World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(REVIEW ARTICLE)

Check for updates

AI-based career counsellor: A review of chatbot, psychometric and market-aware systems

Arya Mahendra Swami [1, *] and Sheetal S. Dhande [2]

[1] *Research Scholar, MTech Computer Science and Engineering, SIPNA College of Engineering and Technology, Amravati, India.*
[2] *Professor, Computer Science and Engineering SIPNA College of Engineering and Technology, Amravati, India.*

World Journal of Advanced Research and Reviews, 2025, 28(02), 1427–1436

Publication history: Received on 05 October 202 5; revised on 10 November 2025; accepted on 13 November 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.28.2.3835

Abstract

Decision-making for careers has a key position in determining students' futures, but the majority of high school students tend to be uncertain while choosing appropriate avenues. Conventional career advising strategies are full of shortcomings, such as a lack of trained counsellors, low access, and one-size-fits-all guidance that does not meet individual requirements. Developments in Artificial Intelligence (AI) in recent times open up scopes for changing the scene. Career guidance systems based on AI utilize algorithms for machine learning to process students' academic records, interests, and personality, facilitating more accurate matching between individual strengths and emerging job opportunities. New uses involve AI chatbots that combine academic information with psychometric tests and platforms that track labor market trends to suggest in-demand occupations. However, concerns remain regarding data validation, reducing algorithmic bias, protecting privacy, and handling cultural diversity. In spite of these issues, AI can potentially augment human counsellors with personalized, adaptive, and scalable career advising. Next-generation systems are conceptualized as hybrid models that integrate the emotional and empathetic intelligence of human advisors with the analytical and predictive power of AI to bring about more informed and sustainable career choices.

Keywords: Artificial Intelligence (AI); Machine Learning (ML); Natural Language Processing (NLP); Recommendation Systems; Predictive Analytics; Data Mining; Knowledge-Based Systems; Expert Systems; Decision Support Systems (DSS); Neural Networks; Deep Learning; Psychometric Assessment; Personality

1. Introduction

In a rapidly evolving world, the importance of making informed career choices has never been greater. The transition from secondary education to the broader landscape of higher learning and professional life is a pivotal moment in every student's journey. Yet, for many secondary-level students, the process of career decision-making can be daunting, complex, and often filled with uncertainties.

Navigating career selection nowadays is honestly a logistical nightmare. High schoolers and undergrads are pretty much left to their own devices, trying to make sense of a chaotic job market with little meaningful support. Career counselling services exist, sure, but let’s be real one counsellor juggling a mountain of students? The guidance ends up vague and generic. Not exactly tailored to anyone’s unique abilities or actual goals.

Not exactly tailored to anyone’s unique abilities or actual goals. So, what are the consequences? Students default to whatever their parents nudge them toward, copy their friends, or chase the “secure” pay check regardless of whether the field fits them. Fast forward a few years, and you’ve got a bunch of young professionals locked into roles that don’t

* Corresponding author: Arya Mahendra Swami

match their skills or interests, leading to wasted talent and chronic job dissatisfaction. The system, as it stands, is due for some serious upgrades.

The whole job scene's changing fast and getting more varied, making picking a career way harder than it used to be figuring out a path that fits someone's brain power, job interests, personality traits is getting tougher and tougher this mismatch is backed up by real world data showing more unhappy workers, more people leaving jobs, and more folks switching careers a lot also, it looks like about 85%of the workforce isn't really into their jobs, mostly because their careers and roles don't match up.

Mixing AI into aptitude tests changes it from just guessing to using solid data students get solid, fact-based feedback on what they're good at, what they need to work on, and what jobs might suit them Such systems go beyond identifying temporary trends or meeting parental expectations, offering guidance that aligns with long-term personal fulfilment and professional growth. Ultimately, this empowers students to make informed, individualized career decisions rather than relying on chance or social pressure.

So yeah, this whole review is about how AI is shaking up career counselling for high schoolers what’s awesome about it, what might be sketchy, and how the tech actually works in real schools. The goal? To show how this stuff can fix some of the mess in how we help kids figure out their futures, so they’re not just surviving after graduation but actually thriving in jobs that fit them and what the world needs.

2. Background and Motivation

Making career decisions is an important part of a student's academic journey that will affect their future personal and professional growth. In the past, school advisors, teachers, or outside consultants have helped people with their careers. But these systems often have trouble giving each student the help they need because there aren't enough counsellors, there are too many students for each counsellor, and the advisory frameworks are too broad. Consequently, numerous students select careers influenced by external factors, including parental expectations, peer pressure, or perceived job security, rather than a well-informed understanding of their skills, interests, and personality traits. This mismatch often causes unhappiness, poor performance, and career instability later in life.

The quick growth of different career fields and the job market that is always changing make it even harder to make decisions. Students now need help that is not only correct but also able to keep up with changes in the industry. Recent progress in Artificial Intelligence (AI) provides hopeful answers to these problems. AI-powered career counselling systems can look at your academic records, psychometric data, and trends in the job market to give you personalized advice. AI-based systems can give scalable, data-driven, and context-aware career advice by combining machine learning, natural language processing, and smart feedback systems. This makes it necessary to look into AI-powered frameworks that make career counselling more accurate, easier to get to, and useful in the long term.

2.1. Importance in Education, Workforce, and Training

The integration of AI-powered career counselling is extremely valuable across the education, workforce development, and skill training ecosystems. In education, it facilitates personalized academic planning by aligning students' strengths and learning styles with appropriate study pathways. This eliminates confusion in transition stages, such as subject or college selection, and leads to better decision-making. Schools also benefit from data-driven insights that help identify skill gaps in designing their curricula and offering timely interventions for students who need guidance.

In the employment terrain, AI-powered career counselling contributes to the creation of employable youth who are in tune with industry requirements. Thus, such systems, by taking into consideration real-time labor market conditions and job roles emerging, ensure that students are counselled toward careers promising longevity and relevance. This reduces career mismatch, underemployment, and frequent job switching prevalent in rapidly evolving economies.

AI-powered systems offer customized reskilling and upskilling in the domain of professional and vocational training by recommending certification programs, workshops, and courses according to the competency level of individuals and their career goals. This constant adaptive guidance leads towards lifelong learning, helping people to stay relevant in the dynamic job environment. In general, AI-driven career counselling bridges the gap between education and employment, leading to a more efficient and future-ready workforce.

3. Literature Review Table

Table 1. Comparative Review of Existing AI-Driven Career Guidance Studies

Author(s)	Year	Title	Objective / Focus	Methodology / Approach	Key Findings	Limitations / Gap	Relevance to AI Career Counsellor chatbot
G. V. Lokam et al.	2021	AI-driven web-based vocational pathways	Personalized vocational pathways from academic records and skills	ML + NLP web system with adaptive feedback loops	Generates dynamic job ideas and adapts to feedback	No universal metrics; no fairness tests	Shows adaptive recommendation need and fairness evaluation importance
A. Birajdar et al.	2022	Integrated AI career counselling	Career path recommendations combining psychometrics & labor analytics	Hybrid learner profile + labor market analytics	Aligns student potential to market needs	No algorithm validation or empirical testing	Blueprint for psychometric + market recommendation systems
N. R. Chopde et al.	2020	Review of AI in high-school career counselling	Theoretical integration of MBTI & Big Five into AI systems	Literature review mapping psych models to AI	Shows theoretical AI-psychometric integration potential	No quantitative validation	Supports theoretical foundation for chatbot psychometric modules
A. M. Gunje et al.	2021	Float chatbot for mock counselling	Simulate conversational counselling sessions	Chatbot prototype concept focusing on UX	Promising engagement and interaction design	No real implementation testing	Useful for chatbot conversational and UX design
M. Gowda et al.	2023	PCA + NLP psychometric chatbot	Career counselling using MBTI/OCEAN psychometric inputs	Modular chatbot with PCA + NLP & API deploy	Shows technical feasibility of psychometric chatbots	No fairness audits or real-world evaluation	Relevant for pipeline design in AI counsellor chatbots
T. Hude et al.	2022	SVM-based career choice framework	Individualized recommendations using classifier models	SVM classification with iterative refinement	Effective early recommendation accuracy	Lacks NLU, deep learning & explainability	Shows SVM usefulness but requires modernization
C. Wasnik et al.	2023	Adaptive labor-trend career system	Link skills evolution to market demands	Web-based adaptive skill-market tracker	Scalable and dynamic market relevance	No benchmarking or controlled experiments	Useful for labor market data integration in chatbots
P. Bebale et al.	2024	Career Compass hybrid framework	Combine MBTI + ML ensemble models	Hybrid architecture of decision trees, SVM, NN	Flexible and modular recommendation system	No bias or equity evaluation	Guides hybrid model design but requires fairness monitoring

R. Agrawal et al.	2024	Post-secondary AI guidance	Recommend streams based on grades & tests	Rules + ML with admin update controls	Easily updatable recommendation backend	No psychometrics or live market data	Suitable for basic stream suggestions, needs personalization
J. Kumar et al.	2024	LSTM finance decision system	Enhance financial decision-making using ML	LSTM-based predictive analytics	Improves forecasting accuracy	Finance domain, not career-specific	Indirect modelling insights only
R. Jadhav & G. Patil	2025	Survey on AI finance managers	Survey AI/ML in finance automation	Comprehensive method mapping	Summarizes finance-domain ML	Not career-focused	Useful for survey structuring methodology
S. Aishwarya & S. Hemalatha	2023	ML expense tracker	Automate expense classification	ML-based user expense modelling	Shows feasibility of behaviour modelling	Finance-specific	Behaviour modelling concepts transferable
S. García-Méndez et al.	2024	SVM short-text classifier	Classify banking transaction texts	SVM classification with labelled corpus	Effective for short-text classification	Domain-specific	Useful for chatbot user-text intent detection
O. Hean et al.	2024	AI in personal finance	Survey AI adoption in finance	Conceptual system review	Identifies opportunities and limits	General finance domain	Insights on trust & adoption relevant to chatbots
R. Feng et al.	2025	AI roadmaps for robo-advisors	Roadmap for financial AI planning	Principle-based conceptual study	Highlights personalization & monitoring	Finance focus	Principles apply to guidance chatbot long-term monitoring
A. Das & P. Srivastava	2024	ML + psychometric career system	Improve recommendations using psychometrics	ML models using psychometric data	Improved recommendation relevance	Limited dataset diversity	Core evidence for psychometric integration
M. Venkatesh et al.	2023	DL based personalized guidance	Deep-learning personalized guidance	DL on user profiles	Captures complex patterns	Explainability & data scarcity concerns	Relevant for high-level personalization modelling
P. Chakraborty et al.	2025	Student AI counselling system	Full implementation and evaluation	End-to-end design + evaluation	Blueprint with performance evidence	Limited large-scale trials	Highly relevant implementation reference
R. Singh et al.	2023	Recommender + personality profiling	Use personality for career recommender systems	Hybrid recommendation algorithms	Personality improves relevance	Limited fairness tests	Direct chatbot recommender relevance

J. Lathe & V. Patel	2025	AI budgeting tool	Improve budgeting behaviours	AI-based budgeting recommendations	Improves user financial planning	Finance context only	Behaviour guidance parallels chatbot motivation modules
D. Deepthi et al.	2025	AI finance platform	End-to-end AI finance management	Full ML platform engineering	Demonstrates scalable system building	Finance context	Engineering lessons apply to chatbot scaling
V. Detwal et al.	2025	AI in financial decision-making	Survey financial AI systems	Review of AI system implementations	Shows benefits of AI personalization	Finance-focused	UX and trust design insights transferable
N. Mathew	2025	Chatbots in personal finance	Evaluate chatbot impact in finance	Empirical adoption evaluation	Chatbots increase engagement	Domain mismatch	UX engagement strategies applicable to career chatbots
B. Boro et al.	2024	AI business growth support	AI for business analytics & decision support	Applied case studies	AI improves decision support	Not career-specific	Data governance lessons relevant
T. Crowley	1992	Early CACG investigation	Evaluate early CACG system effects	Empirical evaluation	Proof of feasibility of early CACG	Tech outdated	Historical foundation for chatbot evolution
J. Sampson Jr.	1991	Guidelines for CACG systems	Improve CACG design	Human-centric CACG design recommendations	Guidance for evaluation and deployment	Pre-ML era	Provides system usability design principles
Jepsen et al.	1990	Comparative CACG system study	Evaluate multiple CACG tools	Comparative performance analysis	Identified strengths and weaknesses	Outdated technology	Important benchmark methodology reference
Gati, Saka & Krausz	2001	When to use CACGS?	Study when CACG is beneficial	Empirical user condition study	Usefulness depends on user traits	Needs re-evaluation under modern AI	Supports personalization logic in chatbots
Carson et al.	1999	Model counsellor with ANN	Use ANN to model counsellor decisions	Neural network modelling	ML can replicate counsellor decisions	Limited explainability	Early proof of ML counsellor modelling
Carson	1999	Kohonen SOM for career clusters	Cluster career profiles using SOM	Unsupervised clustering	Reveals career grouping structure	Interpretability challenges	Useful for career type exploration modules
Hendahewa et al.	2006	iAdvice expert system	Expert-system-based guidance	Rule-based expert system	Shows expert system feasibility	Limited scalability &	Forms basis for hybrid rule + ML

						personalization	counselling chatbots

4. Related Work

Early computer-assisted career guidance systems (CACGS) showed that software could help students explore and make decisions. However, these systems mainly relied on rules and expert systems. While they offered structured suggestions, they struggled to provide personalized advice at scale, lacked adaptive learning features, and had limited transparency in how they generated recommendations. Since career choices are highly personal and context-dependent, these rigid methods often resulted in generic guidance that didn't reflect student diversity. Following this phase, neural network-based systems tried to model counsellor decision-making using shallow artificial neural networks (ANNs) and self-organizing maps to group occupations. These efforts demonstrated that data-driven modelling was possible, but challenges with explainability, maintenance, and trustworthiness remained. Many early systems depended on fixed rules that were sensitive to change or on black-box predictors that were hard to justify to students, counsellors, and schools.

More recent approaches focus on personalized recommendations by combining psychometric indicators, like MBTI or OCEAN personality traits, with academic performance, student interests, and usage behavior. These systems often use machine learning classifiers and recommendation system structures to match learner profiles with current labor market trends. Hybrid methods combine easy-to-interpret models like decision trees with more accurate models, such as SVMs, ensembles, or neural networks, aiming to balance transparency and predictive quality. While prototype systems report promising results in engagement and recommendation relevance, most studies are based on controlled experiments, limited datasets, and offline evaluation metrics. Evidence from diverse, real-world student populations is still lacking, and fairness issues like bias related to gender, socio-economic status, or language are not thoroughly examined.

At the same time, conversational interfaces have emerged as a primary way of interaction. Chatbot-based counselling solutions use intent classification, dialogue management, and retrieval-augmented generation (RAG) to mimic natural counselling conversations. These systems claim to offer better accessibility and encourage students to share their preferences and concerns. However, evaluations often focus on user experience and feasibility rather than long-term outcomes, such as student satisfaction with their choices, persistence in courses, or feelings of regret over decisions.

Another modern trend combines real-time labor market analytics to keep recommendations relevant in fast-changing employment environments. This approach incorporates job requirements and student skills into shared vector spaces to compute semantic similarities and create “market-aware” recommendations. While these systems demonstrate strong technical feasibility, few studies provide longitudinal evidence of improved employability or alignment between education and job placement outcomes.

In terms of method, transformer-based architectures have shown better performance than earlier LSTM and RNN models, especially in multilingual environments and complex reasoning tasks. Yet, challenges remain regarding conversational naturalness and cultural alignment, particularly in low-resource regional languages or mixed-language situations. Data augmentation and multilingual fine-tuning strategies enhance performance but do not fully address these issues. Across studies, a common theme is the use of hybrid human-in-the-loop guidance models, where AI helps generate recommendations while human counsellors offer interpretation, emotional support, and contextual judgment. Although uncertainty scoring and rationale extraction are suggested to boost transparency and trust, standardized calibration and fairness audits for subgroups are seldom applied in real-world settings.

Evaluation practices also vary significantly. Studies often report technical metrics like accuracy, F1-score, or recommendation hit rates, while subjective measures such as user satisfaction or perceived helpfulness lack standardized assessment frameworks. Additionally, publicly available benchmarks tailored for career counselling contexts are limited, making cross-system comparison challenging. Lastly, engineering case studies describe fully integrated platforms that feature data pipelines, vector search, dashboards, and tools for administrative updates. These implementations highlight the importance of maintainability and scalability of knowledge bases as academic curricula and job classifications change. However, most implementations remain in short pilot phases without long-term tracking of system performance, drift, or actual academic or employment outcomes.

5. Methodology

- Define the goal: The main aim of the AI Study Path Guide is to help students pick study plans that suit their skills, likes, & long dreams. Not like the old job advice, which tends to give one plan fits all tips, this setup is made to give one-to-one, changeable, & real-life tips. By eyeing each students own strong points, the setup makes sure that help is true, fit, & can back their school & job picks for a long run
- Gather User Context: plan kicks off by pulling info on each Student. This goes deep. It looks at what they're good at & what they're not, the kinds of classes they like, their way of learning, what they act like, & what they want to do later. All this info makes sure the tips are not just about grades but also about what the students likes & their big plans. This whole-view way lets the system build a strong base to offer spot-on advice for what to study.
- Map Study Options: After the students file is set up, the system fits it to a big list of study paths. This list has lots of school & job paths like Science, Commerce, Arts, Eng, Med, Law, Design, & job skills paths. Each path is nailed down by what you need to learn for it, who it fits, & where it might take you job-wise. This fit check helps the system find not just where a student can do ok, but where they would thrive & be glad.
- Context-Driven LLM Processing: The heart of the tech is in context-use LLMs. The student's data gets mixed with the study path info to make fit advice. The LLM uses thought & plain word work to make top tips. These have clear why's & plans. Methods like RAG take in what the data holds & data from outside like job trends, new fields, & test needs. This makes the tips right more often & helps keep the plan fresh & aimed at the future.
- Feedback & Iteration: A big part of the way it works is its reply system. Once they get tips, students can mark how right & good the advice is. This reply helps the tech shape up the next tips & fit to the student's shift in time. This cycle makes sure the advice grows right. It brings up-to-date plans as students grow in class & life. Not just set, one-off aid, the tech acts as an ongoing, change-ready guide. correct the spelling in this and word choice.
- Suggested Tech Stack
  - Front-end (User Interaction)
    - React / Next.js → Dynamic student portal
    - Tailwind CSS / Material UI → Clean, modern UI
    - React Native / Flutter → Mobile application option
  - Backend (Data & API Layer)
    - Node.js / Express (or Django / Fast API for Python-heavy cases)
    - REST or GraphQL APIs for student profiles & study paths
    - PostgreSQL / MongoDB → Storage for user context and study path data
  - AI/ML Layer
    - LLMs: OpenAI GPT-5 / GPT-4 or LLaMA 3 (fine-tuned for counselling)
    - RAG (Retrieval Augmented Generation) → Fetch study path data
    - Embedding Models (OpenAI embeddings, Sentence Transformers) → Match student profile with study paths
    - Recommendation Engine → Similarity scoring (cosine similarity, semantic search)
  - Knowledge Base
    - Study streams stored in structured formats (JSON + database)
    - External data integration: labor market trends, courses, and exams.
  - Deployment & Infrastructure
    - Cloud: AWS / GCP / Azure
    - Vector Databases: Pinecone / Weaviate / FAISS → Profile-to-study path matching
    - Containerization: Docker + Kubernetes → Scaling and deployment
  - Feedback & Analytics
    - Student dashboard with progress tracking
    - Analytics: Mix panel / Google Analytics
    - Feedback storage → Fine-tuning recommendations

6. Use Case Architecture for Career Counsellor

The UML chart above shows how an AI-based career guidance system works, helping students choose the right academic and career paths. The main roles involved are the AI system, the student, and the human counsellor. The process begins with the student, who provides key details such as academic scores, interests, and career goals. This information forms the foundation for generating career advice. The AI system then processes the data using advanced models like LLMs and a knowledge base. Based on this, it provides ranked study paths and detailed roadmaps tailored to the student's needs. Moreover, the AI system continuously refines its suggestions as students interact with it, give feedback, and rate the recommendations. This makes the guidance adaptive and personalized rather than fixed or one-time.

To ensure that the advice is accurate, practical, and empathetic, the human counsellor reviews the AI-generated suggestions and adds a human perspective. This step helps address AI limitations such as bias, lack of emotional understanding, and insufficient awareness of real-life contexts. The counsellor's role ensures that students receive not only intelligent recommendations but also meaningful support that combines real-world expertise with empathy. Overall, the UML chart illustrates a collaborative cycle where students actively participate, the AI provides smart and evolving career suggestions, and the counsellor enhances them with human insight. This integration creates a reliable, accessible, and future-ready system that gives students clear pathways while balancing the strengths of technology with the care of human guidance.

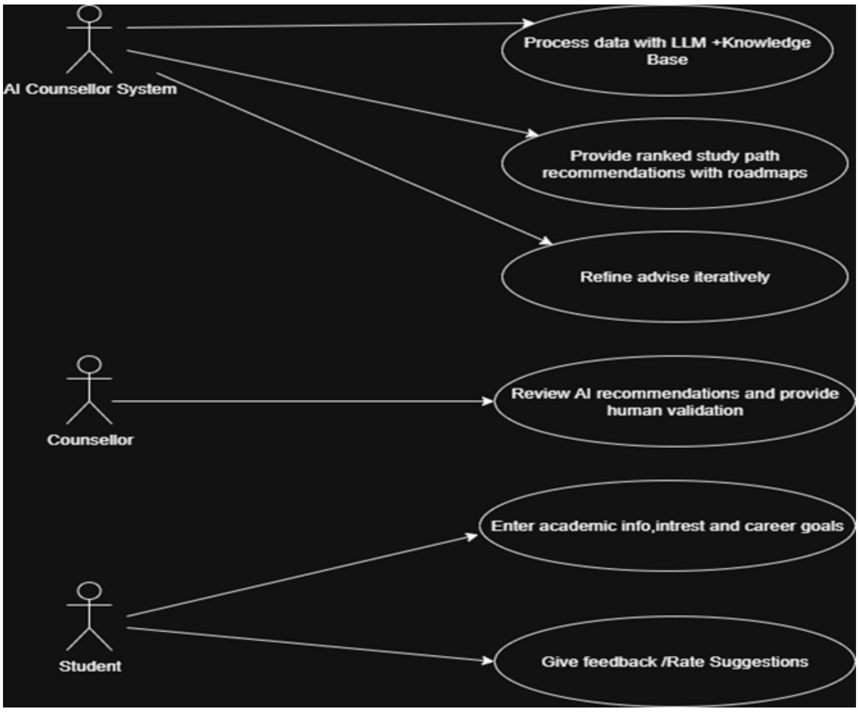

Figure 1 Use case for AI Based Career Counsellor System

7. Research Gap

While AI-based career counselling systems are developing well, several key research gaps remain that affect their reliability, inclusiveness, and real-world impact. One major gap is the lack of external validity and long-term evaluation. Most studies rely on small sample sizes, controlled environments, or short-term user research. Consequently, there is not enough evidence showing whether AI-assisted counselling actually improves student retention, decreases decision mismatches, or leads to better job outcomes over time. To prove practical effectiveness, we need multi-institution, long-term studies that assess how these systems affect academic and career paths in different educational and socio-economic settings

Another gap involves fairness, transparency, and accountability. Many current systems do not consistently evaluate or report how well they perform for various demographic groups, including gender, language background, region, or socio-economic status. The explanations provided to users tend to be vague and do not clearly explain the reasons behind specific recommendations or the system's confidence in its suggestions. Without standardized methods to check for bias and clear auditing processes, there's a risk that AI-driven recommendations could unintentionally worsen inequalities instead of addressing them

A significant gap also exists regarding linguistic and cultural inclusivity. Even though multilingual transformer models have improved conversational and recommendation abilities, they still face challenges with low-resource regional languages, code-mixed communication, and culturally specific preferences for career choices. Very few systems use localized knowledge or culturally sensitive guidance strategies. As a result, the quality of counselling may differ based on a student's language or cultural background, especially in regions with high linguistic diversity.

Operational robustness is another area that lacks exploration. Although the designs and prototypes are well-documented, there is limited research on how to keep these systems functioning over time in educational settings. Issues like content drift, shifts in job market demands, curriculum changes, and the need for ongoing oversight or retraining are rarely discussed. Additionally, strategies for handling data privacy, efficiently deploying resources in rural or low-connectivity areas, and creating fallback methods for system errors are not studied enough, which affects scalability and sustainability

Two methodological gaps also persist in the literature. First, uncertainty-aware recommendations are seldom used or properly calibrated. Systems typically offer suggestions without indicating their confidence levels, which diminishes trust and may lead students to over-rely on or misinterpret the guidance. Second, evaluation frameworks vary widely due to the lack of standardized ground truths for matching students with career paths. Without common benchmarks that reflect real constraints like geography, affordability, and specific institutional opportunities, comparing system performance across different studies is challenging

Finally, even though hybrid counselling models that combine humans and AI are often suggested, there is little empirical evidence on how counsellors and AI systems work together in practice. We know very little about how AI impacts counsellors' workload, whether it improves guidance for underserved groups, or how different explanation formats influence student decision-making. Thorough evaluations of the interactions between counsellors, students, and AI recommendations are essential to change conceptual models into effective strategies for implementation.

8. Conclusion

In conclusion, incorporating AI in career counselling is a landmark advancement in educational systems and student development. With applications of such technologies as data analytics, machine learning, and personalized recommendation systems into conventional counselling practices, institutions transcend the generic and offer individual guidance that adjusts in line with the unique strengths, aspirations, and growth trajectories of each student. This is a marriage of human expertise to AI capabilities, which will ensure that students receive empathetic mentoring (but with data-driven insights) to prepare them for a rapidly changing world of work.

The scope of this transformation indeed extends much further than individual decision making. Institutions could utilize aggregated intelligence from the AI systems to reshape curricula, align programs to industry trends, and mobilize efforts to develop skills preemptively. Policymakers could also tap in these data to make strategies and policies that are nimble and responsive to labor market demands and societal needs. AI, most importantly, redefines what career counselling means. Rather than the static on-and-off service delivered at critical junctures in decision making, career guidance can soon be a continuous, flexible, and lifelong process that accompanies students throughout their educational and professional processes. With platforms powered by AI, which track performance, revise recommendations based on the situations, and change with circumstances as they develop, career guidance is much more than the means toward immediate decisions, but an enduring source for individuals between personal and professional development. In essence, this paradigm shift has the potential to bridge the education-employment divide and get students ready not just for current opportunities but for the world of work that will be.

References

[1] G. V. Lokam, P. S. Patil, A. S. Kukade, A. N. Dhule, and R. A. Kothiwale, “AI-Based Career Guidance System,” International Journal of Creative Research Thoughts (IJCRT), vol. 13, no. 5, pp. c843–c845+, May 2025.

[2] A. Birajdar, S. Jadhav, P. Shinde, S. Shinde, et al., “AI-Powered Career Counselling,” International Research Journal of Engineering and Technology (IRJET), vol. 11, no. 11, pp. 543–? Nov. 2024.

[3] N. R. Chopde, A. V. Sakhare, M. M. Malviya, A. P. Deshmukh, and G. J. Deshmukh, “A Review Paper Based on Making Career Choices and AI Based Counselling Accessible to Secondary Level Students,” Journal of Emerging Technologies and Innovative Research (JETIR), vol. 12, no. 2, pp. c771–c772+, Feb. 2025.

[4] A. M. Gunje, S. Shinde, G. Deshmukh, S. Nadimetala, T. Pawar, and Y. Shinde, “Developing AI Based Career Counselling System,” International Research Journal of Modernization in Engineering, Technology and Science (IRJMETS), vol. 6, no. 5, pp. 10672–10673+, May 2024.

[5] M. G. A., K. M., I. Ashneel, and G. P. Harshik, “AI Based Career Chatbot: Leveraging AI for Career Counseling,” IJARIIE, vol. 10, no. 3, pp. 1338–1344+, 2024.

[6] T. Hude, A. Bagal, A. Kazi, A. Gaikwad, and H. Sarvade, “Review of AI Based Career Counselling,” International Journal of Advanced Research in Science, Communication and Technology (IJARSCT), vol. 4, no. 5, pp. 385–386+, Apr. 2024.

[7] C. Wasnik, A. Lakeshri, M. Chaturvedi, L. Jajoo, and R. Soni, “AI-Powered Career Coaching System: A Data-Driven Approach to Career Guidance,” Journal of Emerging Technologies and Innovative Research (JETIR), vol. 12, no. 3, pp. e238–e240+, Mar. 2025.

[8] P. Bebale, S. Yadav, S. Surve, A. Sayed, and G. Korgaonkar, “Career Compass: AI Based Career Counselling,” International Journal of Innovative Research in Technology (IJIRT), vol. 11, no. 11, pp. 756–758+, Apr. 2025.

[9] R. Agrawal, D. Sawale, S. Kondawar, A. Gupta, and J. S. Pawar, “AI-Driven Student Career Counseling Platform,” International Journal of Innovative Research in Technology (IJIRT), vol. 12, no. 1, pp. 2527–2531, Jun. Ouyang et al. (2022), Training Language Models to Follow Instructions with Human Feedback (InstructGPT / RLHF)

[10] J. Kumar, A. Vishwakarma, N. Sainy, A. Kumar, and R. Aggarwal, “Personal Finance Manager with Predictive Analytics Using LSTM for Enhanced Financial Decision Making,” Int. J. of Research – GRANTHAALAYAH, vol. 12, no. 5, pp. 45–51, May 2024.