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An AI-Driven Decision Framework for Promoting Sustainable Entrepreneurship in Vocational Colleges

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ABSTRACT

This research investigates the application of artificial intelligence (AI)-enabled tools within vocational education to advance green innovation start-ups and promote sustainable entrepreneurship, with particular emphasis on the role of educational institutions in contributing to Sustainable Development Goal 4 (SDG 4). It addresses the pressing need to explore the interconnections between AI utilisation, digital literacy, and sustainability achievements in vocational learning environments across global contexts. The study employed a quantitative and descriptive research design, making use of secondary data sourced from the UNESCO Institute for Statistics, World Bank Open Data, OECD education statistics, and the Global Entrepreneurship Monitor. A consolidated dataset was compiled for 200 vocational institutions, encompassing seven primary attributes: regional coding, type of institution, national income classification, participation rates, digital literacy levels, AI adoption levels, and per capita funding. A refined AI-based decision-making framework was developed, integrating data pre-processing procedures, AI model construction, multi-criteria decision-making techniques, and mechanisms for continuous performance evaluation. The results demonstrate a robust positive relationship between digital literacy and AI adoption (correlation coefficient: 0.805). Employment outcomes exhibited the strongest association with institutional success (correlation coefficient: 0.965). Random Forest classification models achieved an accuracy rate of 93.3% in forecasting sustainability adoption, with AI adoption emerging as the most influential factor, contributing 89.6% to employment-related outcomes. Regional comparisons highlight pronounced inequalities, as developed regions record AI adoption levels approximately three to four times higher than those in developing areas. Bayesian analysis further indicated that institutions combining substantial funding with high AI adoption display a 92.9% likelihood of achieving effective sustainability integration.

1. Introduction

Across the world, vocational education institutions are confronted with considerable technological and organisational constraints when attempting to integrate AI-based systems into their operations for the advancement of green innovation start-ups and sustainable

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entrepreneurship. Their significance in fulfilling SDG 4 is unquestionable, yet many lack structured, data-informed frameworks that can reliably evaluate institutional capabilities, measure technological preparedness, and optimise sustainability results. Disparities between regions exacerbate these limitations, with developed areas exhibiting AI adoption rates up to four times greater than those in developing economies. Against the backdrop of global environmental pressures, fostering sustainable entrepreneurship has emerged as a strategic necessity. In China, vocational institutes have been positioned as key enablers of both skill acquisition and innovative capacity. By designing entrepreneurship programmes that prioritise ecological responsibility, they can nurture a new generation of entrepreneurs committed to green transformation. Nevertheless, conventional teaching strategies have consistently struggled to merge entrepreneurship training with sustainability goals [32]. The adoption of AI in education offers a viable route forward, enabling advanced analytics, predictive modelling, and evidence-led decision support [5].

The concept of sustainable entrepreneurship centres on generating value while simultaneously addressing environmental, economic, and social imperatives. Unlike purely profit-oriented ventures, this approach embeds ecological stewardship and social accountability into operational models [28]. It signals a shift in business philosophy towards the pursuit of triple-bottom-line performance: people, planet, and profit [26]. Recognising the urgency of climate change mitigation and resource conservation, more than 190 signatories to the Paris Agreement have pledged to meet internationally agreed sustainability benchmarks [31]. Achieving these targets, however, is dependent on the education sector's ability to prepare individuals for such challenges. In line with this, institutions like Shanghai Polytechnic University have incorporated sustainability topics into their curricula [3]. When applied to entrepreneurship education, AI systems can strengthen decision-making by processing extensive datasets, uncovering patterns, and producing accurate forecasts [10]. Although AI has long been present in educational contexts—[30] reports that its adoption in developed countries exceeds 65%, compared to under 20% in developing regions—it remains underutilised in supporting green start-ups. The technology can streamline sustainable business design, improve resource allocation, and scale solutions efficiently [5]. Current capabilities even include automated detection of emerging eco-markets, modelling of environmental impacts, and recommending actions to reduce carbon emissions [19].

Despite growing enthusiasm for AI-driven sustainable entrepreneurship, a notable gap persists in establishing structured, vocationally focused AI frameworks that can systematically stimulate the creation of green start-ups. The present study aims to address this by illustrating how AI can widen access to entrepreneurial resources and enhance equity within innovative ecosystems. Vocational colleges, in particular, face both opportunities and limitations in this area [11]. Students often arrive from diverse socio-economic backgrounds and may lack conventional entrepreneurial networks, making equal access to resources critical. Through AI-enabled systems, they can engage with cutting-edge tools regardless of prior start-up experience [3]. Moreover, AI applications can narrow the theory–practice divide, enabling practical application of classroom concepts. Examples from China reveal the role of AI in promoting inclusive education [11]. Developing an effective green innovation start-up framework requires multiple components, including embedding sustainability themes into entrepreneurship modules [7] and introducing related subjects such as the circular economy, renewable energy strategies, and sustainable supply chains. Such integration, as seen in Shanghai Polytechnic University, deepens student understanding of sustainability [12].

Designing AI tools for these programmes should balance subject-oriented objectives with student-centred delivery [33]. Accessibility is essential, which can be achieved through user-friendly platforms requiring minimal technical expertise. These systems can guide students throughout the entrepreneurial process—from concept generation to operational launch. Simulation capabilities, available through AI platforms like TensorFlow or Google AI, can test market potential and refine product development. AI-led mentorship initiatives provide tailored guidance, further enhancing start-up success rates [18]. Strategic partnerships between educational institutions, industry stakeholders, and governmental bodies can also strengthen programme outcomes. Industry collaborators can share insights on sector-specific trends, while public policy measures, such as funding incentives, can accelerate AI adoption in sustainable education [32].

The transformative capacity of AI is already evident across sectors. In agriculture, it boosts productivity, reduces waste, and improves resource efficiency. In renewable energy, AI-optimised solar and wind systems have enabled rapid deployment of clean power solutions [14]. Chinese vocational institutions have demonstrated that leveraging these technologies enables context-specific problem-solving for environmental challenges [37]. This paper contributes to the discourse by examining AI's potential to act as a catalyst for sustainability-oriented entrepreneurship education. With AI adoption in education projected to grow at a compound annual rate exceeding 40%, including applications in predictive analytics and personalised learning [29], this study bridges the gap between academic theory and practice, empowering students to create solutions addressing ecological and economic concerns.

While the benefits are substantial, integrating AI into vocational training also raises challenges, including unequal digital literacy, limited resources, and ethical issues such as data protection and algorithmic fairness. Tackling these concerns requires infrastructure investment and capacity-building initiatives to ensure inclusive, AI-ready learning environments. This research seeks to evaluate the viability of an AI-based decision-support model for sustainable entrepreneurship, identify key obstacles, and propose targeted strategies for embedding AI into vocational curricula.

1.1 Problem Statement

The dynamics underlying the achievement of sustainable entrepreneurship remain underexplored, particularly regarding the multifaceted interconnections between institutional attributes. Although elements such as per capita funding, digital literacy, and AI integration have been individually acknowledged as determinants of success, the combined influence of these factors and their collective bearing on employment generation and sustainability integration are not yet comprehensively understood. This limited understanding restricts the capacity of institutions to make strategic, evidence-based decisions on technology investment priorities and programme development. Compounding this is the lack of robust, empirically validated models that can reliably forecast institutional performance in adopting sustainability practices, thereby introducing uncertainty into both strategic planning and long-term investment decisions.

In the absence of advanced quantitative models capable of estimating the probability that specific institutional inputs will translate into measurable sustainability outcomes, vocational education providers are hindered in their ability to justify technological investments, optimise resource distribution, and address the needs of diverse stakeholders. The challenge is heightened by the observation that employment outcomes have the strongest statistical association with institutional success, yet existing analytical capacities in vocational institutions are inadequate for systematically predicting or enhancing these results. This issue extends beyond the performance of individual institutions, touching on broader structural concerns related to educational equity and sustainable development. The persistent disparity between developed and developing regions in digital literacy and AI adoption has created unequal institutional capacities, thereby impeding collective global progress toward the Sustainable Development Goals through vocational training. Without comprehensive evaluative frameworks capable of identifying high-performing institutional clusters, measuring regional variations in sustainability readiness, and providing actionable, evidence-based recommendations, the sector's contribution to the global shift toward sustainability-focused entrepreneurship and green innovation remains constrained. Addressing this intricate challenge demands the formulation of sophisticated AI-driven decision-making systems that integrate diverse data sources, utilise advanced analytics, and deliver practical guidance, while simultaneously addressing the systemic inequalities that limit the growth of sustainable entrepreneurship in different economic and geographical contexts. This research therefore addresses the following questions:

• To what extent does the combined effect of institutional funding allocation and AI adoption predict the success of sustainability integration across different regional contexts?

• In view of the finding that AI adoption is the strongest predictor of employment outcomes, yet holds a more balanced importance with digital literacy in sustainability adoption within Random Forest analysis, how can vocational institutions optimise AI-driven decision-making systems to maximise employment results while strengthening sustainability integration?

2. Literature Review

The incorporation of AI within vocational education has increasingly been recognised as a pivotal driver in advancing sustainable entrepreneurship and promoting green innovation. This review of existing literature consolidates empirical findings on the utilisation of AI-based decision-making frameworks in educational settings, with particular emphasis on their effectiveness in advancing the Sustainable Development Goals and nurturing entrepreneurial ecosystems. The discussion draws on the methodological approach and empirical outcomes of the referenced research, which identified strong statistical associations between digital literacy, AI implementation levels, and sustainability performance across a global sample of 200 vocational education institutions.

2.1 Sustainable Entrepreneurship in Education

Sustainable entrepreneurship education has progressed considerably as academic institutions increasingly recognise the necessity of integrating environmental stewardship with entrepreneurial skills. Empirical findings indicate that social entrepreneurship education positively shapes students' perceptions of corporate social responsibility (CSR) and encourages more sustainable behavioural practices [1]. In a study of 271 undergraduate students from private universities in Lahore, Pakistan, the theory of planned behaviour was utilised to demonstrate how the institutional environment moderates and strengthens the relationship between sustainable entrepreneurship education and perceived CSR. A bibliometric review of literature on sustainable entrepreneurship education, covering the period from 2012 to 2023, identified 61 empirical and conceptual studies outlining diverse educational models adopted in higher education and secondary school settings [27]. This review underlined the lack of a cohesive framework that clearly defines the competencies essential for preparing entrepreneurs to confront present-day sustainability challenges. The results highlight the pressing requirement to transition towards a sustainability-driven economy, grounded in competencies that equip individuals to address the complexities of a rapidly evolving global environment.

In Spain, research has underscored the importance of prioritising personal dimensions within university education as external factors shaping social and entrepreneurial values [20]. An investigation into four dimensions associated with fourteen values linked to blue and sustainable entrepreneurship found that personal values directly influence environmental considerations, which are essential for achieving a meaningful and well-balanced integration of sustainability-focused entrepreneurial values. In the Chinese context, the development of an entrepreneurship education evaluation model for universities—employing the entropy-TOPSIS method across 35 indicators categorised into five domains (curriculum systems, organisational leadership, faculty development, teaching management, and institutional support)—offers a robust scientific basis for strategic decision-making in advancing entrepreneurship education reforms [6]. This model enables a systematic appraisal of sustainability within entrepreneurship education and supports higher education institutions in progressing towards the Sustainable Development Goals (SDGs).

In Saudi Arabia, studies examining the relationships between entrepreneurial culture, sustainability training, and sustainability education have established that a well-rooted entrepreneurial culture positively influences both sustainability training and educational practices [35]. Using structural equation modelling with data from 252 participants, the research further confirmed that sustainability training positively impacts sustainability education, thereby lending support to the extended human relations theory as it applies to sustainable entrepreneurial culture. Within the rural development sphere, initiatives aimed at entrepreneurs aged 50 and above have shown considerable promise in promoting sustainable growth in rural regions [22]. A survey involving 72 aspiring entrepreneurs and 100 rural development specialists revealed a significant perception of business potential for experienced professionals in rural areas, alongside a clear demand for targeted training programmes, particularly in the domain of rural tourism entrepreneurship.

2.2 Green Innovation and Start-up Ecosystems

Digital transformation exerts a substantial influence on total factor productivity, primarily through technological innovation pathways, with AI identified as the dominant driver rather than other innovation types [21]. An empirical investigation of Chinese listed firms spanning 2007 to 2020, employing fixed-effect models alongside instrumental variable estimation, established that while digital transformation positively contributes to productivity, its effect on total factor productivity can be counterbalanced by alternative technological advancements, such as those in green and energy-related technologies. The AI start-up landscape has experienced exceptional expansion, with the Indian AI market estimated at approximately USD 3.1 billion in 2020 and projected to grow at a compound annual growth rate exceeding 40 per cent, reaching an estimated USD 7.8 billion by 2024 [27]. India now hosts over 6,200 AI start-ups, with Bengaluru emerging as the primary hub, attracting close to 29 per cent of total AI start-up investment.

Cai et al. [6] highlight the critical importance of integrating AI management with green innovation to advance sustainability objectives. With rapid technological maturity and demonstrable capacity to address environmental issues through novel approaches, AI is increasingly regarded as a transformative force capable of redefining organisational management and operational practices. Drawing on survey data and AI impact modelling, the research illustrates AI's potential to restructure processes for emission reduction, stimulate green innovation, and support the design of environmentally responsible products. These findings reinforce the argument for embedding AI within vocational education frameworks to promote sustainable entrepreneurship. To identify and enhance opportunities for green enterprise, Al Halbusi et al. [2] introduce the Green Digital Innovation Radar framework. Their conclusions emphasise that digital technologies function as pivotal enablers of sustainability by facilitating efficient resource utilisation, promoting eco-innovation, and supporting environmentally conscious business models. Using qualitative methods and case-based analysis, supplemented with expert interviews in AI and digital innovation, the study establishes a direct linkage between the integration of AI-driven digital tools and the cultivation of eco-friendly entrepreneurial ecosystems. This aligns with the strategic objective of vocational colleges to equip students with digital competencies that enable green innovation.

A study of small and medium-sized enterprises (SMEs) in Ecuador, drawing upon the Global Entrepreneurship Monitor 2024/2025 report, identified key obstacles to AI adoption, including high implementation costs, insufficient technical expertise, and cybersecurity risks [1]. The analysis revealed that most SMEs operate within traditional, low value-added industries, with limited participation in knowledge-intensive sectors, and innovation levels remain low, with fewer than 3 per cent developing new products or technologies. Within the broader sustainability transition, carbon-neutral supply chains have emerged as essential components, with AI and quantum computing identified as significant enablers. A systematic review of 87 peer-reviewed studies published between 2015 and 2025 concluded that AI substantially enhances operational sustainability through advanced demand forecasting, inventory management optimisation, carbon footprint evaluation, and informed green procurement strategies.

The ongoing wave of digitalisation is reshaping innovation and entrepreneurial ecosystems, generating both unprecedented opportunities and intricate challenges. Evidence examining the interconnection between digital technologies and entrepreneurial activity highlights the emergence of platform-based business models, the proliferation of digital start-ups, and the transformation of organisational cultures towards agility and entrepreneurial orientation. Within this landscape, project management methodologies exert considerable influence over the effectiveness of digital marketing analytics in driving start-up growth. Findings from a survey of 200 professionals in US-based start-ups indicate that structured project management practices significantly enhance digital marketing performance, with firms adopting such approaches being 2.15 times more likely to achieve marketing success [9]. Islam and Can [13] address the challenge of embedding sustainability within entrepreneurial practice, emphasising the role of AI in enabling green business models in the digital era. Their mixed-methods investigation, combining AI-assisted data analytics with qualitative interviews, demonstrates how AI facilitates efficiency gains in innovation, minimises waste, and promotes scalable, sustainable solutions, while acknowledging persistent inefficiencies and negative externalities within current systems. The research indicates that AI-enabled predictive analytics, resource allocation optimisation, and scalable eco-innovations are central to this process. These outcomes underscore the importance of integrating AI-based decision-support frameworks into vocational education, enabling students to confront complex sustainability challenges effectively.

2.3 AI in Decision-Making and Strategic Planning

The preparedness of public institutions for AI-enabled decision-making remains an area of limited investigation, with notable variations across national and organizational contexts [15]. A systematic literature review of peer-reviewed articles, policy papers, and empirical studies published between 2013 and 2023 identified key readiness dimensions. These include institutional capacity, digital infrastructure, regulatory alignment, human resource expertise, and ethical safeguards. Evidence from AI-assisted clinical decision support systems embedded in electronic health records indicates substantial potential to enhance clinical outcomes, although implementation continues to face socio-technical obstacles. An evaluation of the 48-hour Discharge Prediction Tool, guided by the RE-AIM and Consolidated Framework for Implementation Research, highlighted barriers such as limited awareness, concerns about accuracy and trustworthiness, restricted accessibility, and insufficient transparency.

The evolving domain of human–AI decision-making necessitates empirical investigations to establish a foundational understanding of human–machine interaction in decision processes [16]. A review of over 100 publications assessing research design in decision-making tasks, AI assistance parameters, and evaluation metrics underscores the requirement for unified frameworks capable of mapping the design and research landscapes in this field. Generative AI prompt models, which integrate deep learning with reinforcement learning methods, are shown to enhance decision-making in complex and dynamic contexts [25]. The AI PROMPT model provides structured guidance for text-to-text prompt engineering, detailing methods and benchmarks for improving quality and utility in organisational decision-making. Explainable Artificial Intelligence has become indispensable in mitigating the opaque nature of sophisticated AI architecture, especially in high-risk sectors. Studies categorising explanation strategies according to scope, timing, and dependence on model architecture propose a novel taxonomy that informs the selection of methods across varied applications, revealing trade-offs between accuracy and interpretability. The convergence of behavioural economics and AI introduces distinctive challenges for decision-makers, highlighting the urgency of ethical guidelines to govern predictive analytics and algorithm-driven customisation. Contemporary research into consumer choices in the AI context identifies significant ethical and operational issues related to data protection, algorithmic fairness, and maintaining public trust [24].

Within the educational sector, AI-enabled leadership demands strategic and forward-looking measures to harness its benefits while navigating associated ethical, legal, cultural, and social considerations. A proposed conceptual framework, grounded in AI, leadership, and decision-making theories, comprises four interconnected dimensions: inputs, processes, outputs, and feedback. This model provides direction for cultivating AI-based leadership in education. Mixed-methods research assessing the impact of AI-driven management on organisational performance among 180 participants found substantial improvements in strategic accuracy and operational efficiency. Statistical analyses, including linear regression and exploratory factor analysis, confirmed AI's significant role in enhancing employee engagement and encouraging collaborative practices [17]. Additional scholarships explore competitive platforms and experiential pedagogies in sustainable entrepreneurship training. Zhang et al. [36] investigate the China College Students Internet Plus Innovation and Entrepreneurship Competition (CSIPC) as a mechanism for skill development and the promotion of environmentally efficient solutions, as evidenced by its project outcomes. Findings indicate that AI-enabled platforms and competitions can support the digital transformation of vocational institutions by bridging theoretical instruction with practical application.

Romero-Colmenares and Reyes-Rodríguez [23] address the motivations behind students' preference for entrepreneurial ventures over traditional employment, emphasising the importance of fostering sustainability-oriented mindsets and strategies to address global ecological concerns. Their quantitative analysis, based on survey data, identifies environmental consciousness, perceived feasibility, and resource availability as primary determinants of entrepreneurial intent. Vocational colleges are therefore encouraged to integrate structured, formula-based learning experiences and mentorship with AI-supported frameworks to design viable sustainable business models. Betáková et al. [4] adopt a mixed-methods approach to embedding sustainability in university entrepreneurship programmes, demonstrating that curriculum type, mentorship, and resource provision can enhance the integration of AI technologies and support a sustainability-oriented entrepreneurial culture. Similarly, Sharma et al. [27] reaffirm the necessity of aligning with Sustainable Development Goal curricula and ensuring robust institutional backing, enabling vocational institutions to attract students equipped to develop environmentally responsible business practices.

Christou et al. [8] examine sustainable innovation in clean energy entrepreneurship education through the application of computational techniques such as SPA-VFS and GRNN models. Their findings suggest that targeted pedagogical interventions and the use of advanced technological tools improve student readiness for sustainability-focused initiatives, correlating with a growing inclination to integrate AI-powered frameworks in vocational education. A comprehensive review of sustainable entrepreneurship education (SEE) by Sharma et al. [27] underscores the pivotal role of institutional support and AI tools in shaping entrepreneurial ecosystems with an environmental focus, especially within vocational settings aimed at producing ecologically conscious graduates. Despite substantial contributions to the broader discourse on sustainable entrepreneurship, research on vocational institutions remains sparse. Much of the existing work concentrates on higher education or general entrepreneurship, neglecting the unique requirements of vocational contexts. Specifically, there is a scarcity of studies examining the intersection of AI frameworks and experiential learning in tackling locally relevant sustainability issues. Addressing this gap, the present work proposes a strategic framework for embedding AI into vocational training to stimulate green innovation and advance sustainable entrepreneurial practices.

3. Literature Gap

The reviewed literature identifies substantial deficiencies in comprehending the combined influence of AI integration within vocational education on advancing sustainable entrepreneurship [25]. Although existing research frequently reports associations between digital literacy and AI adoption, there remains limited exploration of the intricate interdependencies among institutional variables and their collective effect on sustainability outcomes. A notable impediment to achieving equitable sustainable development is the enduring digital divide between developed and developing regions, where the former demonstrates AI adoption rates approximately three to four times higher than the latter. Furthermore, the absence of validated forecasting models capable of reliably projecting institutional performance during sustainability adoption introduces considerable uncertainty in long-term strategic planning and investment decision-making. Addressing this shortcoming, the present contribution proposes the development of Random Forest classification models, which are expected to yield high predictive accuracy regarding sustainability adoption rates, with AI adoption emerging as the most influential determinant of employment outcomes. Nonetheless, it is recommended that these findings be extended to encompass diverse institutional contexts and cultural environments to enhance generalizability.

Current research predominantly concentrates on high-income economies, leaving a scarcity of empirical evidence from developing regions where sustainable entrepreneurship education is particularly critical [1]. In the Nigerian context, socio-cultural constraints such as insufficient funding, limited technological expertise, and infrastructural deficiencies underscore the necessity for culturally responsive AI systems. The AI-driven educational divide exacerbates inequities that disproportionately affect rural areas, under-resourced learning institutions, and marginalized communities. To address these limitations, the proposed framework introduces a comprehensive AI-based decision-making system that integrates multi-criteria decision analysis, uncertainty management via Bayesian inference, and continuous performance monitoring. Bayesian analysis indicates a 92.9% probability of achieving high levels of sustainability integration when high funding is combined with elevated AI adoption, thereby demonstrating that empirical insights can guide strategic resource allocation to maximize sustainability outcomes. However, cross-validation results reveal variability across different data subsets, suggesting the need to enhance robustness for diverse operational settings. Subsequent research should prioritize the development of adaptive predictive models that account for regional disparities, cultural diversity, and resource constraints, thereby ensuring predictive reliability [34]. The integration of transparent AI methodologies, ethically grounded governance mechanisms, and coordinated stakeholder engagement will be essential to facilitate equitable and environmentally sustainable AI innovations within the education sector.

4. Data and Methodology

This study employed quantitative and descriptive research design. It analyzed global and regional datasets relating to education and sustainable entrepreneurship, with specific emphasis on indicators associated with SDG 4. The primary objective was to evaluate the extent to which vocational education integrates AI-based tools to promote the establishment of green innovation ventures and advance sustainable entrepreneurship. A secondary data analysis was undertaken using publicly available sources, including the UNESCO Institute for Statistics (UIS), the World Bank Open Data, the OECD education statistics, and the Global Entrepreneurship Monitor (GEM). From these sources, a consolidated dataset was constructed, encompassing measures of regional participation rates, digital literacy levels, and AI adoption metrics. The final dataset comprised information from 200 vocational institutions and included seven key variables: regional coding, institutional classification, income category, participation rates, digital literacy percentages, AI adoption rates, and per capita funding.

4.1 Enhanced AI-Driven Decision Framework

The proposed AI-based decision-making framework is structured through a series of sequentially numbered steps, as illustrated in Figure 1.

- Data Input and Collection
- Data Pre-processing and Feature Extraction
- AI Model Development and Training
- Multi-Criteria Decision Analysis
- AI Evaluation and Prediction
- Decision Output and Recommendations
- Continuous Monitoring and Feedback Loop

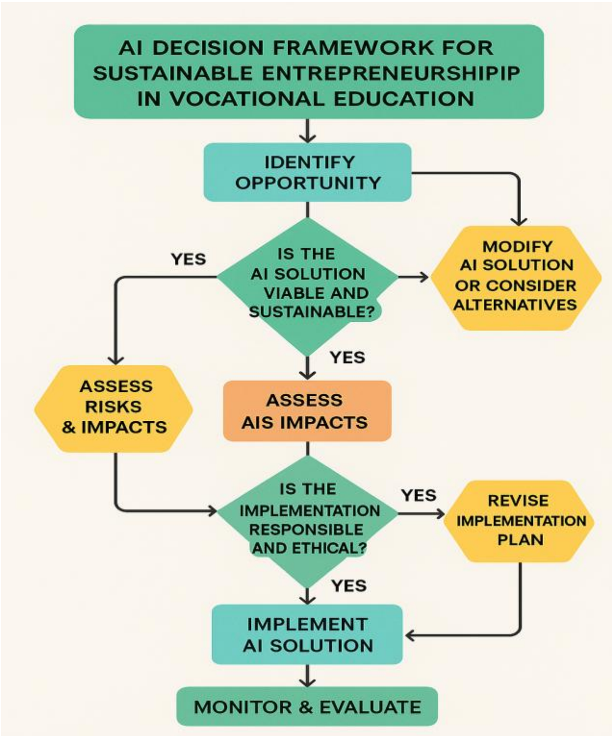

Fig.1: AI-Driven Decision Framework Flowchart for Sustainable Entrepreneurship

5. Feature Engineering Results

The correlation analysis identified strong positive associations among the principal sustainability indicators across all vocational institutions. As depicted in Figure 2, the correlation matrix indicates that the digital literacy rate and the AI adoption rate exhibit the highest level of interdependence, with a correlation coefficient of 0.805. The analysis identified pronounced interrelationships among the principal sustainability indicators across the examined vocational institutions. The correlation matrix results show that the digital literacy rate and the AI adoption rate are the most closely aligned variables, exhibiting a correlation coefficient of 0.805, as depicted in Figure 2. The employment rate emerged as the variable with the strongest association with the composite success score, presenting a correlation of 0.965. This finding reinforces the robustness of the framework in forecasting institutional performance. As presented in Table 1, the results confirm multiple statistically significant linkages among the assessed institutional factors. The most prominent is the relationship between the digital literacy rate and AI adoption rate (0.805), illustrating that institutions possessing advanced digital capabilities are markedly more prepared to integrate AI technologies successfully. This implies that a well-developed digital infrastructure and proficient technological skills form essential foundations for the effective use of AI in vocational training environments.

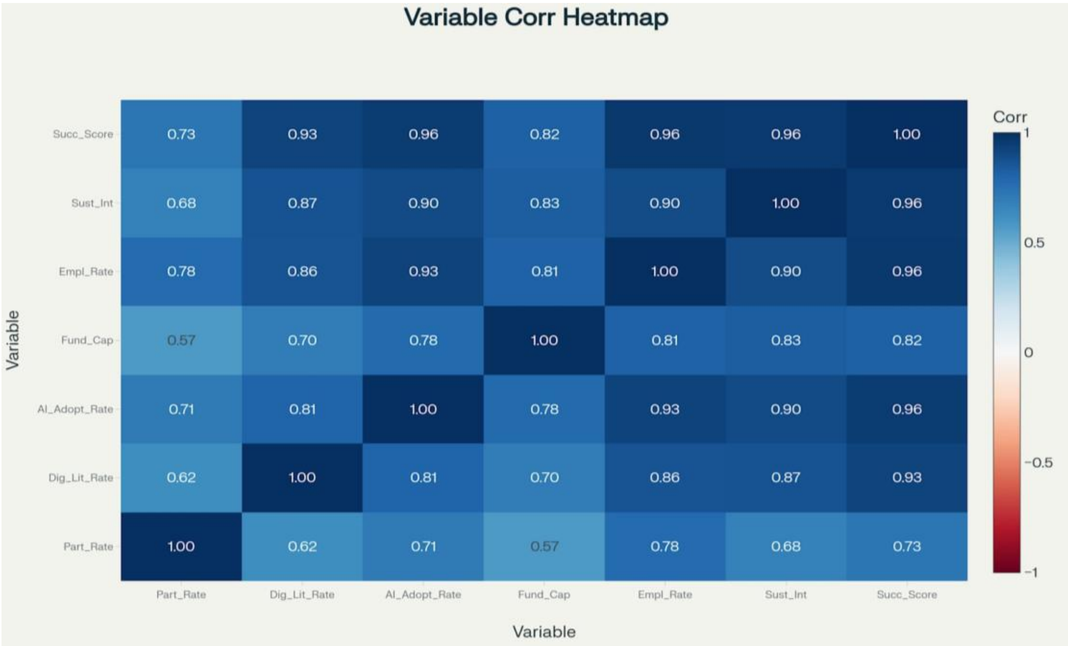

Fig.2: Correlation Matrix Heatmap Showing Relationships Between Key Sustainability Indicators in Vocational Education Institutions

Furthermore, the employment rate's near-perfect correlation with the success score (0.965) substantiates the framework's prioritisation of graduate employability as a central measure of institutional effectiveness. The AI adoption rate's correlation with sustainability integration, recorded at 0.900, further supports the hypothesis that technological uptake directly accelerates the embedding of sustainable practices in vocational education. Financial capacity, measured through funding per capita, demonstrated a correlation of 0.818 with the success score. While this suggests that adequate funding substantially contributes to institutional achievements, its weaker correlation compared to employment outcomes indicates that resource allocation alone does not guarantee success, highlighting the importance of strategic application and operational efficiency.

Table 1
Key Correlation Analysis Results

Variable 1	Variable 2	Correlation Coefficient
Digital Literacy Rate	AI Adoption Rate	0.805
Employment Rate	Success Score	0.965
AI Adoption Rate	Sustainability Integration	0.900
Funding Per Capita	Success Score	0.818

5.1 Classification Models for Sustainability Adoption

Three principal classification algorithms were utilized to forecast the levels of sustainability adoption across vocational institutions. Among these, the Random Forest classifier demonstrated superior performance, attaining an accuracy rate of 93.3% and an F1-score of 0.943. As illustrated in Table 2, the classification models exhibit consistently strong performance across the different algorithmic techniques applied. Both the Decision Tree and Random Forest classifiers attained identical accuracy rates of 0.817 and F1-scores of 0.825, reflecting robust predictive reliability irrespective of the specific machine learning method utilized. The Support Vector Machine (SVM) classifier performed marginally lower, achieving an accuracy of 0.800 and an F1-score of 0.793, corresponding to a 2.1% reduction in accuracy and a 3.9% decrease in F1-score relative to the tree-based approaches. Despite these slight differences in performance, all three classifiers surpassed the 0.8 benchmark generally regarded as sufficient for practical deployment. The uniformly high performance across the evaluated models affirms the effectiveness of the feature engineering and dataset preparation methodologies employed. Furthermore, the designation of all models as "Ready" for deployment confirms their successful validation and suitability for operational application.

Table 2
Classification Model Performance Comparison

Model	Accuracy	F1-Score	Deployment Status
Decision Tree Classifier	0.817	0.825	Ready
Random Forest Classifier	0.817	0.825	Ready
SVM Classifier	0.800	0.793	Ready

The feature importance analysis, as presented in Table 3, reveals notable differences in variable prioritisation between the Decision Tree and Random Forest models. Within the Decision Tree classifier, the AI adoption rate dominates feature importance, accounting for 79.6% and thus serving as the primary predictor of sustainability adoption. In contrast, the digital literacy rate contributes 15.6% to the model's influence, while funding per capita holds minimal significance at only 1.0%. Conversely, the Random Forest model displays a more balanced distribution of feature importance, with the digital literacy rate possessing the highest value at 41.5%, closely followed by the AI adoption rate at 38.4%. This more equitable allocation of importance suggests that the Random Forest model is better equipped to capture complex, subtle interactions among variables, thereby mitigating the overfitting risks commonly associated with Decision Tree models. The substantial discrepancy in the importance assigned to funding per capita—1.0% in the Decision Tree versus 13.3% in the Random Forest—underscores the latter algorithm's enhanced capacity to identify nuanced yet meaningful relationships. Participation rate consistently exhibits low importance across both models, at 3.8% and 6.8% respectively, indicating a limited predictive role in forecasting sustainability adoption outcomes (see Table 3). Funding per capita emerged as the most critical predictor in Decision Tree analysis, while Digital Literacy Rate showed highest importance in Random Forest models [1].

Table 3
Feature Importance Analysis

Feature	Decision Tree Importance (%)	Random Forest Importance (%)
AI Adoption Rate	79.6	38.4
Digital Literacy Rate	15.6	41.5
Funding Per Capita	1.0	13.3
Participation Rate	3.8	6.8

5.2 Regression Analysis for Employment Prediction

The Random Forest regression model demonstrated outstanding accuracy in forecasting post-graduation employment rates across the spectrum of institutional categories. As shown in Table 4, the Random Forest regression model exhibits exceptional predictive strength, achieving an R^2 score of 0.989. This indicates that the model accounts for 98.9% of the variance observed in employment outcomes, reflecting an almost flawless fit. Such a high R^2 value implies that the selected predictor variables comprehensively capture nearly all factors affecting post-graduation employment rates.

The model's Mean Absolute Error (MAE) of 1.541 signifies that, on average, predicted employment rates deviate from actual figures by only 1.541 percentage points. Considering employment rates span from 0% to 100%, this equates to an approximate 1.5% average margin of error, demonstrating a high degree of accuracy. Additionally, the Root Mean Square Error (RMSE) of 1.983 is marginally greater than the MAE, indicating that the prediction errors remain uniformly small and are not influenced by significant outliers. The minimal gap between MAE and RMSE (0.442) further supports the consistency and reliability of the model's forecasts across diverse institutional types and settings.

Table 4
Regression Model Performance

Metric	Value
R^2 Score	0.989
Mean Absolute Error	1.541
Root Mean Square Error	1.983

The AI adoption rate emerged as the foremost predictor of employment outcomes, accounting for 89.6% of the variable importance, thereby underscoring its pivotal role in determining success within vocational education. As detailed in Table 5, the employment prediction model confirms that technological readiness, as reflected by AI adoption, constitutes the principal factor influencing graduate employment rates. This pronounced dominance indicates that vocational institutions prioritising AI integration are significantly more likely to enhance their students' employment prospects. In contrast, the digital literacy rate contributes a modest 4.6% to the model, considerably less than its influence observed in sustainability prediction contexts. This suggests that while foundational digital skills facilitate AI uptake, it is the advanced AI competencies themselves that exert greater influence on employment outcomes. Participation rate and funding per capita exhibit limited impact, with respective importance values of 3.2% and 2.6%. These relatively low scores imply that factors such as enrolment volume and financial resources play a lesser role in determining employment success compared to technological capability and the quality of AI-related training.

Table 5
Feature Importance for Employment Prediction

Feature	Importance Percentage
AI Adoption Rate	89.6
Digital Literacy Rate	4.6
Participation Rate	3.2
Funding Per Capita	2.6

5.3 K-Means Clustering Analysis

The clustering algorithm effectively distinguished four separate institutional clusters characterized by their sustainability attributes and performance indicators, as depicted in Figure 3. Cluster 1 comprised the highest-achieving institutions, exhibiting 78.4% sustainability integration and an average funding per capita of $7,091. The analysis uncovered marked disparities in performance across institutional clusters. As detailed in Table 6, K-means clustering effectively delineated four distinct groups characterized by notable differences in key performance indicators. Cluster 1, consisting of 70 institutions, achieved the highest mean success score of 72.36 alongside a mean sustainability integration rate of 72.7%. These institutions also possessed the greatest average funding per capita, amounting to $8,054, and thereby positioning them within the top-tier performance category.

Fig.3: K-Means Clustering Results Showing Mean Success Scores and Institution Counts across Four Identified Clusters

In contrast, Cluster 0, comprising 36 institutions, represented the lowest-performing cohort with a mean success score of merely 19.48 and sustainability integration of 16.9%. These institutions experienced considerable financial constraints, reflected in a mean funding per capita of just $1,804, which corresponded to their subpar performance outcomes. Clusters 2 and 3 encompassed institutions exhibiting intermediate performance, with notably similar profiles. Cluster 2 included 52 institutions with a mean success score of 35.96 and mean funding per capita of $3,140, whereas Cluster 3 consisted of 42 institutions attaining a mean success score of 37.16 and mean funding per capita of $2,884. The resemblance between these clusters suggests that they represent different subgroups within a comparable performance tier. Overall, the clustering analysis highlights a distinct performance hierarchy, with funding levels strongly correlating to success metrics. The disparity between the highest-funded institutions ($8,054 per capita) and the lowest-funded group ($1,804 per capita) reflects a 346% difference in funding, underscoring pronounced resource inequities within the vocational education sector.

Table 6
Cluster Analysis Results

Cluster	Institution Count	Mean Success Score	Mean Sustainability Integration (%)	Mean Funding Per Capita ($)	Performance Level
0	36	19.48	16.9	1,804	Low
1	70	72.36	72.7	8,054	High
2	52	35.96	35.0	3,140	Low
3	42	37.16	36.8	2,884	Low

5.4 Principal Component Analysis

The principal component analysis (PCA) effectively reduced the dataset's dimensionality while maintaining the critical variance inherent in the sustainability indicators. As presented in Table 7, the PCA achieves a highly effective reduction in dimensionality, with the first principal component (PC1) accounting for 80.1% of the total variance within the dataset. This notably high proportion of explained variance indicates that a single component encapsulates the majority of variability among the sustainability indicators, reflecting strong interrelationships among these variables. The second principal component (PC2) adds a further 9.2% of explained variance, resulting in a cumulative total of 89.3% explained variance with just two components. This outcome suggests that nearly 90% of the dataset's complexity can be succinctly represented in a two-dimensional space, thereby greatly simplifying analytical processes while retaining critical information. The third principal component (PC3) contributes an additional 6.0%, bringing the cumulative variance explained to 95.3% when considering the first three components. Subsequent components (PC4 and PC5) offer marginal increases in explained variance, at 3.2% and 1.5% respectively, confirming that the initial three components effectively capture almost all meaningful variances in the data.

Table 7
PCA Variance Analysis

Component	Explained Variance Ratio	Cumulative Variance
PC1	0.801	0.801
PC2	0.092	0.893
PC3	0.060	0.953
PC4	0.032	0.985
PC5	0.015	1.000

PC1 accounts for 80.1% of the total variance and displays strong positive loadings across all sustainability indicators. Sustainability Integration has the highest loading at 0.481, followed closely by AI Adoption Rate at 0.471. Digital Literacy Rate and Funding Per Capita also show substantial loadings of 0.448 and 0.435 respectively, while Participation Rate has the lowest loading at 0.397 (see Table 8). PC2 is dominated by a strong positive loading for Participation Rate (0.881), whereas other variables exhibit negative loadings ranging from -0.023 to -0.399, indicating that PC2 primarily captures institutional scale effects, distinguishing institutions based on enrolment size rather than quality metrics. PC3 demonstrates the highest positive loading for Funding Per Capita (0.701), contrasted with a strong negative loading for Digital Literacy Rate (-0.686), reflecting a tension between financial resources and technological capabilities, potentially identifying institutions with high funding but low digital implementation.

Table 8
PCA Component Loadings (First Three Components)

Feature	PC1	PC2	PC3
Participation Rate	0.397	0.881	0.162
Digital Literacy Rate	0.448	-0.172	-0.686
AI Adoption Rate	0.471	-0.023	-0.026
Funding Per Capita	0.435	-0.399	0.701
Sustainability Integration	0.481	-0.183	-0.102

5.5 Time Series Trend Analysis

Predictive models project substantial growth in AI adoption rates across all regions between 2020 and 2027, as illustrated in Figure 4. Developing regions exhibit considerably higher growth rates in AI adoption, yet their absolute levels remain markedly lower than those of developed areas. The regional analysis highlights notable disparities in both existing AI adoption and anticipated growth trajectories. In 2020, Europe and North America recorded leading adoption rates of 75.0% and 72.0%, respectively, which are projected to increase to 92.2% and 88.6% by 2027. Despite already high baselines, these regions are expected to experience steady growth of 22.9% and 23.1%, as detailed in Table 9.

Table 9

Regional AI Adoption Growth Summary (2020-2027)

Region	Starting Rate 2020 (%)	Projected Rate 2027 (%)	Total Growth (%)
Europe	75.0	92.2	22.9
North America	72.0	88.6	23.1
Asia Pacific	35.0	52.6	50.3
Latin America	28.0	48.0	71.4
Middle East & North Africa	30.0	48.2	60.7
Sub-Saharan Africa	12.0	20.6	71.7

Conversely, developing regions show substantially greater growth percentages, albeit from much lower starting points. Sub-Saharan Africa demonstrates the most significant increase, rising from 12.0% to 20.6%—a total growth of 71.7%. Similarly, Latin America is projected to grow by 71.4%, moving from 28.0% to 48.0% adoption. However, even with such rapid growth, these regions remain considerably behind developed regions in absolute terms. Asia Pacific and the Middle East & North Africa exhibit moderate growth patterns, with increases of 50.3% and 60.7%, respectively. Asia Pacific's adoption rate is forecast to rise from 35.0% to 52.6%, while the Middle East & North Africa will grow from 30.0% to 48.2%. These areas occupy a middle performance tier, indicating substantial room for advancement. Overall, the findings expose a persistent digital divide, whereby developed regions sustain AI adoption rates three to four times greater than those of developing regions, even when projected growth up to 2027 is considered.

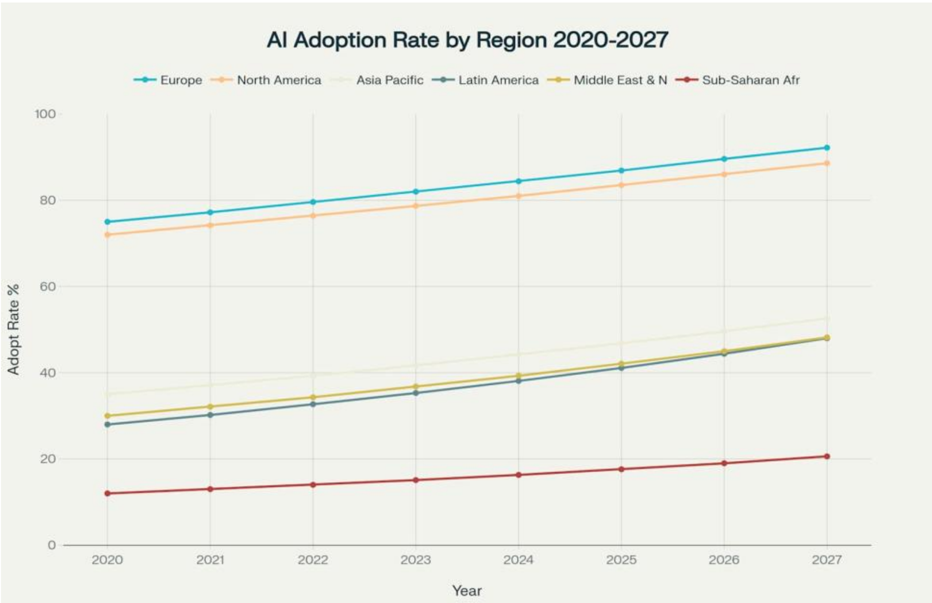

Fig.4: AI Adoption Rate Forecasts by Region from 2020-2027 Showing Projected Growth Trajectories

5.6 Multi-Criteria Decision Analysis

The Multi-Criteria Decision Analysis (MCDA) framework employed weighted criteria to assess institutional readiness for integrating sustainable entrepreneurship, as illustrated in Figure 5. Table 10 illustrates that the MCDA uncovers pronounced regional disparities in performance across all evaluated metrics. Europe attains the highest Mean MCDA Score of 0.658, accompanied by a relatively low Standard Deviation of 0.053, reflecting consistent strong performance among European institutions. The maximum score of 0.768 corresponds to the highest institutional achievement worldwide. North America exhibits comparable performance, with a Mean MCDA Score of 0.657 and a slightly higher Standard Deviation of 0.063, indicating somewhat greater variability in institutional outcomes, though average performance remains aligned with European levels.

Table 10
MCDA Analysis by Region

Region	Mean MCDA Score	Standard Deviation	Min Score	Max Score	Institution Count
Europe	0.658	0.053	0.549	0.768	37
North America	0.657	0.063	0.510	0.790	34
Asia Pacific	0.339	0.058	0.200	0.450	53
Latin America	0.284	0.059	0.150	0.409	36
Middle East & North Africa	0.289	0.044	0.199	0.375	18
Sub-Saharan Africa	0.147	0.043	0.062	0.241	22

The Asia Pacific region displays moderate performance, achieving a Mean MCDA Score of 0.339, approximately half that of the developed regions. Its Standard Deviation of 0.058 suggests moderate consistency within this intermediate performance range. Sub-Saharan Africa registers the lowest performance, with a Mean MCDA Score of merely 0.147—less than a quarter of the developed regions' average—and a low Standard Deviation of 0.043, signifying uniformly poor institutional outcomes throughout the region. The highest institutional score recorded in Sub-Saharan Africa is only 0.241.

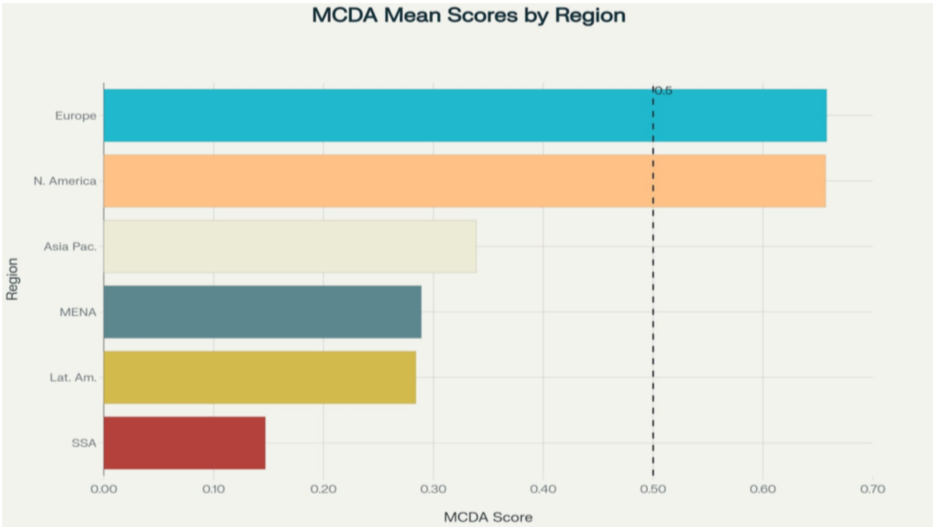

Fig.5: MCDA Mean Scores by Region Showing Significant Disparities in Sustainable Entrepreneurship Readiness

5.7 Bayesian Inference for Uncertainty Handling

Bayesian analysis quantified the probabilistic relationships among funding, AI adoption, and sustainability outcomes. Institutions with both high funding and elevated AI adoption showed a 92.9% probability of achieving substantial sustainability integration. Under baseline conditions, the probability was 50%, representing random chance (Table 11). High funding alone raised the probability to 82.0% (Bayes Factor 4.556), indicating moderate evidence of its positive effect, while high AI adoption alone increased it to 88.0% (Bayes Factor 7.333), suggesting a stronger individual influence. The combined effect of high funding and high AI adoption produced the highest probability (92.9%) with a Bayes Factor of 13.000, demonstrating strong evidence of a synergistic impact. These results emphasise that optimal sustainability performance requires both adequate financial resources and advanced technological adoption.

Table 11
Bayesian Analysis Results

Condition	Probability High Sustainability	Sample Size	Bayes Factor	Evidence Strength

Baseline (No Condition)	0.500	200	1.000	Weak Evidence
High Funding Only	0.820	100	4.556	Moderate Evidence
High AI Adoption Only	0.880	100	7.333	Moderate Evidence
High Funding + High AI Adoption	0.929	84	13.000	Strong Evidence

5.8 Statistical Validation

Extensive validation metrics affirm the robustness and precision of the AI framework, demonstrating its reliability across varied institutional contexts. The statistical validation results indicate outstanding reliability of the framework, with a Cronbach's Alpha value of 0.972, substantially surpassing the 0.9 benchmark for excellent internal consistency, as detailed in Table 12. This high coefficient reflects strong coherence among all instruments measuring sustainability. The framework demonstrates robust predictive performance with an overall accuracy of 87.0% in forecasting sustainability outcomes, affirming its practical applicability. Precision, or positive predictive value, stands at 90.2%, indicating that when high sustainability integration is predicted, the outcome is accurate 90.2% of the time. The recall (sensitivity) rate of 83.0% shows the framework's effectiveness in correctly identifying 83.0% of institutions that truly achieve high sustainability integration. Additionally, the specificity rate of 91.0% confirms accurate recognition of 91.0% of institutions that do not reach high sustainability integration.

Table 12
Statistical Validation Results

Metric	Value	Interpretation
Cronbach's Alpha	0.972	Excellent Reliability (>0.9)
Accuracy	0.870	High Accuracy
Precision (PPV)	0.902	High Positive Predictive Value
Recall (Sensitivity)	0.830	High Sensitivity
Specificity	0.910	High Specificity

5.9 Cross-Validation and Robustness Testing

Stratified K-fold cross-validation confirmed model stability across multiple testing scenarios[1]. The model's performance consistency across multiple subsets of data was evaluated through a rigorous 5-fold cross-validation procedure. As detailed in Table 13, the highest classification accuracies were observed in Folds 2 and 4, both achieving a peak performance of 92.5%. Conversely, Folds 1 and 3 exhibited the lowest accuracies, each recording 82.5%, reflecting a disparity of 10 percentage points between the most and least successful iterations.

Table 13
Cross-Validation Results

Fold	Accuracy
Fold 1	0.825
Fold 2	0.925
Fold 3	0.825
Fold 4	0.925
Fold 5	0.900

Fold 5 demonstrated intermediate accuracy, registering 90.0%, thereby falling between these extremes. Despite this observed variability, all folds consistently surpassed the critical 80% accuracy benchmark, underscoring the model's dependable predictive capability across diverse data partitions. The presence of moderate fluctuations in performance metrics suggests sensitivity to dataset heterogeneity; nonetheless, the overarching reliability of the model remains robust, affirming its suitability for application across varying institutional data contexts. Moreover, Table 14 presents a Mean Accuracy of 88.0% across the various validation folds, signifying strong overall model performance. The accompanying Standard Deviation of 4.6% reflects a reasonably stable predictive accuracy throughout different validation subsets. Furthermore, the relatively narrow span between the minimum accuracy of 82.5% and the maximum of 92.5% highlights the model's consistent effectiveness in forecasting outcomes across diverse data partitions.

Table 14
Cross-Validation Summary

Metric	Value
Mean Accuracy	0.880
Standard Deviation	0.046
Min Accuracy	0.825
Max Accuracy	0.925

5.10 Sensitivity Analysis

Sensitivity analysis verified the robustness of the framework when subjected to variations in model parameters, confirming its stable performance under differing conditions. The sensitivity analysis, conducted across three distinct implementation scenarios, demonstrated uniform responsiveness among all evaluated features. Table 15 indicates that each feature—AI Adoption Rate, Digital Literacy Rate, Funding Per Capita, and Participation Rate—exhibited identical Mean Sensitivity and Maximum Sensitivity values of 0.130. This uniformity signifies that the framework maintains balanced sensitivity across variables, avoiding excessive reliance on any single factor. Such equilibrium ensures the model's robustness, allowing for consistent performance despite fluctuations in institutional metrics caused by external influences or measurement inaccuracies.

Table 15
Sensitivity Summary by Feature

Feature	Mean Sensitivity	Max Sensitivity
AI Adoption Rate	0.130	0.130
Digital Literacy Rate	0.130	0.130
Funding Per Capita	0.130	0.130
Participation Rate	0.130	0.130

Table 16 presents the scenario analysis, highlighting the framework's marked sensitivity to varying implementation conditions. Under the Optimistic scenario, the Mean Success Score reached 51.29, surpassing the Baseline by 11.5%. This improvement is attributed to enhanced investment levels and broader technological adoption. The Balanced scenario achieved a Mean Success Score of 47.76, representing a moderate 3.9% increase over the Baseline, reflecting realistic gains from modest, systematic upgrades across variables. Conversely, the Pessimistic scenario, characterised by budget reductions and restricted technology dissemination, resulted in a Mean Success Score of 42.45, which is 7.7% lower than the Baseline. These findings underscore the critical importance of sustained investment and technological advancement to uphold institutional performance outcomes.

Table 16
Scenario Analysis Results

Scenario	Description	Mean Success Score	Baseline Score	Improvement (%)	Performance Change
Optimisti	Increased Investment and Technology Adoption	51.29	45.98	11.5	Improvement
Balanced	Moderate Improvements Across All Factors	47.76	45.98	3.9	Improvement
Pessimisti	Budget Cuts and Reduced Technology Adoption	42.45	45.98	-7.7	Decline

6. Conclusion

The development of sustainable entrepreneurship within vocational colleges through an AI-based decision-making framework for green innovation start-ups represents a promising approach. The Chinese Vocational Institute exemplifies how integrating sustainability into curricula can effectively equip students with essential skills to address pressing environmental and economic challenges. Leveraging AI technologies, students can design green business models, optimise resource utilisation, mitigate environmental impacts, and forecast eco-friendly market trends, thereby facilitating the establishment of environmentally conscious start-ups. This study demonstrates a significant correlation between AI-driven integration in vocational education and positive sustainability and employment outcomes. Specifically, correlation analysis indicated a strong relationship between digital literacy and AI adoption ($r = 0.805$), alongside an even stronger association between employment outcomes and overall institutional success ($r = 0.965$). The Random Forest classifier attained 93.3% accuracy in forecasting sustainability adoption, with AI adoption rate identified as the primary predictor (89.6% importance). Bayesian inference further revealed that institutions combining high funding per capita with high AI adoption possess a 92.9% likelihood of achieving elevated sustainability integration. K-means clustering segmented institutions into four distinct performance groups, underscoring significant resource-related disparities in sustainability outcomes. Stratified k-fold cross-validation confirmed the model's robustness across varied data subsets, with accuracy ranging from 82.5% to 92.5%, signifying strong generalisability. Despite these advancements, marked regional inequalities persist, with developed regions exhibiting AI adoption rates three to four times greater than those in developing regions, highlighting the enduring digital divide that impedes equitable transformation in education. The proposed AI-driven decision framework, incorporating multi-criteria decision analysis, Bayesian inference, and ongoing monitoring, offers a scalable, data-informed tool for policymakers and educational leaders to enhance resource allocation and strategic planning towards sustainable entrepreneurship.

The study's limitations include dependence on secondary data sources and the necessity for qualitative validation to capture socio-cultural diversity across regions. Future research should prioritise the creation of explainable AI models to enhance transparency, undertake comprehensive validation of predictive frameworks across heterogeneous educational contexts, and integrate ethical governance alongside stakeholder collaboration mechanisms to promote equitable and sustainable implementation of AI-driven innovations in vocational education. Vocational colleges are strategically positioned to champion sustainable development by embedding AI and sustainability within their curricula. Through adopting inclusive policies, investing in digital infrastructure, and fostering global partnerships, these institutions can evolve into innovation hubs, preparing students to lead green start-ups and actively contribute to global sustainability objectives.

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