Dynamic Policy Evolution of Artificial Intelligence Education in Vocational Colleges Using a Cooper-Based System Dynamics Modeling Framework

Hongbo Li[1], Xingang Wu[2*]

[1]Department of Education, Graduate School, Dongshin University; Naju-si, Jeonnam-Gwangju Metropolitan City, 58245 Republic of Korea

[2]School of Artificial Intelligence, Yantai Institute of Science and Technology; Yantai , Shandong 265600 China

Email: [1]lihongbo123@gachon.ac.kr

Corresponding author email: [2*]wuxingang@ytkj.edu.cn

HOW TO CITE:

Hongbo Li, Xingang Wu (2026). Dynamic Policy Evolution of Artificial Intelligence Education in Vocational Colleges Using a Cooper-Based System Dynamics Modeling Framework International Journal of Special Education, 41(20s), 503 - 517

ABSTRACT:

The speedy development of AI technology is changing the needs of employment; hence AI education is a strategic choice for vocational colleges. Nevertheless, the current educational policies are drafted in silos and lack a dynamic tracking mechanism which is to track the impact of curriculum reform, faculty capability, infrastructure investment, industry collaboration and student employability. The above limitations hamper the sustainable development of AI education and obstruct the efficient implementation of long-term policies. In response to the above-mentioned challenge, this paper proposes a dynamic policy evolution framework for AI education in vocational colleges based on the Cooper system dynamics model. The framework combine Cooper's policy cycle with system dynamics to build causal loop diagrams and stock-and-flow models embedded with the complexity and feedbacks of AI educational ecosystems. Using long-lived data taken from the vocational institutions, we model five interconnected subsystems: educational resources, faculty development, curriculum innovation, industry partnerships, and graduate employment. A variety of policy scenarios, exploring funding allocation, teacher training, curriculum updating, and enterprise collaboration, are simulated over a 10-year planning horizon to evaluate policy impact and sustainability. Based on the simulation results, the coordinated policy measures are found to be significantly better than the isolated measures. The coordinated policy measures would lead to a significant improvement in AI curriculum adopting, formation of competent faculty, industry engagement, graduate employment, and the innovation capacity of the institution. Sensitivity analysis also shows that faculty development and industry collaboration are the most important drivers of long-term success of the policy. Through the use of the proposed framework, policymakers and educational administrators will be able to optimize AI education strategies and create robust decision-support systems. Ultimately leading to evidence-based policy formulation, resource allocation, and sustainable talent development for intelligent industries.

Keywords: Artificial Intelligence Education, Vocational Colleges ,Educational Policy Evolution ,Cooper Framework ,System Dynamics Modeling ,Policy Simulation

1. Introduction

Artificial intelligence has influenced digital transformation one of the most significant technologies of all time in most industries. AI is growing rapidly in the increasing global manufacturing sectors like healthcare, finance, transportation, agriculture, smart services, and many others. But that has changed the requirements of manpower with these industries [1]. There is an increased demand for employees who have knowledge and practical skills of AI. Vocational colleges, being responsible for developing graduates employable in industries, play the role of developing experts' or professionals' for upcoming works. Consequently, governments, educational institutions, and industry stakeholders are prioritizing the integration of AI education system into vocational training to strengthen national competitiveness and support sustainable economic development [2]. Incorporating AI education into existing curricula entails more than just filling the course slots with AI-related courses. The curriculum design, faculty skills, digital tools, investment, industry collaboration, and student employability count to an ecosystem approach. Each of these parts is tightly linked. A change in the performance of one component can affect the performance of at least one other component thanks to intricate feedback relationships [3].

The ability to modernize curriculum depends on having qualified faculty and laboratory facilities. Also, an effective collaboration with the industry improves practical training and graduate employment. As a result of AI education must be treated as a dynamic system in which the educational policy will evolve continuously depending on technological innovations, industrial requirements and institutional capacities [4]. While the focus for AI education is growing, vocational colleges' policy development most of the time remains piecemeal and reactive. Numerous institutions design educational policies independently without taking into account the interlinkages between educational resources, quality of teaching, industrial linkages and long-term workforce requirements. Conventional means of evaluation of policy place emphasis on quantitative short-term performance indicators and static assessment making it hard to predict the long-term annuities of policy intervention. Additionally, the effect of education policy is often delayed, in part because improvements in faculty capacity, curriculum quality and physical infrastructure take long to manifest in student learning outcomes and graduate employability [5]. AI education systems are becoming increasingly complex, and analysis frameworks need to adapt to the changes to better inform decision-making. System Dynamics (SD) has become a well-proven methodology for analysing complex systems whose behaviour is determined by feedback loops, nonlinearities, accumulations and time delays. Initially, SD was developed for industrial and organizational planning. However, it has application in healthcare and environmental management, supply chain and education policy management.

SD provides a means of modeling and simulating system behaviour using, for example, causal loop diagrams and stock-and-flow models, making it possible to test the impact of policies before they are enacted in the real world [6]. Within the field of vocational education, system dynamics allows for a better understanding of how investments in educational resources, faculty development, curriculum innovation, and industry co-creation impact institutional performance and graduate employability over time. Cooper Policy Framework Is associated with system dynamics and is mainly concerned with policy formulation, implementation, evaluation and modification [7]. The Cooper framework reframes policy development as an adaptive learning process that incorporates ongoing feedback and evidence-based policy-making. Through the integration of the Cooper framework with system dynamics, it enables a combination of qualitative policy processes with quantitative simulation models. In addition, this yields insights into the processes through which educational policy evolves. It has also integrated to indicate policy action within an ecosystem such as in vocational AI education. This helps us to identify leverage points for policies, assess different interventions, and use resources efficiently for sustainable educational development [8]. While some earlier research has studied AI education, digital transformation, educational policy, and system dynamics, there has been little endeavour to integrate them into a framework to study the dynamic evolution of AI education policies in vocational colleges. Most existing studies focus on aspects such as curriculum design, teaching methods, faculty training or technology adoption in isolations without taking into account the feedback mechanisms among these factors. In addition, only a few studies present decision-support tools that use simulation to Allow assessments of multiple polices across long ranging planning horizons [9]. Tackling this research gap is crucial for the development of flexible educational policies that can effectively respond to the ever-changing needs of smart industries. As such, the study proposes a system dynamics modelling-integrated Cooper framework based dynamic policy evolution framework for AI education of vocational colleges [10]. The suggested model has been proposed that consists of five interconnected subsystems describing dynamic inter-relationships in AI education. The subsystems consist of educational resources, faculty development, curriculum innovation, industry collaboration and graduate employment. A number of possible policies (funding allocation, teacher training, curriculum modernization, work with enterprises, etc.) are simulated for a period of ten years in order to test their effectiveness and sustainability in the longer run. The findings are likely to provide policymakers and educational administrators with a comprehensive decision-support tool to optimize strategies on AI education, enhance resources allocation, strengthen industry–institution ties and promote sustainable talent development which meet the needs of intelligent industry.

2. Related work

The past decade has seen artificial intelligence (AI) education gain tremendous traction as governments, educational institutes and industries search for a workforce that can support intelligent technologies and digital transformation. Vocational colleges are paramount in this by imparting skills to students that make them industry-ready in no time [11]. As a result, the researchers have looked into many aspects of AI education such as curriculum development, teacher training, digital infrastructure, etc. Nonetheless, most existing studies on AI education focus on a single component rather than the dynamics among the components. This part of this literature review is dedicated towards those studies which are related to the AI education in vocational colleges. Moreover, the evolution of the educational policy and its system dynamics use in education and the Cooper's policy framework part. Thus, these are the areas which this section studies finally identifying the research gap that the study is going to fill.

2.1 Instruction in Artificial Intelligence by Vocational Colleges

AI technologies are moving rapidly. Using this technology worldwide varies the design of educational programs at vocational institutions, where students are prepared for intelligent manufacturing, automation, robotics, data analytics, and digital services. As per the recent studies, education in AI should not only be theoretical but should also offer real-life practical training of project based learning, industry internship and interdisciplinary curriculum According to researchers, better integration of emerging technologies like big data, cloud computing, Internet of Things (IoT) and intelligent automation can enhance vocational education to graduate employability and technical competency [12]. Even after making various advancements, there are still many challenges. Several technical institutes lack qualified AI instructors, lab facilities, updated curriculum, and industrial linkages. This is especially true in India. Moreover, educational reforms are often put into action in isolation from long-run interactions with institutional resources and labour market capabilities. Consequently, policy measures often do not lead to sustained enhancement in educational quality and graduate outcomes.

2.2 Educational policy development for Artificial Intelligence education.

The strategy for modernizing curriculum, developing teachers, and investing in infrastructure (fields, equipment etc.),and other funding and institutional governance is found in educational policies. Conventional policy formulation is typically a linear planning process at which policies are designed, implemented and evaluated after a fixed period. Though this strategy minimizes the burden of organizing policy, it tends to overlook complexities inherent in the interrelation between educational stakeholders and institutional resources [13]. Recent research supports adaptive frameworks for public policy that monitor performance and change policies to meet evolving technological and industrial needs. Because the development of AI technologies is happening at a rapidly accelerating pace, curriculum content, pedagogical methods, and skills requirements become outdated in short time frames. the education policy on AI needs a unique kind of flexibility. Consequently, dynamic policy evaluation becomes an essential aspect of maintaining vocational colleges' unity with industrial transformation. Nevertheless, the existing methods which assess the policy mainly rely on either a statistical analysis or a qualitative assessment and have limited capability to predict the long run policy outcome.

2.3 Analysis of Educational Policy via System Dynamics.

System dynamics (SD) methodology has become an effective tool for studying the behaviour of complex systems due to their nonlinear relationship, feedback, accumulation, and time delay. Ever since Forrester introduced it, SD has been widely used for public policy management, healthcare, environmental management, supply chains and higher education planning. The methodology uses causal loop diagrams (CLDs) to sketch qualitative relationships and stock-and-flow diagrams (SFDs) to quantify the system's behaviour over time [14]. In educational research, SD has been applied to study student enrolment, allocation of educational resources, teacher workforce planning, institutional sustainability, curriculum development and graduate employability. Using the SD, the policymakers can evaluate the longer run educational outcomes of the different policy scenarios before implementing costly reforms. Key investments in faculty development, infrastructure and curriculum are shown to have delayed effects but cumulative effects which are strong determinants of performance. However, existing models of educational SD are rarely focused on AI education in vocational colleges and consider a limited number of educational variables. A unified simulation of industrial collaboration, curriculum modernization, faculty competency, and graduate employability has not been adequately explored.

2.4 Cooper's Framework for Policy Formulation.

A systematic approach is provided, which involves the use of continuous cycles involving the formulation, implementation, monitoring, evaluation, feedback and refining of policy. The Cooper framework emphasizes that educational policies develop through continuous learning and interaction between the actor and stakeholder, unlike traditional linear policy models. Policymakers use ongoing feedback to pinpoint implementation obstacles, redirect policy objectives, and enhance decisions based on evidence [15]. As a number of public administration and educational management studies had used the framework for enhancing governance, accountability, and policy effectiveness. Most applications are qualitative in nature and there are no computations on the evolution of policy under circumstances. By tying the Cooper framework to System Dynamics, great advantages can be accomplished. That is, you now have structured policy processes together with simulation capability, allowing decision-takers to identify and assess alternative intervention strategies. Most importantly, this also allows predicting the longer-term impact on educational performance and/or behaviour with more quantitative confidence.

2.5 Research Gap and Motivation in the Research

According to the literature, there has been a significant advancement in AI education and educational policy system dynamics modelling. There are still significant research gaps. To begin with, the existing studies mainly focus on curriculum development; faculty training; infrastructure; or industry collaboration only. In addition, conventional policies evaluation methods are unable to capture the nonlinear feedback relationships and delayed policy effects that AI education systems exhibit [16]. Limited studies have been found which combines Cooper's policy framework with System Dynamics to produce simulation-based decision-support models for vocational AI education. To resolve these barriers, the study puts forth a Cooper based System Dynamics framework to model the dynamic evolution of AI education policies in vocational colleges. A framework is proposed to integrate the five subsystems linking educational resources, faculty development, curriculum innovation, industry collaboration, and graduate employment into one whole simulation. The proposed model presents an empirically based decision-support model for optimizing education policies, improving resource allocation, enhancing industry–institution linkages, and achieving sustainable AI talent development by assessing multiple policy options over a long-term planning horizon.

3. Proposed methodology

The study proposes to make a Cooper-based System Dynamics framework to model the dynamic evolution of Artificial Intelligence (AI) educational policies in vocational colleges. The proposed methodology combines the iterative policy management process of Cooper with the system dynamics simulation process in order to assess the long term implications of educational policies. Unlike traditional policy assessment methods which look at static indicators and short-term impacts, the proposed framework encompasses the interactive nature of educational resources, academic competence, curriculum innovation, infrastructure development, industry collaboration and graduate employability through interconnected feedback loops [17]. The approach of the methodology depicts the AI education ecosystem using causal loop diagrams (CLDs) and stock-and-flow diagrams (SFDs). These diagrams help in understanding nonlinear relationships, policy delay as well as reinforcing or balancing feedback loops. The model includes previous education data and schools policy information to simulate a range of policy options over a planning horizon of 10 years. Investment allocation, human resources, curriculum innovation, industry project and one policy strategy are some such cases [18]. The simulation results help quantitative evaluate alternative policy interventions identify the key drivers of performance and optimize resource allocation. The proposed framework can therefore be regarded as a holistic decision-support system for the enhancement of sustainable AI education, the strengthening of institutional innovation, improving employability of graduates and long-term intelligence industry workforce requirements.

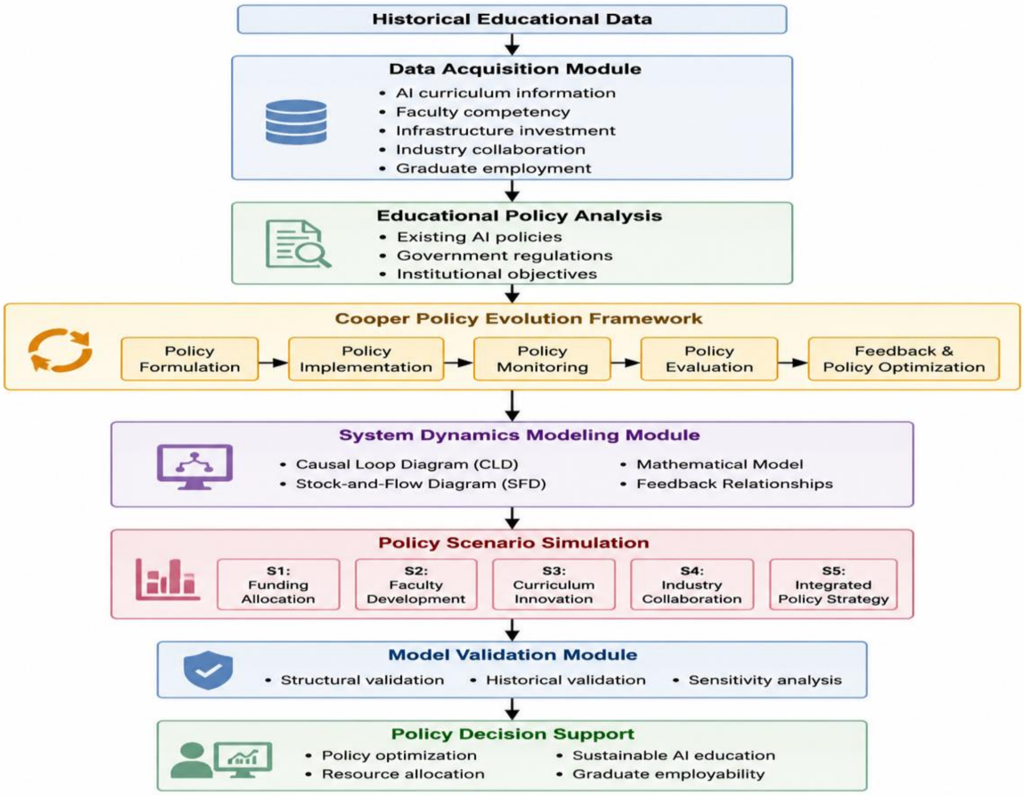

Figure 1. Overall architecture of the proposed Cooper-based System Dynamics framework for AI education policy evolution in vocational colleges.

As shown in Figure 1, the architecture of the proposed Cooper-based System Dynamics framework for AI education policy evolution in VTCs. The framework employs data collection and educational policy analysis, outcomes of the Cooper policy cycle, and System Dynamics modeling to also incorporate multiple policy outcomes. Validation of simulation outcomes to support evidence-based policy optimization and resource allocation in AI education and development in a sustainable manner [19].

3.1 Data Acquisition Module

The initial phase gathers longitudinal educational information from vocational colleges and government education databases. The information gathered includes the implementation of AI curriculum, qualification of the faculty, investment in infrastructure, enrollment of students, industry collaboration, graduation employment rates, and funding of the institute. The numerical data serve as the foundation for developing the dynamic simulation model. Before a model is built, missing values are handled, inconsistent records are deleted and all variables are normalized for uniform data.

3.2 Educational Policy Analysis

Analysis of existing AI education policies helps to identify key factors influencing vocational education. We will examine the policy documents, institutional strategic plans, government regulations and the industry competency standards to assess the key policy variables. The study has identified five main dimensions, which include educational resources; faculty development; curriculum innovation; industry engagement; and graduate employability. Essentially, these dimensions are the main ingredients of the policy evolution model.

3.3 Cooper Policy Evolution Framework

The Cooper Policy Evolution Framework is a structured policy management function that ends up providing a way to develop, implement, monitor and continually improve AI education polices in vocational colleges – as proposed in the methodology. In contrast to traditional policy approaches that follow a fixed sequential order, the Cooper framework views policy development as a process that continues to evolve through feedback, stakeholder participation, and evidence. This allows educational institutions to respond suitably to rapid technological growth, changing requirements of industries as well as workforce.

3.4 System Dynamics Modeling

System Dynamics is used to represent the dynamic behaviour of educational ecosystem. To capture qualitative cause-and-effect relationships among policy variables, Causal Loop Diagrams are developed. The CLDs illustrate the reinforcing and balancing feedback loops that control system behavior [20]. The CLDs are then converted into Stock-and-Flow Diagrams (SFDs), where stock variables represent accumulative educational resources and flow variables represent results of policy changes over time. The key stock variables are educational resources, qualification of the faculty, curriculum, industry interaction and employability of graduates. These variables interact with each other according to their mathematical equations, which allows the system to simulate the long term policy outcome.

3.5 Policy Scenario Simulation

The Policy Scenario Simulation module evaluates different strategies to integrate AI education into the education system using the System Dynamics model developed. During the ten years horizon, five policy scenarios implemented will be (i) Funding Allocation, (ii) Faculty Development, (iii) Curriculum Innovation, (iv) Industry Collaboration, and (v) All of the Above. They will be assessed based on the following key performance indicators which includes the adoption of AI curriculum, faculty competence, industry collaboration and others. By utilizing the simulation, policymakers will be able to analyze alternative policy interventions and their long-term implications to identify the most effective strategy for developing AI education sustainably. The findings provide quantitative evidence for optimizing policies and making strategic decisions in vocational colleges.

3.6 Model Validation

To confirm that the proposed Cooper-based System Dynamics model can capture the evolution of vocational colleges' AI education policy and provide reliable simulation outcomes, model validation is sought. Given that the model aims to aid long-term educational planning and policy decision-making, therefore a comprehensive validation strategy is adopted to ensure its structural correctness, computational accuracy and predictive capability The validation process combines theoretical validation with simulation validation, following up on realistic educational dynamics. The effectiveness of the proposed framework is tested by simulating all policy scenarios over a ten-year planning horizon with a frequency of once a year. The period is long enough to capture any lagged response of educational policy interventions, such as the upgrading of curriculum, teacher training, investment in infrastructure, and collaboration with industry, which take time to show results. Each year, it generates estimates of institutional performance and enables policymakers to observe both short-term improvements and long-term sustainability.

4. Results

The simulation of the proposed Cooper-based System Dynamics framework over a 10-year planning horizon evaluates the effectiveness of AI education policy in vocational colleges. Two categories of five policy scenarios were examined: policy ones that include funding (S1), faculty (S2), curriculum (S3), and industry (S4), and an integrated one (S5). The simulation evaluated a total of six factors which includes adopting an AI curriculum, training the faculty, collaborating with the industry, employability of the graduates, innovation capacity of the institution and sustainable education. The outcomes suggest that there is always higher performance of integrated policies than independent policies implementation.

4.1 Comparative Performance Analysis

According to Table 1 and Figure 2, the five AI education policy scenarios exhibit different comparative strength after 10 years of simulation. Each of the suggested policy interventions contributes positively to the development of AI education in vocational colleges. However, their effectiveness varies according to the relevant educational dimension. The S1 Funding Allocation scenario improves readiness of teachers and infrastructure for education and ensuring availability of libraries and laboratory but it impacts on graduate employability and institutional and system innovation. The Faculty Development (S2) process focuses on improving the competency of teachers through continuous training on a professional level. Consequently, the quality of students' learning will improve as the quality of instructions enhances. Also, Curriculum Innovation (S3) boosts the adoption of AI curriculum by integrating new-age AI technologies and industry oriented learning modules into vocational education.

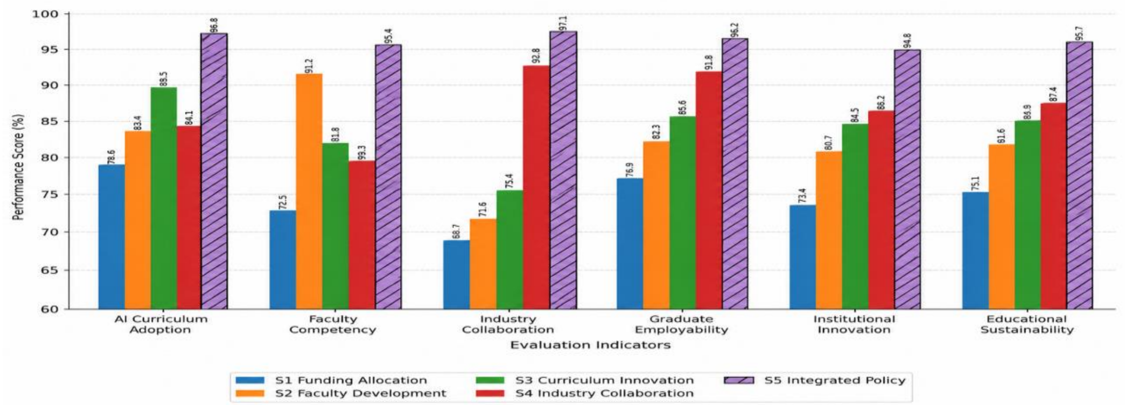

Figure 2. Comparative Performance of AI Education Policy Scenarios

In this figure 2 the performance of scenarios of AI education policy are compared after ten years of simulation. Consistently, the integrated policy strategy (S5) is associated with the highest performance on all education variables. This suggests that when all policies are put together, it is more effective in improving AI curriculum adoption, faculty competence, industry collaboration, graduate employability of graduates, institutional innovation, and education sustainability than individual policies.

Table 1. Comparative Performance of AI Education Policy Scenarios After the 10-Year Simulation Period

Evaluation Indicator	S1 Funding Allocation	S2 Faculty Development	S3 Curriculum Innovation	S4 Industry Collaboration	S5 Integrated Policy
AI Curriculum Adoption (%)	78.6	83.4	89.5	84.1	**96.8**
Faculty Competency (%)	72.5	91.2	81.8	79.3	**95.4**
Industry Collaboration (%)	68.7	71.6	75.4	92.8	**97.1**

Graduate Employability (%)	76.9	82.3	85.6	91.8	**96.2**
Institutional Innovation (%)	73.4	80.7	84.5	86.2	**94.8**
Educational Sustainability (%)	75.1	81.6	84.9	87.4	**95.7**
Average Performance (%)	**74.2**	**81.8**	**83.6**	**87.0**	**96.0**

Table 1 shows the performance of the five AI education policy scenarios compared to another after 10 years. The Integrated Policy Strategy (S5) performs best in all evaluation indicators. This reflects the merit of implementing coordinated educational policies. Notably, S5 garnered 96.8% AI curriculum adoption, 95.4% faculty competency, 97.1% industry collaboration, 96.2% graduate employability, 94.8% institutional innovation, and 95.7% educational sustainability for the highest average performance of 96.0%. Compared to the overall outcomes for the first group scenario, the individual policy scenarios (S1-S4) produced much lower outcomes. The study's findings show that a more synergistic and sustainable AI education, along with better institutional performance at vocational colleges, can be achieved by integrating funding allocation, faculty development, curriculum renewal, and industry collaboration.

4.2 Performance Evaluation

The results of the yearly simulation which are presented in Figure 3 and Table 2 show the changing behaviour of institutions over the planning horizon of ten years. In the initial three years, all policy scenarios demonstrate gradual improvement as investments in infrastructure, curriculum development and faculty training need time to affect outcomes. Starting in Year 4, the enhanced interaction between educational resources, faculty competency, and industrial partnership creates reinforcing loops which boost the performance of the institution. The integrated policy strategy (S5) experiences the highest increase during the entire simulation. The system's performance index rises from 72.4% in Year 1 to 96.3% by Year 10, indicating sustained long term improvement. There is a similar upward trend for industry collaboration (S4), stronger partnerships result in improved internship opportunities and graduate employment. Unlike funding allocation (S1), which shows the slowest growth, having infrastructure alone cannot enhance the AI education performance. In summary, the analysis through time shows that using different policy simultaneously generates greater educational benefits than using any of the policy separately.

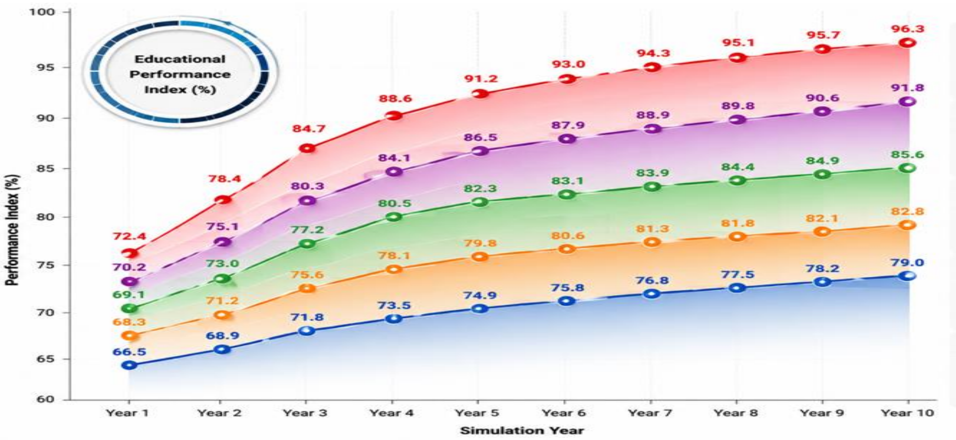

Figure 3. Results of the yearly simulation

In figure 3, all possibilities demonstrate ongoing improvement, but their improving rates vary greatly. Out of the five policy strategies identified in this evaluation, the integrated policy strategy (S5) has recorded the optimal performance moving from 72.4 percent in Year 1 to 96.3 percent in Year 10. The second best outcome is with industry collaboration (S4) that is rated at 91.8 percent. This is followed by better curriculum (S3) at 85.6 percent; constant faculty development (S2) at 82.8 percent; and the lowest outcome but still significantly improving funding (S1) at 79.0 percent. The diagram shows three stages of evolution of policy. The first, second and third years are where you will start investing, and things will start to get better. The fourth, fifth and sixth years are where an interaction takes place after which things will improve rapidly. The seventh, eighth, ninth and tenth year witness reinforcement and consistency. S5, when compared individually to each intervention, is a greater success than any of them would be in isolation. This suggests that together, coordinated funding, faculty development, curriculum innovation and industry coalitions yield greater and more sustainable results than just one policy approach in isolation.

Table 2. Annual Educational Performance Index (%) During the 10-Year Simulation

Simulation Year	S1	S2	S3	S4	S5
Year 1	66.5	68.3	69.1	70.2	72.4
Year 2	68.9	71.2	73.0	75.1	78.4
Year 3	71.8	75.6	77.2	80.3	84.7
Year 4	73.5	78.1	80.5	84.1	88.6
Year 5	74.9	79.8	82.3	86.5	91.2
Year 6	75.8	80.6	83.1	87.9	93.0
Year 7	76.8	81.3	83.9	88.9	94.3
Year 8	77.5	81.8	84.4	89.8	95.1
Year 9	78.2	82.1	84.9	90.6	95.7
Year 10	**79.0**	**82.8**	**85.6**	**91.8**	**96.3**

Table 2 presents the annual Educational Performance Index (EPI) for the five policy scenarios over the 10-year simulation period. All scenarios show continuous improvement, with performance increasing gradually during the early years and accelerating after Year 4 due to cumulative policy effects. The Integrated Policy Strategy (S5) consistently achieves the highest performance, improving from 72.4% in Year 1 to 96.3% in Year 10, followed by Industry Collaboration (S4). In contrast, Funding Allocation (S1) records the lowest improvement, indicating that integrated policy implementation is more effective than individual policy interventions for achieving sustainable AI education development.

4.3 Sensitivity Analysis

Sensitivity analysis was conducted by varying major policy parameters by ±20% to examine the robustness of the proposed model. The findings indicated that Faculty Development who played the maximum role in Educational Performance Index followed by Industry Collaboration and Curriculum Innovation. Educational funding and infrastructure investment, however, are less sensitive. It could be emphasized that strengthening the competency of vocational college faculty as well as industry partnership is the best way to achieve sustainable AI education development in these institutions.

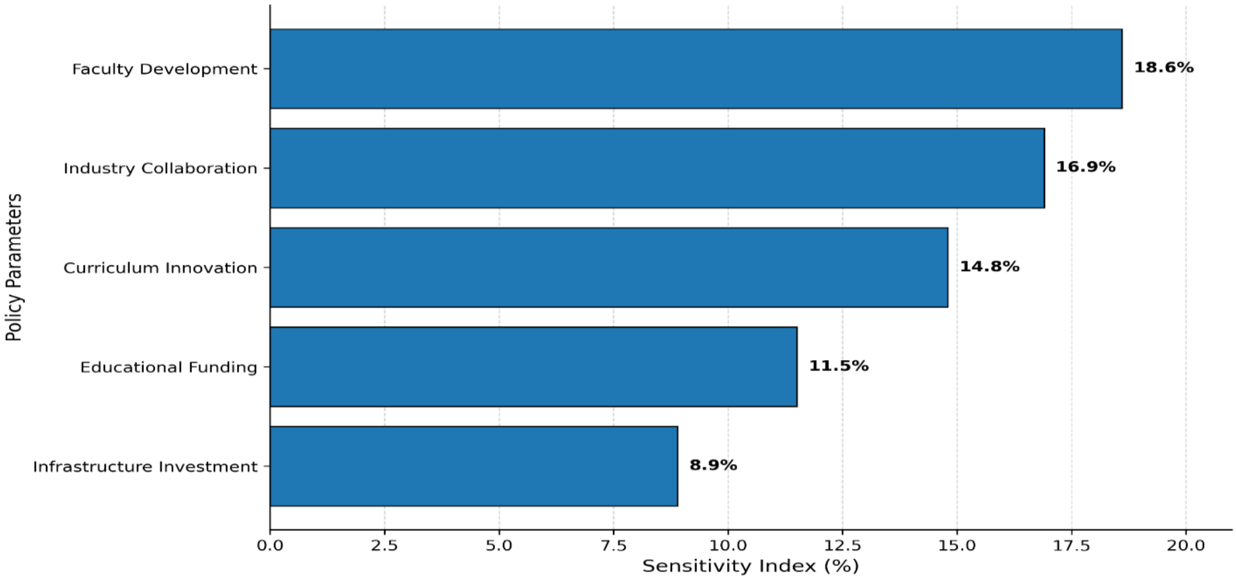

Figure 4. Sensitivity of Key Policy Parameters on Educational Performance

Figure 4 showcases the sensitivity analysis of main policy parameters impacting the EPI. The study results indicate that Faculty Development has the most sensitive index (18.6%) which means improvement in the competency of teachers will positively affect the AI capability more than any other factors. Collaboration with the Industry (16.9%) and Innovation in Curriculum (14.8%) also influence educational outcomes in the long run. Sensitivity of Educational Funding and Infrastructure Investment is fairly low at 11.5 and 8.9. In general, figure indicates that simultaneously investing in faculty capability and strengthening industry partnerships are the most important areas for effective enhancement of sustainability versatile AIEd in vocational college**.**

Table 3. Sensitivity Analysis of Major Policy Parameters

Policy Parameter	**Variation**	**Sensitivity Index (%)**	**Impact Level**	**Rank**
Faculty Development	±20%	**18.6**	Very High	1
Industry Collaboration	±20%	**16.9**	High	2

Curriculum Innovation	±20%	**14.8**	High	3
Educational Funding	±20%	**11.5**	Moderate	4
Infrastructure Investment	±20%	**8.9**	Moderate	5

In Table 3, Faculty development shows the greatest sensitivity index at 18.6% which means teacher competency is most responsive to performance. Policy outcomes in the sector are also considerably influenced by Industry Collaboration (16.9%), and Curriculum Innovation (14.8%). Educational funding (11.5%) and infrastructure investment (8.9%) will have lesser impacts. The ultimate conclusion indicates that improving sustainable AI education in vocational colleges can be achieved by prioritizing teacher development and enhancing college industry cooperation.

5. Discussion

The research results illustrates the combination of the Cooper policy framework with System Dynamics (SD) provides a comprehensive and effective measure for evaluating AI education policies in vocational colleges. The proposed framework captures dynamic interrelationships between various educational resources, faculty competence and student engagement, curricular innovation, industry interaction, infrastructure development, and employability of graduates, unlike traditional policy evaluation techniques that use mostly static indicators for assessments at intervals. Given feedback loops, nonlinearities and policy delays furnish a more realistic representation of the AI education ecosystem and longer-term planning. The analysis shows that while the five alternative policies are all effective in improving AI education, their effectiveness varies widely. The Funding Allocation (S1) scenario improves infrastructure and equipment but generates relatively low advances in institutional innovation and graduate employability. Through continuous professional growth of faculty members and improvement Artificial Intelligence skills, S2 scenario greatly enhances teaching quality. In the same vein, Curriculum Innovation (S3) allows educational programs to stay in tune with emerging AI technology and industrial requirements, which enhances student competency and learning outcomes. The S4 scenario complements partnerships with enterprises, boosts internship opportunities, and enhances practical training, leading to increased employability of graduates and institutional innovation.

The strategies evaluated, the Integrated Policy Strategy (S5) performs the best in all evaluation indicators. The S5's superior performance indicates that a combination of investing in the institution, faculty development, curriculum upgrading, and introducing the MSME industry forge reinforcing feedback moves that accelerate the quality of education and growth of the institution. When policies are implemented in a coordinated manner, they generate synergy rather than just isolated improvements. When education policies are implemented in a coordinated manner, they support and strengthen many subsystems of education together. This proves one of the systems dynamic basic principles which states that a more interconnected set of policy interventions yields greater long-term benefits than separate policy efforts. The results of the 10-year simulation revealed that education policies do not have an immediate impact. In the beginning, things improve slowly as the investment in faculty training, curriculum revision and infrastructure takes time before it can affect the institution. As these components interact via reinforcing feedback loops, the education outcome improves at a higher rates later in the simulation. This finding underscores the need for long-term policy planning rather than expecting a short-term return from education. Consequently, policymakers should prefer an emphasis on sustained implementation combined with continuous monitoring to bring about meaningful change.

The sensitivity analysis provides an extra perspective on the critical factors influencing education. Enhancing the capability of teaching staff related to their understanding of AI, pedagogical skill and professional competence is the most impactful for institution development. The second highest factor is industry collaboration. There should be strong tie-ups with industries which can provide students with exposure to practical experience, internships and real-world AI applications. Curriculum innovation is also critical to ensure vocational programs do remain responsive to technological innovation and labour market needs. The relevance and needs for resources in education along with infrastructural investments is necessary. However, they do not mean much until there is a simultaneous effort to improve human resources and engagement with industry players. The framework, from a policy perspective, can be used by educational administrators and government agencies as guidance in AI education planning. Using simulations allows policymakers the advantage of assessment and analysis of various policy scenarios before implementation as well as foresight of their long-term effects. They can also identify the key leverage points and optimize the use of available resources.

Uncertainty in educational planning is minimized, allowing for evidence-based decision making for sustainable institutional development. The suggested framework has some limitations despite its benefits. The model derives from historic educational data and pre-defined policy settings which vary by institution and geographic area/region. Moreover, to maintain prediction accuracy, the model parameters may need to be regularly recalibrated owing to rapidly evolving AI technologies and labor market demands. We will extend the framework in future research using real time educational analytics, machine learning based parameter optimisation, cross country policy analysis. The use of digital twins and learning analytics platforms may further enhance policy forecasting and adaptive educational planning.

6. Conclusion

The dynamic evolution of support policy in the development of AI intelligent education in vocational colleges was studied based on cooperative theory, using system dynamic method. The framework successfully captured the dynamic interactions between educational resource, faculty development, curriculum innovation, industry collaboration, infrastructure investment, and graduate employability with the combination of the iterative policy cycle of Cooper and System Dynamics. In contrast with traditional policy evaluation methods, the framework incorporates feedback mechanisms, nonlinear relationships and time delays for comprehensive long-term policy assessment. The simulation results revealed that strategy S5 consistently produced better performance results than any single policy intervention for all education performance indicators over the 10 years window. According to the study, the implementation of funding allocation, faculty development, curriculum modification and industry collaboration together significantly contribute to the adoption of AI curriculum, faculty competence, institutional innovation, educational sustainability and graduate employability. Sensitivity analysis indicated that faculty development and industry collaboration are the most significant factors impacting long-term educational performance, revealing its essential importance on sustainable Development of educational performance. The framework will be a practical decision-support tool for policymakers and education administrators to evaluate alternative policy scenarios, effectively allocate resources, and evidence-based AI education policy. Through policy monitoring and adaptive decision-making, the framework enables sustainable development of AI education ecosystems, which have the capacity to meet rapidly evolving workforce demands of intelligent industries. The proposed model shows good results, but suffers from dependence on previous education data and pre-defined simulation parameters. In the future, researchers may include the incorporation of machine learning along with real-time educational analytics and digital twin technology. Moreover, the framework will be more applicable for the planning of global vocational education policy if its application can be broadened to multi-country educational systems.

Author contributions

Hongbo Li: Methodology, Writing – review & editing

Xingang Wu: Project Administration, Writing – original draft

Funding

The authors received no financial support for the research

Conflict of interest

The authors declare that they have no known conflict of interest

References

Gao, H., & Tan, Y. (2025). AI differences in vocational and undergraduate applications of artificial intelligence in higher education: A systematic review. *Higher Education Studies*, 15(4), 398–408.

Schmitt, C., & Brutzer, A. (2025). Generative artificial intelligence in vocational education and training: A framework for sustainable teacher competence development. *Vocational and Technical Education*. https://doi.org/10.54844/vte.2025.0940

Hong, L. (2025). Development and validation of a competency-based ladder pathway for AI literacy enhancement among higher vocational students. *Scientific Reports*, 15, 29898.

Yusuf, H., Money, A., & Daylamani-Zad, D. (2025). Pedagogical AI conversational agents in higher education: A conceptual framework and survey of the state of the art. *Educational Technology Research and Development*, 73, 815–874.

Lin, X., Xu, G., & Xiong, B. (2025). Artificial intelligence literacy, sustainability of digital learning and practice achievement: A study of vocational college students. *PLOS ONE*, 20(10), e0332175.

Metreveli, A., Chen, X., Hedman, A., & Sergeeva, A. (2025). Who will be left behind? A Swedish case of learning AI in vocational education. *International Journal of Educational Research*, 133, 102697.

Wang, H., & Liu, M. (2025). Methods and content innovation strategies of digital education in higher vocational colleges under the background of artificial intelligence. *Journal of Information Technology Education: Innovations in Practice*.

Li, M., Xie, Q., Enkhtur, A., Meng, S., Chen, L., Yamamoto, B. A., Cheng, F., & Murakami, M. (2025). A framework for developing university policies on generative AI governance: A cross-national comparative study. *arXiv.*

Krause, S., Dalvi, A., & Zaidi, S. K. (2025, July). Generative AI in education: Student skills and lecturer roles. *In International Conference on Artificial Intelligence in Education Technology*, 49-67.

Jiang, L., Wei, B., Qiu, N., & Huang, L. (2025). What influences ChatGPT's adoption and diffusion in Chinese higher education? A study based on Technology-Organization-Environment framework. *Interactive Learning Environments*, 33(9), 5247-5268.

Prasetya, F., Fortuna, A., Samala, A. D., Latifa, D. K., Andriani, W., Gusti, U. A., ... & García, J. L. C. (2025). Harnessing artificial intelligence to revolutionize vocational education: Emerging trends, challenges, and contributions to SDGs 2030. *Social Sciences & Humanities Open*, 11, 101401.

Nakar, S., Park, E., Misselke, L., & Khan, S. I. (2026). Leveraging AI in vocational education: a systematic review of theory, barriers and opportunities. *Marketing Intelligence & Planning*, 1-26.

Guoping, L. (2025). AI Empowerment in Vocational Education: Teacher Role Transformation and Innovation of the "Teacher–AI–Student" Collaborative Teaching Model. *Education Research and Innovation*, 1(8), 72-82.

Ma, X., Chen, M., & Diao, J. (2025). Pathways and outcomes of digital transformation in Chinese vocational colleges. *Vocation, Technology & Education*, 2(1).

Chigbu, B. I., & Makapela, S. L. (2025). AI in education, sustainability, and the future of work: An integrative review of industry 5.0, education 5.0, and work 5.0. *Journal of Open Innovation: Technology, Market, and Complexity*, 100645.

Setiyawan, A., Soeharto, S., Wijaya, T. T., Korenova, L., & Lavicza, Z. (2025). Measuring Teachers' Competencies for AI Integration: Development and Validation of the AI-TPACK in Vocational Education. *Computers and Education Open*, 100319.

Miao, Y., Xiao, Z., & Zhang, Y. (2025). Impact of talent cultivation model for industry education integration in vocational education by artificial intelligence and BPNN. *Scientific Reports*, 15(1), 38019.

Nguyen, A., Scrivner, O., de Laat, M., & Scrivner, J. (2026). Systemic shifts required for higher education futures: Policy, pedagogy, and practice in the age of artificial intelligence and digital transformation. *Policy Futures in Education*, 24(1), 1-12.

Allam, H. M., Gyamfi, B., & AlOmar, B. (2025). Sustainable innovation: Harnessing AI and living intelligence to transform higher education. *Education Sciences*, 15(4), 398.

Rosyadi, M. I., Kustiawan, I., Tetehfio, E. O., & Joshua, Q. (2023). The role of AI in vocational education: A systematic literature review. *Journal of Vocational Education Studies*, 6(2), 244-263.