"Mapping Multidisciplinary Subject Combinations to Career Outcomes: A Computational Model Inspired by NEP 2020"

Tanishka Gaikwad[1], Shreya Joshi[1], Krutika Nikumbh[1], Mrs. Ashwini Garkhedkar[2]
[1, 2]MCA Department, PES Modern College of Engineering, Pune, India

***Abstract*— The National Education Policy (NEP) 2020 establishes a transformative framework for Indian education, emphasizing flexibility, interdisciplinarity, and holistic learning. However, students often face difficulty linking multidisciplinary subject selections to meaningful career outcomes. This paper presents a computational model that maps multidisciplinary subject combinations to potential career trajectories, aligning with NEP 2020's learner-centric vision. The proposed framework integrates artificial intelligence (AI) reasoning and natural language processing (NLP) techniques, including TF- IDF and cosine similarity, to analyze student inputs—subjects, IQ, EQ, and aptitude—and recommend career domains consistent with NEP guidelines. The model is implemented using Fast API, MongoDB, and React, enabling real-time processing, subject mapping, and result visualization. Experimental evaluation demonstrates that computational reasoning can effectively operationalize NEP's multidisciplinary philosophy, improving policy-aligned career guidance for secondary-level learners.**

***Keywords*— NEP 2020, multidisciplinary education, educational computing, AI reasoning, NLP similarity, decision- support systems, career guidance.**

I. INTRODUCTION

The National Education Policy (NEP) 2020 aims to create a learning environment that encourages thinking, adaptability, and learning across different subjects. By not dividing subjects too strictly, like science, commerce, and arts, it lets students pick a mix of subjects that match their interests and goals.

Even with these changes, students still find it hard to see how their subject choices lead to jobs. Traditional guidance systems are based on fixed groups, which don't fit well with NEP's structure. There is a gap in having a system that connects flexible learning with real-world job opportunities.
This research introduces a model called "Mapping Multidisciplinary Subject Combinations to Career Outcomes," which turns NEP's idea of flexible learning into a system that gives real results. The model uses AI and natural language processing to give personalized career suggestions to students. This shows how technology can help make NEP's vision into practical tools for students.

A. Problem Statement

Even though NEP 2020 supports learning across subjects, there is no system that uses technology to connect different subject choices with possible jobs. Existing systems either stick to old subject groups or use fixed tests, which aren't flexible enough for NEP's approach.

This research aims to create a smart model that:
1) Understands what subjects a student likes and what they are good at
2) Uses AI and natural language processing to find links between subjects and jobs
3) Gives students ranked career suggestions that match NEP 2020's goals.

This model turns NEP 2020's idea of flexibility into a digital tool that helps students make informed choices about their future after completing 10th grade.

II. LITERATURE REVIEW

Educational guidance has moved from traditional counselling to intelligent systems that use data and computation to help students make decisions.

Sharma et al. (2021) created a framework for career guidance using natural language processing. They used TF-IDF vectorization and cosine similarity to understand the connection between student interests and career options. Their work showed how text-based techniques can improve recommendations and how AI can improve the quality of guidance by looking at language patterns.

Verma et al. (2023) and Patel and Mehta (2023) explored machine learning methods to predict career outcomes based on academic performance and behavior data. They used models like Decision Trees, KNN, and Naive Bayes to classify students into suitable career paths. Their findings showed that machine learning systems are better than static methods because they can learn from patterns. This suggests that data-driven systems have a lot of potential for future educational guidance.

Joshi and Gupta (2020) developed a rule-based system for academic counseling. This system used predefined logic rules to match student inputs to subjects and streams. Their study highlighted the importance of clear reasoning, interpretation, and structured decision paths in education. However, their system was limited by fixed subject categories and didn't support the flexible, multidisciplinary approach encouraged by recent policies.

Saxena and Tripathi (2021) studied expert systems for career matching. They found that traditional rule-based systems are restricted to fixed academic categories and have little flexibility for students studying interdisciplinary subjects. Similarly, the NCERT My Career Advisor Portal uses basic psychometric tests but lacks AI-driven adaptability and integration with multidisciplinary subject clusters.

Kumar et al. (2022) looked at how AI can support the National Education Policy (NEP) 2020.They discussed the importance of AI-enabled personalization, adaptive assessments, and flexible academic paths to match the policy's goals of holistic and interdisciplinary learning. They also pointed out gaps, like a lack of intelligent tools for subject selection and insufficient computational systems to operate the policy at school levels.

Reddy and Banerjee (2021) focused on cognitive analytics, emphasizing how aptitude, interest, and behaviour traits—such as IQ and EQ—can help generate accurate and personalized guidance. Their work supports the use of structured assessments in modern guidance systems to improve reliability.

Deshmukh et al. (2022) proposed a hybrid model that combines rule-based logic with machine learning. Their research suggested that purely deterministic systems might not be enough without adaptive learning components, especially for diverse student profiles.

Rao and Mishra (2021) explored integrating AI-driven recommendation engines into school-level platforms. Their model used interest, skill, and behaviour analysis to create personalized learning paths for students. While the system improved personalization, it didn't include NEP-specific features like interdisciplinary subject recommendations.

Banerjee et al. (2022) presented a competency-based student profiling system aligned with modern educational reforms. The system mapped skills like problem-solving, verbal reasoning, and emotional stability to career categories. However, it relied heavily on human evaluation and lacked computational automation, limiting its adaptability and scalability.

Chatterjee and Kulkarni (2023) studied using AI-enabled knowledge graphs to link subjects with career paths. Their system tried to build relationships between subjects, skills, and career outcomes. While promising, the authors noted that the system didn't consider NEP-oriented subject clusters or psychometric assessments like IQ and EQ.

Singh and Rao (2022) developed a predictive model using regression and clustering to categorize students into Science, Commerce, Humanities, or Vocational streams. While effective for traditional systems, it didn't support NEP's interdisciplinary flexibility, which allows students to choose subject combinations across domains.

Ahmed and Kapoor (2024) proposed an AI-based guidance platform that combined machine learning and natural language processing to interpret student data and recommend suitable academic paths. The system included behavioural scoring and adaptability but followed traditional stream-based structures instead of NEP's flexible, multidisciplinary approach.

From the literature, it's clear that while a lot of research has been done on AI-driven educational guidance, very few systems operationalize the interdisciplinary structure of NEP 2020 or combine subject combinations, aptitude measures, and emotional intelligence into a single model. Most existing systems are either machine learning-based prediction models or static rule-based frameworks with limited emphasis on policy-linked reasoning.

The proposed NEP-Based Career Recommendation System addresses this by integrating NEP-approved subject clusters, rule-based mapping, AI-assisted assessments, and a scalable architecture that can adapt to future machine learning improvements. This system is a practical, policy-aware, and intelligent solution to improve career guidance in the context of NEP 2020.

III. SYSTEM ARCHITECTURE

The proposed Rule-Based NEP Career Recommendation System is designed as a modular, multi-layered framework that combines educational assessment with computational reasoning. The architecture supports personalization, scalability, and alignment with the National Education Policy (NEP) 2020, enabling students to explore multidisciplinary pathways based on their skills, interests, and assessments.

A. Overall Design

The architecture includes four main layers, each handling specific functions:

1) ***Presentation Layer***:

This is the system's user interface and handles all student interactions:

a) Built using React.js and Tailwind CSS for a responsive and accessible design.

b) Provides modules for:

- User registration and login
- Subject and interest input
- IQ, EQ, and aptitude assessments
- Displays the final career recommendation dashboard with graphs, scores, and explanations.

2) ***Application Layer***:

This layer connects the front-end and back-end parts of the system:

a) Developed using FastAPI (Python) to manage API routing, input validation, and user sessions.

b) Receives and processes user data before sending it to the reasoning engine.

c) Ensures smooth integration with the database and external visualization tools.

3) ***Reasoning Engine (Core Logic Module):***

The reasoning engine is the part of the system that makes smart decisions:

a) It uses a rule-based model with "if-then" rules based on relationships between subjects and careers as per NEP guidelines.

b) It combines different types of assessments like IQ, EQ, Aptitude, and interest in subjects to suggest personalized career options.

c) It uses TF-IDF vectorization and cosine similarity to better understand how similar subjects, keywords, and career descriptions are.

d) It creates a list of career paths in order of relevance and adds tags to explain the reasoning, making the process clear and easy to understand.

4) Database Layer:

The database layer handles storing and getting data in a structured or semi-structured way:

a) Implemented using MongoDB, enabling schema flexibility and horizontal scalability.

b) Key collections include:

- *Student Profiles – personal details, test scores, and preferences*
- *Subject Pools – NEP-aligned subject clusters and domain keywordsCareer*
- *Knowledge Base – career descriptions, rules, and mappings*
- *Recommendation History – logs of generated results for analytics and improvement*

c) Supports high scalability for institutional or large-scale deployment.

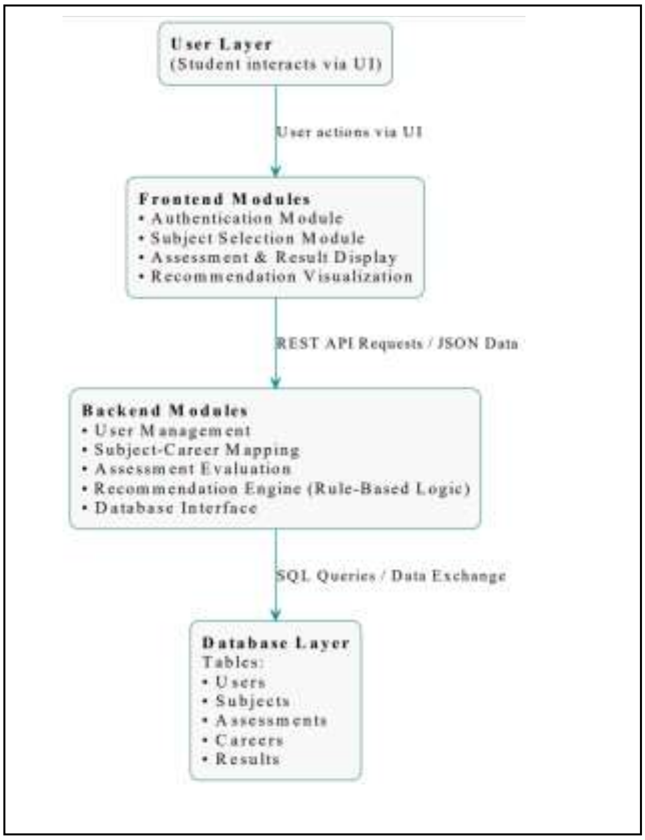

Fig. 1. System Architecture

IV. WORKING OF SYSTEM

The NEP-Based Career Recommendation System follows a structured workflow that integrates subject selection rules, cognitive and emotional assessments, similarity analysis, and rule-based reasoning. The system ensures compliance with NEP 2020's multidisciplinary subject framework while generating personalized career recommendations for students.

A. Subject Input and Selection Rules

Students begin by selecting 4 or 5 subjects, following NEP 2020's multidisciplinary structure. Subjects must be chosen across the following four groups:

1) Group 1 – Languages (Compulsory): English, Hindi, Sanskrit, French, Marathi, etc. Students may select 1, 2, or 3 languages.

2) Group 2 – Mathematics & Science: Physics, Chemistry, Biology, Mathematics, Computer Science, Artificial Intelligence, Environmental Science, etc.

3) Group 3 – Humanities & Social Sciences: History, Geography, Psychology, Economics, Political Science, Sociology, etc.

4) Group 4 – Arts, Vocational & Interdisciplinary: Fine Arts, Design, Music, Performing Arts, Coding, Robotics, Media Studies, etc.

The system ensures:

1) Minimum one subject from Group 1.

2) Remaining subjects can be multidisciplinary (any of Groups 2, 3, or 4).

B. Adaptive Assessment Generation

Based on selected subjects, the system automatically generates an aptitude test:

1) If 4 subjects selected → 5 questions per subject

2) If 5 subjects selected → 4 questions per subject

Additionally, every student attempts:

1) 8 IQ questions

2) 8 EQ questions

This creates a personalized assessment aligning with the student's academic choices.

C. Rule-Based Reasoning Engine

The core logic uses NEP-aligned rule-based mappings with "if–then" inference patterns:

1) If (Physics + Math) and High IQ → Engineering, Data Analytics

2) If (Biology + High EQ) → Healthcare, Nursing, Counseling

3) If (Psychology + EQ High) → Behavioral Science, Human Services

4) If (Commerce/Economics + High Aptitude) → Finance, Business, Management

5) If (Arts + High EQ) → Design, Journalism, Creative Media

6) If (Computer Science/AI + High IQ) → Software Development, AI Technician

These rules ensure deterministic and interpretable recommendations.

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D. *Subject–Career Similarity Using TF-IDF*

The system uses a method called TF-IDF to convert subjects into numerical values and then uses cosine similarity to compare a student's chosen subjects with career options.

This allows for a better match according to NEP 2020, such as:

1) Arts + Technology → UX/UI Design
2) Economics + AI → Financial Analytics
3) Psychology + Computer Science → Cognitive Science

By mixing rules with AI-based similarity, the system becomes smarter and more adaptable.

E. *Calculation of Fitness Score*

Each career option is given a final score using this formula:

$$\textit{Fitness Score} = 0.6 \times \textit{Subject Fitness} + 0.2 \times IQ + 0.2 \times EQ$$

Where:

1) Subject Fitness comes from both rules and similarity analysis.
2) IQ represents the student's logical thinking ability.
3) EQ represents how well the student fits the emotional needs of a career.

This formula helps make the recommendations more balanced and accurate.

F. *Career Prediction and Final Output*

After considering all the inputs, assessments, and rules, the system gives the final results:

1) Top Three Career Options - The system shows the top three career areas, ranked by their fitness score.
2) Frontend Displays:
   a) Final scores for IQ, EQ, Aptitude, and Subject Fit.
   b) Top three career recommendations.
   c) Visual charts like bar and pie graphs for better understanding.

V. SYSTEM SCREENS AND FUNCTIONAL MODULES

This part describes the main screens of the NEP-Based Career Recommendation System.
Each screen is designed for easy use by students, counselors, and administrators.

A. *Student Registration and Login*

1) Lets students create an account using email and password.
2) Uses FastAPI and JWT tokens for secure login.
3) Has options for logging in and signing up.
4) Provides safe access to tests and results.

Fig. 2. Student Sign-In Interface

Fig. 3. User Login Interface

If the user is new, then they can create an account. After creating an account, the user is prompted to lodin using their credentials.

B. *Dashboard*

Shows main menu options: Select Subjects, Take Test, View Result, Profile.

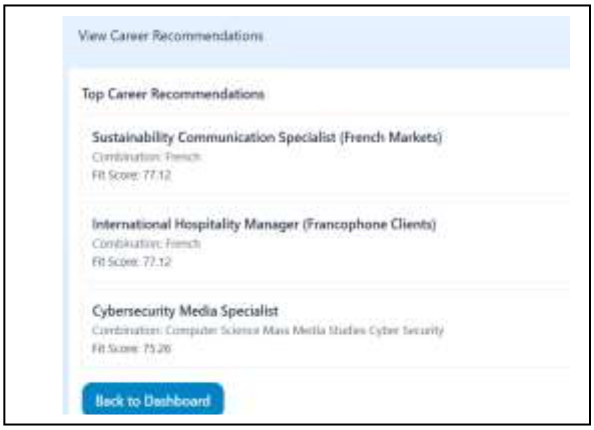
Fig. 4. User Dashboard

C. *Subject Selection*

Students select 4 or 5 subjects across four NEP-compliant groups:

1) Group 1: Languages (Compulsory)
2) Group 2: Maths & Science
3) Group 3: Humanities & Social Science
4) Group 4: Arts & Vocational

The interface validates:



1) *Minimum 1 language*
2) *Max 5 subjects*
3) *Subjects must be chosen from permitted multidisciplinary combinations*

Fig. 5. Subject Selection Interface

D. Assessment Module

1) *The assessment engine loads questions based on the selected*
2) *subjects.*
3) *The test structure includes:*
   a) *4 subjects → 5 questions each*
   b) *5 subjects → 4 questions each*
   c) *Includes 8 IQ questions and 8 EQ questions.*
4) *Has a timer and navigation tools.*

Fig. 6. Assessment Interface

E. Result & Recommendation

Fitness Score Breakdown:

1) *Subject Fitness contribution*
2) *IQ Score contribution*
3) *EQ Score contribution*
4) *Final weighted score*

Visualization Graphs:

1) *Bar graphs showing marks*
2) *Pie charts showing total percentage*

Fig. 7. Assessment Result

Displays the final career guidance including: Top Three Career Domains-Ranked by their fitness score.

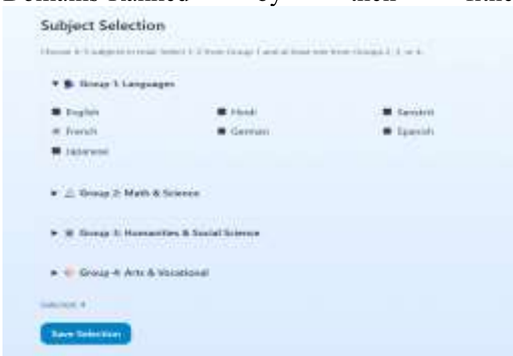


Fig. 8. View Career Recommendations

VI. APPLICATIONS

A. NEP 2020 Subject Choice Guidance

The system helps students pick a variety of subjects across different areas, as planned in the NEP 2020, so they don't have to stick to traditional groups like Science, Commerce, or Arts.

B. Student Self-Assessment Platform

It gives a detailed look at a student's IQ, emotional intelligence, talents, and interests.This helps them understand their strengths early and make better choices about their education.

C. Educational Institutions' Stream Allocation System

Assists schools in allocating suitable XI–XII subjects based on the student's assessment fitness score, not only marks.

D. Ed-Tech Career Guidance Integration

Can be embedded in learning apps or portals to recommend courses, skill paths, and study plans aligned with chosen subjects.

E. Rural and Underserved Student Support

Provides accessible, structured counseling for students lacking professional advisors, especially in remote regions.

F. Parent Awareness and Decision-Support Tool

Helps parents understand their child's strengths and recommends suitable academic paths, reducing pressure-driven choices.

G. Institutional Data Analytics for Planning

Helps schools analyze trends in student interests, aptitude strengths, and subject popularity for better academic resource planning.

VII. ADVANTAGES

A. *NEP 2020-aligned career gudance.*

The system follows the NEP 2020 structure, letting students choose subjects from different areas and get advice that fits new educational changes.

B. *Personalized and Data-Driven Suggestions.*

It uses a student's IQ, emotional intelligence, talents, and interests to offer specific guidance, not one-size-fits-all advice.

C. *Encourages Multidisciplinary Learning.*

The system recommends careers that combine different fields, like Science and Arts or Commerce and Technology, as encouraged by NEP 2020.

D. *Real-Time Career Predictions.*

It instantly analyzes student input, helping make quick decisions during counseling or school assessments.

E. *Fair and Bias-Free Support.*

The system uses rules and TF-IDF similarity to avoid human biases and gives consistent help to all students.

F. *Clear Recommendation Process.*

The system shows reasons why a career is suggested, like subject fit or talent match, making the process more trustworthy and easier to understand.

G. *Scalable and Flexible Design.*

Built with Fast API, React, and MongoDB, the system can handle more users, include machine learning models, and easily expand the number of subjects and career options.

H. *Useful for Schools Without Counselors.*

This tool helps schools in rural or less developed areas where trained counselors may not be available.

VIII. LIMITATIONS

A. *Rule-Based and Not Adaptive.*

The system uses fixed rules and TF-IDF similarity, so it cannot improve or learn without manual updates.

B. *Limited Assessment Coverage.*

IQ, emotional intelligence, talent, and subject-based tests are fixed and may not capture all student abilities or educational differences in different regions.

C. *Subject Flexibility is Limited*

Students can only choose up to 4-5 subjects from pre-set groups, which doesn't fully reflect the flexibility provided by NEP 2020.

D. *Career Database is Limited*

Only a fixed number of NEP-aligned careers are included, so new or specialized careers may not be available unless updated.

E. *Relies on Accurate Inputs*

Incorrect or random student answers can lead to wrong recommendations, affecting how reliable the system is.

IX. CONCLUSION

The NEP-Based Career Recommendation System offers a clear, data-driven way to guide students in choosing subjects and finding suitable career paths aligned with NEP 2020.

By combining subject-interest analysis, IQ and emotional intelligence tests, rule-based reasoning, and TF-IDF similarity matching, the system gives personalized and transparent recommendations. This system supports multidisciplinary learning and is accessible, scalable, and useful for schools, counsellors, parents, and students, especially in places without expert guidance. Although it currently uses fixed rules and a limited career database, it sets up a good foundation for future use of machine learning, adaptive assessments, and more career options. Overall, this system is a big step towards modern, inclusive, and policy-based career guidance, helping students make better educational choices and prepare for various future opportunities as planned by NEP 2020.

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