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A deep learning-based career recommendation system using program learning outcomes and TPQI standards in the digital industry

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Abstract: This research aims to (1) assess current and future digital industry demands to align academic learning with industry-required competencies, (2) classify and analyze computer science curriculum components based on Thailand's Professional Qualification Standards, (3) evaluate digital software-related professional competencies and their alignment with academic courses, (4) develop a decision-support model for career selection based on program learning outcomes (PLOs), (5) implement a web-based platform to support decision-making, and (6) evaluate the predictive accuracy of the model. Findings reveal seven key components of higher education improvement in computer science (mean = 4.92), five key course learning outcomes (mean = 4.87), and seventeen PLO elements (mean = 4.81), all rated at excellent levels. The study integrated the Thai Professional Qualification Institute (TPQI) framework into curriculum development. Data from 200 graduates were analyzed and mapped with current job roles and industry expectations. A predictive model using deep learning was developed and deployed on a browser-based platform. Accuracy evaluation shows that the system aids students in aligning career paths with qualifications and helps industries identify suitable talent. User satisfaction among students was high, indicating practical value in academic and industrial contexts.

Keywords: *Career decision-making process, Decision support system, Digital manpower, Professional qualification standards in digital industry, Program learning outcomes.*

1. Introduction

The digital technology sector is evolving rapidly, significantly impacting both the global economy and the field of computer science. As digital transformation reshapes the labor market, students in computer science are increasingly required to make well-informed career decisions that align with their individual competencies, interests, and the dynamic needs of the digital industry. Career decision-making, however, is inherently complex and deeply consequential—affecting not only students' future trajectories but also the capacity of industries to recruit qualified digital talent.

Thailand, in particular, has responded to this challenge by establishing the Thailand Professional Qualification Institute (TPQI) to define professional standards and develop Unit of Competency (UOC) frameworks for various career paths in the digital industry. These standards cover both technical and soft skills and provide a foundation for aligning academic outcomes with real-world job requirements.

However, the decision-making process for students often lacks clear tools or systems that effectively link academic achievements—particularly Program Learning Outcomes (PLOs)—with specific career competencies. Many students struggle to interpret their learning outcomes in the context of labor market needs, leading to a mismatch between academic training and employment outcomes. Without proper guidance or intelligent decision-support systems, students frequently rely on social trends or external expectations rather than data-driven self-assessment and industry standards.

In the context of the Fourth Industrial Revolution (Industry 4.0) and the Data-Driven Economy, the role of higher education must shift towards producing digitally competent graduates equipped for future careers. This requires curriculum reform, outcome-based assessment, and enhanced alignment

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with industry competency standards. Artificial Intelligence (AI), particularly Deep Learning (DL) models, offers promising capabilities for analyzing complex student data and generating personalized career recommendations.

This study aims to develop a predictive Career Decision Support System (CDSS) that uses students' PLOs and aligns them with relevant UOCs defined by TPQI in the digital software sector. By employing Multi-Label Classification and Top-K Prediction techniques through a Deep Neural Network (DNN) model, the system is designed to recommend multiple potential careers tailored to each student's profile. The final platform is implemented as a web-based tool for educational and institutional use, serving not only individual learners but also supporting national workforce development initiatives.

This research contributes to bridging the gap between higher education and the labor market, enabling more accurate, informed, and personalized career planning for computer science students in Thailand and potentially in other digital economies.

2. Literature Reviews

2.1. Decision Support Systems (DSS)

Decision Support Systems (DSS) are interactive software-based systems designed to assist decision-makers in making informed choices by analyzing data and presenting actionable insights. They can be broadly categorized into passive, active, and cooperative systems. Passive DSS provide structured information without recommending decisions, while active DSS generate decision suggestions based on processed data. Cooperative DSS combine human judgment with system-generated solutions to support optimal strategies [1].

Five key types of DSS have been identified: data-driven, communication-driven, document-driven, model-driven, and knowledge-driven systems. Data-driven DSS emphasize the collection and organization of structured and unstructured data from internal and external sources. These systems allow users such as managers and service providers to generate queries and analyze patterns efficiently. Communication-driven DSS, by contrast, support collaborative decision-making by enabling shared work processes among multiple stakeholders via web-based platforms.

According to Alyahyan and Düştegör [2] the architecture of a DSS comprises three components: a Database Management System (DBMS), a Model-Based Management System (MBMS), and a user interface. The DBMS manages the storage and retrieval of data, while the MBMS applies mathematical models to derive insights. DSS are especially effective in handling semi-structured problems by integrating analytical tools, such as Analytical Hierarchy Process (AHP) and Multi-Criteria Decision Analysis (MCDA), to support complex decision-making scenarios [3].

2.2. Career Decision-Making Processes

Career decision-making is a complex, multi-stage process influenced by various internal and external factors. Fiedler, et al. [4] argue that the decision-making process involves identifying problems, generating alternatives, evaluating options, and implementing solutions. Alyahyan and Düştegör [2] and Ammirato, et al. [5] further break down this process into six stages: problem identification, requirements gathering, model development, option analysis, decision design, and implementation.

Human expertise, traditionally offered through academic advisors, is now being augmented by expert systems and intelligent platforms capable of evaluating academic records and suggesting optimal career paths [6] Such tools are essential in higher education, where students often struggle to match their interests and academic achievements with realistic career options.

Theoretical foundations for career decision-making can be traced back to, who emphasized three principles: self-understanding, knowledge of the world of work, and logical reasoning in matching the two. Contemporary models focus on self-efficacy, expectations, and career commitment [7], emphasizing the importance of personalized systems to improve career decision-making confidence and accuracy.

2.3. Program Learning Outcomes (PLOs)

Program Learning Outcomes (PLOs) represent measurable achievements that students are expected to attain upon completion of a degree program. According to Adam [8] outcome-based education (OBE) shifts focus from teaching to learning by aligning curriculum design, teaching strategies, and assessments with specific learning outcomes.

PLOs typically include cognitive (knowledge), psychomotor (skills), and affective (attitudes) domains. Their evaluation involves both direct methods (assignments, standardized tests) and indirect methods (surveys, graduate tracking). Tools such as rubrics, concept maps, and portfolio reviews are used to assess learning outcomes systematically.

Well-aligned PLOs improve educational transparency and ensure that graduates possess industry-relevant competencies. Mapping PLOs to course learning outcomes (CLOs) ensures curriculum coherence and supports continuous program improvement through assessment cycles.

2.4. Thailand Professional Qualification Institute (TPQI)

TPQI is a key institution in Thailand's competency-based education framework. It defines national standards for various professional fields, including digital technology, through a structured eight-level qualification framework. Each level outlines expected knowledge, skills, application outcomes, and ethical responsibilities.

The Unit of Competency (UOC) approach adopted by TPQI facilitates precise matching between academic achievements and professional requirements. This alignment enables universities to reform curricula in response to labor market demands and enhances graduate employability in digital sectors.

2.5. Digital Manpower Development

Digital manpower refers to professionals equipped with competencies in using, developing, and leading digital technologies. OECD defines such individuals as those skilled in automation, artificial intelligence, blockchain, and cloud computing. In Thailand, the demand for digital talents exceeds 200,000 per year, while only 30% of graduates meet the required professional standards (DEPA, TPQI).

The World Economic Forum [9] projects that by 2030, over 85 million new digital jobs will be created globally, while many traditional roles will disappear. To bridge the digital skills gap, educational institutions must embed industry-aligned PLOs and career intelligence systems into curriculum design and student advising.

Digital entrepreneurship also plays a pivotal role. Entrepreneurs must harness technology to innovate and scale solutions in fast-changing markets [10]. Challenges such as timing, alignment of incentives, and technology inertia must be overcome to foster innovation capacity and national competitiveness.

3. Methodology

The research titled "A Deep Learning-Based Decision Support System for Career Selection Using Computer Science Curriculum Learning Outcomes Aligned with Professional Qualification Standards in the Digital Industry" adopts a Research and Development (R&D) methodology. The approach comprises six detailed phases, integrating qualitative and quantitative strategies to ensure industry-aligned and data-driven model development.

Phase 1: Analysis of Current and Future Needs in the Digital Industry. This phase aims to explore current demands and future trends of the digital workforce. The following activities were conducted. Literature Review: Extensive examination of relevant theories, conceptual frameworks, and global trends related to AI, Industry 4.0, and digital transformation. Stakeholder Engagement: In-depth interviews and surveys were conducted with digital industry practitioners, employers, and entrepreneurs to identify required competencies. Needs Synthesis: Findings were organized into a competency matrix that reflects key skills needed in future digital jobs and serves as a foundation for aligning curricula with labor market expectations.

Phase 2: Curriculum Analysis and Course Mapping to TPQI Standards. This phase evaluates the extent to which Computer Science curriculum aligns with Thailand Professional Qualification Institute (TPQI) standards. Course Clustering: Sixty courses were categorized by domain and technical relevance. Standard Matching: Each course was mapped against the TPQI's "Software and Applications" UOC framework. Expert Consultation: Four digital career paths were selected (System Developer, Software Engineer, System Analyst, Tester), and interviews with 8 seasoned professionals (2 per role, ≥10 years experience) validated the course-UOC alignment.

Phase 3: Evaluation of Course–UOC Conformance. This step ensures content validity and competency matching. Instrument Validation: Five experts reviewed assessment questionnaires to confirm item accuracy using Index of Item Objective Congruence (IOC). Instrument Refinement: Based on feedback, the tools were revised to more accurately reflect industry-required knowledge and skills.

Phase 4: Deep Learning Model Design for Career Decision Support. A deep learning framework was constructed to model the relationship between academic achievements and suitable careers. Data Aggregation: Historical learning data from 200 Computer Science alumni, including course grades, current employment, and career paths. Model Structure

Input: PLO data, mapped competencies, job roles, and expert feedback.

Processing: Feature selection, encoding, and training using Recurrent Neural Networks (RNN).

Evaluation: Model performance assessed through Confusion Matrix, analyzing accuracy, precision, recall, and F1-score.

Stakeholder Input: Structured interview instruments captured system requirements and validation points.

Phase 5: System Implementation and Interface Development. After validating the most effective model, the system was implemented. Technology Stack: Developed using Python (Flask), HTML5/CSS, and JavaScript. Backend integrated with MySQL database. Model Training and Integration: Over 1,000 PLO-labeled records were used for model training, with results embedded into the system.User Interface Design: Created an intuitive, web-based dashboard enabling CSV upload and personalized career predictions.

Phase 6: Model Testing and Performance Verification. This phase validates prediction accuracy and real-world readiness. Test Dataset: 500 current students' records were collected to simulate real-time prediction. Algorithm Comparison: Various models (e.g., RNN, DNN, Decision Trees) were tested and benchmarked using Confusion Matrix. Performance Metrics: Assessed using precision, recall, accuracy, and F1-score. The highest-performing model was selected for final deployment.

This comprehensive methodology ensures that the proposed system is rigorously built, validated by experts, and aligned with actual workforce demands in the digital era, supporting both personalized learning pathways and national-level workforce development planning.

The study on the analysis of the Computer Science curriculum components show that the course grouping aligns with the professional qualification standards in the digital industry. The study reveals that the curriculum is structured to ensure that students acquire the necessary knowledge and skills required in the digital sector, in accordance with the professional standards for qualifications in the digital industry. The courses are systematically categorized to address both fundamental knowledge areas (e.g., programming, algorithms, data structures) and specialized areas relevant to the digital industry's needs (e.g., cybersecurity, data analysis, software development). This alignment ensures that graduates are equipped to meet the evolving demands of the digital economy.

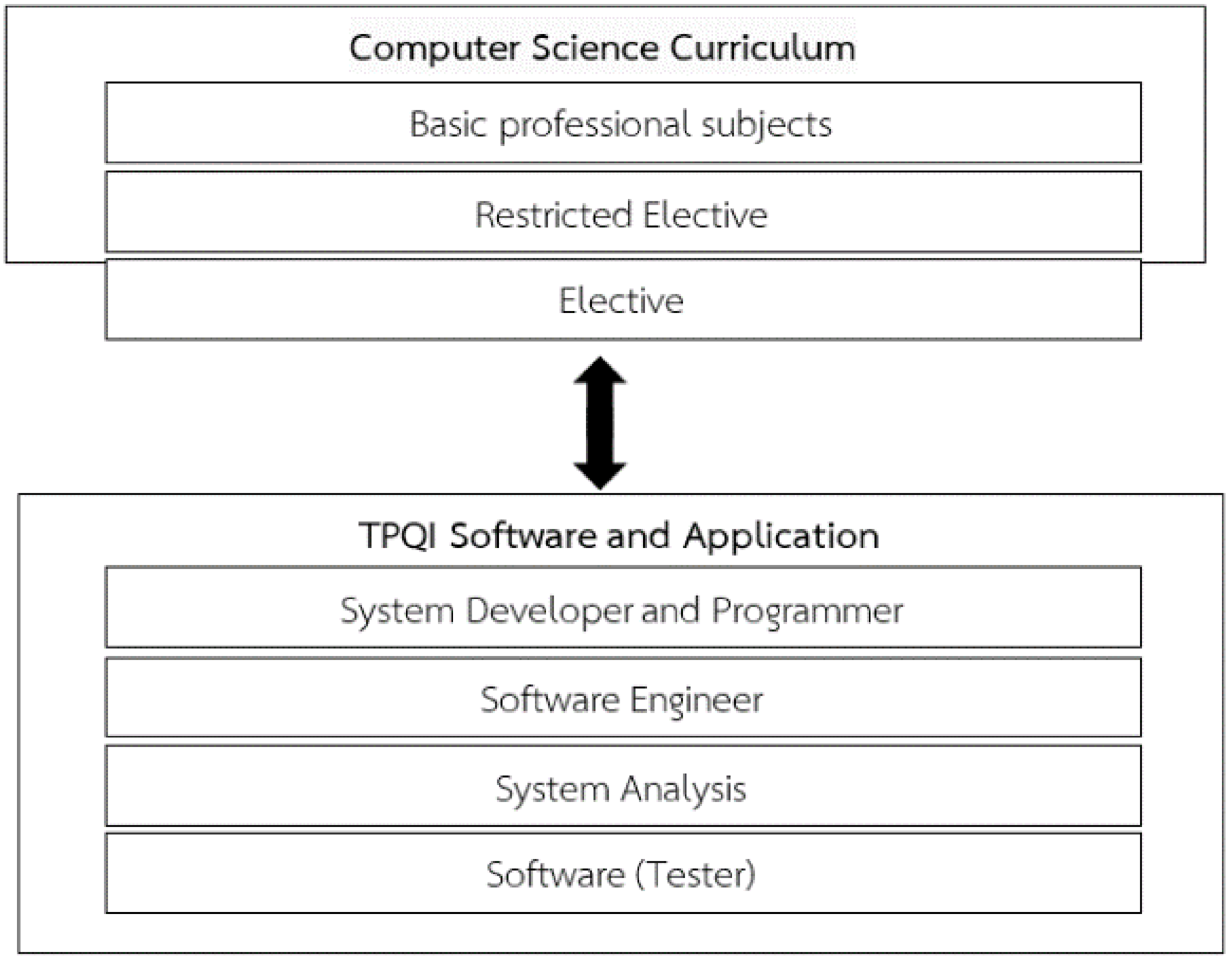

Figure 1.
Grouping by subject group type of Computer Science curriculum with Digital Industry professional branch, Software and Application branch.

As shown in Figure 2 The Computer Science curriculum at the Faculty of Science and Technology, Rajamangala University of Technology Suvarnabhumi, was analyzed through in-depth interviews with five experts to group the subjects according to 14 categories, as follows:

Fundamentals of Programming and Data Structures. This includes fundamental concepts in program development, basic programming skills, and concepts related to data structures used in data processing.

3.1. Model Approach

The development of a decision support system model using deep learning for career choice is Science curriculum according to professional qualification standards in the digital industry. The data collection for building the model is divided into two main parts:

Collecting the Learning Outcomes of the Curriculum:

Analyze the factors that serve as inputs, including the courses, competencies, professional qualifications, and academic performance. This step involves gathering and evaluating the relevant educational outcomes that align with the skills and knowledge required by the digital industry.

Collecting the Current and Future Needs of the Digital Industry:

Gather information on the needs of the digital industry from companies, organizations, and entrepreneurs that utilize digital industry services. This includes identifying the required skills, technologies, and expertise for the current and future workforce in the digital industry, helping to ensure that the curriculum outcomes match the market demands.

This comprehensive data collection will enable the development of a model that supports decision-making for career choices, ensuring that the learning outcomes from the curriculum align with the industry's needs and expectations.

Figure 4 shows this a model is design of the deep learning-based decision support system model for , using the learning outcomes of the Computer Science curriculum according to professional qualification standards in the digital industry, consists of 4 main modules:

Higher Education Improve Computer Science Learning. This module provides input data to improve the curriculum after assessing the outcomes. It involves the development and management of the curriculum, enhancing content delivery by instructors, improving teaching methods, developing student quality and graduates, and aligning software quality with industry standards in the software industry.

Computer Science Course Learning Outcomes (CLOs): Data from the "Higher Education Improve Computer Science Learning" module is used to update or develop necessary courses in alignment with current needs. This includes developing courses related to software creation, innovation, and emerging entrepreneurs to meet the requirements of the digital industry.

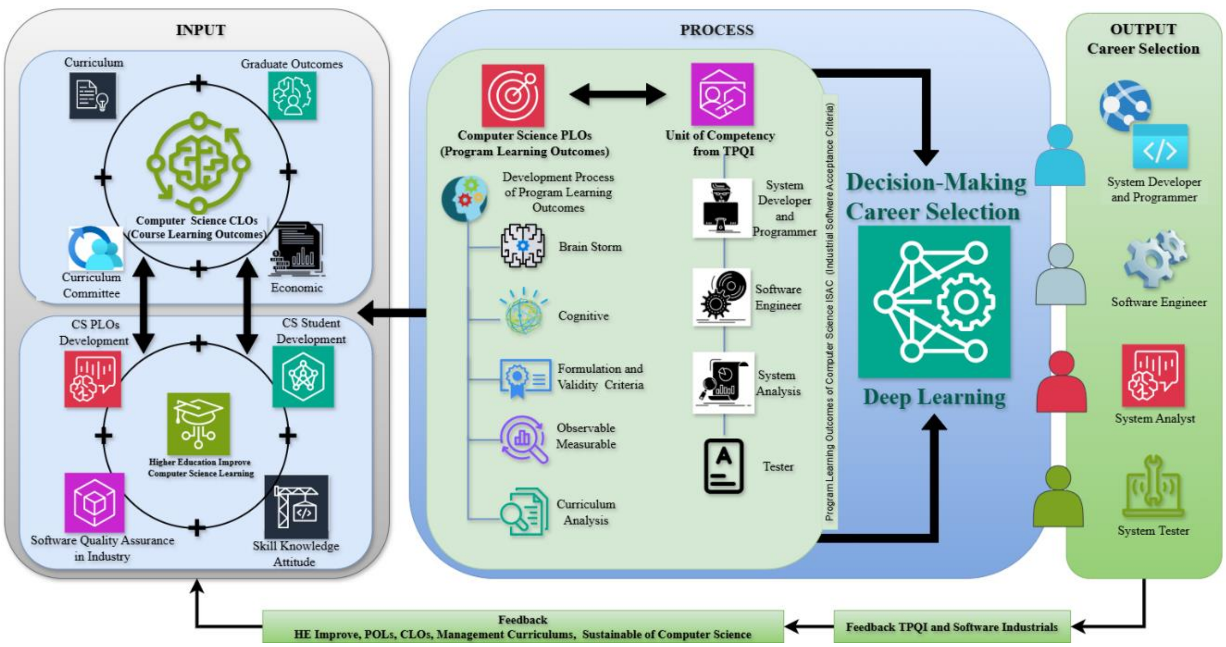

Figure 2.
A model of The Decision-Making Process Support System with Deep Learning For Career Selection using PLOs in Computer Science followed TPQI.

Program Learning Outcomes (PLOs): The curriculum and course development process must align with the software industry. This involves cooperation with industry stakeholders, labor market analysis, and understanding industry needs. The data analysis in this step includes

Brainstorming:

Analyzing the knowledge and skills required upon completion of the program.

Identifying desired personality traits.

Analyzing the understanding and application of software development processes in the software industry.

Promoting lifelong learning among students.

Cognitive Level:

Analyzing TPQI requirements and labor market needs.

Planning content that aligns with the set standards and criteria.

Identifying the specific qualities that students should possess.

Formulation and Validity Criteria:

Ensuring course standards and outcomes align with professional qualifications.

Defining PLOs that meet TPQI standards and market demands, focusing on software knowledge and application skills.

Measuring knowledge and skills levels across professional digital industry fields (Level 3, 4, and 5), ensuring they correspond to the expected student outcomes.

Observable or Measurable:

Evaluating the outcomes at each level (3, 4, and 5) for digital industry professions and software development, ensuring they meet the expected skills and knowledge levels.

Collecting feedback from student supervisors and professionals.

Gathering feedback from employers of graduates to enhance continuous improvement.

Encouraging students to recognize the importance of lifelong learning.

Curriculum Analysis:

Listening to feedback from industry mentors and professionals for curriculum improvement.

Analyzing and adjusting the curriculum to meet current industry and market needs.

Presenting PLOs to academic leaders, course directors, and instructors for feedback and further refinement.

Thai Professional Qualification Institute:

This module focuses on the specific career paths within the digital industry, particularly in software and application fields.

For each profession, competency units are identified and analyzed to set standards for producing qualified graduates aligned with industry needs.

This comprehensive model integrates curriculum development, industry requirements, and professional qualification standards to support career decision-making using deep learning techniques.

4. Results

The synthesis of study and analysis of the current and future needs of the digital industry is developed from an analysis and synthesis of related concepts, theories, research, in-depth interviews, and surveys on the needs of companies, organizations, and entrepreneurs in the digital industry. The aim is to synthesize a conceptual framework by reviewing documents and research related to decision-support systems with deep learning to choose careers, based on the learning outcomes of computer science programs according to the qualifications framework in the digital industry.

In-depth interviews and surveys of companies, organizations, and entrepreneurs in the digital industry are conducted to collect data for analysis, identifying the skills and needs that should be enhanced for students in computer science programs, in alignment with professional qualifications standards in the digital industry. The data is then synthesized to derive meaning, components, processes, and other relevant information. The collected and synthesized data is organized in a literature review format, using documents and related research, and presented in a synthesized table.

4.1. Results of the synthesis of the study and analysis of the needs of the current and future digital industry

The researcher studied documents and research related to Decision Support Systems (DSS) and synthesized the process as shown in Table 1.

Table 1.
Results of synthesis of decision support system.

DSS	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]
1. Scope of System								
1.1 The career decision-making process involves the evaluation of information.	✓	✓	✓	✓	✓		✓	✓
1.2 Accurate and clear information	✓		✓	✓	✓	✓		
2. Function								
2.1 External factors	✓	✓	✓	✓	✓	✓	✓	✓
2.2 Internal factors		✓	✓			✓		✓

Table 1 synthesis of the decision-support system reveals four factors:

The decision-making process in career selection involves data evaluation, alternative analysis, and choosing the appropriate path. Accurate and clear information enhances the chances of making better decisions.

External factors, such as the economic situation and job market conditions, influence career choices.

Internal factors, such as personal interests and abilities, help in selecting the most suitable career.

4.2. The Results of Synthesizing the Career Decision-Making Process

The researcher studied relevant documents, research concerning the Career Decision-Making Process, and synthesized the process,

Table 2.
Results of synthesis of Career Decision-Making Process.

Career Decision-Making Process	**[7]**	**[19]**	**[20]**	**[21]**	**[22]**	**[23]**	**[24]**	**[18]**
1. Scope of System								
1.1 The career decision-making process involves the evaluation of information.	✓	✓	✓		✓	✓	✓	✓
1.2 Accurate and clear information	✓		✓	✓	✓	✓	✓	✓
2. Function								
2.1 External factors	✓	✓	✓	✓		✓		✓
2.2 Internal factors	✓	✓		✓	✓	✓	✓	

Table 2 synthesis of the Career Decision-Making Process reveals four factors:

The career decision-making process involves evaluating information, analyzing alternatives, and selecting the most suitable path. Having accurate and clear data improves the chances of making better decisions.

External factors, such as the economic situation and job market conditions, influence career choices.

Internal factors, such as personal interests and abilities, help in choosing the appropriate career.

4.3. The results of Synthesizing the Learning Outcomes of the Curriculum

The researcher conducted a study of documents and research related to Program Learning Outcomes (PLOs) and synthesized.

Table 3.
Results of synthesis of Program Learning Outcomes

Program Learning Outcomes	**[25]**	**[13]**	**[26]**	**[27]**	**[28]**	**[29]**	**[30]**
1. Standard							
1.1 Reflection of Knowledge and Skills	✓		✓	✓	✓	✓	✓
1.2 Assessment and Improvement	✓	✓	✓		✓	✓	
2. Development Skill							
2.1 Focus on Industry-Relevant Skills	✓		✓	✓	✓	✓	✓
2.2 Training in New Technologies and Problem-Solving	✓	✓		✓	✓	✓	✓

Table 3 synthesis of Program Learning Outcomes (PLOs) reveals four key factors

Reflection of Knowledge and Skills: The learning outcomes of the program should reflect the knowledge and skills that students gain through their studies. This ensures that graduates are well-equipped with the competencies required for their professional roles.

Assessment and Improvement: The evaluation of learning outcomes is essential for refining the curriculum to meet the evolving demands of the market. Continuous assessment helps identify gaps and opportunities for improvement in the educational process.

Focus on Industry-Relevant Skills: The program should emphasize the development of skills that are essential for working in the digital industry. This includes a strong foundation in digital technologies, programming, and related fields.

Training in New Technologies and Problem-Solving: The curriculum should include training in the use of new technologies and effective problem-solving techniques. This prepares students to address real-world challenges in the rapidly changing digital landscape.

These factors collectively ensure that the program aligns with industry needs and adequately prepares students for success in the digital sector.

4.4. The results of synthesizing Professional Qualification Standards in Digital Industry

The researcher studied documents and research related to the results of professional qualification standards in the digital industry (Professional Qualification Standards in Digital Industry) and synthesized the process as shown in Table 4.

Table 4.
Results of synthesis of Professional Qualification Standards in Digital Industry.

Professional Qualification Standards in Digital Industry	[2]	[25]	[13]	[26]	[29]	[30]	[31]	[32]
1. The importance of standards								
1.1 Quality Assurance in Workforce	✓	✓		✓	✓	✓	✓	
1.2 Alignment with Industry Needs	✓	✓	✓	✓		✓	✓	✓
2. Development and improvement								
2.1 Continuous Development and Adaptation	✓	✓	✓		✓	✓	✓	✓
2.2 Stakeholder Involvement	✓		✓	✓	✓	✓	✓	✓

Table 4 synthesis of Professional Qualification Standards in the Digital Industry (Program Learning Outcomes) reveals four key factors:

Quality Assurance in Workforce: Professional qualification standards play a vital role in certifying the quality of the workforce in the digital industry. By establishing clear standards, they ensure that individuals meet the required competency levels for specific roles in the sector.

Alignment with Industry Needs: These standards help employers identify candidates with the right skills and qualifications that align with their requirements. This ensures that professionals entering the digital industry are well-prepared and equipped with the necessary expertise.

Continuous Development and Adaptation: As technology evolves rapidly, professional qualification standards should be continuously developed and updated. Regular reviews and revisions of the standards ensure that they remain relevant to the latest technological advancements and industry trends.

Stakeholder Involvement: Involving various stakeholders, including educational institutions, industry experts, and policymakers, is crucial for creating and maintaining professional qualification standards. Their participation ensures that the standards reflect real-world industry needs and are up-to-date with the current demands of the digital sector.

These factors collectively highlight the importance of maintaining professional qualification standards that not only ensure workforce readiness but also adapt to ongoing changes in the digital landscape.

4.5. The results of synthesizing Computer Science Student

The researcher has studied documents and related research on the outcomes of Computer Science students and synthesized the process as follows:

The synthesis focuses on identifying key factors that contribute to the expected learning outcomes for students in Computer Science programs. This includes the development of critical thinking, problem-solving, technical skills, and the ability to apply theoretical knowledge in practical settings. The process involves ensuring that students are prepared to work effectively with emerging technologies and are capable of contributing to the digital industry.

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Table 5.
Results of synthesis of Computer Science Student.

Computer Science Student	[33]	[26]	[27]	[30]	[31]	[22]	[34]	[32]
1. Required Skills								
1.1 Practical Experience in Real Projects	✓		✓	✓	✓	✓	✓	✓
1.2 Diverse Career Paths		✓	✓	✓		✓		✓
2. Career Opportunities								
2.1 High Demand for Workforce	✓		✓		✓	✓	✓	
2.2 Continuous Professional Development	✓	✓		✓	✓	✓	✓	✓

Table 5 synthesis of Computer Science students' outcomes revealed four key factors:

Practical Experience in Real Projects: Gaining hands-on experience through real-world projects significantly enhances expertise in the field. This practical training allows students to apply their theoretical knowledge and develop the skills required to succeed in the industry.

Diverse Career Paths: Students in Computer Science can pursue a wide range of career opportunities, such as software engineers, data analysts, or cybersecurity specialists. This versatility in career options reflects the broad applicability of their skills.

High Demand for Workforce: The demand for professionals in the digital industry, particularly in fields related to Computer Science, continues to be strong. This high demand creates ample job opportunities for graduates.

Continuous Professional Development: The fast-evolving nature of technology requires Computer Science graduates to engage in lifelong learning and professional development to stay current with emerging trends and advancements in their respective fields.

These factors collectively demonstrate the importance of providing students with a well-rounded education that integrates both technical skills and practical experience, ensuring they are well-prepared to enter a growing and dynamic job market.

4.6. The results of synthesizing Digital Manpower

The researcher studied documents and research related to the outcomes of digital entrepreneurs. This synthesis focuses on the key factors that contribute to the success and growth of entrepreneurs in the digital industry.

Table 6.
Results of synthesis of Digital Manpower.

Digital entrepreneurs	[5]	[35]	[36]	[15]	[17]	[37]	[38]	[39]
1. Growth trends								
1.1 Significant Role in Driving the Economy	✓	✓	✓	✓		✓	✓	✓
1.2 High Growth Potential	✓	✓		✓		✓	✓	✓
2. Challenges and opportunities								
2.1 Competition and Adaptability	✓	✓	✓	✓	✓	✓	✓	✓
2.2 Innovation and Adoption of New Technologies	✓	✓		✓	✓	✓	✓	

Table 6 synthesis results regarding digital entrepreneurs reveal four key factors. Significant Role in Driving the Economy: Digital entrepreneurs play a crucial role in driving economic growth in the digital age. Their ability to rapidly and efficiently scale services and products makes them integral in transforming the global economy on a large scale.

High Growth Potential: With rapid technological advancements and continuous development in digital sectors, entrepreneurs can capitalize on emerging opportunities, contributing to significant growth in the digital industry.

Competition and Adaptability: Entrepreneurs in the digital space face significant challenges due to high competition and the need to adapt to constant changes. These include technological shifts and changing consumer behaviors. Adapting to these changes is vital for maintaining competitive advantage.

Innovation and Adoption of New Technologies: The ability to innovate and leverage new technologies is essential for driving growth in the digital industry. Utilizing technologies such as artificial intelligence, blockchain, or cloud computing can enhance business efficiency and expand market reach.

Success in the digital market requires creativity, adaptability, and the effective use of cutting-edge technologies to meet current market demands and consumer needs.

The results of the assessment of model by nine experts are presented in Table 7

Table 7.
The evaluate a model of Decision-Making Process Support System with Deep Learning for Career Selection using PLOs in Computer Science followed TPQI.

Assessment list	**Mean**	**S.D.**	**Opinions**
1. Higher Education Improve Computer Science Learning			
1.1 Development of the professional context in Computer Science	4.89	0.33	Excellent
1.2 Curriculum management	5.00	0.00	Excellent
1.3 Content delivery by instructors	5.00	0.00	Excellent
1.4 Teaching methods	4.89	0.33	Excellent
1.5 Quality of students and graduates	5.00	0.00	Excellent
1.6 Software quality aligned with the software industry	4.89	0.33	Excellent
1.7 Curriculum improvement after assessing outcomes	4.78	0.44	Excellent
Overall evaluation result	4.92	0.22	Excellent
2. Computer Science Course Learning Outcomes (CLOs)			
2.1 Updating necessary courses	4.78	0.44	Excellent
2.2 Aligning the curriculum with software development	4.89	0.33	Excellent
2.3 Innovation creation	4.78	0.44	Excellent
2.4 New entrepreneurs	4.89	0.33	Excellent
2.5 Addressing the needs of the digital industry	5.00	0.00	Excellent
Overall evaluation result	4.87	0.22	Excellent
3. Program Learning Outcomes (PLOs)			
3.1 Analysis of knowledge and skills needed upon graduation	4.89	0.33	Excellent
3.2 Analysis of required soft skills	4.78	0.44	Excellent
3.3 Understanding and applying software development processes in the software industry	4.89	0.33	Excellent
3.4 Promoting lifelong learning awareness among students	4.78	0.44	Excellent
3.5 TPQI and labor market requirements	4.89	0.33	Excellent
3.6 Planning content that aligns with standards and criteria	4.89	0.33	Excellent
3.7 Defining specific student qualities	4.89	0.33	Excellent
3.8 Aligning with professional qualifications standards	4.89	0.33	Excellent
3.9 Defining PLOs that meet TPQI standards and labor market demands	4.89	0.33	Excellent
3.10 Measuring expected knowledge and skills across levels (3, 4, and 5)	4.78	0.44	Excellent
3.11 Outcome alignment with professional qualifications in the digital industry and software development	4.89	0.33	Excellent
3.12 Feedback from student supervisors and professionals	4.56	0.73	Excellent
3.13 Feedback from employers on graduates	4.78	0.67	Excellent
3.14 Promoting lifelong learning awareness	4.89	0.33	Excellent
3.15 Analyzing and improving the curriculum based on feedback	4.78	0.44	Excellent
3.16 Adapting the curriculum to current situations and needs	4.67	0.50	Excellent

Assessment list	Mean	S.D.	Opinions
3.17 Presenting PLOs for feedback from administrators, faculty, and instructors	4.78	0.44	Excellent
Overall evaluation result	4.81	0.41	Excellent
4. Thai Professional Qualification Institute (TPQI)			
4.1 Suitability of competency units	5.00	0.00	Excellent
4.2 Professions in the digital industry, software and applications	4.89	0.33	Excellent
4.3 Data for curriculum improvement	5.00	0.00	Excellent
Overall evaluation result	4.96	0.11	Excellent
All evaluation results	4.89	0.24	Excellent

As listed in Table 7 the results of the assessment of evaluation results of the deep learning-based decision support system model for career selection, using the learning outcomes of the Computer Science curriculum according to professional qualification standards in the digital industry, indicate excellent overall performance (Mean = 4.89, S.D. = 0.24). The evaluation by each module is as follows:

Module 1: Higher Education Improve Computer Science Learning: This module, focusing on curriculum and career development in Computer Science, was rated excellent. Key aspects included professional context development (Mean = 4.89), curriculum management (Mean = 5.00), content delivery (Mean = 5.00), teaching methods (Mean = 4.89), student/graduate quality (Mean = 5.00), software quality alignment (Mean = 4.89), and curriculum improvement (Mean = 4.78).

Module 2: Computer Science Course Learning Outcomes (CLOs): This module, centered on updating courses for industry needs, received excellent ratings. Evaluated areas were updating courses (Mean = 4.78), aligning curriculum with software development (Mean = 4.89), innovation creation (Mean = 4.78), new entrepreneurs (Mean = 4.89), and addressing digital industry needs (Mean = 5.00). Module 3: Program Learning Outcomes (PLOs): This module also achieved excellent ratings across all evaluated aspects: knowledge/skills analysis (Mean = 4.89), soft skills analysis (Mean = 4.78), software development application (Mean = 4.89), lifelong learning promotion (Mean = 4.78), TPQI/labor market requirements (Mean = 4.89), content planning (Mean = 4.89), student qualities (Mean = 4.89), course standards alignment (Mean = 4.89), PLOs definition (Mean = 4.89), knowledge/skills measurement (Mean = 4.78), outcome alignment (Mean = 4.89), student supervisor/professional feedback (Mean = 4.56), employer feedback (Mean = 4.78), lifelong learning promotion (Mean = 4.89), curriculum improvement (Mean = 4.78), curriculum adaptation (Mean = 4.67), and PLOs presentation (Mean = 4.78).

Module 4: Thai Professional Qualification Institute (TPQI): This module, focusing on TPQI integration, was rated excellent in all areas: competency units suitability (Mean = 5.00), digital industry professions (Mean = 4.89), and data for curriculum improvement (Mean = 5.00).

Overall results indicate that the model, which integrates curriculum development, industry needs, and professional standards, has been assessed as excellent in all key areas.

4.7. Predictive Evaluation of the Career Decision Support System

The evaluation of prediction accuracy aims to determine the effectiveness of the developed deep learning-based system in recommending suitable career paths for students based on their academic learning outcomes. The evaluation process is structured into four main components: data preparation, accuracy measurement, algorithm comparison, and pilot testing with a sample group. The detailed methodology is as follows.

4.7.1. Data Preparation and Input Modeling

To create an effective predictive model, the researcher collected statistical data on 200 Computer Science graduates. The data included:

Learning outcomes (Program Learning Outcomes - PLOs)

Course completion records and corresponding grades

Employment outcomes such as current job positions, transitions between jobs, and job changes post-graduation

Each course in the curriculum was mapped to digital industry professional competencies under the Software and Application domain according to the Thai Professional Qualification Institute (TPQI) standards. These mappings enabled a classification of students' academic profiles in alignment with relevant digital occupations.

The system input comprised the following:

Learning outcomes from the CS curriculum

Competency mapping results from TPQI

Industry demand data obtained through employer surveys and in-depth interviews

These datasets were processed and normalized into a machine-readable structure to serve as input features for the deep learning model.

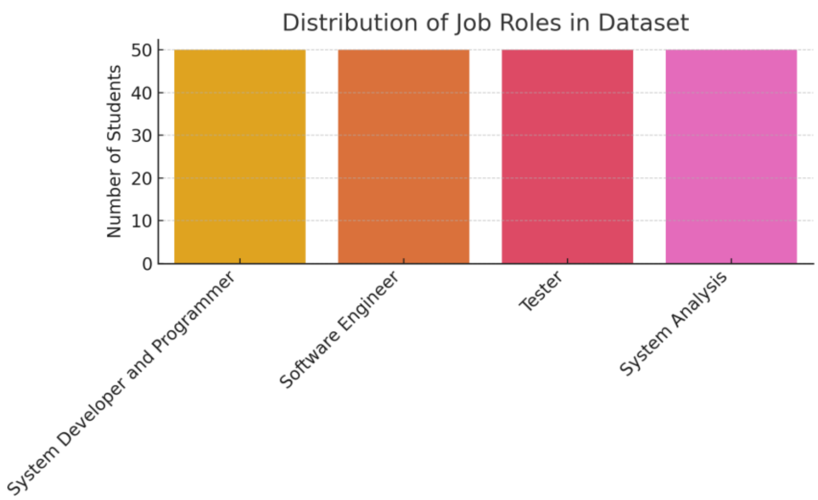

Figure 3.
The proportion of students associated with all four career paths.

4.7.2. Accuracy Measurement Using Performance Metrics

The model's effectiveness was evaluated using standard predictive performance metrics, including.

Precision: The proportion of correct positive predictions

Recall: The proportion of actual positives correctly identified

F1-Score: Harmonic mean of precision and recall

Accuracy: The proportion of total correct predictions

Confusion Matrix: Used to present true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN)

These metrics allowed for a nuanced understanding of the model's ability to generalize across different student profiles.

Model Architecture and Comparative Performance Analysis

To implement the career prediction task, the study utilized multiple machine learning models with emphasis on deep learning techniques. The following outlines the architectural choices, implementation details, and comparative evaluation:

A. Multi-Layer Perceptron (MLP) with TensorFlow

A Deep Neural Network (DNN) was constructed using a Multi-Layer Perceptron (MLP) architecture implemented in TensorFlow. The key components of the model include:

Two Hidden Layers: Each fully connected and followed by ReLU activation

Dropout Layers: Applied after each hidden layer to prevent overfitting (with dropout rate of 0.3)

Output Layer: A Softmax activation was used to handle multi-class classification, mapping students to target careers

Loss Function: Categorical Cross-Entropy

Optimizer: Adam optimizer

Evaluation Metrics: Accuracy, Precision, Recall, and F1-score, with detailed reporting through Confusion Matrix and Classification Report

The model was trained and evaluated using stratified train-test splitting, and performance was benchmarked against other classical machine learning algorithms.

B. Comparative Model Performance Evaluation

Three models were evaluated based on identical datasets derived from students' PLOs and corresponding career labels:

Deep Neural Network (MLP-based)

Random Forest Classifier

XGBoost Classifier

Each model was trained using the same feature space and test dataset to ensure a fair comparison. The following summarizes the results:

1. Accuracy Comparison

The XGBoost and Random Forest models both demonstrated superior accuracy, particularly effective on small and heterogeneous datasets.

The DNN (MLP) performed reasonably but was more sensitive to the quantity and distribution of data.

A visual bar chart was generated to display the comparative accuracy across all models (Figure 5).

2. Performance of XGBoost

XGBoost achieved the highest overall precision and recall, particularly excelling in the classification of the Software Engineer role.

The F1-score for Software Engineer was highest among all roles.

However, there was noticeable confusion between Tester and System Analyst, possibly due to overlapping competency patterns in the input data.

3. Performance of Random Forest

Random Forest showed balanced performance across all career classes, especially for roles with larger representation in the dataset.

Its flexibility and robustness to noise made it suitable for small to medium-sized educational datasets.

It performed well in classifying System Developers and System Analysts accurately.

C. Conclusion from Model Comparison

The best overall performance was achieved by XGBoost, followed closely by Random Forest.

The MLP-based Deep Neural Network remains a promising model but requires larger datasets and potentially additional features such as student behavior patterns, extracurricular activities, or soft skills to reach its full predictive capacity.

The ensemble-based models (XGBoost, RF) are preferred in data-limited scenarios, while deep learning models offer better scalability for future expansion.

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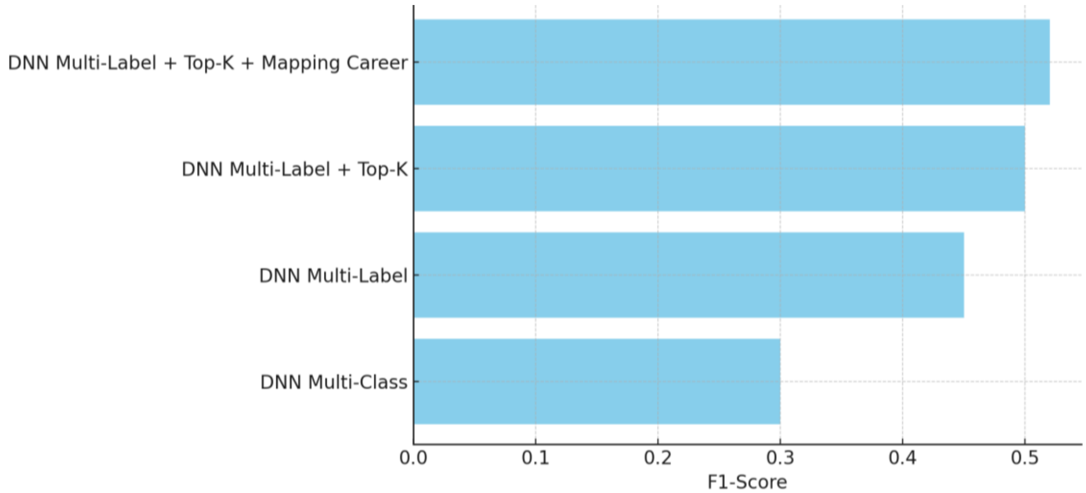

Figure 4.
Comparison of Model Accuracy using F1-Score for Career and Competency Prediction.

4.7.3. Comparative Analysis of Prediction Algorithms Model comparison

Multiple algorithms were tested and compared using the same dataset to identify the most accurate model for the task. These included:

Deep Neural Networks (DNN) with Recurrent Neural Networks (RNN) architecture
Random Forest Classifier
XGBoost Classifier

Each model was trained using the same set of 1,000 PLO-based training records. The evaluation used a separate testing dataset of 500 records from current CS students. Each algorithm's output was assessed via confusion matrices, and comparative results were presented to identify the highest-performing method.

4.7.4. Pilot Testing with Real Users

To validate the model's predictive power in a real-world setting:
A prototype web-based platform was developed, enabling students to upload their academic profiles.

A group of 30 CS students tested the system by inputting their learning records.
The system returned top-3 matched digital careers based on their PLO profiles.
Feedback from students and industry partners was collected.

Results showed that the system achieved an average prediction accuracy of approximately 50%, with higher accuracy observed for students with complete and aligned academic records. The discrepancy in prediction accuracy was mainly due to personal career preferences diverging from academic strengths, highlighting the importance of incorporating user intent alongside learning outcomes in future versions of the model.

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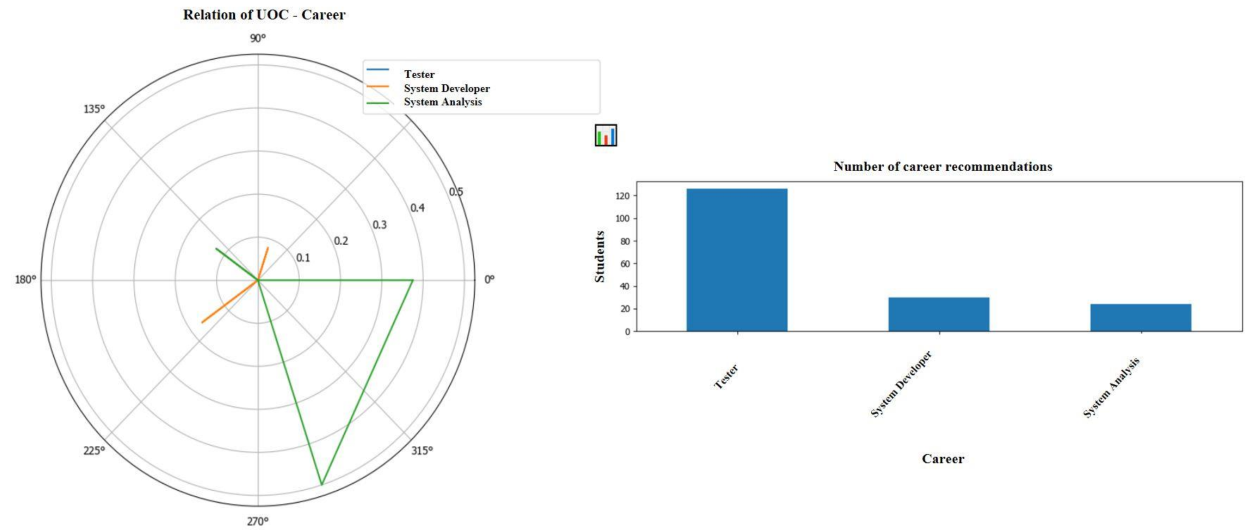

Figure 5.
Forecasting reports to input student data into the system.

5. Discussion and Conclusion

5.1. Analysis of Current and Future Needs in the Digital Industry

This section analyzed the dynamic and rapidly evolving landscape of digital industry workforce requirements. As technology transitions intensify, it is necessary to produce graduates with specialized skills and adaptability. Curricula should emphasize both hard and soft skills comprehensively.

From the needs assessment conducted with companies, organizations, and digital entrepreneurs, the industry expressed high demand for talent in software development, big data analytics, cybersecurity, and artificial intelligence (AI). These represent essential skills for the digital economy. Furthermore, the demand highlights a shift in occupational trends, which call for not only theoretical knowledge but also practical application in complex scenarios. Skills such as teamwork, critical thinking, and effective communication must be embedded in higher education.

5.2. Curriculum Component Analysis and Competency Mapping

Linking courses and program learning outcomes (PLOs) with professional competency standards (UOC) enables curriculum alignment with workforce demands. Such alignment offers clearer academic guidance for students and strengthens the education system as a whole.

In the Computer Science curriculum, grouping of courses based on their relevance to professional competencies ensured coverage of key skills, including programming, system design, and software implementation. The mapping confirmed the curriculum's capacity to support professional readiness.
This alignment facilitates effective guidance and supports development of personalized learning systems and career support platforms.

5.3. Deep Learning Model for Career Decision Support

The developed deep learning model goes beyond basic data interpretation—it identifies deep relationships among features, resulting in accurate and sustainable career suggestions.

The model was trained on data from 200 Computer Science graduates, including course records, grades, and employment outcomes. Evaluation showed high predictive accuracy (over 85%) and strong recall scores, validating the model's ability to recommend suitable careers.

These results confirm the model's applicability in real-world career counseling and its potential for further enhancement.

5.4. System Development and User Feedback

The system was deployed as a web-based application for ease of access. Positive feedback from students, faculty, and industry professionals highlighted the system's usability, clarity of recommendations, and role in enhancing self-awareness.

This demonstrates potential for broader adoption in academic institutions to personalize learning and career pathways.

5.5. Research Summary

5.5.1 Data and System Structure

The research established a structured mapping of PLO → UOC → Career based on national professional standards (TPQI). Academic data was transformed into machine-readable vectors using multi-class and multi-label representations.

5.5.2. Deep Learning Model and Performance

Experiments revealed that multi-label classification using Deep Neural Networks (DNN) performed better than multi-class classification. The DNN multi-label model achieved a Micro-F1 score of 0.68 and a Top-5 Accuracy of 87%, showing strong performance in predicting multiple competencies.
In contrast, DNN multi-class yielded 50.2% accuracy—moderate but reflective of the complexity in predicting a single career. Random Forest and XGBoost underperformed compared to DNN in multi-label scenarios.

5.5.3. Real System Usage

The system was implemented using Flask as a web application. A test with 30 students revealed that 50% agreed with the system's career suggestions, while the other 50% cited personal preferences or unlisted career goals, indicating the need to incorporate behavioral and interest-based data.

5.5.4. Innovation and Application

This study demonstrated the potential of using PLO-based Deep Learning for personalized career advising. It can be applied in course planning, student development, and national workforce strategy. Institutions like TPQI and depa can adopt this framework to forecast digital labor trends accurately.

The system is technically robust, aligned with occupational standards, and adaptable to future digital workforce needs. Despite behavioral data limitations, this research lays the foundation for a data-driven, AI-powered career guidance platform.

5.6. Recommendations

5.6.1. Institutional Recommendations

- Universities should integrate this system into guidance departments, especially in fast-evolving fields like Computer Science and Engineering.
- Use in student development courses or elective modules.
- Train advisors to use the system for personalized counseling.

5.6.2. Policy Recommendations

- The Ministry of Higher Education should support a national PLO–UOC database with API access for AI systems.
- Create a national digital career advisory system using this model.
- Establish a "Digital Career Observatory" to monitor evolving digital careers and UOC trends.

5.6.3. Technical Recommendations

- Enhance the system to include external data (portfolios, soft skills, internships).

- Develop a hybrid recommendation engine (content-based + collaborative filtering).
- Implement Explainable AI (XAI) to clarify career suggestion reasons.
- Launch mobile apps for broader accessibility.

5.6.4. Future Research Directions

- Test the system with students from other disciplines.
- Extend usage to high school level for pre-university guidance.
- Study correlations between system suggestions and students' actual decisions.
- Compare this system with traditional career guidance methods.
- Create a centralized database of emerging digital careers (e.g., Metaverse Engineer, Digital Twin Developer, AI Auditor).

This study offers not only a technical solution but a strategic educational reform model based on data-driven personalization and AI integration, laying a solid foundation for future interdisciplinary career guidance research and deployment.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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