E4	1	1	0	0	4	4	4	3	4	3	4	3	3	3	2
E5	2	2	3	3	0	5	4	3	4	3	3	2	2	2	4
E6	2	2	3	4	4	0	5	3	5	4	3	3	2	3	4
E7	1	1	2	3	3	4	0	3	4	3	3	2	2	2	3
E8	2	2	3	3	4	3	3	0	4	3	3	3	3	3	4
E9	2	2	1	4	4	5	4	3	0	4	4	3	3	4	2
E10	4	4	2	3	3	3	3	4	4	0	4	3	3	3	2
E11	3	3	3	3	3	3	3	3	4	4	0	3	3	3	4
E12	4	4	4	3	3	3	3	3	4	3	4	0	4	4	5
E13	2	2	2	2	3	3	3	3	3	4	4	4	0	3	5
E14	2	2	3	4	3	4	3	3	4	3	3	4	4	0	3
E15	3	3	4	4	3	4	4	4	4	4	4	5	5	5	0

Table B2. Crisp Relation Matrix (T)

Enabler Code	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0.0079	0.0607	0.1964	0.0845	0.499	0.4532	0.4554	0.6324	0.1919	0.8566	0.1746	0.2019	0.2168	0.1632	0.4564
2	0.3124	0.0082	0.1448	0.1129	0.458	0.3712	0.4965	0.6324	0.1919	0.6523	0.3148	0.4048	0.1892	0.1348	0.3788
3	0.056	0.0563	0.008	0.6628	0.7567	0.8314	0.7522	0.7567	0.2978	0.1962	0.1965	0.2343	0.1098	0.4987	0.5397
4	0.056	0.0563	0.008	0.0079	0.8469	0.9298	0.8343	0.5824	0.6106	0.1962	0.2798	0.2154	0.1919	0.4064	0.4077
5	0.1129	0.1132	0.1964	0.7538	0.008	0.7104	0.651	0.674	0.7516	0.2708	0.375	0.5785	0.1423	0.4077	0.5301
6	0.1129	0.1132	0.1964	0.5455	0.8706	0.0076	0.8537	0.7151	0.7537	0.3349	0.1965	0.3253	0.1098	0.744	0.6218
7	0.056	0.0563	0.2051	0.3526	0.8246	0.6083	0.0077	0.4629	0.5689	0.1962	0.3833	0.5381	0.1574	0.5904	0.5307
8	0.1129	0.1132	0.1964	0.2515	0.7879	0.7867	0.7417	0.008	0.3558	0.1962	0.3265	0.3958	0.2478	0.7134	0.4609
9	0.1129	0.1132	0.0562	0.2795	0.4837	0.6694	0.5279	0.3533	0.0077	0.303	0.3324	0.3954	0.2154	0.5801	0.19
10	0.2795	0.2798	0.113	0.1962	0.8178	0.8104	0.8133	0.8706	0.8605	0.0079	0.7519	0.4048	0.5369	0.4481	0.6731
11	0.1962	0.1965	0.1964	0.278	0.7456	0.6636	0.7411	0.8178	0.8648	0.7925	0.0082	0.2712	0.4875	0.4891	0.4526
12	0.3349	0.3358	0.908	0.8217	0.5413	0.4852	0.5368	0.3809	0.4495	0.1962	0.2798	0.0077	0.2739	0.844	0.7239
13	0.1129	0.1132	0.113	0.1129	0.2288	0.1917	0.1919	0.7157	0.1919	0.3306	0.3932	0.3582	0.0077	0.2996	0.9356
14	0.1129	0.1132	0.1964	0.9356	0.7567	0.8688	0.759	0.5413	0.8648	0.2983	0.1965	0.8411	0.2739	0.0079	0.6218
15	0.8523	0.797	0.908	0.8745	0.7873	0.8993	0.9022	0.5836	0.8648	0.7446	0.8735	0.9632	0.9632	0.7649	0.0079

Table B3. Normalised Direct Relation Matrix (A)

Enabler Code	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15
E1	0.0007	0.0051	0.0167	0.0072	0.0423	0.0385	0.0386	0.0537	0.0163	0.0727	0.0148	0.0171	0.0184	0.0139	0.0387
E2	0.0265	0.0007	0.0123	0.0096	0.0389	0.0315	0.0421	0.0537	0.0163	0.0553	0.0267	0.0343	0.0161	0.0114	0.0321
E3	0.0048	0.0048	0.0007	0.0562	0.0642	0.0705	0.0638	0.0642	0.0253	0.0166	0.0167	0.0199	0.0093	0.0423	0.0458
E4	0.0048	0.0048	0.0007	0.0007	0.0719	0.0789	0.0708	0.0494	0.0518	0.0166	0.0237	0.0183	0.0163	0.0345	0.0346
E5	0.0096	0.0096	0.0167	0.064	0.0007	0.0603	0.0552	0.0572	0.0638	0.023	0.0318	0.0491	0.0121	0.0346	0.045
E6	0.0096	0.0096	0.0167	0.0463	0.0739	0.0006	0.0724	0.0607	0.0639	0.0284	0.0167	0.0276	0.0093	0.0631	0.0528
E7	0.0048	0.0048	0.0174	0.0299	0.07	0.0516	0.0007	0.0393	0.0483	0.0166	0.0325	0.0457	0.0134	0.0501	0.045
E8	0.0096	0.0096	0.0167	0.0213	0.0668	0.0667	0.0629	0.0007	0.0302	0.0166	0.0277	0.0336	0.021	0.0605	0.0391
E9	0.0096	0.0096	0.0048	0.0237	0.041	0.0568	0.0448	0.03	0.0007	0.0257	0.0282	0.0335	0.0183	0.0492	0.0161
E10	0.0237	0.0237	0.0096	0.0166	0.0694	0.0688	0.069	0.0739	0.073	0.0007	0.0638	0.0343	0.0455	0.038	0.0571
E11	0.0166	0.0167	0.0167	0.0236	0.0633	0.0563	0.0629	0.0694	0.0734	0.0672	0.0007	0.023	0.0414	0.0415	0.0384
E12	0.0284	0.0285	0.077	0.0697	0.0459	0.0412	0.0455	0.0323	0.0381	0.0166	0.0237	0.0007	0.0232	0.0716	0.0614
E13	0.0096	0.0096	0.0096	0.0096	0.0194	0.0163	0.0163	0.0607	0.0163	0.028	0.0334	0.0304	0.0007	0.0254	0.0794
E14	0.0096	0.0096	0.0167	0.0794	0.0642	0.0737	0.0644	0.0459	0.0734	0.0253	0.0167	0.0714	0.0232	0.0007	0.0528
E15	0.0723	0.0676	0.077	0.0742	0.0668	0.0763	0.0765	0.0495	0.0734	0.0632	0.0741	0.0817	0.0817	0.0649	0.0007

Table B4. Total-relationship Matrix (Q) for Enablers for the Use of GenAI

	E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**	**E11**	**E12**	**E13**	**E14**	**E15**
E1	0.01629	0.01989	0.03662	0.04241	0.09219	0.08764	0.08766	0.09678	0.06134	0.09687	0.04430	0.05167	0.04136	0.05467	0.07724
E2	0.04171	0.01537	0.03326	0.04487	0.08917	0.08098	0.09099	0.09695	0.06094	0.08134	0.05520	0.06797	0.03899	0.05263	0.07130
E3	0.02271	0.02182	0.02551	0.10148	0.12694	0.13173	0.12506	0.11609	0.08190	0.04803	0.05050	0.06378	0.03584	0.09294	0.09263
E4	0.02134	0.02054	0.02387	0.04418	0.12873	0.13383	0.12622	0.09831	0.10348	0.04649	0.05507	0.05966	0.04057	0.08235	0.07881
E5	0.02876	0.02775	0.04314	0.10911	0.06851	0.12417	0.11890	0.11107	0.11945	0.05644	0.06641	0.09205	0.04051	0.08831	0.09338
E6	0.02948	0.02841	0.04367	0.09589	0.14007	0.07111	0.13727	0.11647	0.12277	0.06252	0.05437	0.07615	0.03912	0.11610	0.10258
E7	0.02272	0.02185	0.04211	0.07495	0.12663	0.10953	0.06048	0.08940	0.10047	0.04743	0.06368	0.08599	0.03922	0.09716	0.08916
E8	0.02705	0.02611	0.04120	0.06739	0.12523	0.12395	0.12027	0.05360	0.08465	0.04797	0.05947	0.07582	0.04625	0.10734	0.08533
E9	0.02314	0.02242	0.02426	0.05936	0.08931	0.10274	0.09163	0.07189	0.04517	0.05032	0.05336	0.06642	0.03843	0.08705	0.05467
E10	0.04739	0.04588	0.04217	0.07389	0.14753	0.14552	0.14554	0.14163	0.14155	0.04547	0.10616	0.08974	0.07996	0.10292	0.11763
E11	0.03769	0.03657	0.04451	0.07493	0.13523	0.12791	0.13329	0.13153	0.13591	0.10330	0.04251	0.07407	0.07249	0.10005	0.09502
E12	0.04956	0.04811	0.10393	0.12289	0.12031	0.11608	0.11878	0.09714	0.10201	0.05614	0.06299	0.05240	0.05475	0.12733	0.11620
E13	0.02709	0.02602	0.03242	0.04559	0.06855	0.06554	0.06528	0.10083	0.05972	0.05524	0.06147	0.06487	0.02558	0.06521	0.11378
E14	0.03210	0.03094	0.04837	0.13287	0.13926	0.14725	0.13799	0.10990	0.13813	0.06349	0.05828	0.12080	0.05526	0.06465	0.10978
E15	0.10278	0.09565	0.11921	0.15214	0.18046	0.18716	0.18691	0.15247	0.16979	0.12492	0.13323	0.15522	0.12756	0.15352	0.09366

Table B5. Degree of Prominence and Net Cause/Effect Values for the GenAI use in Rural Educational Settings (Authors Own Work)

Barrier Codes	r	c	Prominence (r+c)	Ranking	Relation (r-c)	Impact
E1	0.90693	0.52980	1.43672	14	0.37713	Cause
E2	0.92167	0.48733	1.40900	15	0.43434	Cause
E3	1.13695	0.70425	1.84120	12	0.43269	Cause
E4	1.06347	1.24196	2.30543	11	-0.17849	Effect
E5	1.18797	1.77813	2.96610	3	-0.59015	Effect
E6	1.23598	1.75515	2.99113	2	-0.51918	Effect
E7	1.07076	1.74627	2.81703	4	-0.67551	Effect
E8	1.09163	1.58407	2.67571	6	-0.49244	Effect
E9	0.88019	1.52727	2.40746	9	-0.64709	Effect
E10	1.47298	0.98596	2.45894	8	0.48703	Cause
E11	1.34501	0.96700	2.31201	10	0.37801	Cause
E12	1.34861	1.19661	2.54521	7	0.15200	Cause
E13	0.87719	0.77590	1.65309	13	0.10129	Cause
E14	1.38906	1.39224	2.78130	5	-0.00318	Effect
E15	2.13470	1.39116	3.52586	1	0.74353	Cause

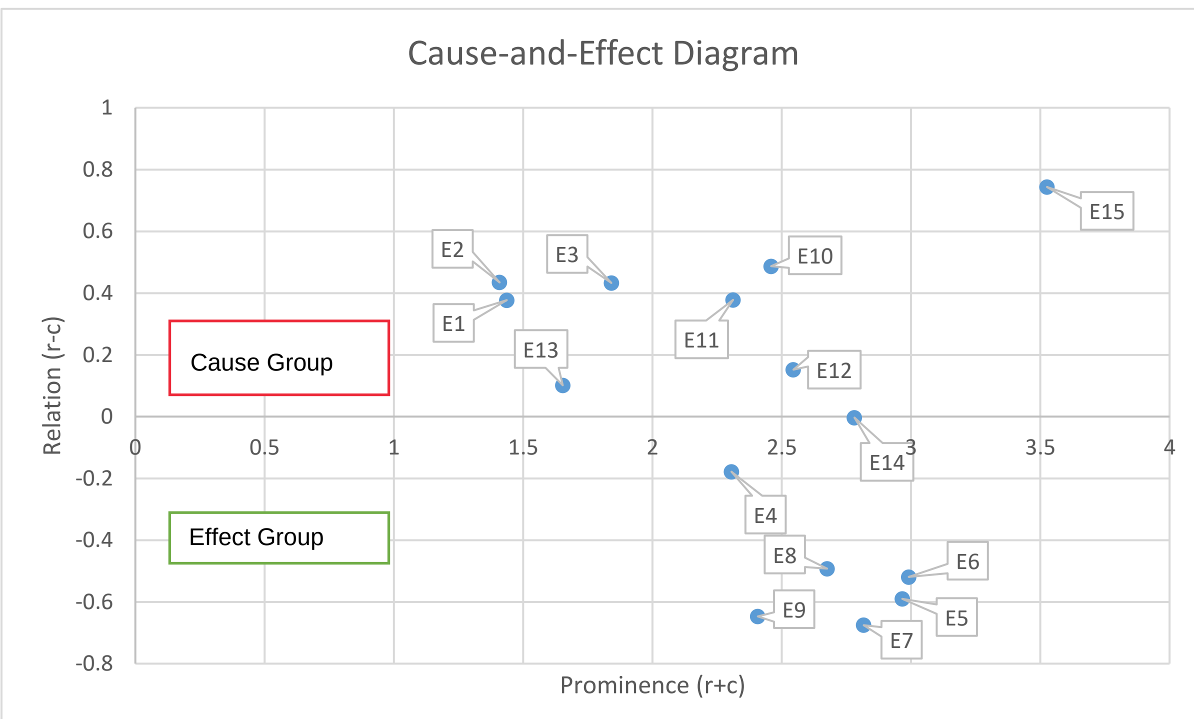

Figure B1. Causal Relationship Among the Enablers (Authors Own)

Appendix C: General Questions Asked from the Respondents (Teachers/Academicians/Working Professionals/Government Officials/Pediatricians)

Open-ended questions:

1. Please tell us about your **background**.
2. What are the **issues** confronted by teachers and students in **traditional education systems**?
3. Do you have some sort of **awareness** regarding GenAI? If so, please let us know what you **understand** about GenAI.
4. What are your **thoughts** and **experiences** on using GenAI platforms?
5. What are the **potential benefits** of using GenAI in rural schools?
6. Is the current school infrastructure **sufficient** to effectively use GenAI? What support is **needed for the use** of GenAI?
7. In your opinion, what is the most **critical enabler** for GenAI use in rural educational settings?
8. How will GenAI help **teachers** while teaching in rural schools?
9. Which subjects would you think will help rural **students** while using GenAI?
10. What **skills** (Critical thinking/ analytical thinking & others) will students learn while using GenAI platforms?
11. Is there any role for **parents** in GenAI education?
12. What can go **wrong** with using GenAI for rural education?
13. What **ethical considerations** should **stakeholders** keep in mind when using GenAI?

About the Authors

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