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Does Generative AI affect the career readiness of disadvantaged youth? Evidence from India

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Abstract

This thesis investigates the effect of Generative AI (GenAI) technologies within school settings for disadvantaged youth in India, focusing on its impact on career readiness. Conducted through a randomised control trial (RCT) across multiple low-income and government schools in India, the study looks into how GenAI tools might close educational disparities and improve career prospects for underprivileged students. The findings show the significant effects of GenAI on enhancing educational goals and career knowledge. Moreover, the research points to the dual benefits of GenAI: its capability to support students and their diverse learning needs and assist teachers in strong pedagogy. Additional emphasis was placed on the responsible use of the GenAI tool, with ethical guidelines ensuring that it complements classroom learning rather than replacing students' active efforts.

Keywords: Youth, career readiness, disadvantaged, Generative AI(GenAI)

Chapter 1. Introduction

The National Youth Policy describes “youth” as everyone between the ages of 15 and 29 (NYP, 2014). The word “youth” is frequently used to refer to the time between dependent childhood and adult freedom. UNESCO (n.d.). India has become the most populated country in the world as of 2023, with an estimated 1.428 billion people (17.8% of the world’s population). Of these, 18.6% are children under the age of 17, and 27.2% are young adults (projected) between the ages of 15 and 29. (Youth in India, 2022) The youth of India make up roughly 83% of the unemployed workforce, and from 2000 to 2022, the proportion of young people with secondary or higher education among all unemployed Indians doubled, from 35.2% to 65.7%. (Krishnan,2024). Therefore it raises big concern for the employability of the youth and what steps could be taken in the forefront to support it.

According to the OECD (n.d.), career readiness is the ability of young people to compete in a labour market that is always evolving. This entails providing them with the know-how and abilities needed to excel in adult jobs. Career readiness encompasses a variety of transferable abilities that can be used as one advance in their career in addition to the hard skills required to do a particular job. It entails developing objectives, picking up new skills, and getting ready for a career. (Forage, 2023) OECD also points out that to be ready for a career the youth should have an intervention before the age of 15 to be successful in their life. But, the schools in India are not able to provide that support for students in public and low-income schools.

An individual who is between the ages of 10 and 19 who is deprived of the social, economic, and/or educational possibilities that other teenagers in their society experience because of a variety of uncontrollable circumstances is known as a disadvantaged, vulnerable, and/or marginalised adolescent (DVMA). They comprise elements at the familial, individual, and societal levels (e.g., disability, ethnicity), as well as social (e.g., economic disparity, violence, stigma, racism, migration). (Auerwald & Piatt, 2017) Access to fundamental possibilities such as education and skill development is greatly uneven and is not based on the needs of India's diverse youth population. That is why this community is highly affected by inequalities and therefore it is imperative that special attention is provided to them regarding education so that they can support their livelihood.

The goal of the National Education Policy (NEP) 2020 is to develop a more student-centric educational system that allows students the freedom to follow their passions and develop their talents at the same time. This policy, if properly executed, will eventually help our youth become more employable. (Sachdeva, 2021). The National Youth Policy 20203 aims to create an education system that is in line with the NEP 2020 and provides all young people with life skills and job prospects. It makes certain that young people have access to viable livelihood options that will motivate them to remain in rural areas and revitalise the economy, create jobs through techniques tailored to the needs of individual microregions, encourage social and informal entrepreneurship, and assist the gig economy (NYP, 2023). Although these policies have not been able to implement any positive change towards youth skilling, there is a huge requirement for real-world experience in classrooms which these policies promise.

The complexity of the issue is indeed multidimensional. Young individuals from underprivileged backgrounds often lack the financial means to access high-quality education. Their educational opportunities are largely influenced by the conditions of their schools and the support they receive from their communities. Moreover, parents who are constantly striving to provide for their families may not have the time or knowledge to guide their children's educational paths. As a result, schools bear the primary responsibility for helping these students succeed in life. However, teachers in public schools are often so overwhelmed with administrative tasks that they struggle to implement differentiated learning in the classroom and go beyond the basic curriculum. This limited exposure hinders the provision of a robust, skill-based education that encourages growth through values rather than mere content. The incorporation of AI has shown promise in addressing this issue, as it has proven effective in reducing teachers' workload and guiding students' learning with ethical instruction.

The thesis delves into the exploration of access and scrutinises the significant role that socioeconomic status plays in determining the educational and life outcomes of disadvantaged youth. We conducted a Randomised Control Trial in schools across India to observe the impact of GenAI in classrooms and its potential for teaching and learning of students and teachers. The research investigates the constraints imposed by income and how it contributes to a substantial digital divide for students from low-income backgrounds. We aim to study how these gaps can be bridged, and how a shift in pedagogy, coupled with access to AI, can guide the path towards career readiness.

The structure of the paper unfolds as follows: Initially, we delve into the case and research rationale, examining the concept of GenAI on a global scale before narrowing our focus to India. In the third and fourth chapters, we turn our attention to the theoretical framework and literature review, deeply exploring theories and literature within the context. The fourth chapter provides a detailed account of the experiment's methodology and design. The fifth chapter scrutinises the ordinal logistic model, its descriptive statistics, and its regression results. Finally, in the sixth and seventh chapters, we consider the implications of our findings and the limitations of our study, concluding with a summary of the RCT, a look at future research, and a final conclusion.

Chapter 2. Case Study and Rationale

2.1 Wave of Gen AI and its impact on education in schools.

Generative AI has been used to integrate more technology, making education more accessible and digitalized for easier and more effective access. Higher education could undergo a transformation as a result of the possible impact of GenAI technologies, especially large-scale language models like Chat Generative Pre-trained Transformer (ChatGPT), which present new avenues for improving student engagement, teaching, and learning (Hu, 2023). The current generation of students are finding Generative AI accessible and beneficial in enhancing their learning efficiency. The number of ChatGPT users has surpassed 180.5 million and continues to grow. It is evident that the current education system is struggling to keep up with the rapid growth of digital tools. Less than 10% of the more than 450 schools and universities surveyed globally by UNESCO in a recent study reported that their institutions had specific guidelines or institutional rules in place addressing the usage of generative AI applications (UNESCO, 2023). Institutions must continue to be flexible and receptive to new technologies, incorporating them thoughtfully into their educational programs. The goals of using GenAI should be to improve administrative tasks, support and enhance the learning process, and advance the welfare of staff and students

(Partovi, 2024) This integration can facilitate students' constant growth and make schooling more purposeful by providing opportunities to translate their knowledge. It can also save teachers time in planning and preparing classroom resources. However, the use of GenAI needs regulation, and implementation of stronger policies has become necessary in schools to ensure that GenAI is used appropriately and not for cheating. Additionally, as a tool generated by humans, it is afflicted with bias, which can perpetuate pre-existing biases in the system. The swift advancements in AI have generated significant ethical worries owing to its capacity to incorporate prejudices, contribute to environmental deterioration, and jeopardise human rights, among other perils. The hazards linked with AI are already worsening existing inequities, leading to additional harm to excluded people. (UNESCO, 2023) .

2.2 The skill gap in India and the lack of skills among youth

In a country where the demographic dividend is considered a benefit, the lack of adequate knowledge about career development, choice and management pose a significant threat to this potential powerhouse (Sadacharam, 2024). The majority of the youth, which forms 50% of the Indian population (Jack, 2018), are unaware of their own skills and potential career options they may have other than the traditional pathways. According to Agarwal (2020), only 93% of students are aware of a limited number of career options, despite there being over 250 available. This lack of awareness, combined with existing skill gaps, can limit the future prospects of underprivileged youth due to their socioeconomic status and lack of confidence. According to the OECD (2024), some groups of students encounter more obstacles than others in achieving their goals when they enter the workforce, even if they have the same qualifications as their more privileged peers. A mere 25% of students aged 14-18 who are enrolled in school can read a grade-level 2 book in their regional language, and 90% of them have access to smartphones. According to ASER (2024), the data indicates a significant skills gap among rural Indian youth, and the current NEP 2020 has not fulfilled its promises.

Disadvantaged communities typically have lower levels of achievement, high dropout rates, and in extreme cases, complete exclusion from education (Tilak, 2002). In communities where basic education is a challenge, students often lack access to career guidance and coaching. Guidance systems can help students plan for their working lives, gain knowledge, experience, and skills, and activate their human capital to maximise their chances of fulfilling their career ambitions (OECD, 2024). Therefore, young people have limited access to career support that can help them identify their skills and build a path to focus on their career. The Indian school system needs to be reshaped. The traditional focus on just grades must be replaced with a skill-building approach to focus on the development of practical skills. This can boost confidence and provide direction for the careers of young people. This shift is imperative to bridge the gap and make them competent for their future careers.

2.3 Research gap and application of research findings

Most previous research in India has also been of quantitative nature, looking at relationships between poverty and school enrolment or educational outcomes (Filmer & Pritchett, 2001; Tilak, 2018). There has been little research on doing a quantitative analysis of the Impact of AI. GenAI has the potential to revolutionise the educational landscape by reducing manual labour for teachers and alleviating the burden on schools for grading, assessments, lesson planning, and other systemic processes (McKinsey & Company, n.d.). This could result in a fundamental shift in job roles for some and a change in how they allocate their time to others.

The rapid integration of GenAI technology into the operations of the wealthiest nations and businesses is automating tasks such as marketing, sales practices, research and development, and even mundane tasks like to-do lists and summary reports (Deonandan, 2023). This highlights the importance of the ethical application of GenAI, especially in educational settings.

Teaching, which is fundamentally a social interaction (Giannini, 2024), cannot be replaced by GenAI. GenAI should be viewed as a proactive tool to enhance student learning and performance.

According to Ellingrud & Sanghvi (2023), GenAI is changing the game, with more educated workers experiencing the greatest impact. This presents an opportunity to level the playing field for disadvantaged youth. However, no empirical studies have been conducted to understand how GenAI affects the career readiness of youth.

This study aims to investigate the impact of GenAI on the career readiness of youth. The lack of access to GenAI could increase the gap for disadvantaged students, leading to further repercussions of inequality that already exists in the system. Therefore, this study is crucial in shaping the future of education in the era of GenAI. The subsequent sections of this paper will delve deeper into this critical issue.

Chapter 3: Theoretical Framework

3.1 The Social Cognitive Career Theory

Robert W. Lent created the Social Cognitive Career Theory (SCCT) in 1994, drawing inspiration from Albert Bandura's Self-Efficacy theory. There are five connected models in it. The early models (Lent, Brown, & Hackett, 1994) concentrate on the variables impacting educational and career interests, decisions, and performance. One such variable is perseverance. The fifth model (Lent & Brown, 2013) examines how we handle routine work and special difficulties throughout our careers, while the fourth model (Lent & Brown, 2006a, 2008) focuses on pleasure and well-being in academic and career settings.

The core of SCCT's career development model is a three-point interaction model consisting of three factors: result expectations (the anticipated consequences of an activity), personal objectives (the level of desire to pursue a particular action), and self-efficacy (the belief in one's ability to successfully carry out the action). (Buthelezi et al, 2010). The theory emphasises the direct impact of self-efficacy and outcome expectancies on goals by analysing the broader context in which individuals make decisions linked to their careers (Lent, 1994).

Wang et al. (2022) evaluate how a person’s coping efficacy may influence their decision to address obstacles to their professional progress and the success of these efforts. Significant impediments may prevent someone from pursuing a career, even if they have strong self-efficacy, positive result expectancies, and interests that fit the role (Brown & Lent, 1996). Lent (1994) also makes the argument that our environment has a big influence on the careers we choose. These include immediate situational elements that come into play while choosing a vocation, as well as background contextual influences that influence our interests and self-perception. These two categories of circumstances impact our career decisions, demonstrating the significance of both our current and historical contexts in shaping our professional choices.

According to Lent et al. (1994), contextual factors have an impact on learning experiences, which in turn shapes people's professional preferences and decisions. These include contextual affordances in the background that assist people in developing their interests and self-perceptions, as well as contextual effects during decision-making that impact job choices. Family and social support are examples of factors that fall under more than one of these categories and have varying effects on a person's academic and professional achievement. Increased social support and specific personality qualities are associated with more engaged behaviour in the workplace (Hirschi et al., 2011). The distinction between confidence to overcome real-world challenges and confidence to execute certain activities under ideal conditions is acknowledged (Swanson & Woitke, 1997; Lent, 2000).

The use of SCCT for individuals at risk of employment and occupational barriers was initially proposed by Chartrand and Rose (1996). For instance, SCCT has helped immigrant high school students by preventing dropouts and promoting academic success and career readiness through academic support and increased awareness of their own capabilities (Silva, 2017). Yuen (2022) evaluated an SCCT-based career intervention program for middle school children with mild special education needs, finding that it positively impacted the students' career, social and personal development, self-efficacy, and sense of purpose.

Career intervention strategies based on SCCT include goal setting, self-regulation, building support, coping with barriers, expanding choice options, facilitating work performance, and promoting job satisfaction (Lent, 2013). Rapid technological changes in society have destabilised traditional employee-employer relationships, leading to a new model of boundaryless careers (Arthur & Rousseau, 1996). Thus, SCCT suggests further development of support systems for individuals from diverse backgrounds in this new era of technological advancement.

3.2 Digital Divide Theory

Jan Van Dijk’s digital divide theory addresses the inequality that exists between those who have access to internet technology and those who do not. (Van Dijk, 2017) The framework developed by him tells us that societal inequalities lead to unequal distribution of resources, which in turn limits access to digital technologies. This unequal access, influenced by not knowing how to use technologies, leads to unequal societal participation, which brings us back to the initial inequalities. The theory has taken into account important covariates such as age, gender, race/ethnicity, intelligence, personality and health. It therefore suggests that existing inequalities in society lead to further inequalities.

The theory looks at three levels of inequality: Access to technology, skills, and use and enjoyment of benefits. (Van Dijik, 2017). The theory suggests that inequality is not only about access to the tool but also the lack of skills to understand and use them effectively. Fang et.al (2019) were able to analyse in their paper that according to social position, age and other markers of inequality, individuals who do not have a higher social position face additional life challenges compared to those who do. This suggests that disadvantaged communities have less access and are more likely to face more inequalities if the right support and resources are not allocated to them.

In their paper, Chisango (2021) discusses how both external and internal factors play an important role in access to digital tools. External factors include infrastructure and accessibility, while internal factors include beliefs, attitudes, and motivation to use.

Intrinsically, the main role depends on the teachers and their factors to use it in the classroom. They were able to conclude that negative attitudes towards ICT and inadequate ICT infrastructure lead to greater divides in schools.

Fang et al. (2019) concluded that there is a limited social justice perspective on the digital divide, which aims to highlight the disparities in access to technology that people face throughout their lives. Van Dijk's approach does not address the structural and systemic issues at the root of this social construct known as the "digital divide." Consequently, the application of the social justice framework for bridging the digital divide highlights the importance of identifying and addressing the multiple levels of inequality in access and use that different individual may encounter. Such disparate barriers require socially conscious intermediaries who, in addition to addressing the challenges of ICT use, address the complex issues of ICT access by reorganising current institutions and procedures to allow for a more equitable distribution of resources. This points to and urges a redistribution of resources, and more active work on policies to reduce this digital divide, as well as a greater focus on ICT, would help to reduce the current widening gap.

3.3 Technology Acceptance Model

The Technology Acceptance Model was developed by Fred Davis in 1989 and is concerned with how users accept and use technology. TAM suggests that user motivation can be explained by three factors: perceived ease of use (PEOU), perceived usefulness (PU) and attitude towards use. (David, 1986). TAM is the most common ground theory in the e-learning acceptance literature (Abdullah & Ward, 2016). TAM claims that PEOU and PU both have an impact on people attitudes regarding adopting technology. It claims that consumers would adopt a favourable attitude towards technology if they find it to be helpful and simple to use. The degree to which an individual has consciously planned to carry out or refrain from carrying out a particular future activity is known as Behavioural Intention (BI), the fourth component (Davis, 1989).

TAM also suggest that external variables have an impact on PEOU and PU's acceptability of using new technology. In this paper, the aspect of how GenAI as a tool facilitates the lesson planning of teachers and also increases the access of students to different learning materials will be explored.

Fathema (2015) talks about the incorporation of computer and internet technologies in the learning process, and by providing multiple teaching and learning tools, LMSs provide a virtual way for increased and faster communication between students and teachers, providing speed and effectiveness in the educational processes. Lee, Cheung and Chen (2005) also found that perceived usefulness and perceived enjoyment have an impact on students' attitudes towards and intentions to use Internet-based learning media. In addition, Pajo and Wallace (2001) identified personal barriers (lack of knowledge, skills, training, role models and time), attitudinal barriers (lack of confidence in technology, unwillingness to work with technology, concerns about student access) and organisational barriers (inadequate technical support, hardware, software, instructional design, lack of recognition of the value of online teaching) that hindered this implementation of digital teaching. Thus, the connection with the intrinsic approach to digital tools is affected by access, and the barriers to learning that are not provided can lead to limited or no use of them.

Chapter 4. Literature Review.

4.1 GenAI in Education and Career Readiness.

The literature on GenAI in education is now booming, although there are few studies focusing on its impact on schools, with most studies focusing on higher education. Chiu (2023), however, explored how GenAI is changing our schooling from the perspective of teachers and principals in eastern Hong Kong. The study concluded that there is a need for AI literacy as part of the school curriculum to prepare students for future technological landscapes, with a strong need for students to develop strong digital literacies to effectively use and understand GenAI technologies. The paper emphasises the need for integration and addresses the current needs of students in today's education systems.

Chan and Lee (2023) looked at how Gen Z perceived the technology and possibilities of GenAI compared to teachers. They found that students found these tools beneficial for their productivity and to improve their learning and were optimistic about using the tools. They also pointed out the concerns of the teachers which solidifies the need for a solid ethical framework that is required to govern its needs in ethical settings. The paper also discussed the potential of how GenAI can help schools seize the opportunity to implement teaching methods that address the diverse needs of students, thus focusing on differential learning methods to help each child in the classroom.

Similarly, students of the current generation prefer a work environment that assists and provides learning and opportunities for professional self-development because they know that their education does not provide sufficient skills to cope with real problems in life. (Baskoro, 2023). In their paper, Baskoro et.al 2023, the writers looked at GenAI as a tool in the classroom and how it could be used to improve critical thinking which is an important skill for students to learn. The paper used the GenAI tool as an independent variable on student learning in the students born between 1995 and 2010. They were able to observe high task performance among students while using these tools. Although, the paper didn't comment on how they looked at the learning needs of students who faced difficult learning in the classroom.

The AI literacy curriculum experiment was conducted by Lee. et al. (2021) with the underrepresented community in STEM, focusing on the middle school students (10-14), showed positive results on their career readiness using GenAI. They found that the right exposure to the students with a properly designed workshop resulted in more growth for students from the underrepresented community. The paper also looked at the accessibility and relevance of the content and how, when broken down properly, it provides the right direction for the student's learning, helping them to gain more interest and enthusiasm in the classroom. The findings also suggest that such educational initiatives can play a crucial role in preparing a diverse next generation for the challenges and opportunities of an AI-driven future.

Ali et. al (2024) was able to explore the idea of working on dreams in their classrooms. The intervention used generative AI for educational purposes and measured how it can significantly enhance both the technical understanding and creative capacities of students, and prepare them for the future. The paper was able to conclude that it helped in developing creative expressions and broadening their future career prospects. Students reached creative learning objectives by using prompt engineering to create their future dreams, gained technical knowledge by learning the abilities, limitations, text-visual mappings and applications of generative AI, and identified most potential societal benefits and harms of generative AI. (Ali, 2024). The sample population in the research also had students from all socio-economic needs thus focusing on inclusivity in the classroom.

This literature points us in the direction of understanding the significant role of GenAI in the classroom and shaping the future. It highlights three important things, students are open and curious to learn with GenAI, teachers can address the diverse needs of students in the classroom and make it more inclusive, and thirdly, with the right pedagogical and ethical approach the tool can have an impact and build strong skills and foundations for students, which I explore further in my thesis.

4.2 Socioeconomic Status and Student Outcomes

The relationship between socioeconomic status (SES) and educational attainment has been widely studied and commented upon. There is a consistent positive relationship between family SES status and student outcomes. Broer et. al (2019) discuss in their book how differences in attainment are related to student background and how the substantial variance in student attainment is usually explained by SES. Furthermore, they found that the gap in student achievement between low and high SES has increased over time from 1995 to 2005. This suggests that the educational gap is narrowing and widening over time in the absence of appropriate intervention in the Islamic Republic of Iran. This implies that the family's socioeconomic status significantly influences the academic outcomes of students.

Perry et al. (2011) also examined the impact of SES on students' education and its real-world significance. They examined how student outcomes and school SES are related, as well as how these relationships varied for kids from various socioeconomic origins. Using PISA data, they discovered that improvements in a school's mean SES are linked to increases in academic success for all students, independent of SES and students of low SES had lower grades constantly. This also demonstrated how SES affects students' academic performance and points to the need of more support for students from low SES.

Ranjan Ray (2000) points out that a child from a backward community is more likely to be involved in wage labour than to be enrolled in school as compared to children from other communities. There is a strong correlation between the awareness level of adult household members and the education of children.

In disadvantaged contexts, parents may feel excluded from and uninvolved in their children's lives at school, and unable to help with academic work (Grant, 2009; Hanafin & Lynch, 2002). Therefore parents are likely to trust the educational system as their understanding is bleak about the educational pursuits and outcomes of the students and can only act as support figures.

However, Chatterjee et. al(2021) in their study of disadvantaged youth in Banglore found that with proper support and a conducive environment, students show positive results. They concluded in their research that despite socioeconomic challenges, the presence of resilience and high aspirations, nurtured by supportive figures, played a significant role in academic success. However I feel that this is only possible with students of high order, students with low potential struggle a lot and with constant neglect from home and teachers in school, they face academic loss. Therefore differential learning is important in this context and the focus on skills rather than academics is imperative which was further highlighted that structured support systems at multiple levels can significantly enhance educational outcomes.

In the report Challenging Social Inequality Through Career Guidance, the OECD talks about the reverse effect of how career preparation can address these SES inequalities. The report looks at PISA 2018 data and sees that low SES students can be expected to have lower levels of career development due to a lack of support, so they should be provided with this support first and foremost. Secondly, the report builds on building the professional capacity of both students and teachers to provide this support to students, as well as creating resources to address these issues. Finally, it builds on fostering a critical understanding of the labour market that can help build social capacity. This literature is essential to point in the direction of creating social mobility and better equipping teachers and students to navigate and help them succeed in the career paths they can choose and build.

4.3 Hypothesis.

The literature review and theoretical framework lay a robust foundation for research addressing the career readiness needs of disadvantaged youth. According to Harding (2010), residing in disadvantaged areas can breed mistrust in the educational system, a sentiment that may be perpetuated and reinforced by older locals or peers who drop out of school. Therefore, it's imperative for schools to build trust with students and aid in the development of their self-esteem.

Students have shown a preference for computer learning over traditional instruction (Kinzie . et. al, 1988), and they perceive technology as a tool to enhance their chances of school success (Bowman & Mertz,1997). This leads to a logical conclusion that computers and self-esteem are complementary. The advent of technology as an instrument can assist students from disadvantaged communities in gaining self-esteem and achieving stronger outcomes.

Participants in technology-enriched classrooms appeared to score significantly higher (Page, 2002), indicating positive outcomes. Therefore, the hypothesis we explore in this thesis is:

Increased use of GenAI in the classroom as a teaching and learning tool leads to increased career readiness.

The research will further delve into this hypothesis, aiming to provide a comprehensive understanding of the role of GenAI in enhancing career readiness among disadvantaged youth. This exploration is crucial in shaping future educational strategies and interventions, ultimately contributing to the broader goal of educational equity.

We will use a Randomized control trial (RCT) for this research because we want to see the causal effect of GenAI on career readiness and it would provide us with reliable results. The randomization in control and treatment will help us understand that the observed differences in student performance are because of the treatment and not by other factors. RCTs have played a central role in seeking to determine whether an intervention is having a discernible and measurable effect on students' learning and development (Torgerson 2001)

Chapter 5: Methodology

5.1 Setting and Participants

This study was conducted in collaboration with Teach for All and Teach for India[1] as the implementing partner of the experiment, targeting low-income schools in urban and

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[1]Teach For All is a global network of independent organizations working to expand educational opportunity and develop collective leadership to ensure all children can fulfill their potential.
Teach For India, a part of the Teach For All network, is a non-profit organization that recruits college graduates and professionals to serve as full-time teachers in low-income schools in India for two years.

semi-urban areas across India. The low income schools (public or private) are the schools which have no fees or little fees for families to afford (mostly bellow 12000 INR ~ 150 euros a year). The schools selected for this study were characterised by limited access to GenAI technologies and a lack of structured career preparation programmes or dedicated career coaching. This setting was considered appropriate for exploring the potential benefits of incorporating advanced technological tools into the educational practices of disadvantaged communities. The intervention was targeted at socio-economically disadvantaged students and schools, where students' access to resources, opportunities and support systems can be more limited (OECD, 2023) so that they could potentially experience a more significant and measurable impact from the introduction of GenAI technologies, thereby offering a clearer insight into the effectiveness of such interventions in bridging educational and digital divides.

A randomised control trial (RCT) was used to establish the study design. Within this RCT framework, both the control and intervention groups were provided with a conventional work readiness curriculum. However, the intervention group received an additional educational component - the integration of Generative AI (ChatGPT) tools into their curriculum. This GenAI tool was not limited to classroom instruction but was also extended to students for individual practice, with the aim of increasing both engagement and learning outcomes. Notably, the experiment did not include a pure control group.

The participant recruitment process involved an opt-in approach among Teach for India Fellows, initiated 4 weeks before the start of the trial. As shown in Table 1, an initial pool of 40 teachers expressed interest, which was refined to 28 teachers who committed to implementing the intervention. Finally, participation was consolidated to 18 schools, representing a cohort of 751 students from grades 7 to 10. This selective approach ensured a diverse group of students for the RCT, including students from economically disadvantaged backgrounds, in line with Teach for India's mission to improve education in underprivileged communities. The design of this study allowed for rigorous testing of the hypothesis that GenAI tools can significantly improve career readiness among this population, and provide insights into the broader applicability and impact of such technological interventions in educational contexts.

During the randomisation phase, 426 and 325 students were allocated to the intervention and control groups, respectively. The intervention was followed by the follow-up phase, during which post-intervention surveys were collected. A total of 380 surveys were returned, but after removing duplicates and mismatched IDs, the effective number was reduced to 343.

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Enrollment
Estimate of teachers who opted in: n = 40
Participated: n = 18 (didn't roll in n = 22)
Estimate of students at the time of enrollment: n = 769
Participated: n = 751 (duplicates removed, n = 18; all students are
between the ages of 13-18 from low-income private or government schools)
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Randomisation
Allocated to the intervention group: n = 426
Allocated to the control group: n = 325
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Follow-up and Analyses
Post-intervention follow-up returned: n = 380 (duplicates removed n = 11
and non-matching IDs to pre-survey were removed = 26, final n = 343)
Intervention group: n = 177 (response rate 41.5%)
Control group: n = 166 (response rate 51%)
Lost to follow up: n = 408
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Data: Pre and post-treatment Data

Table 1: Student size across the time period of the study

5.2 Intervention and Randomization

The intervention provided as tools were detailed lesson plans provided to both groups. The plans were based on the principles of connectedness, awareness, mastery, agency and well-being (TACL, n.d.) for the best exposure and experiential learning of the students. The lesson plans were structured based on three thematic areas: how students explore, experience and think about their potential future in work. (Covacevich et.al 2021).

The first lesson plan, “Discovering our strengths and weaknesses”, was designed to guide students towards self-reflection and self-awareness. The second lesson plan, “Exploring Career Paths with a Global Lens”, aimed to broaden students’ horizons beyond local or traditional careers, which are often influenced by socio-economic status (SES). The third lesson plan, “Create a Personal Development Plan with SMART Goals”, was crucial in moving students from theoretical understanding to practical application. The essence of this plan was to help students create a tangible and actionable plan for their future, with SMART goals providing clarity and direction.

The key difference in the design of the instruments for the two groups was in the pedagogical approach. The design for the treatment group focused on using ChatGPT as a means of delivering information and as a platform for students to ask questions and engage in guided practice. This allowed students to tailor ChatGPT’s support to their specific needs, essentially training the AI to act as a career coach. In contrast, the control group experienced content delivery with teacher-led exploration and discussion.

Randomisation of students into the intervention and control groups, as shown in Table 1, was performed using an online software tool Research Randomiser to ensure an unbiased distribution. This critical step was taken to remove any form of selection bias by ensuring that each student had an equal chance of being allocated to either group. The use of such software is common in experimental design as it assists in the creation of comparable groups and strengthens the validity of the study’s findings by reducing systematic differences between group members. Therefore we had near to zero issues of non-compliance. There were two groups in randomization - treatment and control and the randomization was done school wise to avoid any spillover.

5.3 Pre and Post Treatment Survey

Two surveys were administered: a pre-treatment and a post-treatment in the study. Both were designed with reference to the Programme for International Student Assessment (PISA) standards, ensuring the data collected was internationally comparable. The survey responses for their demographics, income, access to AI and technology, career awareness and readiness. The pre-treatment aimed to establish a baseline for students. It included questions about students' prior exposure to AI, their perceived abilities in using AI platforms, and their initial career aspirations. The survey also assessed students' awareness of the skills needed in the 21st-century workforce. The post-treatment was conducted after the intervention and aimed to capture any changes in the students' perspectives and skills regarding AI and career readiness. It focused on changes in knowledge and attitudes towards AI, as well as career-related skills and competencies. The details of the survey can be seen in the appendix.

5.4 Lesson Plan Implementation

The lesson plan was sent across to teachers in March, with the experiment period extending from March 1st to April 7th. Teachers were instructed to incorporate the lesson plans into their regular classroom schedules. Each lesson was designed to fit into a 45-minute interval, aligning with the standard classroom instruction time. To ensure students had ample opportunity to engage with the content and reflect on it, the lesson plans were scheduled to be implemented weekly. This pacing allowed students to return with questions and a deeper understanding at each new session. The tentative dates set for the lesson plans were the 11th, 18th, and 25th, enabling teachers to integrate them into their monthly curriculum planning.

In the treatment group, the lesson plans were designed to utilise laptops, projectors, and tablets. However, understanding that resources may vary, alternate methods were provided in the lesson plans to accommodate classrooms with limited resources, even down to a single computer. Furthermore, an open line of communication was established for teachers to ask questions or seek clarity through WhatsApp or Email, ensuring they felt supported throughout the implementation process. This approach aimed to create a conducive environment for both teaching and learning, enhancing the overall effectiveness of the lesson plans.

5.5 Data Collection and Empirical Strategy

Our data collection process was divided into two stages: the pre-treatment and the post-survey. The pre-treatment was initiated in the first week of March, with a deadline of 9th March for students to complete their responses. For teachers, the post-treatment was open until 10th April. The primary focus of this study was to measure three outcome variables: educational goals, career knowledge and career confidence. Each of these variables was categorical and assessed using a Likert scale to capture the intensity of the respondent's feelings or perceptions.

For educational goals, students were asked about their highest desired level of education. The question was: "What is the highest level of education you would like to achieve?" Respondents could choose from several predefined options, ranging from "not sure" and "less than high school" to "high school", "vocational training", "undergraduate" and "postgraduate". This approach helped to gauge students' educational aspirations and the diversity of expected educational outcomes. Career knowledge was assessed by asking students to rate their familiarity with the types of jobs and degrees they were interested in pursuing. The specific question asked was: "How much do you know about the types of jobs and degrees you want to pursue?" Responses ranged from "a lot" to "some", "a little" and "not at all", providing a range of self-assessed knowledge about careers. Career confidence was measured by asking: "How confident are you about your future career?" The options provided were "very confident", "somewhat confident", "not very confident" and "not confident at all".

For our independent variables, to assess socio-economic status (SES), we used a combination of questions that were indirectly indicative of students' SES. These included "Do your parents own a car?", "What are the number of rooms relative to the number of people in the household", "How many non-curricular books do you have at home ?", and "What of the following do you have?" -" a silent place to study, a computer or tablet, and extra tutoring or educational support". We weighted all of them equally and created one of our independent variables "Income" which we logged further for skewness. In addition, parental education was recorded through "What level of education have your parents or guardians attained?" These questions helped to understand the educational background of the family, which was an important factor in shaping students' educational and career aspirations as per the SCCT theory. It is imperative to note that all SES-related questions were optional, which reduced the sample size by 225 as students chose not to provide this information.

For empirical strategy after randomization, as it was good, we ran ordinal logistic regression by regressing the outcome variable on the treatment with the outcome variables on the baseline

$$Logit(P(Y \leq j)) = \alpha\_j + \beta_1 \times Treatment + \beta_2 \times Outcome\ Variable\ at\ Baseline \quad \text{- - - - - - - -} \ (1)$$

Then we controlled for parental education and income as they adjusted for potential confounding effects that SES might have on both the accessibility to educational resources (like AI tools) and career readiness.

$$Logit(P(Y \leq j)) = \alpha\_j + \beta_1 \times Treatment + \beta_2 \times Outcome\ Variable\ at\ Baseline + \beta_3 \times Logged\ Income + \beta_4 \times ParentalEducation \quad \text{- - - - - - - - (2)}$$

Since the intervention was conducted during a school event and it was crucial to measure its impact, we also aimed to investigate the impacts by the school, therefore we adjusted for fixed effects by the school. This specification aids in separating the treatment impact from any variables unique to the school that could affect the results, such as variations in the school's resources, culture, or demographic makeup.

$$Logit(P(Y \leq j)) = \alpha\_j + \beta_1 \times Treatment + \beta_2 \times Outcome\ Variable\ at\ Baseline + \beta_3 \times Logged\ Income + \beta_4 \times Parental\ Education + \beta_3 \times School\ Fixed\ Effects \quad \text{- - - - - - - - (3)}$$

Lastly, we conducted an interaction to determine and research which student groups are more affected by the intervention. This model is also useful since it enables us to investigate whether the intervention's effects differ for various age cohorts, exposing differential responsiveness that may be related to different developmental stages or degrees of previous exposure to professional education.

$$Logit(P(Y \leq j)) = \alpha\_j + \beta_1 \times Treatment + \beta_2 \times Outcome\ Variable\ at\ Baseline + \beta_3 \times Age\ Group + \beta_4 \times Treatment \times Age\ Group \quad \text{- - - - - - - - (4)}$$

These regressions were run for all three outcome variables to study the probability of j by treatment, The clustering at the school level was ensured to correct for any intra-school correlation, ensuring robust standard errors that reflect the grouped nature of the data.

5.6 Ethical Considerations

By the standards of research ethics, students were asked by their teachers to provide written consent from their parents or guardians and they were collected and stored. This was a crucial step to ensure that the rights, integrity and privacy of the research students were protected as they were under the age of 18. Both verbal and written information about the study was provided in a clear and understandable way. This included the purpose of the study, the procedures to be followed, and the potential benefits. It was emphasised that participation was completely voluntary and that students had the full right to agree or refuse to participate without any consequences.

Once consent had been given, students were asked to complete a baseline questionnaire. This was designed to collect baseline data and establish a starting point for the study. A note was displayed at the top of the Google form, thanking students for their valuable contribution to the study and stating that they agreed to the study. All ethical considerations were met throughout the study. The research was conducted in a way that respected the dignity and autonomy of the students, and all data was treated with the utmost confidentiality.

Chapter 6: Results

6.1 Sample Statistics

Table 2 shows the consolidated sample statistics for all variables used in the study, providing a detailed comparison between the control group (0, N = 325) and the treatment group (1, N = 426). The category distribution of each variable is tested for statistical significance using chi-squared tests, as indicated by the accompanying p-values.

First, on the level of parental education, 42% of the control group and 36% of the treatment group reported having parents with less than a high school education. Conversely, 23% of the control group and 27% of the treatment group reported that their parents had completed tertiary education, suggesting a slight upward shift in educational attainment within the treatment group.

In terms of age, the control group had a larger proportion of the youngest cohort, with 31% aged 12, compared to 39% in the treatment group. The majority of both groups were in the 13-14 age group, with a higher percentage in the treatment group (42%) compared to the control group (50%).

In terms of educational goals, aspirations differed significantly between the groups. In the treatment group, 12% aspired to a bachelor's degree, while only 14% of the control group had the same aspiration. The aspirations for a high school diploma or equivalent were almost similar between the groups, with 14% in the control group and 15% in the treatment group. Notably, 28% of the treatment group aspired to a Master's degree or higher, which was significantly higher than the 40% in the control group.

Importantly, in terms of career knowledge, both groups reported similar levels of understanding, with 47% of the control group and 42% of the treatment group claiming to have some knowledge of career-related aspects. In the control group, 36% reported being very confident about their career prospects, compared to 49% in the treatment group. Concerning experience with GenAI and comfort with technology did not differ significantly between the two groups, with almost half of each group having some experience with GenAI and a similar distribution reporting varying degrees of comfort with technology. Perceptions of school support showed that 57% of the control group felt they were "very well supported" compared to 54% of the treatment group, although this was not statistically significant.

Finally, the availability of career advice and access to the Internet showed no significant differences between the control and treatment groups, with a substantial majority having access to the Internet and over 40% in both groups reporting having received career advice. In addition, most of the p-values, especially those for parental education level, job knowledge, experience with GenAI, technical comfort, and internet access, exceed the 0.05 threshold, indicating that randomisation was successful in creating two groups with comparable characteristics before the experiment.

Characteristic	0, N = 325[1]	1, N = 426[1]	p-value[2]
Parents' Education			0.3
1-Not sure	57 (18%)	85 (20%)	
2-Less than high school	138 (42%)	152 (36%)	
3-High school	56 (17%)	76 (18%)	
4-Tertiary education	74 (23%)	113 (27%)	
Other	0 (0%)	0 (0%)	
Age			0.044
12	100 (31%)	167 (39%)	
13-14	164 (50%)	181 (42%)	
15+	61 (19%)	78 (18%)	
Educational Goal			0.004
Bachelor's degree	46 (14%)	52 (12%)	
High school diploma or equivalent	45 (14%)	65 (15%)	
Less than high school	21 (6.5%)	38 (8.9%)	
Master's degree or higher	131 (40%)	121 (28%)	
Not sure	71 (22%)	121 (28%)	
Vocational or technical training	11 (3.4%)	29 (6.8%)	
Job Knowledge			0.6
A little	86 (26%)	117 (27%)	
A lot	63 (19%)	95 (22%)	
Nothing at all	23 (7.1%)	34 (8.0%)	
Some	153 (47%)	180 (42%)	
Career Confidence			<0.001
Not at all confident	9 (2.8%)	3 (0.7%)	
Not very confident	63 (19%)	56 (13%)	
Somewhat confident	135 (42%)	159 (37%)	
Very confident	118 (36%)	208 (49%)	
Experience with GenAI			0.6
No	172 (53%)	217 (51%)	
Yes	153 (47%)	209 (49%)	
Tech Comfort			0.8
Never used	24 (7.4%)	24 (5.6%)	
Not at all comfortable	6 (1.8%)	7 (1.6%)	
Not very comfortable	37 (11%)	58 (14%)	
Somewhat comfortable	108 (33%)	135 (32%)	
Very comfortable	150 (46%)	202 (47%)	
Is school Helping?			0.049
Not at all	14 (4.3%)	6 (1.4%)	
Not very well	27 (8.3%)	46 (11%)	
Somewhat well	98 (30%)	142 (33%)	
Very well	185 (57%)	230 (54%)	
Unknown	1	2	
Career Guidance			0.7
No	193 (59%)	245 (58%)	
Yes	132 (41%)	181 (42%)	
Internet Access			>0.9
No	7 (2.2%)	9 (2.1%)	
Yes	318 (98%)	417 (98%)	

Data from the pre-survey. P-values are based on Chi-squared tests.

[1] n (%)

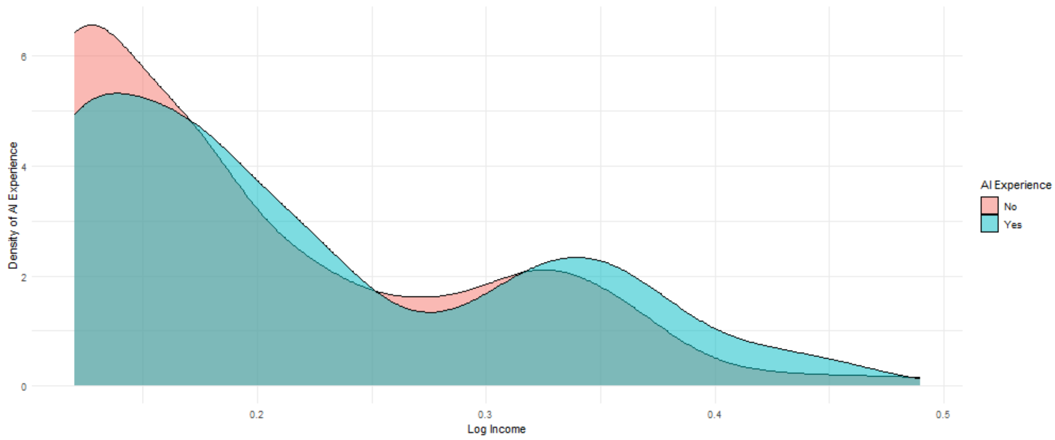
[2] Pearson's Chi-squared test

Data Source: pre-treatment Data

Table 2 Descriptive statistics of the treatment and control Group

5.2 Descriptive Statistics

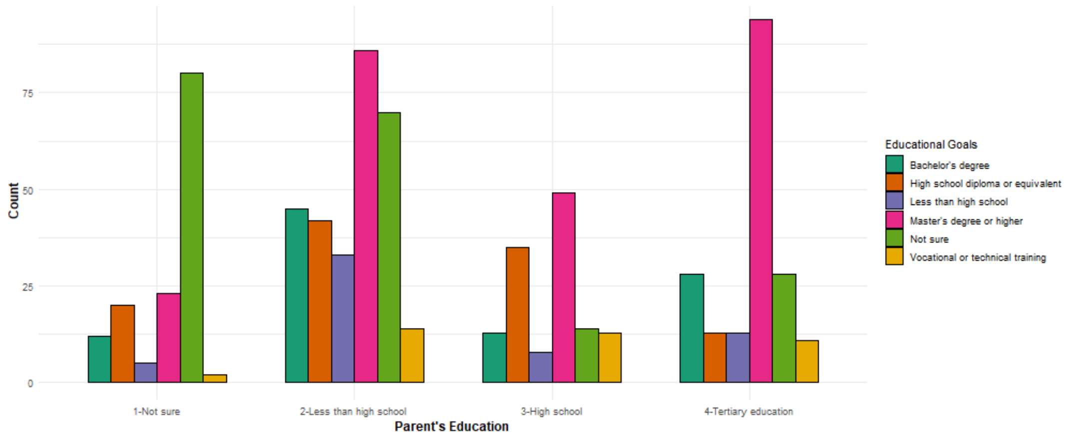
Parent's education and Logged income



Data source: Pre-treatment data

Figure 1: Density plot of AI experience and Parental Income

In the density plot in Figure 1, we compare the distribution of AI experience across different levels of logged income for the students. We can see from the distribution that there is a wider spread of students with no AI experience across all income levels. This suggests that regardless of income, a significant number of students have not been exposed to AI. As expected, as we move into the higher income brackets, we see a pink area superimposed on the teal, indicating that students with AI experience are more prevalent at these higher income levels, as suggested by the digital divide theory. This suggests a correlation where higher parental income is associated with greater exposure to AI. Thus confirming the theory of the digital divide.

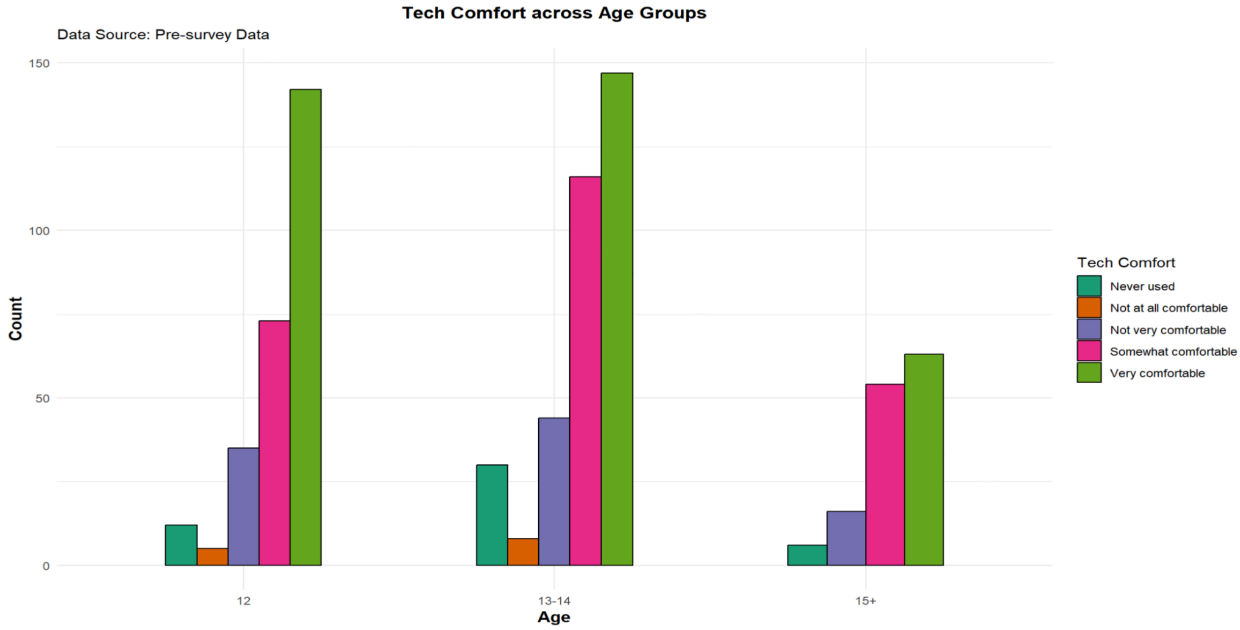


Data source: Pre-treatment data

Figure 2: Distribution of students' educational goals with parents' educational background.

In Figure 2, we see students' educational aspirations categorised by the educational level of their parents. We observe that the highest educational aspirations are those of students whose parents have tertiary education, as the highest percentage of students aspire to a Master's degree. Conversely, students whose parents have less than a high school education are more likely to be unsure about their educational goals or to aspire to a high school diploma or vocational training. The "not sure" category for "parents not sure" gives a strong indication of this, as we discussed in the SCCT theory. This suggests that there is a strong correlation between parent's educational attainment and their children's aspirations and that parents' education plays a strong role in their children's future.

Age and Technology comfort and usage

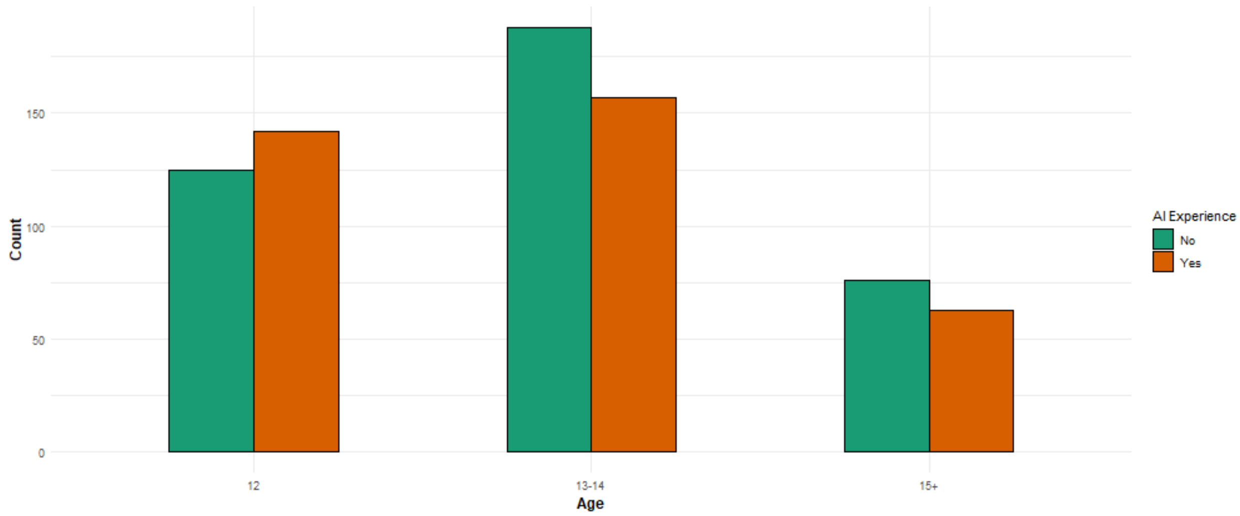


Data source: Pre-treatment data

Figure 3: Distribution of student's age and their technological comfort across age groups.

In Figure 3, technological comfort can be predicted across age groups using the TAM framework. We 12-year-olds are in the early stages of forming attitudes towards technology, with a significant number indicating limited comfort and being exploratory and shaped by basic experiences with technology. For students aged 15 and over, the marked increase in those who are very comfortable with technology may reflect a culmination of continued exposure and positive interactions with technology, resulting in high levels of perceived ease of use and usefulness, as predicted by the TAM. This level of comfort suggests that students in this age group are moving beyond mere acceptance to proficient use, which could have implications for their approach to learning and future career paths.

AI Experience across Age Groups:

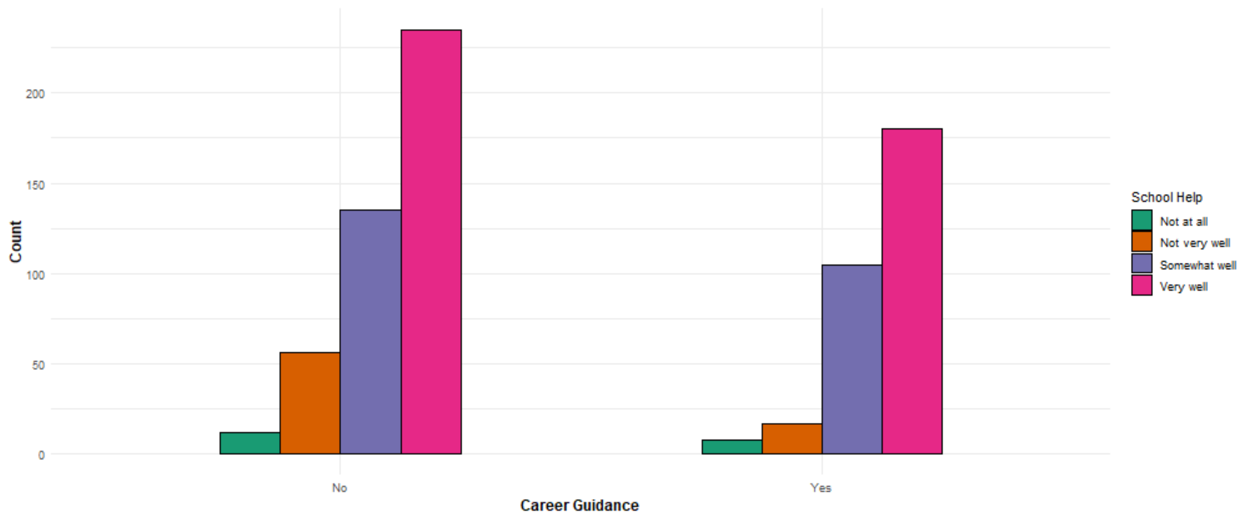


Data source: Pre-treatment data

Figure 4: Distribution of students' age and their AI experience across age groups.

In Figure 4, we see that younger students, under 13, may find AI tools more useful and easier to use due to their early exposure and adaptability, leading to higher usage. However, for students aged 13 and above, the perceived usefulness and ease of use might be lower, possibly due to less exposure or training. Therefore, targeted interventions to increase their familiarity with AI tools could increase their uptake and use.

Education in School



Data source Pre-treatment data

Figure 5: Distribution of career guidance by education provided in schools.

In Figure 5, we see the bar graph of school educational learning and the availability of career guidance. Students who have access to career guidance are more likely to feel that their school helps them “a lot”, while those who do not have career guidance are more likely to feel that their school helps them “a little” or “not very much”. It’s worth noting that the absence of guidance correlates with a lower perception of school help, which is consistent with social cognitive career theory, which emphasises the role of learning experiences in career development. This discrepancy highlights a potential gap in holistic education where academic learning is not complemented by practical career guidance.

It also points to a potential mismatch between what is taught in schools and what is required for career readiness.

6.2 Regression Analysis.

In this section, we focus on analysing the impact of treatment on three key outcome variables - educational goals, vocational knowledge and vocational confidence. Through these models, we aim to look deeply at the effect of treatment in the four regressions for each of the outcome variables.

Education Goals.

TABLE 3: Regression Analysis: Model Summary for Education Goals

	Dependent variable:			
	Education Goals Post Treatment			
	Ordered Logistic		Generalized linear Fixed-effects	Interaction
	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
Treatment	0.91*** (0.20)	1.18*** (0.26)	1.22*** (0.35)	0.64 (0.48)
Age - 12				ref
Age - 13-14				1.34*** (0.44)
Age - 15+				0.73 (0.48)
Education Goals- Not sure	ref	ref	ref	
Education Goals- Postgraduate	0.22 (0.27)	0.17 (0.37)	0.05 (0.52)	0.23 (0.29)
Education Goals- Less than High School	0.95** (0.46)	0.62 (0.74)	0.30 (0.92)	1.01**(0.48)
Education Goals- High School	2.30*** (0.31)	1.82*** (0.37)	0.74 (0.65)	2.13***(0.31)
Education Goals- TVET	1.12** (0.51)	0.67 (0.61)	0.17 (0.77)	1.01**(0.52)
Education Goals- Undergraduate	2.08*** (0.31)	1.85*** (0.40)	0.48 (0.59)	2.10**(0.32)
Log Income		0.03(1.53)	0.01 (2.02)	
Parents Edu -Not sure	ref	ref	ref	
Parents Edu -Less than high school		1.56*** (0.33)	1.18** (0.51)	
Parents Edu -High school		2.29*** (0.41)	2.11*** (0.62)	
Parents Edu -Tertiary education		1.01* (0.42)	0.64 (0.58)	
Treatment* Age - 12				ref
Treatment* Age - 13-14				1.48*** (0.56)
Treatment* Age - 15				1.83*** (0.61)
Constant			15.52*** (0.67)	
Observations	343	226	226	343
Log Likelihood			-109.61	
Akaike Inf. Crit.			243.22	
Bayesian Inf. Crit.			284.27	
Note:	*p<0.1; **p<0.05; ***p<0.01			

Data Source = Pre & Post Survey Data

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0.95

Table 3: Model summary of ordinal logistic regression of educational goals with controls (parental income and parental education) and fixed effects by school

In Model 1 from Table 3, where we do not control for any variables other than educational goals baseline, the odds ratio for treatment is 0.91 (statistically significant), suggesting that treated students are 9% less likely to pursue higher educational goals compared to those who did not receive the treatment.

In Model 2, we controlled for parental education and parent's logged income, we saw that the odds ratio for treatment is 1.18, which is statistically significant. This suggests that students who received the treatment are 18% more likely to pursue higher educational goals compared to those who did not receive the treatment. When we observe educational goals, students who are unsure of their goals serve as the reference group. Students aiming for less than high school education have significantly lower odds (OR = 0.62,), indicating they are 48% less likely to aim for this level of education. High school aspirants have higher odds (OR = 1.82), suggesting they are 82% more likely to aim for high school completion, which is statistically significant. Students aiming for technical and vocational education (TVET) have significantly lower odds (OR = 0.67) indicating they are 33% less likely to opt for TVET and it was not statistically significant. Undergraduate aspirants have higher odds (OR = 1.85), implying an increase of about 85%.

In Model 3, which applies fixed effects by school, the odds ratio for treatment is 1.22 (statistically significant). This suggests that, after accounting for differences between schools, treated students are 22% more likely to pursue higher educational goals compared to those who did not receive the treatment.

For educational goals, students aiming for less than high-school education have lower odds (OR = -0.35), indicating they are less likely to aim for this level of education. High school aspirants have odds of 0.74 and students aiming for technical and vocational education (TVET) have significantly lower odds (OR = 0.17, $p < 0.05$), indicating the treatment has less effect on them. Undergraduate aspirants have higher odds (OR = 0.48), implying a decreased likelihood, although it's not a reliable statistical difference. The results for this model lack statistical significance although the treatment did show a positive effect.

In Model 4, which focuses on interaction, the treatment is not statistically significant. However, the interaction of treatment and students aged 13-14 had an odds ratio of 1.48 which was significant. For students aged 15 and above the odds ratio was 1.83. This suggests that these students are 83% more likely to have higher education goals when they receive the treatment compared to the baseline of students aged 12.

Career Knowledge

TABLE 4 : Regression Analysis: Model Summary for Career Knowledge

	Dependent variable:			
	Career Knowledge Post Treatment			
	Logistic		Generalized Linear Fixed-effects	Interaction
	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)
Treatment	1.19*** (0.29)	1.65*** (0.38)	1.65*** (0.38)	0.40 (0.71)
Age - 12				ref
Age - 13-14				0.72 (0.69)
Age - 15+				0.30 (0.70)
Career Knowledge - Less	ref	ref	ref	ref
Career Knowledge - More	2.31*** (0.29)	2.07*** (0.38)	2.07*** (0.38)	2.42*** (0.30)
Logged Income		9.96*** (2.41)	9.96*** (2.41)	
Parents Edu- Not Sure	ref	ref	ref	ref
Parents Edu- Less than high school		0.62 (0.53)	0.62 (0.53)	
Parents Edu- High school		2.18*** (0.77)	2.18*** (0.77)	
Parents Edu- Tertiary education		0.66 (0.61)	0.66 (0.61)	
Treatment*Age -12				ref
Treatment*Age -13-14				4.01*** (0.86)
Treatment*Age- 15+				4.57*** (0.88)
Constant	2.79*** (0.25)	2.04*** (0.65)	2.04*** (0.65)	4.96*** (0.63)
Observations	343	226	226	343
Log Likelihood	-150.01	-94.98	-94.98	-145.00
Akaike Inf. Crit.	306.01	203.97	205.97	304.01
Bayesian Inf. Crit.			233.33	
Note:				*p<0.1; **p<0.05; ***p<0.01

Data Source = Pre & Post Survey Data

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0.95

Table 4: Model summary of ordinal logistic regressions for career knowledge with controls (parental income and parental education) and fixed effects by school.

In Model 1, we don't control for any variables and provide a basic understanding of the treatment effect. The odds ratio for treatment is 1.19, which is statistically significant. This suggests that students who received the treatment are 19% more likely to have higher career knowledge compared to those who did not receive the treatment.

When we look at career knowledge levels, students with more "Carrer knowledge - More" had an odds ratio of 2.31 compared to the baseline with "Carrer knowledge - Less". Thus implying that the risk of the effect of treatment is higher by 131 % for the students who went through treatment in the more category.

In Model 2 and Model 3 we had similar results, after controlling for parents' logged income and education. The odds ratio for treatment is 1.65, which is statistically significant This indicates that, after accounting for parents' income and education, treated students are 65% more likely to have higher career knowledge compared to those who did not receive the treatment. When we look at career knowledge levels, students with more "Carrer knowledge - More" had an odds ratio of 2.07 compared to the baseline with "Carrer knowledge - Less". Thus implying that the risk of the effect of treatment is higher by 107 % for the students who went through treatment in the more category.

For interaction, the treatment has a statistically significant positive impact on career knowledge for students aged 13-14, with an odds ratio of 4.01. This suggests that these students are approximately 301% more likely to have higher career knowledge when they receive the treatment. For students aged 15 and above, the treatment has an even stronger odds ratio of 4.57 ($p < 0.01$). Thus confirming that all the students closer to graduating from school had a higher impact and it aligns with their post-school outcomes.

Career Confidence

TABLE 5 : Regression Analysis: Model Summary for Career Confidence

	Dependent variable:			
	Career Confidence Post Treatment			
	Logistic		Generalized linear Fixed-effects	Interaction
	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
Treatment	0.58* (0.33)	0.83** (0.41)	0.49 (0.75)	0.08 (1.13)
Age - 12				ref
Age - 13-14				0.15 (1.09)
Age - 15+				0.12 (1.12)
Career Confidence - Less	ref	ref	ref	ref
Career Confidence - More	5.49*** (0.36)	7.01*** (0.47)	10.56*** (0.55)	6.35*** (0.37)
Log Income		1.14 (2.40)	1.25 (2.59)	
Parents Edu- Not Sure	ref	ref	ref	ref
Parents Edu- Less than high school		1.06* (0.54)	1.15* (0.60)	
Parents Edu- High school		3.37*** (0.87)	3.47*** (0.93)	
Parents Edu- Tertiary education		0.49 (0.60)	0.46 (0.66)	
Treatment* Age - 12				ref
Treatment* Age - 13-14				7.69*** (1.20)
Treatment* Age - 15+				14.85*** (1.30)
Constant	2.05*** (0.31)	1.35** (0.68)	1.39 (0.85)	10.88*** (1.04)
Observations	329	218	218	329
Log Likelihood	-129.04	-84.31	-82.18	-125.81
Akaike Inf. Crit.	264.07	182.61	180.35	265.62
Bayesian Inf. Crit.			207.43	
Note:				*p<0.1; **p<0.05; ***p<0.01

Data Source = Pre & Post Survey Data

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0.95

Table 5: Model summary of logistic regressions for career confidence with controls (parental income and parental education) and fixed effects by school

In Model 1 for career confidence, which is an ordered logistic regression model without controlling for any variables, the odds ratio for treatment is 0.58 (not statistically significant) This suggests that students who received the treatment are approximately 42% less likely to have higher career confidence compared to those who did not receive the treatment. When we look at career confidence levels, students who have “Carrer confidence- More” have an odds ratio of 5.49, suggesting they are 449% more likely to be confident compared to those who are less confident.

In Model 2, after controlling for parents' logged income, the odds ratio for treatment is 0.83, which is statistically significant at the 5% level. This indicates that, after accounting for parents' income, treated students are approximately 17% less likely to have higher career confidence compared to those who did not receive the treatment and it was statistically significant. When we look at career confidence levels, students who have "Carrer confidence - More" have an odds ratio of 7.01, suggesting they are 601 % more likely to be confident compared to those who are less confident.

In Model 3, which applies fixed effects by school, the odds ratio for treatment is 0.49, which is not statistically significant. This suggests that, after accounting for differences between schools, treated students are approximately 51% less likely to have higher career confidence compared to those who did not receive the treatment. However, this difference is not statistically reliable. When we look at career confidence levels, students who are "Carrer confidence- More" about their career have an odds ratio of 10.56, suggesting they are 956% more likely to be confident compared to those who have "Career confidence - Less".

For interaction, between students aged 15 and above and treatment, the odds ratio is 14.85 and for the age 13-14 the odds ratio is 7.69 and both are statistically significant. This indicates that these students are 669% more likely to have higher career confidence when they receive the treatment for age group 13-14 and its doubled for age 15.

The robustness of the experimental design is evident when comparing the outcomes of Model 1 and Model 2 across the three outcome variables. Despite the variations in sample sizes, the results demonstrated a thorough consistency, therefore indicating that the models' performance was not significantly influenced by the size of the data set.

Figure 6, 7 and 8 offers insights into the model's coefficients plots for the three outcomes with and without controls other than the baseline. For educational goals, the treatment is more effective when the model was clustered compared to normal log regression. For carrer knowledge, the coefficient are above 1 for both the models, signifying that the effect of the treatment was the highest on it. Lastly for career confidence, the coeffecient are below 1 indicating less effect of treatment.

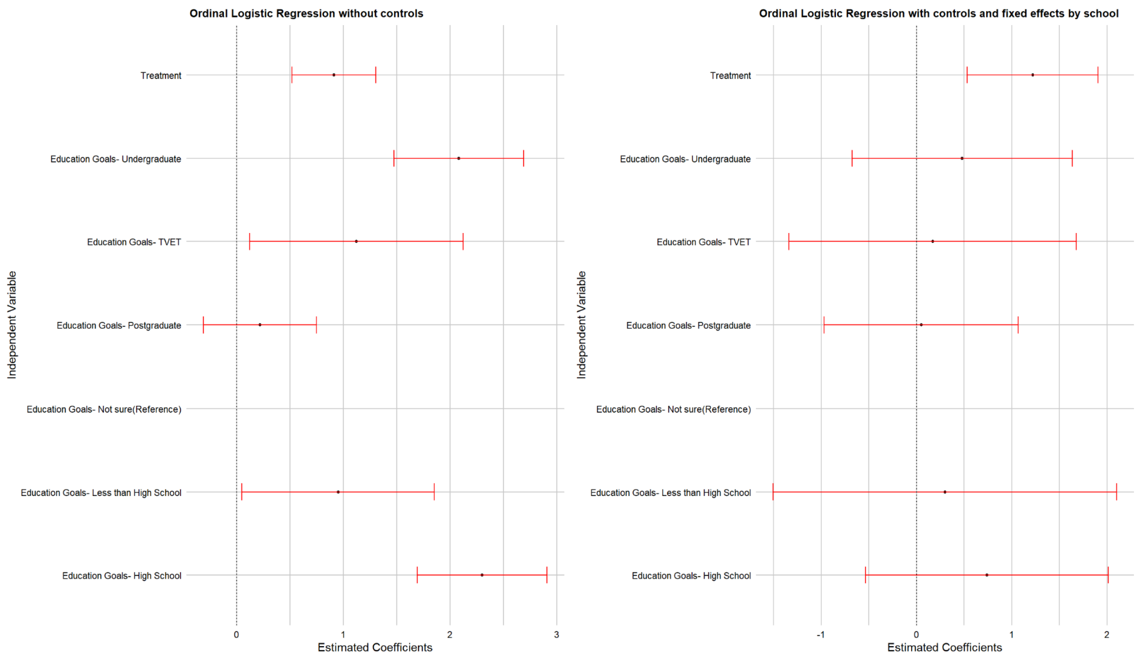

Figure 6: Coefficient plot of educational goals for the ordinal logistics model models without and with controls. Data source: Pre and Post Treatment data

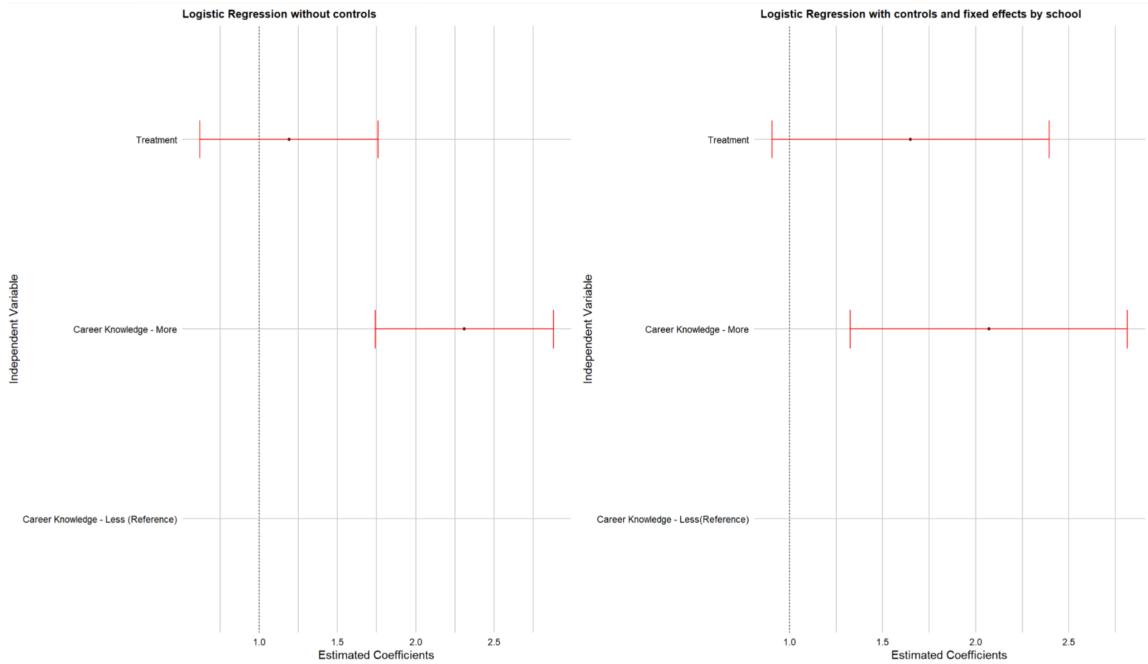

Figure 7: Coefficient plot of career knowledge for the logistics models without and with controls. Data source: Pre and Post treatment data

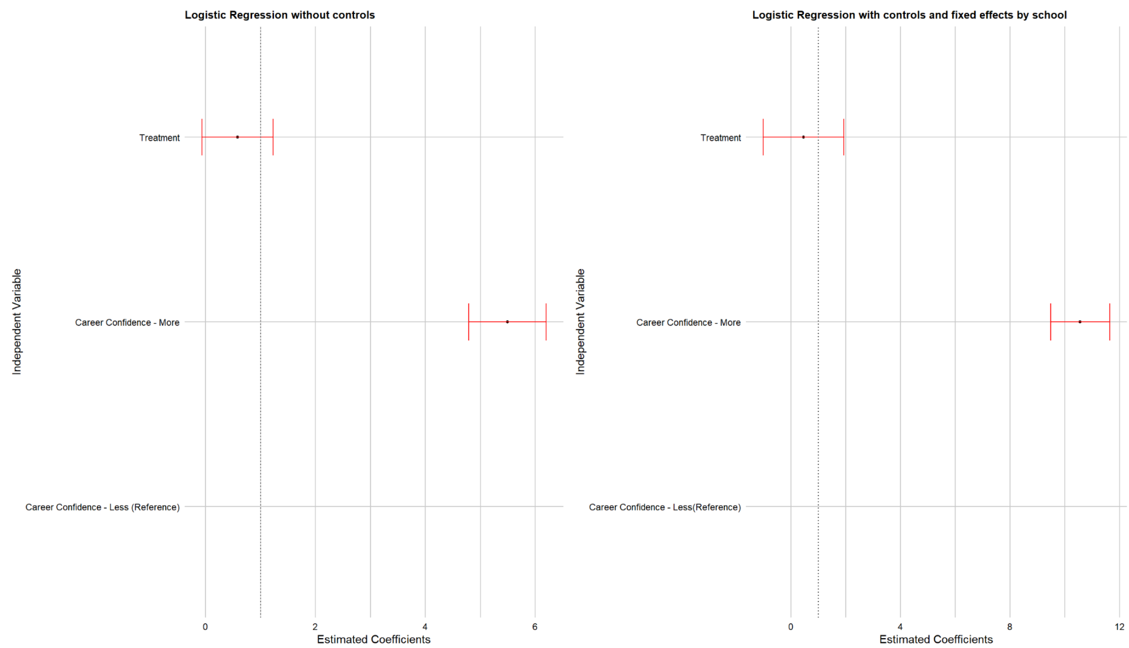

Figure 8: Coefficient plots of career confidence for the logistics model without and with controls. Data source: Pre and Post treatment data

Chapter 7: Discussion

7.1 Interpretation of Results

This thesis explored the impact and implications of Generative Artificial Intelligence (GenAI) technologies on the career readiness of disadvantaged youth in India using an RCT design, with a focus on how these technologies were used in a pedagogical and learning context in the classroom. This research deepened the focus on the pedagogy and benefits of GenAI and broadened the motivation of students, resulting in a positive impact on students' perspectives on their career paths and future preparation. By using a quantitative method, the research was able to capture the substantive impact of using AI in the classroom.

The results show that by providing learning experiences and exposure to a variety of career alternatives, the treatment had a statistically significant positive impact on student's educational goals, suggesting that exposure to GenAI tools increased their aspirations for higher levels of education. In addition, the study showed a shift in pedagogy from traditional learning with the use of GenAI to an exploratory approach which instils more curiosity in students, which is essential in shaping students for the future and making them leaders for their communities. The study also showed that while GenAI has the potential to improve student performance, this is only possible through guided teacher instruction, highlighting the importance of using AI with ethical guidance and a question-based approach, where it acts as a guiding tool rather than an answering tool.

When controlling for socio-economic factors, the impact of GenAI interventions showed a positive growth in improving career readiness for all three outcomes in the models. The digital divide theory holds and addresses the potential for students from disadvantaged communities to harness its effectiveness for their benefit, the results show the reality that positive intervention yields positive tech comfort which in retrospect has a positive impact on their educational goals. In the Indian context, unequal access to technology is a major issue, reflecting wider socio-economic inequalities and creating barriers to the consistent provision of GenAI benefits, which would require active policy intervention.

Subsequently, parental education also influenced the use of GenAI on students' career preparation, which was not so strongly influenced by the regression results. The impact is obvious as the beliefs, educational background, motivation and attitudes of parents have been shown to significantly influence achievement (Hidayatullah, 2023). In the Indian context for disadvantaged youth, the perceptions and ideas of parents play a pivotal role in exposure, and they rely entirely on schools and teachers for their children's development due to their lack of personal knowledge. The results showed that even with less parental education, the students can grow and learn more and GenAI works well in exposing them to binaries beyond their limits, thus pushing them more.

However, the results for career confidence were mixed, with some models showing les o no impact of the treatment. This discrepancy highlights the need for further investigation into the factors influencing career confidence among disadvantaged students. The study also uncovered interesting interaction effects between the treatment and age groups. Notably, students aged 15 and above experienced more significant positive impacts on educational goals and career knowledge compared to their younger counterparts. This finding suggests that GenAI interventions may be particularly beneficial for older students who are closer to making critical career decisions.

In summary, the potential of GenAI to improve academic performance and career readiness is significant. However, its success depends largely on addressing the socio-economic inequalities that limit access to technology due to the digital divide in India. This study urges for policies that mitigate these inequalities and cultivate an inclusive learning environment where all students have access to cutting-edge technological resources. It also calls for ongoing research to assess the impact of GenAI and ensure that its integration into education systems aligns with the evolving needs of society and the workforce. The study highlights the transformative power of targeted educational interventions in shaping students' career aspirations and confidence. It highlights the role of education in broadening students' horizons, empowering them to dream bigger and strive to achieve those dreams.

In the context of the Career Goals, this study provides a model of how targeted interventions can effectively guide students towards higher aspirations and greater confidence in their future careers.

7.2 Limitations of Research

Although the study showed a significant impact, it was not without its limitations. The first limitation was attrition in the sample size, mainly due to the timing of the study. The time coincided with the beginning and end of the academic year for the schools involved. Four schools started the study but couldn't complete it. Three of them had exams at the end of April and couldn't take part in the final survey, and one school had students who left their town when the school closed at the end of the year. These exogenous factors contributed to reducing the number of students in the follow-up survey.

The second limitation was the length of the study. The study only lasted for one month. It's therefore difficult to comment on long-term benefits and how we can measure them. Long-term benefits, such as sustained improvements in career readiness, and increased motivation. It is crucial to understand the full impact of the intervention but requires a longer period of observation to measure effectively.

The third limitation is the context of the study. The study is specific to Teach for India schools and teachers. The schools, although in partnership, are low-income schools and may have limited infrastructure, but the teachers have received extensive training in relevant pedagogy. The teachers/fellows have a strong sense of purpose and willingness to work in the classroom. These limitations should be taken into account when interpreting the generalizability of the results of the study.

The fourth limitation concerns the sample size, which was relatively small for the final analysis due to the attrition rates and logistical challenges mentioned earlier. The smaller sample size reduces the statistical power of the study, making it challenging to detect smaller effects of the intervention that might be significant. Additionally, a smaller sample limits the generalizability of the findings.

The last limitation was the use of English as the language to get the forms filled in, there was a lot of debate on the mode of form would be in regional languages but the students find it difficult to read in their regional languages as well. Therefore the students who filled it out might be high-order children, therefore there is a possibility that the students who filled it out might be those and the dropouts might be high-potential children who need this intervention the most.

Despite these limitations, this study contributes to the growing research in the field of using GenAI in education to address educational and career readiness challenges faced by disadvantaged communities. As the integration of GenAI tools in educational settings continues to evolve, further research and collaboration among stakeholders will be crucial to ensure equitable access, ethical implementation, and positive outcomes for all students.

7.3 Recommendations for Further Research

The exploration of GenAI's impact on disadvantaged youth in India is a relatively new area of study, offering ample opportunities for further research. One area that could benefit from additional investigation is the relationship between GenAI and career confidence, as the current study did not find a significant effect.

The study's design could also be enhanced by adopting a longitudinal approach, which would allow researchers to observe the impact of GenAI over time. Additionally, expanding the scope of the research to include various types of schools could provide insights into potential exogenous variables that may affect different schools at different levels. A larger-scale study could lay a solid foundation for understanding other variables that were not accounted for in the initial research.

Future research should aim to replicate this study in diverse contexts, such as government schools, private schools, and schools in rural areas. This would help to understand the impact of GenAI in a variety of settings.

Another aspect to consider is the use of regional languages. Investigating whether a higher response rate can be achieved and whether all students can be actively involved throughout the process when regional languages are used could be beneficial.

Finally, adopting a mixed-methods approach could provide a more detailed understanding of the experiences of students and teachers. This would add a strong qualitative foundation to the research, complementing the quantitative data by knowing the experience and learnings of the students.

In summary, while the initial study provides valuable insights, there are several areas where further research could enhance our understanding of GenAI's impact on disadvantaged youth in India.

Chapter 8. Conclusion

The goal of this study was to determine the impact and potential of Generative Artificial Intelligence (GenAI) in improving the career readiness of underprivileged youth in India. The study provided insightful results and information on the benefits of incorporating GenAI into the school environment for educational goals and career knowledge. The significant results confirmed the application of using GenAI in underprivileged classrooms can show positive results. The study was able to create an impact and build a strong foundation for students who never had exposure to such classes.

The study also highlights the importance of addressing the socio-economic inequalities that hinder access to these technologies and create a digital divide. It calls for proactive policies and inclusive initiatives to ensure that all students, regardless of their socio-economic situation, can benefit from GenAI. GenAI indeed comes with a lot of bias, but the focus should be on feeding it with local context and knowledge so that it can help contextualise and build those connections for the students and help them accordingly. The lesson plans used in the classroom had a strong focus on removing that bias for more fruitful results which is a key point to be focused upon.

The study also highlights the need for more research on disadvantaged youth with larger samples in scenarios focused on career readiness. There was a lack of literature on measuring career readiness in India, therefore skilling programs should be implemented at a larger scale with an RCT approach. It also recommends the use of a mixed-methods approach and the use of regional languages in data collection to gain a deeper understanding of the experiences of students and teachers and focus on leaving no child behind.

The study concludes by highlighting the transformative potential of GenAI in influencing students' career aspirations and confidence, and the importance of education in encouraging them to set higher goals and work towards them. It is intended that this research will act as a springboard for further investigation, supporting ongoing efforts to use GenAI to provide every student with access to high-quality education and equal opportunities under ethical considerations.

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Declaration of Interest Statement

The author declares no conflict of interest nor any financial gain or other personal benefits arising from the application of this research. The research was carried out to meet the requirements of the author's MPP degree.

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Appendix (Available on request. ***)***

- AI and Normal Lesson Plans.
- Pre-treatment and Post-treatment Forms
- Data

Statement of Authorship

I hereby, confirm and certify that this Master's Thesis is my work. All ideas and language of others are acknowledged in the text. All references and verbatim extracts are properly quoted and all other sources of information are specifically and designated.

DATE: 29th April, 2024

NAME: Sumit Anand

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Statement of academic integrity related to the use of Artificial Intelligence tools

I acknowledge the use of artificial intelligence-based tools to support the writing of this thesis, aimed at finding synonyms or alternative sentences.

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