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ECONOMIC TRANSFORMATION IN THE DIGITAL AGE: THE NEXUS BETWEEN LEARNING AND INNOVATION

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ABSTRACT

This research examines the implications of new generation digital learning technologies for the transformation of skill formation and economic outcomes under a now-ubiquitous educational environment. It adds them to the background of establishing interdependencies of adaptive learning technologies (ALT), digital learning platforms (DLP), and learning design innovation (LDI) as contributory and crucial determinants outcome as economic impact (EI) with mediating role of skill acquisition (SA) and moderating role of socioeconomic status (SES). Convenience sampling method is used to conduct a self-questionnaire based survey on social media channels and subsequently applied structural equation modelling on the responses of 377 individuals. The study established that of ALT, DLP and LDI improved learning outcomes dramatically through experience as well as democratization. Results showcased the importance of innovative learning design in enhancing organizational performance and learning effectiveness. Indeed, DLP can be harnessed to strengthen learning in educational institutions pursuance of knowledge sharing, skill development and improving development in the economy. This research supports the understanding of the change dynamics of digital learning and inspires educational institutions and policymakers alike to adjust and survive against an increasingly digital educational landscape. The proposed model provides novel insights of how digital educational technologies and socioeconomic variables interplay to drive skill development and economic transformation in the digital age.

Keywords: *Adaptive learning technologies, digital learning platforms, learning design innovation, skill acquisition, economic impact and socioeconomic status*

1. INTRODUCTION

The digital era has substantially transformed human life from how we learn, to how we improve ourselves to how we address lifelong learning. Learning in this era therefore ushers a whole new wave of growth, innovation and productivity across industries; therefore, inevitably comes with consequential implications for economy and education itself (Ziomek, 2021)EU documents and survey results. A comparative analysis of the opinions of employees, managers and trade union representatives is carried out based on the results of a survey in an industrial company where stationary work is required. The results show that in the Greater Poland (Wielko-

polska. New technologies for digital learning, such as online learning platforms and adaptive learning systems, have opened up new pathways for skill acquisition (He et al., 2022). Educators, representatives, and organizations must become aware of the financial implications arising from these technological changes with the use of digital learning to improve their bottom lines. According to Massimiliano Nuccio & Sofia Mogno (2023), these tools empower individuals to shape their education based on their professional and personal objectives and learn at their own pace, and ultimately govern their employability and earning potential.

Digital learning is an application of usage of digital technologies and resources that seek to advance education and training with prevailing scalable and accessible ways of learning over the normal conventional methodologies of teaching (Zhang et al., 2024). Millions of people across the globe have greater access to education that promotes inclusiveness and writes away education obstructions through DLP such as Massive Open Online Courses (MOOC) and mobile learning applications. As Francis & Weller (2022) points out, these learning platforms play an unique role in building creative capacities that cannot be replicated in the physical classroom environment because of the unique learning experiences they offer. In light of this customization, trainees are able to concentrate on areas of weakness while enhancing their skill sets to a greater extent, which elevates their economic significance. In today's knowledge-driven economy, skills are increasingly being recognized as an economic competitive advantage (Macklem, 2016). In light of the shift in demand from labour-intensive activities to cognitive and technological expertise prompted by the digital era, workers must continually adapt to new technological developments.

Using DLP and adaptive technologies is one of the main ways learning determines economic growth. According to Rohs & Ganz (2015), the usability of excellent educational opportunities was disrupted recently by digital platforms such as Khan Academy, Coursera, and edX that enable students to take courses in variety of categories from top-tier colleges and universities at a fraction of the cost of traditional education. These platforms empower everyone by providing affordable prices, flexibility, and self-paced learning formats that allow a wide range of individuals to earn valuable skills. As explained by Barikzai et al. (2024), in developing countries may not have access to available traditional educational resources, digital learning has the most significant effect in terms of availability. As Susilana et al. (2024) asserts, adaptive technologies focus learning by identifying where in their educational path students are and adjusting the relevance or relative difficulty of the learning material, thereby increasing retention and engagement. According to Ziomek (2021)EU documents and survey results. A comparative analysis of the opinions of employees, managers and trade union representatives is carried out based on the results of a survey in an industrial company where stationary work is required. The results show that in the Greater Poland (Wielkopolska, these qualities are essential for productivity outcomes in substantial economic accumulation for knowledge-intensive firms, which are the backbone of our new economies. This type of technology tends to add on the learning outcomes and promote the likelihood of gaining skills by covering various methods of learning and processes.

Economic inequality makes the adoption of digital education undesirable despite many useful economic consequences. In their research, Ahmed (2020) pointed out that those people having some financial freedom are unable to avail the digital technology, high-speed internet and digital fluency that are necessary to gain productive outputs from the digital learning system. Individuals who belong to struggling socioeconomic categories and have challenges accessing digital education resources can restrict their financial possibilities as they contribute to inequality. An additional response has come from the appearance of public-private partnerships, whereupon multinational companies such as Google and Microsoft collaborate with other governments and non-profits in order to offer disadvantaged communities easily accessible training in digital skills.

Innovative learning design accesses advance digital education success by creating learning ex-

periences that are customized, dynamic and engaging (Szántó et al., 2024). According to more recent research Aji & Napitupulu (2005), states that gamification techniques, which include incorporating components from gaming into the classroom, improve engagement, motivation, and completion rates. Moreover, considering proficiency in technology is imperative for many rewarding professions, the current economic climate imposes a high value on these capabilities. Studies have indicated that these innovations strengthen learning outcomes while facilitating the acquisition of skills in ways that comply with the requirements of the modernization workforce.

Besides improving knowledge sharing with the public, the effects of e-learning impact other outputs generated by the economy including an increase in gross domestic product growth level, employment level, and also productivity. According to World Economic Forum (2021) findings, communities that have specialized in digital learning and reskilling are likely to sustain more economic growth and have their future challenges managed by automation and artificial intelligence. Additionally, given that establishments are more inclined to invest in sectors with a stable talent pool, a workforce possessing a wide range of capabilities has the potential to gain foreign investment. Additionally, through the use of digital learning in businesses will achieve economic benefits by increasing efficiency among employees and reducing training costs. As Kuznia & Ellis (2014), found that organizations which makes use of digital learning when combined with other employee development programs perceive a remarkable return on investment through boosted employee efficiency and reduced directive expenses while improving faster skill acquisition. Besides, due to this monstrous economic potential, digital learning cloths out to be a significant thrust of innovation and economic growth in both public and private sectors. The conceptual linkage between overcoming economic inequality and achieving economic resilience through enhanced skill acquisition is effectively visualized in Fig. 1, which illustrates how the implementation of affordable digital learning platforms and adaptive technologies serves as a critical bridge to foster inclusive growth and innovation.

1. 1. NOVELTY AND CONTRIBUTION OF THE STUDY

Unlike prior studies that primarily examined either access to digital learning technologies or their general educational outcomes (Rohs & Ganz, 2015), this research uniquely integrates ALT, DLP, and LDI together with SES to holistically explain their combined impact on SA and economic outcomes. The study provides novel empirical evidence demonstrating that LDI such as gamification and adaptive learning modules not only enhance educational engagement (Aji & Napitupulu, 2005) and can significantly influence economic outcomes through skills development. In addition, the model suggested provides tangible implications for policymakers, academics, and organizational leaders to connect digital learning strategies with economic transformation goals (World Economic Forum, 2021). This contribution addresses a critical research gap and responds to the evolving needs of a digitally-driven global economy.

1. 2. RESEARCH OBJECTIVES

By exploring the interplay between SES, ALT, DLP, and LDI, this research pinpoints actionable methods and best practices to create an effect in terms of SA and EI. This study attempts to examine the interaction of these constructs in relation to economic and educational prospects. First, the methodology for integrating ALT, DLP, and LDI strategies will be described in detail.

- To evaluate the relationship between digital learning platforms and skill acquisition, with a focus on economic impact at individual and community levels.
- To explore how adaptive learning technologies contribute to bridging skill gaps influenced by socioeconomic disparities.
- To identify the interplay between socioeconomic status, digital tools, and skill acquisi-

tion, aiming to propose strategies for equitable educational outcomes.

- To evaluate how incorporating learning design innovation into educational institutions to promote skill development can help the economy.
- To analyse the impact of socioeconomic status on the adoption and effectiveness of adaptive learning technologies and digital learning platforms in education.
- To investigate the role of learning design innovation in enhancing skill acquisition across diverse socioeconomic groups.

2. LITERATURE REVIEW

2. 1. ADAPTIVE LEARNING TECHNOLOGIES

Adaptive learning technologies are intelligent digital systems that adapt learning experiences by altering learning boundaries, substance types, and feedback in response to each learner's performance and specifications. These technologies greatly benefit educational and professional training environments by providing an individualized learning experience that can enhance engagement and comprehension.

Johnson et al.'s (2015), Competency-Based Adaptive Model is a model that involves skill mastery, and they utilize technological tools to give individuals tailored content and assessments until they can demonstrate that they are knowledgeable in each area. This model focuses on the long-term retention, and it reduces knowledge gaps to make sure that learners have enough passion for core competencies before moving forward. These types of models have been found to be especially helpful when designing professional training, by considering they are aligned with the prevailing industry standards, since they prioritize readily quantifiable aptitudes that are required for career advancement.

The Competency Based Adaptive Model was effectively implemented using ALT in the study by Ghailani et al. (2014), to personalize the learning experience for each individual. The two key learning scenarios in this model are the guided scenario, in which learners follow predetermined instructions from the system to improve their skills, and the other one is free scenario in which learners choose the competency levels they wish to achieve. This dual approach learning scenarios acts as pathway to the individual's learning preferences and flexibility. The authors represented the competencies and educational resources by using the ontologies which enabled dynamic composition of learning units according to the needs of the learners. The approach also included a self-assessment phase, whereby students critically review their own work. This leads to a period of improvement whereby they produce better outputs against criticism. It is such a process where the students can pass through their courses in an efficient manner and enhances the general learning experience.

2. 2. DIGITAL LEARNING PLATFORMS

Digital learning platforms include online systems that incorporate distinctive digital technologies, resources, and learning modules to facilitate accessible teaching. These platforms provide the opportunity for both a learner and an educator to access, share, and possibly create educational materials; but it should always inspire application in flexible, self-paced, and collaborative learning options. Education is made both accessible and personalized with assessments and multimedia resources. The increasing use of digital solutions in education has made these platforms essential for generating inclusive, scalable, and compelling learning potential (Adilova et al., 2025).

Personalized Learning Model (PLM) was designed by Pane et al. (2015) that optimises instruction, quickness, and content to correspond with the needs of every particular student. With the objective of personalizing resources and activities according to specific learning preferences

and levels, the digital platforms that deploy this style of learning render applications for algorithms and data analytics. These kinds of platforms bolster students incremental fundamental mastery while permitting learners to make progress at their own pace.

In the study by Khanal & Pokhrel (2024), the evaluation of DLP was conducted through the lens of Personalized Digital Learning Environments (DLEs) utilizing the Private Learning Intelligence (PLI) framework. PLM is developed for the sake of meeting the needs of all types of learners without compromising the privacy of the individuals (Hamdan Al-Abbadi et al., 2025), the research study was carried out by integrating the principles of federated machine learning inquiries. The authors described what kind of data in DLE can be employed to customize the models which can modify the way of learning experiences and are presented to learners as per their usage and preferences. This enables this approach suitable to solve particular problems, such as the data privacy concern along with the need for more personalized learning choices for improving the overall effectiveness of the educational technology design. It only proves how PLI tends to make DLP become a more interactive yet highly engaging resource for the learners subsequently bringing in more individual-centered learning environment into all users.

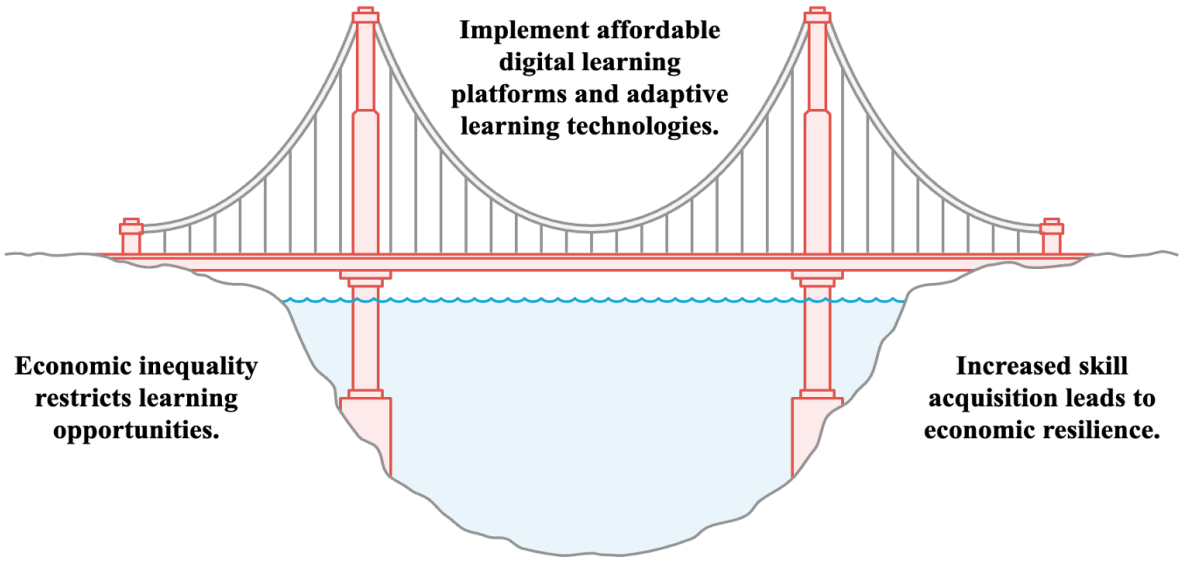
2. 3. LEARNING DESIGN INNOVATION

Learning Design Innovation refers to the techniques and practices that employ innovative and research based design practices to improve the effectiveness and engagement of educational experiences. The primary intentions of innovations in learning design are to achieve readily quantifiable learning goals, facilitate active learning, and nurture essential competencies such as collaboration, creativity and critical thinking. These approaches to design play an imperative part in empowering learners in continually evolving digital and professional settings.

Kolodner (2002), developed the model called Learning by Design (LBD). This model emphasizes project based learning where students solve authentic problems of the world. Thus, the LBD model focuses on ideas in problem-based and experiential learning that stimulate constant improvement of students ideas in the development of critical thinking and problem-solving competencies. LBD simplifies innovative learning designs by facilitating well-organized, collaborative initiatives.

In the study “Learning by Design Using MATLAB” by Ababneh et al. (2019), the LBD model evaluation was conducted by employing its implementation into a Technology Enhanced Learning (TEL) environment in the Madinah College of Technology. The assessment emphasized in many ways of LBD to move from conventional teaching through lectures to more involvement-based and student centered. By enabling students to personalize their educational experiences, the study assessed motivation, engagement, and learning outcomes. The use of MATLAB, graphical user interface managed to solve demanding computational problems and thus the students boosted their critical thinking. Further, the advantages of the blended learning approach were considered where the learning opportunities would be maximized as they could interact with content both face-to-face and online. Thus, the assessment indicated LBD improved student performance and reduced instructor effort, which means a more effective and efficient learning process.

Figure 1. Transitioning to Effective Learning for Economic Growth



Note: This figure illustrates how economic inequality hinders the adoption of digital learning by limiting access to essential technologies, resources, and opportunities.

Source: Authors' Own Work

2. 4. THEORETICAL BASIS FOR MODEL CONSTRUCTS

The research model constructs discussed here are underpinned by several foundational theories. Digital Divide Theory (DDT), was proposed by van Dijk (2005), explains socio technical gap in which a group of people, most often belonging to the lower social classes of society, have little or no access to digital technologies and consequently, are poorly educated and economically disadvantaged. DDT provides context to socioeconomic status and the issue of accessibility to adaptive learning technologies, digital learning environments, and learning design innovations (Kuzmak & Kuzmak, 2023). Social Stratification Theory by Weber (1978), explains how social and economic class systems operate and how they funnel privileged resources and opportunities into some groups at the expense of others. Collectively, these theories explain how having a certain socioeconomic standing can lead to insufficient acquisition of skills, and consequently, limited mobility within the economy. Human Capital Theory, was proposed by Becker (1993) noting that modern economies often require educated individuals, he quoted education and training as a means of achieving productivity and increase in receivable income. This validates the assertion that skill acquisition mediates the relationship between digital learning and economic development in the model. Finally an augmented view of systems theory by Ludwig & John (1974), puts the pieces together through interactions of all these systems like adaptive learning technologies, digital learning platforms and innovations, skills acquisition, socio economic status, and impacts of education and changes from the education.

2. 5. RELATED WORKS

A research study conducted by Mabhele & Van Belle (2019), to propose a conceptual model for adaptive learning technologies in higher education. The research insights indicated that the effective organisations and learning-specific constrains can be addressed by an integration of Transformative Framework for Learning Innovation to the Emerging Learning Technologies Model. The ALT paper defined its objective, which relates to tailoring learning to every stu-

dent's way according to his learning style toward a better increase in active involvement and performance by such students. The study of White (2020), inquires the effectiveness of adaptive learning technologies in improving student learning outcomes in an undergraduate management information course. The study, which exploited McGraw-Hill's LearnSmart, found no significant connection between scores from tests and adaptive learning technologies usage, implying that even though students embraced the technology it was unable to boost their educational performance as a substitute for adding traditional learning methods. We implemented adaptive learning technologies to create personalised learning experiences that align with each students reactions, ensuring their compatibility with Bloom's Taxonomy competencies. The researchers Singh & Alshammari (2021), conducted a study examining the impact of digital technology enabled personalized and adaptive learning on student performance in Saudi Arabia. According to their findings, those technologies promote adaptability and commitment among students, particularly during the COVID-19 pandemic. Specifically addressing these research gaps related to applying technology in a learning environment, the study utilized the Technology Organization Environment (TOE) framework to construct a model that emphasizes how these adapative learning technologies may allow educational experiences to accommodate the demands of each student involved and leading to improve the overall learning achievements.

The research study by Faustmann et al. (2019), investigates the determinants that contribute to the success of DLP. This platforms allows teachers to connect with students, students with other students, and all of them with their common interests and other groups, collectively building an ecosystem that ensures knowledge sharing, community learning, and accessibility of learning to all, regardless of their respective niches. Conducting an empirical study with 486 participants, the authors examined the obstacles and motivations associated with the use of digital learning platforms with to discover main success factors, which could influence future platform designs. In this research, the digital learning platforms are used as instances for knowledge entrepreneurs and customers, thereby facilitating innovative learning approaches that use emerging technologies in conjunction with traditional learning. This integration promotes engagement and embraces a multiplicity of learning styles through interactive elements. In the research article (Gameil & Al-Abdullatif, 2023), authors examined the effectiveness of DLP in enhancing instructional design competencies and learning engagement in preservice teachers in Saudi Arabia specifically using Google Classroom. In a quasi-experiment, using pre and post-tests the researchers analysed the cognitive and application skills of 61 participants. More advanced forms of collaboration and skill acquisition in teacher preparation programs will be productively assisted by digital platforms, according to the authors study's results, which showed considerable progress in these areas. The study by Oroni & Xianping (2023), investigates the role of digital learning platforms as mediators between social media capability and academic performance. This research states that integration with structures of learning is necessary because, with it, more resources will be available, even greater involvement and cooperation amongst the students, and, most importantly, eventually lead to better academic achievement. The researchers also ended up with the conclusion that whenever the students could manage their social media appropriately and effectively, they would have better academe. The above findings thus underscore the introduction of digital learning platforms in educational institutions as means of enhancing academic performances through the best use of social media resources.

Ayas (1996), inquires an innovative learning design which may improve an aircraft manufacturing company performance. The study suggested a project network topology for effective communication and learning across projects and integrates within self-managing teams. Within 6 months of this design, project performance increased by 7%, proving that a structured learning style could substantially enhance organisational creativity and performance. The results

emphasize how organizational strategy, culture, and systems must be aligned to accommodate a learning environment. In cultural context (Zhang, 2009), "Technology supported learning innovation" gives in-depth insights on complexities related to education reforms implementation through systems perspective. Specifically, the findings points to the need for principle-based change which engages teachers in both macro and micro reflective practices to facilitate deep changes in learning cultures, is an indication that simply introducing new technologies or teaching methods are notably ineffective. Learning design innovation is seen in underlining the all-inclusive understanding of the learning cultures, combining systemic properties and specific pedagogical strategies for true educational change (Vlasenko, 2023).

The study by Furinto et al. (2023), explored on perceived socio-economic status (PSES), which is correlated and linked between financial and digital literacy mediating digital investment choices. The results depict the fact that both digital and financial literacy enhance investment decisions, while PSES serves as an important mediator. That is, while low socioeconomic status often accompanies more extreme financial literacy-a fact which affects people's confidence and their ability to make sound investment decisions-the point underlines the importance of socioeconomic status in financial decision making. Wang et al. (2023), in their paper studied the impact of subjective socioeconomic status on e-learning among Chinese college students. It shows that higher subjective socioeconomic status optimizes self-efficacy and perceived social support, both in turn leads to enhanced e-learning engagement. According to the study, students from higher socioeconomic status have a better chance of receiving social support, thus improving their learning experiences, whereas students from lower socioeconomic backgrounds might encounter it difficult because they have less equipment and support systems. Njeri & Taym (2024), study evaluates the interconnections among socioeconomic status and secondary school students' access to technology-enhanced learning. According to researchers, higher socioeconomic status students have access to more digital tools and resources, giving them access to more educational opportunities. However, two of the biggest obstacles that low socioeconomic status students faces are limited access to technology and a poor understanding of digital technologies. This exacerbates learning inequities and underscores the critical need to bridge the digital achievement gap.

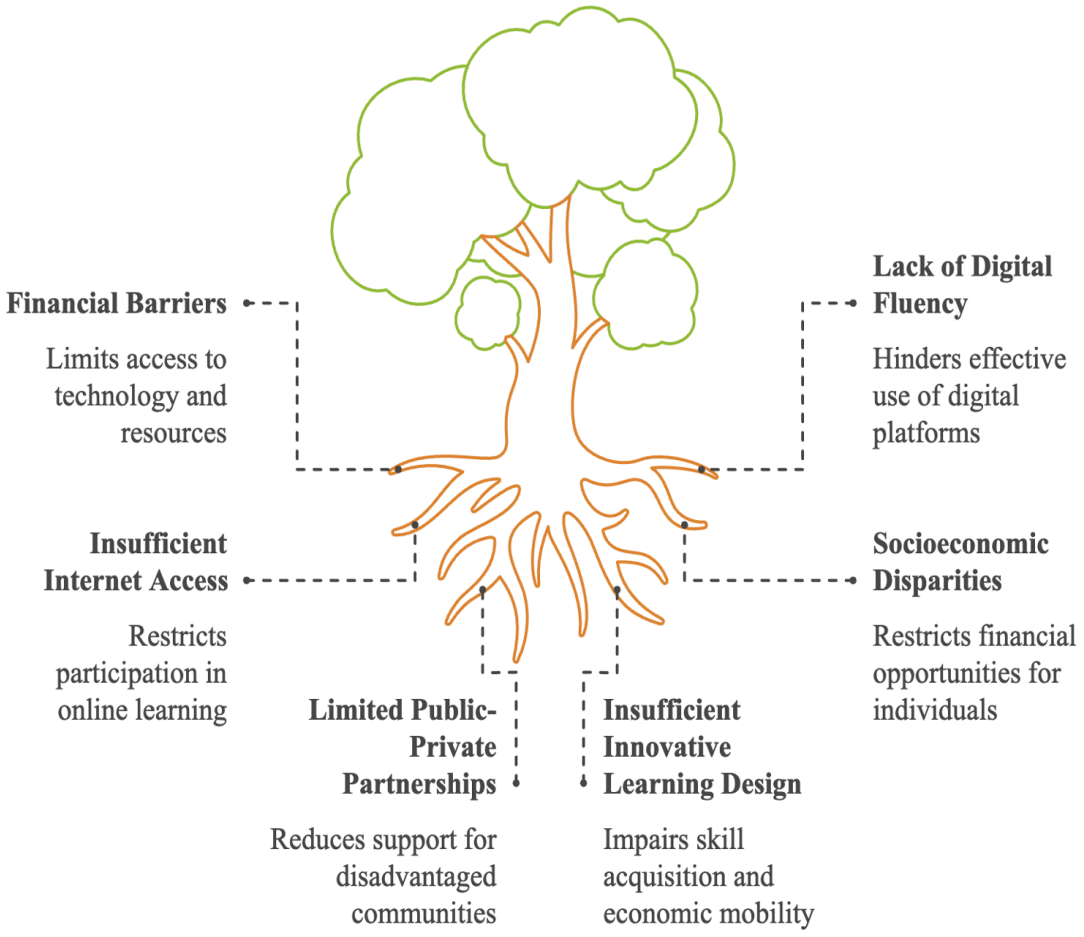
The research by Adavbiele (2014), examines how SA programs affect the SES of youths in Edo State, Nigeria. Although these programs have the potential to generate employment opportunities and encourage self-reliance, but their success is limited by insufficient funding, professional trainer surpluses and inadequate facilities. The younger generations should develop their skills through skill improvement training sessions which might allow them not only to face the workforce but also lower unemployment rate while improving socioeconomic conditions. The study by Fergusson (2022), investigates various learning methods used in Work Based Learning (WBL) and explains the importance of reflective practice. The outcomes show that implementation of WBL programs in diversified teaching methods thriving to improve learning capabilities of students and improve their relations with surrounding environment. The study by Ganguli et al. (2024), examines how Saudi Arabia's skill development landscape changed during the COVID-19 pandemic through the use of national online learning platforms. Young learners focused on general and computer skills, but the crisis drove a significant rise in online course enrolment especially affecting more older employees who needed to learn telework skills. Acquisition of skills was also key in supporting professions all along the pandemic, showing just how economic shocks affect how one makes decisions regarding their education pursuits and then how that carries on to flourish in the marketplace.

In the study by Bassanini et al. (2000), the investigation of how knowledge and technology relate to the economic growth in OECD nations is covered. This would mean that, despite big

differences across countries, factors such as human capital and ICT investments are quite contributory to productivity growth and development. The authors argue that these would include appropriate labour market regulations and R&D investments for bringing about technical improvement and economic success and, moreover, that this particular study's focus on impact for economics is important as it demonstrates how investments in technology and human capital might be the means of actually raising productivity, which is able to stimulate overall growth in the economy. According to Driskell's (2022) research, "Impact of New Technologies on Economy and Society," technical developments, which increase industrial operations productivity and efficiency, which are essential for promoting economic growth. To foster collaboration between the public and commercial sectors, the study emphasises on how technology enables the provision of superior goods and services. The economic benefits of enhanced operational efficiency and innovation helps to promote widespread prosperity. Driskell argues that adaptive regulatory systems must evolve to handle risks from fast-paced technological changes, while promoting fair societal advantages and preventing monopolistic formations.

The upstream barriers that prevent fair access to digital learning through financial limitations, restricted access to the internet, and socioeconomic disparities can be conceptually depicted as Fig. 2, illustrating how these roost causes together obstruct a wide acceptance of learning experiences in the digital age.

Figure 2. Economic Inequality Limits Learning Adoption in Digital Era



Note : This figure illustrates how economc inequality hinders the adoption of digital learning by limiting access to essential technologies, resources, and opportunities.

Source: Authors' Own Work

2. 6. COMMON TRENDS OBSERVED IN RELATED STUDIES

A comprehensive review of the related works exposes several intersecting trends which drive the digital learning progression and its economic implications. First, existing studies have a focus on strategic integration between ALT and DLP to promote personalized learning pathways, SA, and learner engagement (Mabhele & Van Belle, 2019; Singh & Alshammari, 2021; Faustmann et al., 2019). A second prominent trend is the significance of SES, as both an enhancer and a constraint in digital education adoption learning outcomes (Wang et al., 2023; Njeri & Taym, 2024; Furinto et al., 2023). Significantly, several studies emphasize that unequal access to technology and illiteracy in the digital age are major factors contributing to skill imbalances between social class groups. Furthermore, the literature indicates a growing integration between technological innovation, learner-centered design approaches, and social-economic inclusivity that are not only seen as determinants of educational success but also for broader economic development respectively (Oroni & Xianping, 2023; Gameil & Al-Abdullatif, 2023; Bassanini et al., 2000). Taken together, these insights combine to emphasize the need for more comprehensive model that addresses both technological, pedagogical and societal issues if one wishes to succeed with scaling and impact of digital educational initiatives.

2. 7. RESEARCH GAP

From various surveys over the literature, it seems that the link between SES and the implementation of ALT, DLP have to studied more. Moreover, the role of LDI in addressing socioeconomic inequalities to increase skill development and economic effects has not been under enough analysis and has been inadequately reported. Therefore, the purpose of this research was to identify how SES, ALT, DLP, and LDI can collaborate with one another to facilitate appropriate skill building and to enhance the economy.

3. PROPOSED RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

The hypothesis that were developed in line with the model as illustrated in Fig. 3, as follows :

H_1 : Adaptive learning technologies has a positive direct impact on skill acquisition.

H_2 : Digital learning platforms has a positive direct impact on skill acquisition.

H_3 : Learning design innovation has a positive direct impact on skill acquisition.

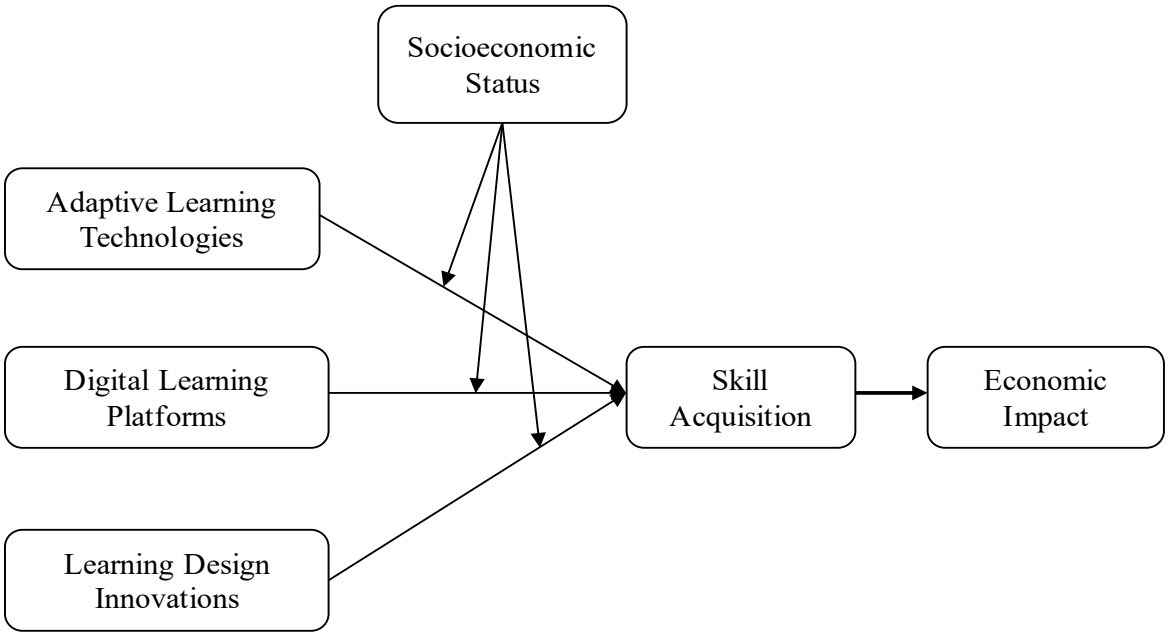
H_4 : There is an effect of mediating influence of skill acquisition on economic impact.

H_5: There is an impact of socioeconomic status on adaptive learning technologies of skill acquisition.

H_6 : There is an impact of socioeconomic status on digital learning platforms of skill acquisition.

H_7 : There is an impact of socioeconomic status on learning design innovation of skill acquisition.

Figure 3: Proposed Research Model



Note : This model serves as a foundation for examining how digital innovations in education contribute to skill development and economic growth, particularly in diverse socioeconomic contexts.

Source: Authors' Own Work

4. RESEARCH METHODOLOGY

4. 1. RESEARCH DESIGN

The research employed a convenience sampling technique, to assesses the relationships between the ALT, DLP, LDI and the effects of SES on SA and EI. This paper employs a methodology that involves the collection and analysis of source data.

4. 2. SAMPLE AND DATA COLLECTION

In April 2024, a total of 425 respondents were collected from students and employees across organisations/institutions around Tamil Nadu region to concurrently understand the EI in the digital era, of which 377 were decisive to be permissible. A total of 30 institutions has been taken for this study. We have developed a questionnaire using Google Forms, which features a five-point Likert scale: strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5).

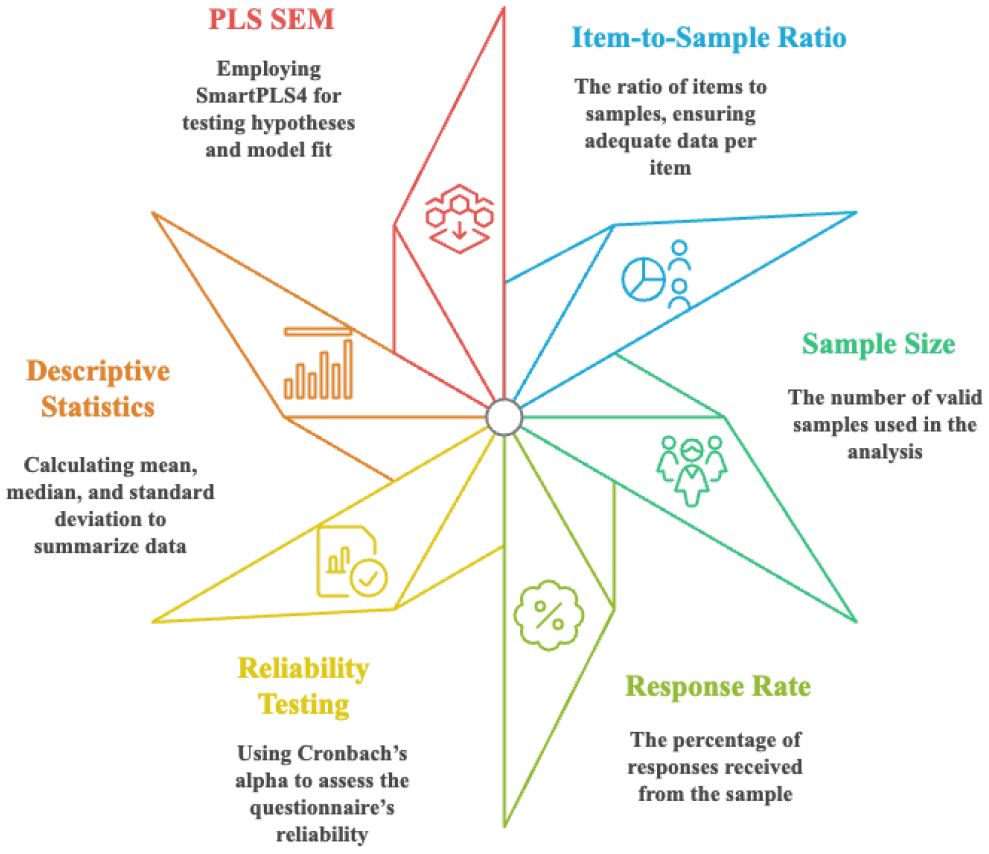
4. 3. MEASUREMENT SCALES

We divide the form into two sections: one for demographics such as gender, age, educational background, employment status, location, income level, access to technology, and learning style preference, and another for characteristic variables like ALT, DLP, LDI, SES, SA, and EI. For ALT and LDI six-item custom scales were developed, based on Mabhele & Van Belle's (2019);White's (2020) and Zhang's (2009) frameworks. Six-item scales for DLP were adopted from Oroni & Xianping (2023). Whereas, for SES and SA six-item scales were taken from Adavbiele (2014). Finally, for EI six-item scales were adopted from Bassanini et al. (2000). We then distribute the form to respondents to collect data. We distribute the questionnaire through various social media channels such as email, WhatsApp, and LinkedIn. The respondents primarily relate to learning in the digital era and are experiencing the EI, which has fulfilled our aim to reach a targeted and relevant audience for the study.

4. 4. ANALYSIS OF DATA

The analysis used 377 valid samples, and the response rate is 88.7%. According to Westland (2010), researchers suggest a general guideline of selecting a 1:10 ratio, meaning one item for every 10 samples. This study includes 36 items, and 377 samples that meet the criteria and contribute to sample acceptability. We used Cronbach's alpha to test the questionnaire's reliability. We conducted a thorough analysis using descriptive statistics that included mean, median, and standard deviation values. Finally, SmartPLS4 is used for partial least square structural equation modelling (PLS SEM) wherein hypotheses are investigated by PLS Bootstrapping and model fit by the PLS SEM Algorithm. The PLS SEM algorithm yielded statistically significant results, including path coefficients, path loadings, R^2 values, composite reliability and validity as measured by Cronbach's alpha and composite rho_c, as well as discriminant validity. The detailed data analysis process used in this study is visualized in Fig. 4 detailing the important statistical techniques and validation methods used to ensure the accuracy, reliability, and robustness of the research findings.

Figure 4: Comprehensive Data Analysis Overview



Note : This figure presents an integrated overview of the key analytical components employed in the study to ensure data validity, reliability, and model robustness.

Source: Authors' Own Work

5. RESULTS

5. 1. DEMOGRAPHICS

Table 1 consists of demographic data of 377 respondents. There were 207 male, accounting for 54.9%, and 170 were female, 45.1%. Place of residence of the respondents also shows that 283 were living in urban area and 94 in rural area. The highest number of respondents were in the category of 18-29, 207 in number, then were aged 30-39 being 88 in number, 40-49 with 74 in number and 50 & above with 8. In total, 169 have graduated, 114 have attained masters' degrees, 75 have their associates degrees while just 19 have some level of education either complete or incomplete.

The result shows the employability status consisting of 192 students, 137 employed and 48 unemployed, and their income level, with 67 having low income, 218 having middle level, and 92 having high income. Major demographics have to be observed with access to technology, with high access to technology among 194 respondents contributing 51.5%, followed by 114 with moderate access, contributing 30.2%, and 69 with less/no access, contributing 18.3%, and learning style preference comprising 197 respondents who prefer visual learning style, contributing 52.3%, followed by 114 with auditory preference, contributing 30.2%, and 66 with kinaesthetic preferences, contributing 17.5%, respectively.

Table 1. Descriptive Statistics of Demographic Variables Taken up in the Study

Participant Profile (n=377)			
Demographic Profile	Categories	Frequency	Percentage
Gender	Male Female	207 170	54.9 45.1
Age	18 - 29 years old 30 - 39 years old 40 – 49 years old 50 years and above	207 88 74 8	54.9 23.3 19.6 2.2
Educational Background	High School or Less Some College/Associate Degree Bachelor's Degree Master's Degree	19 75 169 114	5.1 19.9 44.8 30.2
Location	Urban Rural	283 94	75.1 24.9
Employment Status	Student Employed Unemployed	192 137 48	50.9 36.3 12.7
Income Level/Family Support/Educational Support Systems	Low Income Middle Income High Income	67 218 92	17.8 57.8 24.4
Access to Technology	High Access : Regular access to devices and high-speed internet Moderate Access : Limited access to devices or slower internet Low/No Access : Minimal or no access to devices and internet	194 114 69	51.5 30.2 18.3
Learning Style Preference	Visual : Prefers learning through images, diagrams, and visual aids Auditory : Prefers learning through listening, such as lectures and discussions Kinaesthetic : Prefers hands-on activities and learning by doing	197 114 66	52.3 30.2 17.5

Source: Authors' Calculation

5. 2. STRUCTURAL EQUATION MODELLING

Analysis has been carried out using SMART PLS 4 to ascertain the results of constructive variables. PLS SEM has been determined by performing measurement model test and structural equation model. Through the PLS SEM algorithm, model fit, construct validity and reliability, and discriminant validity have been tested. Hair et al. (2021), said that the measure of reliability should range from 0 to 1, with values of 0.60 to 0.70 considered to be the lower limit of acceptability, and an increase in the number of items shows the raised threshold value.

Table 2 provides reliability and validity tests. It assesses the validity of six constructs, each consist of six items along with their associated path loadings as shown in Fig. 6. The Cronbach's alpha for ALT is 0.853, for DLP are 0.868, LDI are 0.802, SES are 0.875, SA are 0.805, and 0.803 for EI. All the scores are above 0.7, which infers the data is reliable. Composite reliability is considered to be a more reliable indicator of internal consistency since it can show that all the indicator loadings in the population are equal and consistent with the basic conceptions of PLS-SEM. The average variance extracted (AVE) is 0.576 in the case of ALT, 0.603 of DLP, 0.507 for LDI, 0.617 for SES, 0.510 of SA, and 0.509 of EI. The recommended score for AVE is >0.5 (Hair et al., 2011); all the variables have demonstrated over 5. This further ensures the reliability of the data.

Table 2. Reliability and Validity Test

Constructs	Items	Loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Adaptive Learning Technologies (ALT)	ALT1	0.838	0.853	0.890	0.576
	ALT2	0.780			
	ALT3	0.799			
	ALT4	0.743			
	ALT5	0.710			
	ALT6	0.673			
Digital Learning Platforms (DLP)	DLP1	0.817	0.868	0.901	0.603
	DLP2	0.814			
	DLP3	0.811			
	DLP4	0.675			
	DLP5	0.806			
	DLP6	0.724			
Learning Design Innovations (LDI)	LDI1	0.790	0.802	0.859	0.507
	LDI2	0.589			
	LDI3	0.788			
	LDI4	0.759			
	LDI5	0.658			
	LDI6	0.664			

Constructs	Items	Loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Socioeconomic Status (SES)	SES1	0.831	0.875	0.906	0.617
	SES2	0.783			
	SES3	0.795			
	SES4	0.806			
	SES5	0.709			
	SES6	0.784			
Skill Acquisition (SA)	SA1	0.871	0.805	0.856	0.510
	SA2	0.776			
	SA3	0.788			
	SA4	0.457			
	SA5	0.495			
	SA6	0.786			
Economic Impact (EI)	EI1	0.815	0.803	0.858	0.509
	EI2	0.737			
	EI3	0.659			
	EI4	0.750			
	EI5	0.475			
	EI6	0.789			

Source: Authors' Calculation

5. 2. 1. DISCRIMINANT VALIDITY

In order to analyse Discriminant Validity, the Fornell-Larcker criterion principles were used. According to the criterion, it examines whether the measurement model constructs are distinct. This criterion demands that the square root of the AVE of every construct is larger compared to its correlation with any other construct (Fornell & Larcker, 1981).

In Table 3, the square roots of AVE for ALT is 0.759, DLP is 0.777, and SES at 0.785, which are greater than their respective correlations with other constructs. However, EI, LDI and SA have correlations that approach or exceed their respective square roots of AVE, suggesting that these constructs may not be entirely distinct from one another.

Table 3. Discriminant Validity (Fornell-Larcker Criterion)

	ALT	DLP	EI	LDI	SA	SES
ALT	0.759					
DLP	0.551	0.777				
EI	0.428	0.523	0.713			
LDI	0.489	0.616	0.698	0.712		
SA	0.529	0.659	0.615	0.629	0.714	
SES	0.434	0.624	0.626	0.704	0.710	0.785

Source: Authors' Calculation

5. 2. 2. COLLINEARITY STATISTICS (IVF)

In assessing multicollinearity in SEM context using SmartPLS, the Variance Inflation Factor (VIF) is the most commonly used statistic. According to Hair et al. (2022), no serious multicollinearity prevails if VIF is less than 5; however, if it's above this, then a problem exists. The "Collinearity Statistics" of SmartPLS easily derives VIF, which is going to be used for testing whether the predictor constructs have good relationships with each other. All values below 3 indicate that the model does not suffer from collinearity concerns, thereby ensuring the reliability of the results, as suggested by Henseler et al. (2015). The VIF values for all items, as presented in Table 4, are below the threshold of 3, indicating no collinearity issues in the model.

Table 4. Collinearity Statistics (IVF)

	Variance Inflation Factor (VIF)
ALT1	2.229
ALT2	2.028
ALT3	2.210
ALT4	1.847
ALT5	1.598
ALT6	1.354
DLP1	2.205
DLP2	2.105
DLP3	2.150
DLP4	1.545
DLP5	2.007
DLP6	1.493
LDI1	1.743
LDI2	1.324
LDI3	1.980
LDI4	1.792
LDI5	1.408
LDI6	1.354
SES1	2.584
SES2	2.267
SES3	2.039
SES4	2.115
SES5	1.672
SES6	1.889
SA1	2.716
SA2	1.803
SA3	1.875
SA4	1.554
SA5	1.524
SA6	1.904
EI1	1.891
EI2	1.707
EI3	1.390
EI4	1.696
EI5	1.214
EI6	1.710
SES x ALT	1.000
SES x DLP	1.000
SES x LDI	1.000

Source: Authors' Calculation

5. 2. 3. MODEL FIT ANALYSIS

Model fit analysis how well a model reproduces data. In model fit, we observe Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) values. SRMR is an absolute measure of fit. Byrne (2013), deems the fit adequate if the SRMR is less than 0.05. However, Henseler et al. (2014) points out that a perfectly specified model can still yield SRMR values of 0.06 or greater. According to Hu & Bentler (1998), PLS models are considered to have a reasonable fit when the SRMR score is 0.08 or higher. Furthermore, Kock (2024) suggests that some contexts tolerate a cut-off of 0.10, even though low SRMR values indicate a good fit. The incremental fit measure NFI was used in order to test the adequacy of fit in the SEM. Bentler & Bonett (1980), explain that NFI ranges between 0 and 1, where values close to 1 represent a better fit for a model. In Table 5, the estimated model's SRMR value is 0.082, indicating a perfect fit, while the NFI value is 0.740, indicating a better model fit.

Table 5. Model Fit

	Saturated model	Estimated model
SRMR	0.075	0.082
Chi-square	1937.083	2021.359
NFI	0.751	0.740

Source: Authors' Calculation

5. 2. 4. COEFFICIENT OF DETERMINATION ANALYSIS

R-squared (R^2) and adjusted R-squared are two of the primary goodness-of-fit measures in terms of the PLS-SEM model's adequacy. The measure of R^2 expresses the amount of variance explained in the dependent variable, where a value above 0.50 is seen to represent a substantial amount of explained variance (Henseler, 2009). Falk & Miller (1992), have recommended that a minimum value of R^2 considered to be adequate is at or greater than 0.10. Furthermore, Cohen (2013) categorizes the R^2 values as weak: 0.02, moderate: 0.13, and substantial: 0.26. In a nut-shell, for good model fit assessment, the R^2 value should be more than 50%, thus a very strong explanatory power of the model.

As can be seen in Table 6, Fig. 5 and Fig. 6, the results indicate that EI accounts for 51.1% of the variance in the model with a moderate explanatory power; $R^2 = 0.511$. SA explains 65.3% of the variance, with a high impact on the outcome variable; $R^2 = 0.653$. Both the R^2 values are above the minimum threshold of 0.2 and thus, indicate that the relationships in the model are meaningful and represent a mediating effect (Hair et al., 2021). The results, therefore, depict that both EI and SA explain the dynamics of the model significantly.

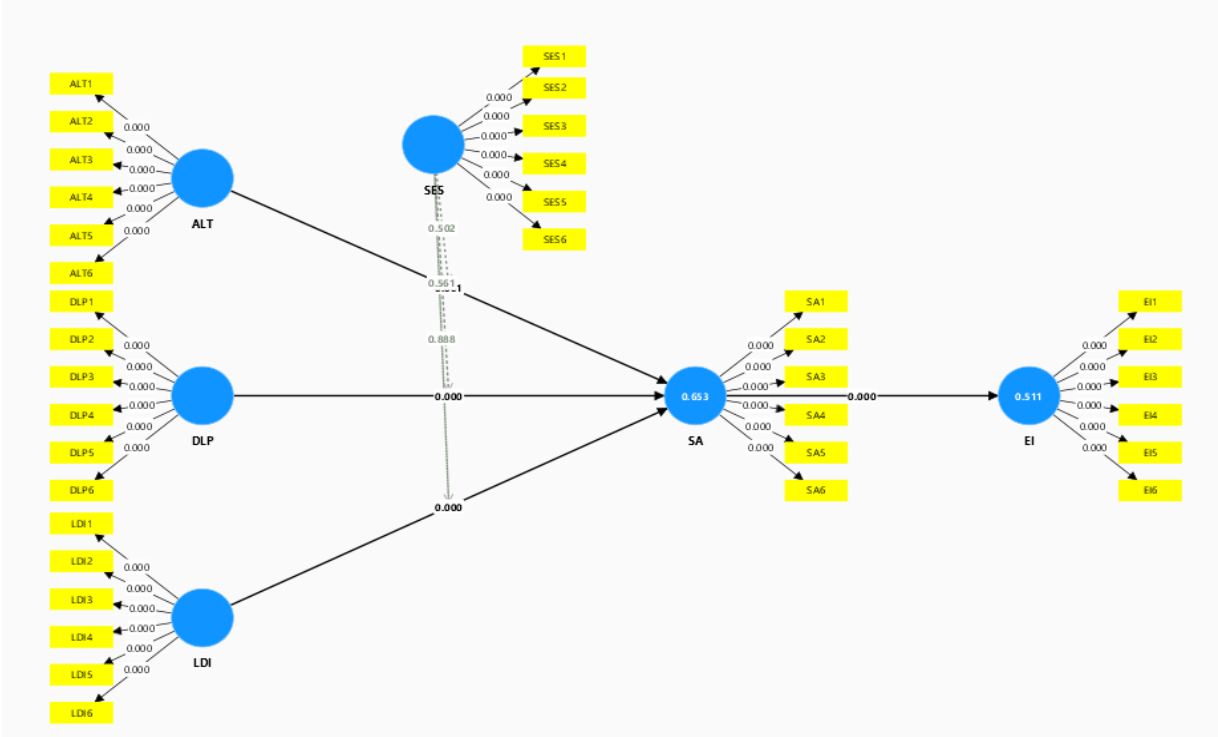
Table 6. R-square

	R-square	R-square adjusted
EI	0.511	0.510
SA	0.653	0.647

Source: Authors' Calculation

Path diagrams are essential in SEM as they visually represent hypotheses and the interactions between components (Hair et al., 2011; Hair et al., 2021).

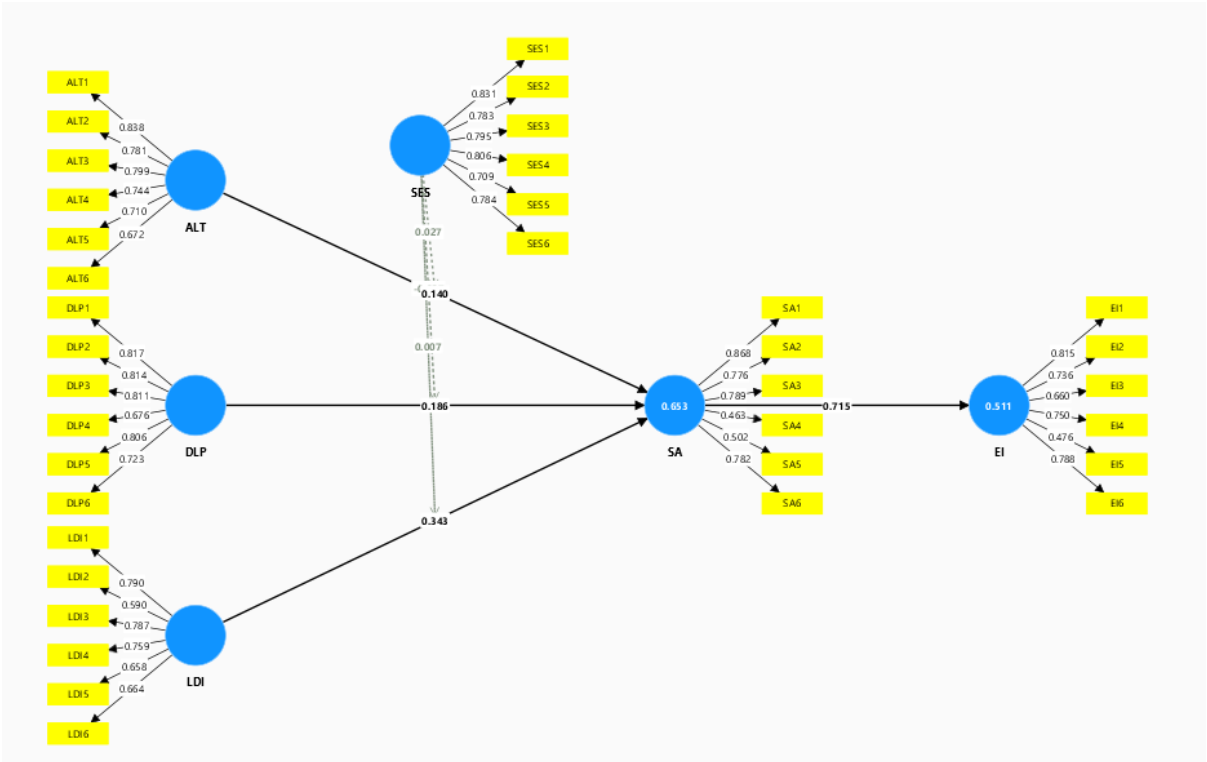
Figure 5. Bootstrapping Analysis



Note : The figure illustrates the bootstrapping results of a SEM, showcasing p-values and the relationships among latent variables: ALT, DLP, LDI, SES, SA, and EI.

Source: Authors' Calculation

Figure 6: PLS SEM Algorithm Analysis



Note : The figure presents the PLS-SEM Algorithm results, illustrating path coefficients, factor loadings, and R^2 values within the model.

Source: Authors' Calculation

5. 2. 5. MODERATION MEDIATION ANALYSIS

Moderation-mediation analysis of SmartPLS assists a researcher in examining relationships of variables. A mediator explains the relationship of an independent variable and the dependent variable, while the moderator alters the strength or direction of the relationship between those variables (Hair et al., 2022). The analysis is conducted by estimating both direct and indirect effects as shown in Table 7.

As present in the table below are the pathways and their implications on EI. The indirect effects of ALT, DLP, and LDI, the mediation function of SA, on EI read to 0.100, 0.133, and 0.245, respectively, to mean that all contribute to positively affecting EI through SA. Directly, SA exhibits very significant effects on EI, measuring at 0.000.

The indirect effect of SES on EI via SA is 0.212. Interaction terms comprised of SES as a moderator along with ALT, DLP, and LDI have nonsignificant effects, that is, 0.020, -0.019, and 0.005 respectively. This means SES has not been significantly contributing in a moderator role about any of these relationships. Taken together, these findings draw upon mediation and moderation equally importantly as avenues to explain how education and technology may impact economics indirectly through SA.

Table 7. Moderation Mediation Analysis

Paths	Effects	Path Values
ALT → SA→ EI	Indirect Effect	0.100
DLP → SA→ EI	Indirect Effect	0.133
LDI → SA → EI	Indirect Effect	0.245
SA→ EI	Direct Effect	0.000
SES → SA → EI	Indirect Effect	0.212
SES x ALT → SA → EI	Indirect Effect	0.020
SES x DLP → SA → EI	Indirect Effect	-0.019
SES x LDI → SA → EI	Indirect Effect	0.005

Source: Authors' Calculation

5. 2. 6. EVALUATION OF HYPOTHESES

Such path analysis uses various statistics arising in computing beta values, such effects size value being f^2, t-statistics and their p-values. The strength by which an endogenous variable is suggested is given by R^2 or the effect value of a dependent variable and its related independent variable accounted for by beta values. An f^2 less than 0.02 shows minimal influence while from 0.15 to 0.35, which indicates moderate to considerable influence (Cohen, 2013). R^2 defines the ability of the model toward prediction, and the thresholds are defined as statistically significant at 0.75, 0.50, and 0.20 respectively (Hair et al., 2019). The significance of pathways is determined through t-statistics and p-values derived from bootstrapping; a t-statistic greater than 1.96 and a p-value less than 0.05 indicate significant route coefficients, allowing for the rejection of the null hypothesis (Hair et al., 2022).

The relationships between the variables of interest were assessed using SEM. PLS-SEM will be used to determine relationships between predictor variables and outcome variables as well as relationships between mediating factors and moderating variables (Lowry & Gaskin, 2014; Sarstedt, 2019). This allows for an understanding of how an independent variable may influence a dependent variable through some mediator, as well as considering the extent to which a moderator can influence the strength or even direction of such relationships.

From Table 8 and Fig. 5, Hypothesis H1 indicates that ALT has a positive significant impact on

SA with β = 0.140, t-value = 3.367, and p-value = 0.001. Likewise, Hypothesis H2 indicates that DLP also has a positive impact on SA (β = 0.186, p < 0.001). Hypothesis H3 The LDI has an incredibly strong effect on SA, β = 0.343, p <.001. Results show good support for all three hypothesis. Furthermore, Hypothesis H4 demonstrates a robust relationship where SA significantly impacts EI with a beta value of 0.715 and an impressive t-value of 19.750 (p < 0.001). On the contrary, hypothesis regarding the moderating effect of SES (H5, H6, and H7) were not significant since for all three interactions, p-values are above 0.05, which in turn indicates that SES is not having a significant moderation effect on the relationship of concerned constructs with SA. In this way, results from the study are an ultimate affirmation of Hypothesis H1, H2, H3, and H4 while rejecting the moderating effects proposed in Hypothesis H5, H6, and H7.

Table 8: Hypothetical Relationships

Hypothesis	Beta	t-value	p-value	f-square	Decision
H1 (ALT → SA)	0.140	3.367	0.001	0.033	Significant
H2 (DLP → SA)	0.186	3.597	0.000	0.044	Significant
H3 (LDI → SA)	0.343	6.845	0.000	0.145	Significant
H4 (SA → EI)	0.715	19.750	0.000	1.045	Significant
H5 (SES x ALT → SA)	0.027	0.672	0.502	0.002	Insignificant
H6 (SES x DLP → SA)	-0.027	0.582	0.561	0.001	Insignificant
H7 (SES x LDI → SA)	0.007	0.140	0.888	0.000	Insignificant

Source: Authors' Calculation

Table 9. Summary of Hypothesis

Hypothesis	Hypothesis Testing/ Analysis Statements	Accepted/ Rejected
H1	Adaptive learning technologies has a positive direct effect on skill acquisition	Accepted
H2	Digital learning platforms positively influences skill acquisition	Accepted
H3	Learning design innovation positively influences skill acquisition	Accepted
H4	There is an effect of mediating influence of skill acquisition on economic impact.	Accepted
H5	There is an impact of socioeconomic status on adaptive learning technologies of skill acquisition	Rejected
H6	There is an impact of socioeconomic status on digital learning platforms of skill acquisition	Rejected
H7	There is an impact of socioeconomic status on learning design innovation of skill acquisition	Rejected

Source: Authors' Calculation

6. FINDINGS

1. The study involved 377 respondents, making it 54.9% male and 45.1% female. Almost three-quarters of the total, 283 participants, come from urban areas, although 55% fall under the age group of 18 to 29 years. Finally, 169 participants are graduates, and earned their master's degree. Employment status showed that 137 individuals were employed and 48 are unemployed, with income levels predominantly in the middle income range of 57.8%.
2. The internal consistency of the data was confirmed because all constructs demonstrated strong reliability with Cronbach's alpha values above 0.70 which represents the accept-

able threshold. Whereas, the AVE scores of all the constructs were above the threshold minimum value of 0.5 set to test the validity of the model.

3. Discriminant validity was established by the Fornell-Larcker criterion, in which most constructs were proved to be different from each other. A few correlations approached or exceeded their respective AVE square roots, indicating that some of the constructs overlap.
4. The hypotheses regarding relationships between variables are supported by the analysis. ALT, DLP, and LDI all positively influenced SA and had beta values that were significant with p-values so low that the relationships are extremely strong. The hypothesized moderation of SES for these relations is statistically not significant.
5. The goodness of fit of the model was checked through R-squared values. SA explained 65.3% and EI explained 51.1% of the variance in the respective model. This gives insight into how education could facilitate the advance of technological improvement in a meaningful relationship with variables under study.
6. To further contextualize the findings, results from this study can be compared with a real-world setting. For example, that DLP have a positive impact on SA corresponds to a real-world project, such as with Coursera, to join forces with governments during the COVID-19 pandemic to improve employability skills of those who have been displaced from employment (World Economic Forum 2021). Similarly, the impact of SES mirrors observed disparities in digital education adoption across urban and rural schools globally, as emphasized in studies by Wang et al. (2023).
7. Compared to earlier research, such as Rohs & Ganz (2015), which focused mainly on accessibility, the current study extends the discussion by demonstrating how LDI like gamification, adaptive content significantly improves SA and economic outcomes. This alignment with practical initiatives and divergence from prior models underscores the novelty and applied significance of the present research findings.

7. DISCUSSION

One of the major issues of comparison is the relationship between SES and engagement in digital learning. Our findings were in conformity with Wang et al.,'s (2023), suggesting that the more the subjective SES, the greater would self-efficacy and perceived social support be for engaging into e-learning. However, our study illustrates a more complex relationship as SES influences educational outcomes but does not have the moderating effect with ALT, DLP, and LDI, as suggested by other previous studies. This is a variation from previous studies and it reflects complexity in the socioeconomic factors of digital learning.

Consistently good with previous literature, DLP had an important impact on the outcome of education. Our result supported Faustmann et al.'s (2019) that DLP really works as a democratizer for learning through educational outcomes but went a bit beyond because it showed the particular mechanisms that improved learning outcomes by proper resource use of social media. As LDI, the results were in line with Ayas (1996) that actualized organizational performance from the actualization of innovative learning design; whereas the current study introduces how this development will take place in the new and interactive forms that engage SA. Our results therefore confirm the findings of Falk & Miller's (1992) regarding benefits on learning through rapid progression assessment and content adjustment; however, our study shows more explicit patterns on how these adjustments impact SA and economic outcome.

The accessibility aspect of digital learning shows both similarities and differences with previous research. The results of this study support the observations made by Johnson & Becker (2017) about technological access barriers, but we found that innovative learning designs can help reduce these barriers by offering personalized learning approaches.

The key major finding in this study is the significant mediation effect that SA has on the EI, suggesting that this education interventions would most significantly have greater impact by developing skills. It ties into existing literature on knowledge and growth and technology.

8. CONCLUSION

In conclusion, findings of the study mirror complex interrelations among ALT, DLP, LDI, and their impact on SA and EI. A structured PLS-SEM analysis was applied for the conduct of the study, wherein the measurement and structural models are estimated to test for both validity and reliability. The model's results confirm hypothesis H1, H2, H3 and H4; hence, ALT, DLP, and LDI are significant influencers of SA, and SA successfully mediates the relationship towards EI.

The results indicate that SES makes a nuanced contribution only when it operates as a signifier of displaying direct impacts but no moderating influence of the primary relationships to be significant. Better access to digital learning resources on either employees or students brings along associated skill developments; however, the relation is much more complex than what had been theorized so far. The study's findings indicate that DLP serves as an effective democratiser of education, while ALT successfully personalises learning experiences. LDI has proved to be most effective in enhancing organizational performance and learning outcomes. This study will be relevant to the learning institution and organizational leadership. Recommendations to implement an integrated digital learning strategy will be implemented. Findings would be applicable to the academic institutions and corporate bodies in the betterment of their learning ecosystem. Findings would be recommended to be implemented all-inclusive DLP and workshops toward the betterment of SA and economic outcomes. The implications of the study go beyond individual learning outcomes to broader EIs like improved workforce productivity and organization efficiency. Based on these findings, practical and specific policy suggestions have been set out to advise educational institutions, governments, curriculum designers, corporate organizations and development agencies on how best to use digital learning to improve economic outcomes.

9. IMPLICATIONS

This research suggests the following implications for education practice, policy, and economic development. In general, results above indicate that DLP contributes significantly to economic growth, mainly through SA and development of the workforce. For this reason, organizations and learning institutions should invest further in digital learning infrastructure to achieve relevance in the knowledge-driven economy. These are important study findings in regard to SES that have implications for policymakers. Disparities found between access and digital comprehension further suggest a dire need for interventions across the divide of access. Thus, both government and educational institutions have a role and must ensure provision of technological access together with training for digital literacy in underprivileged populations.

To fully encompass the research findings, the results are further extended to cover all core constructs and relationships found in the model. More specifically, the positive effect of ALT, DLP, and LDI on SA provides the evidence for educational institutions and corporates to consider integration of personalized learning as a top priority. Also, the significant mediating role of SA on EI shows the strategic need for skill acquisition enhancement for economic planning at the national level. Although SES was not a significant moderator, the direct effect of SES on digital access indicates the need for policy interventions to bridge access gaps. These comprehensive implications reinforce the importance of a holistic, technology-driven educational ecosystem aligned with economic transformation goals.

This research, too, has implications into the reality of learning design. Since ALT success in education personalization informs that such an institution should make extra efforts to implement flexible, learner-centered approaches, that suggests that organizations will invest in the outcomes of more interesting learning experiences. Lastly, economic implications lead business organizations to treat digital learning as a strategic investment because, as the returns on investment in DLP show, organizations may benefit extensively by systematically incorporating these technologies.

10. SPECIFIC RECOMMENDATIONS BASED ON FINDINGS

1. Educational Institutions: Should invest in ALT that dynamically adapt learning content to the individual's need by plan-based assistance, which in turn could lead to a better learning outcome (Findings: H1 supported).
2. Policy Makers: Consider prioritizing increasing digital infrastructure access for lower socioeconomic groups to address the disparities in digital learning and enhance inclusive skill development (Findings: SES impacts access but does not moderate learning outcomes significantly).
3. Curriculum Designers: Must integrate LDI such as gamification and adaptive modules in order to significantly value learner engaged and economic outcomes (Findings: H3 strongly supported).
4. Corporate Organizations: Need to consider the inclusion of DLP in the workforce training strategies to improve productivity and economic performance, particularly targeting young employees (Findings: DLP impact on SA confirmed).
5. Government and NGOs: Should collaborate with online education providers to subsidize or sponsor skill development programs focused on digital literacy and employability for disadvantaged communities (Findings linked to real-world examples e.g., Coursera -COVID initiative).

11. LIMITATIONS AND FUTURE RESEARCH

This research has some limitations since the relationships between DLP and EI were studied under a particular context, hence limiting its applicability under a wider context. In the future, it is advisable to look at a broader geographical scope beyond present limitations and consider other sectors such as manufacturing and banking. The implementation of digital learning technologies will provide additional insights into cultural and regional variations. Research in future needs to examine how emerging technologies merge into more existing platforms to create better economic benefits.

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