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Leveraging Algorithmic Integration in Industrial Technology Education for Achieving a Skilled and Inclusive Society

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Abstract
This research determined participants' opinions on leveraging algorithmic integration in Industrial Technology Education for achieving a skilled and inclusive society. The study area was technical colleges in Rivers State. A descriptive research design was utilized for the study. The target population included all (46) teachers in the four Technical Colleges owned by Rivers State. Due to the relatively small size of the population, census sampling was used to draw the entire population for this research. The study was designed to address three research questions. A validated questionnaire consisting of 21 items was used to elicit information from respondents. Data were collected from participants through the administration of a four (4) point rating system of Very High Extent (VHE), High Extent (HE), Low Extent (LE), and Very Low Extent (VLE), assigned numerical values of 4, 3, 2, and 1, respectively. The researcher and three research assistants administered the instrument to participants at the same time and collected it from them after it had been completed. Data were analyzed using mean statistics. Items having a mean rating of 2.50 and above were considered Agree, while items below 2.50 were considered Disagree. Results revealed that integrating Decision Tree, Artificial Neural Networks, and Generative Adversarial Networks algorithms significantly contributes to the development of a skilled and inclusive society. Consequently, it was recommended, among other that the curriculum in Industrial Technology Education (ITE) be strategically redesigned to incorporate algorithmic integration.

Keywords: Algorithm Integration, Decision Tree, Artificial Neural Networks, Generative Adversarial Networks, Skilled, Industrial Technology

Introduction

The development of many societies has been attributed to the availability of skilled manpower. Skill is a measurable capability that directly influences performance outcomes, particularly in domains where technical, behavioral, and psychological factors intersect (Iso-Ahola, 2024). Iloma and Ikenyiri (2022) defined skill as the ability to perform tasks effectively and efficiently through acquired knowledge and practical experiences. Skill is therefore a cultivated proficiency that empowers individuals to execute tasks with accuracy and consistency, which is developed through deliberate practice, experiential learning, and structured training. Skill enhances economic productivity, social mobility, youth empowerment, technological adaptation, and poverty reduction. According to Findlay (2019), skills are essential bedrocks for work and employment and for individual economic prosperity, impacting health, well-being, and social and civic life. Thus, building a skilled society is imperative to the socio-political and economic development of any nation. A skilled society embraces a unified framework for skills and terminology to equip its workforce for emerging challenges, fostering resilience and continuous learning. According to the World Economic Forum (2025), a skilled society adopts a common skills language and taxonomy to prepare its workforce for future challenges, ensuring adaptability and lifelong learning. Hosseinioun et al. (2025) opined that a skilled society is characterized by a nested architecture of human capital, where foundational and specialized skills are distributed across the population to support diverse career paths and social mobility. This suggests that social mobility, health, social well-being, and technological advancement could be significantly imparted by a skilled and inclusive society.

A skilled and inclusive society therefore integrates skill-building into its core institutions and public policies, especially through education, to enable individuals and communities to rise above systemic and societal obstacles and inequities. Industrial Technology Education (ITE) as an aspect of Technical Vocational Education and Training (TVET) is one among several educational programmes designed to achieve this. TVET involves the teaching and learning of practical and theoretical knowledge that enables learners to manipulate tools, materials, and processes for problem-solving (Akpan & Essien, 2022). Iloma and Ikenyiri (2022) posited that TVET is a pragmatic instructional process that equips learners with skills for enhancing, innovating, and maintaining technological systems. ITE significantly supports the development of skills for green economies and inclusive growth. ITE aims to produce skilled personnel in applied sciences, technology, and commerce at sub-professional levels; provide individuals with vocational and technical abilities that would enable them to be employed and be self-reliant; develop and promote entrepreneurial skills to foster economic empowerment, among other things (National Policy on Education, Federal Republic of Nigeria, 2013). Further, the programme is aimed at reducing unemployment by preparing learners for gainful employment, preparing students for further studies in technology-related fields, foster technological literacy and innovation among young Nigerians (FRN, 2013). In line with this, the United Nations Educational, Scientific and Cultural Organization (UNESCO, 2022) emphasizes the integration of science and technology into the curriculum to foster innovation, skill acquisition, and economic development. Skilled and inclusive societies ensure that everyone contributes and benefits from social and economic growth despite gender and class differences (International Labour Organization ILO, 2024). Murphy (2025) opined that a skilled and inclusive society increases productivity and innovation by ensuring equal opportunities for everyone. Inclusiveness reinforces collaboration and teamwork among classes and supports social interaction within the workforce, which are vital for collective progress. A skilled and inclusive workforce in workplaces leads to richer learning experiences and better problem-solving skills, which often result in higher productivity. Thus, the need for adopting a facilitating instructional strategy could be necessary in achieving a skilled and inclusive society.

Instructional strategies are deliberate techniques employed by teachers to organize and deliver content in ways that enhance student understanding and retention (Iloma, 2020)**.** They are purposeful plans and actions taken by teachers to facilitate the acquisition of knowledge and skills (Borich, 2013). Instructional strategies in TVET could refer to sequential instructional activities designed to facilitate learning and improve academic performance. It is pedagogical approaches that incorporate collaborative learning, explicit teaching, and exploratory methods to facilitate active participation, cognitive development, and academic motivation among students through engaging practices and interactive techniques. Several researchers, such as Harnal (2025), have asserted that learning strategies using digital tools promote teamwork and peer-to-peer interaction. Incorporating technology-oriented teaching methods, such as algorithmic approaches, into Industrial and Technical Education (ITE) could greatly support the realization of educational objectives. Through the utilization of adaptive tools and flexible content delivery, digital learning techniques also broaden access to education by assisting a diverse range of learners, including those with physical challenges. Algorithmic integration in ITE could be significant in building a skilled and inclusive society. As described by Russell and Norvig (2010), an algorithm is a finite series of precisely defined, computer-executable steps designed to address problems or carry out computations, often enabling artificial intelligence systems or machines to acquire knowledge autonomously. Sipser (2012) posited that algorithms are abstract representations of computational processes, designed to transform input data into desired outputs. By leveraging data-driven insights, algorithms can tailor educational experiences, ensuring that learners receive content suited to their existing knowledge and skill levels (Elsevier Education Team, 2021).

According to Leong (2025), algorithmic systems in education enable adaptive learning platforms that personalize instruction based on learners' performance, thereby enhancing engagement and improving learning outcomes. Algorithmic tools can adapt content for learners with disabilities or language differences, promoting inclusiveness and equal learning opportunities (Delia, 2025). Deckker and Sumanasekara (2025) opined that AI-powered simulations and virtual environments enhance skill acquisition, promote data-driven decision-making, and help keep TVET curricula up to date by monitoring technological advancements and industry needs. The importance of algorithms in enhancing instructional activities in education has made it exist in several forms, such as Decision Tree Algorithm,

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Artificial Neural Networks, and Generative Adversarial Networks. Integrating Decision Tree Algorithm (DTA) in ITE could be significant in achieving a skilled and inclusive society. Decision Tree Algorithms are machine learning models that employ a tree-like framework to represent decisions and their potential outcomes (Imienye & Jere, 2024). According to GeeksforGeeks (2025), these algorithms function by dividing sets of data into subsets based on certain criteria, forming a hierarchical structure in which each leaf node delivers a prediction. This design makes them highly understandable and visually accessible, supporting a clearer understanding of the decision-making process. Han and Kamber (2011) further described decision trees as flowchart-style structures, where internal nodes correspond to attribute tests, branches indicate possible outcomes, and leaf nodes denote class labels. Within instructional activities in Information Technology Education (ITE), decision trees enhance learning by simplifying complex tasks, ensuring easy interpretation, and accommodating both categorical and numerical data. DTA could significantly impact academic performance, especially in the acquisition of practical skills.

Several studies have highlighted the educational potential of DTA in enhancing skill development and inclusiveness. For instance, Rahman and Lee (2021) reported that DTAs assist institutions in allocating teaching resources more effectively by identifying students' academic needs and course requirements, thereby enhancing the achievement of educational objectives. Similarly, He (2024) opined that DTAs detect risk of poor performance among students by analyzing their data and thus encourage proactive support to help such students perform better irrespective of barriers and challenges. According to Zhang et al. (2022), DTAs have the potential to expose gaps in instruction by analyzing student results and thus provide opportunities and resources for continuous improvement, ensuring that students indicate better performance. This study therefore determined respondents' opinions on the extent to which leveraging DTA in ITE impacts achieving a skilled and inclusive society. Leveraging Artificial Neural Networks Algorithm (ANNA) could also enhance the building of a skilled and inclusive society if integrated into ITE. ANNAs are computational architectures modeled after the human brain, composed of interlinked units (neurons) that transmit and process information across successive layers (Hammad, 2024). As noted by LeCun, Bengio, and Hinton (2015), these algorithmic systems strive to identify hidden associations within datasets by emulating neural activity. Aggarwal (2018) portrays ANNAs as layered constructs of interconnected nodes that convert input signals into meaningful results through adaptive weights and activation mechanisms. Likewise, Zarei et al. (2022) describe them as assemblies of simple processing elements that collectively execute intricate operations by replicating the parallel functioning of biological neurons. Unlike conventional programming, ANNAs discern patterns and resolve tasks by acquiring knowledge from data rather than relying on explicit instructions, thereby promoting ethical, inclusive, and sustainable competencies aligned with industrial requirements.

ANNA has been cited by several scholars as a useful tool that enhances learning and inclusiveness when integrated in education. For instance, Samuel et al. (2025) asserted that ANNA-driven educational technologies expand access for diverse learners, including those with disabilities, and strengthen technical skills by tailoring instruction to align with individual learner needs through an adaptive learning environment, thereby fostering inclusiveness in education. Similarly, Melo-López et al. (2025) posited that ANNA supports multilingual and multicultural educational contexts, offers assistance such as speech recognition and adaptive interfaces, and reduces barriers by adapting content delivery to varied socio-economic and cultural contexts, thus promoting learning. The study determined the extent to which leveraging ANN integration in ITE institutions enhances the building of a skilled and inclusive society. Generative Adversarial Networks (GAN) algorithms are yet another type of algorithm that could be integrated in ITE. Sharma, Sharma, and Biju (2024) highlight that Generative Adversarial Networks (GANs) are influential instruments for both data creation and forecasting, extensively applied in domains such as image generation, text-to-image conversion, and counterfeit image detection, particularly in facial forgery analysis. These are generative architectures that learn to replicate the distribution of training datasets by producing new instances that closely resemble authentic data, employing a game-theoretic framework (Wikipedia contributors, 2024). As Gormley (2024) explains, GANs belong to a category of generative models that construct synthetic data by positioning a generator against a discriminator—the generator attempts to deceive the discriminator with fabricated samples, while the discriminator endeavors to differentiate genuine data from false. In instruction, GAN integration could improve precision and accuracy and enhance quality outputs in workshop practices. GANs create adaptive educational materials that align with individual student needs, enhancing personalized learning pathways that promote performance and inclusiveness (Wang et al., 2025). According to Bethencourt-Aguilar et al. (2023), GANs generate culturally relevant educational materials, supporting multilingual and multicultural classrooms, thereby enhancing skill and inclusiveness. The study determined the extent to which leveraging GAN integration in ITE institutions enhances the building of a skilled and inclusive society.

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This study aimed to determine respondents' perception of the extent to which leveraging algorithmic integration in ITE enhances the achievement of a skilled and inclusive society. Specifically, this study determined respondents' perception on the extent to which leveraging:

1. Decision Tree algorithmic integration in ITE for achieving a skilled and inclusive society
2. Artificial Neural Networks algorithmic integration in ITE for achieving a skilled and inclusive society
3. Generative Adversarial Networks algorithmic integration in ITE for achieving a skilled and inclusive society

The study was guided by the following research questions.

1. To what extent does leveraging Decision Tree algorithmic integration in ITE enhance achieving a skilled and inclusive society?
2. To what extent does leveraging Artificial Neural Networks algorithmic integration in ITE enhance achieving a skilled and inclusive society?
3. To what extent does leveraging Generative Adversarial Networks algorithmic integration in ITE enhance achieving a skilled and inclusive society?

Methodology

The research was conducted in technical colleges located in Rivers State, Nigeria. A descriptive research design was employed for the investigation. The study population comprised 46 instructors drawn from four government-owned technical colleges in Rivers State. Given the relatively small and manageable size of the population, a census sampling technique was adopted, thereby including all members in the study. The inquiry was guided by three research questions. Data collection was facilitated through a validated questionnaire containing 21 items, designed to obtain responses from participants. The instrument utilized a four-point scale, ranging from Very High Extent (VHE), High Extent (HE), Low Extent (LE), to Very Low Extent (VLE), with corresponding numerical values of 4, 3, 2, and 1, respectively. Administration of the instrument was carried out by the researcher with the assistance of three research aides. The completed instruments were retrieved immediately upon completion. Data analysis was performed using mean statistics. Items with a mean score of 2.50 and above were interpreted as "Agree," while those below 2.50 were categorized as "Disagree."

Results

Research Question 1: To what extent does leveraging Decision Tree algorithmic integration in TVET enhance achieving a skilled and inclusive society?

Table 1: Aggregate value of respondents' perception on the extent to which leveraging Decision Tree algorithmic integration in ITE enhances achieving a skilled and inclusive society

SN	Items	VHE	HE	LE	VLE	Mean	Decision
1	Promotes innovation in teaching and learning strategies to accommodate all learners.	31	7	5	3	3.43	HE
2	Provides improved career guidance for TVET students.	22	16	4	4	3.22	HE
3	Enhances transparency and fairness in accessing various classes of students.	24	13	5	4	3.24	HE
4	Help identify at-risk students early to reduce dropout rates.	22	12	7	5	3.11	HE
5	Improve accuracy of predicting students' performance and provide ways of helping the weak.	21	18	5	2	3.26	HE
6	Breaks down practical instruction to accommodate marginalized groups.	25	12	6	3	3.28	HE
7	Identify best learning approach for different categories of ITE learners.	24	13	5	4	3.24	HE
	Grand Mean					**3.25**	**HE**

The result of the analyzed data obtained from the items in Table 1 indicated that, to a great extent, it is the perception of respondents that Decision Tree algorithmic integration in ITE enhances the building of a skilled and inclusive society. This conclusion was supported by the mean scores obtained for each item, all of which exceeded the benchmark value of 2.50. The computed grand mean of 3.25, being above the cut-off point, further substantiates this finding. Overall, the results indicate that respondents strongly believe that the application of Decision Tree algorithmic integration within ITE significantly contributes to the attainment of a more competent and inclusive society.

Research Question 2: To what extent does leveraging Artificial Neural Networks algorithmic integration in ITE enhance achieving a skilled and inclusive society?

Table 2: Aggregate value of respondents' perception on the extent to which leveraging Artificial Neural Networks algorithmic integration in ITE enhances achieving a skilled and inclusive society

SN	Items	VHE	HE	LE	VLE	Mean	Decision
8	ANN-powered learning aligns ITE training with dynamic labour market demands	20	19	4	3	3.22	HE
9	Provides instructions that enhance practical skill acquisition among physically challenged learners	24	16	4	2	3.35	HE
10	Each student is provided with a peculiar learning experience	21	15	8	4	3.23	HE
11	Promotes student engagement by utilizing adaptive tutoring methods	28	10	6	2	3.80	HE
12	Helps to ensure that learning experiences are personalized based on individual student behavior and performance	27	12	4	3	3.37	HE
13	Promotes learners' industrial skill competency experiences	25	19	1	1	3.48	HE
14	Enhances early detection of learning difficulties and provides timely support for all learners	31	8	3	4	3.43	HE
	Grand Mean					**3.41**	**HE**

The results of the analyzed data obtained from items in Table 2 indicated that respondents perceived each of the items of the instrument. This was evidenced by the fact that the mean ratings obtained for all items exceeded the established cut-off value of 2.50. The computed grand mean of 3.41 further confirmed this outcome, being well above the benchmark. The overall result therefore showed that it is the perception of respondents that, to a high extent, leveraging Artificial Neural Networks algorithmic integration in ITE enhances achieving a skilled and inclusive society.

Research Question 3: To what extent does leveraging Generative Adversarial Networks algorithmic integration in ITE enhance achieving a skilled and inclusive society?

Table 3: Aggregate value of respondents' perception on the extent to which leveraging Generative Adversarial Networks algorithmic integration in ITE enhances achieving a skilled and inclusive society

SN	Items	VHE	HE	LE	VLE	Mean	Decision
15	Enable realistic simulations that enhance hands-on skill acquisition in ITE.	31	7	5	3	3.43	HE
16	GAN-generated content helps represent diverse cultural and occupational scenarios in training.	22	16	4	4	3.22	HE
17	GAN integration encourages student-led experimentation.	24	13	5	4	3.24	HE
18	Promotes inclusive design thinking among ITE students	22	12	7	5	3.11	HE
19	Support the creation of inclusive digital learning environments for all classes of ITE students.	21	15	8	4	3.23	HE
20	Enhance virtual reality and augmented reality experiences in technical training.	28	10	6	2	3.80	HE
21	Improve accessibility for learners with disabilities through adaptive visuals.	27	12	4	3	3.37	HE
	Grand Mean					**3.34**	HE

The results of the analyzed data obtained from items in Table 3 indicated that respondents perceived each of the items of the instrument. This was evidenced by the fact that the mean ratings obtained for all items exceeded the established cut-off value of 2.50. The computed grand mean of 3.34 further confirmed this outcome, being well above the benchmark. The overall result therefore showed that leveraging Generative Adversarial Networks algorithmic integration in ITE enhances achieving a skilled and inclusive society.

Discussion

Findings showed that leveraging Decision Tree algorithmic integration in ITE enhances achieving a skilled and inclusive society. This finding aligns with that of Rahman and Lee (2021) that DTAs assist in identifying students' academic needs and course requirements, thereby enhancing students' achievement and inclusiveness. The finding also corroborates that of He (2024), who opined that DTAs detect risk of poor performance among various classes of students and help such students perform better irrespective of barriers and challenges by encouraging proactive support and an environment that enhances performance and an inclusive society. The finding also aligns with the work of Zhang et al. (2022), who observed that Decision Tree Algorithms (DTAs) expose gaps in instruction, provide opportunities and resources for continuous improvement, and ensure that students indicate better performance, which often results in enhanced learning and inclusiveness. Findings further showed that leveraging Artificial Neural Networks algorithmic integration in ITE enhances the achievement of a skilled and inclusive society. This finding corroborates that of Samuel et al. (2025) that ANNA expands access to diverse learners, including those with disabilities, through an adaptive learning environment, thereby fostering inclusiveness and performance in education. The finding also aligns with that of Melo-López et al. (2025) that ANNA supports multilingual and multicultural educational contexts, offers assistance to physically challenged individuals through adaptive interfaces, and hence reduces barriers in content delivery to varied socio-economic and cultural contexts, thus promoting learning. Findings further showed that leveraging Generative Adversarial Networks algorithmic integration in ITE enhances the achievement of a skilled and inclusive society. This finding is in line with that of Wang et al. (2025) that GANs create learning environments that align with individual student needs, enhancing personalized learning and promoting performance and inclusiveness. The finding also corroborates that of Bethencourt-Aguilar et al. (2023) that GANs support multilingual and multicultural classrooms by creating an adaptive learning environment, thereby enhancing skill and inclusiveness.

Conclusion

From the results obtained, the researcher concluded that leveraging Decision Tree algorithmic integration in ITE enhances the achievement of a skilled and inclusive society. It was further concluded that leveraging Artificial Neural Networks algorithmic integration in ITE enhances the building of a skilled and inclusive society. It was also concluded that leveraging Generative Adversarial Networks algorithmic integration in ITE enhances the achievement of a skilled and inclusive society.

Recommendations

As a result of the findings, it was recommended that:

1. Opportunities for training and retraining of ITE educators on algorithmic utilization should be provided by government and other organizations
2. ANN facilities be provided in ITE institutions to enhance building a skilled and inclusive society
3. Opportunities for Generative Adversarial Networks algorithmic integration in ITE should be enhanced for building a skilled and inclusive society.

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