

An Explainable AI Framework for Career Assessment of Students in Emerging Economies

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Abstract

Choosing a career continues to be one of the major challenges for students in emerging countries because of the lack of access to professional counseling, the fragmented nature of digital resources and the poor fit between personal traits and the realities of the labor market. While most AI-based system lack psychometric foundation and transparency, traditional counseling is customized but challenging to scale. In accordance with fairness and human supervision principles, this study suggests an integrated explainable AI framework that integrates psychometric intelligence, multimodal student data, transparent recommendation mechanisms and labor-market signals. The study proposes a modular conceptual architecture for career assessment, highlights important fragmentation gaps and synthesizes current methodologies. The proposed framework offers a basis for creating career decision assistance systems that are scalable, comprehensible and context-aware. It could be used in educational institutions, career counseling programs at the policy level and online platforms to enhance opportunities.

Keywords: Career assessment, Explainable AI, Psychometric evaluation, Emerging economies, Student decision support

Introduction

In emerging economies the career decision is often made with few information and with limited labour market information that is incomplete, informal or urban-biased. Between 2025 and 2035 about 1.2 billion young people in emerging market and developing economies are expected to reach working age [1], [2]. The International Labour Organization reports that two in three young adult workers in developing economies hold qualifications that do not match well to their jobs [3]. India illustrates the same tension at national scale. The All India Survey on Higher Education records 4.50 crore enrolled students in 2023-24 and a gross enrolment ratio of 30.0 [12], [13]. In the Periodic Labour Force Survey for July 2023-June 2024 the unemployment rate was 3.2 per cent for persons aged 15 years and above and 10.2 per cent for youth aged 15-29, rising to 14.7 per cent in urban areas [14], [15]. The ILO-IHD India Employment Report 2024, using NSS and PLFS evidence, finds that unemployment rises with education while the supply of formal skilled work remains thin [16].

Reported published systems already predict course or career fit and attach SHAP or LIME explanations [5], [6]. Large language models have been tested as career advisors across ten African countries and showed limited awareness of national labour markets, languages and policy [4]. Those systems are useful as software precedents. They were not designed around official statistical systems such as AISHE and PLFS, informal work or a counsellor who can reject a score. Most published systems are trained on single country, often high-education samples and treat explanation as an add-on to accuracy. They rarely model informal work, household constraints or the need for a counsellor to contest a score. This paper discusses a critical point related to an assessment pipeline to be structured so that predictions are useful, contestable and locally legitimate.

The Section 2 reviews labour-market and XAI evidence and places official Indian statistics inside that review. Section 3 states design principles. Section 4 specifies the five layers. Section 5 discusses fairness, privacy, and duty of care. Section 6 assigns institutional roles. Section 7 specifies an evaluation protocol. Section 8 concludes.

Background and Related Work

One major stream is labour-market diagnosis for career assessment. ILO Global Employment Trends for Youth 2024 and the ILO-IHD India Employment Report 2024 document over-education, NEET concentration among young women, and a gap between credentials and available work [3], [16]. World Bank jobs analysis places the same facts in a decade-long cohort of 1.2 billion young people reaching working age [1], [2]. Those reports specify the constraint. They do not specify a scoring pipeline.

The second stream is machine-learning career and course recommendation. Faruque, Khushbu and Akter train classifiers on computer-science and software-engineering surveys and attach explainable outputs [5]. Ghosh et al. use XAI to study engineering-student interest [6]. Ma, Yang and Ren survey explainable course recommenders and emphasise justification over accuracy alone [10]. Counterfactual methods on Belgian public-employment data show how a “what would have to change” narrative can name skills rather than immutable traits [9]. Hooshyar and Yang show that SHAP and LIME can disagree on feature rank in educational models [11]. Across this stream the typical sample is a campus or a formal vacancy file.

The third stream is general-purpose language models used as advisors. Eze, Lunn and Berhane compared six models on computing-career prompts for ten African countries and reported average contextual awareness of national ecosystems and policy of 35.4 per cent [4]. That result is why a chatbot is not given the final rank in the framework below.

A. Official Indian evidence: scale, mix and labour-market gap

Figure 1 shows AISHE enrolment rising from 3.42 crore in 2014-15 to 4.50 crore in 2023-24. GER, published for selected years on the 2011 population projection, rose from 23.7 to 30.0 [12], [13]. Female GER in 2023-24 was 31.2 against male GER of 28.9. Enrolment of this size is why a counsellor-only service cannot be the sole channel and why Layer 5 includes paper and offline modes.

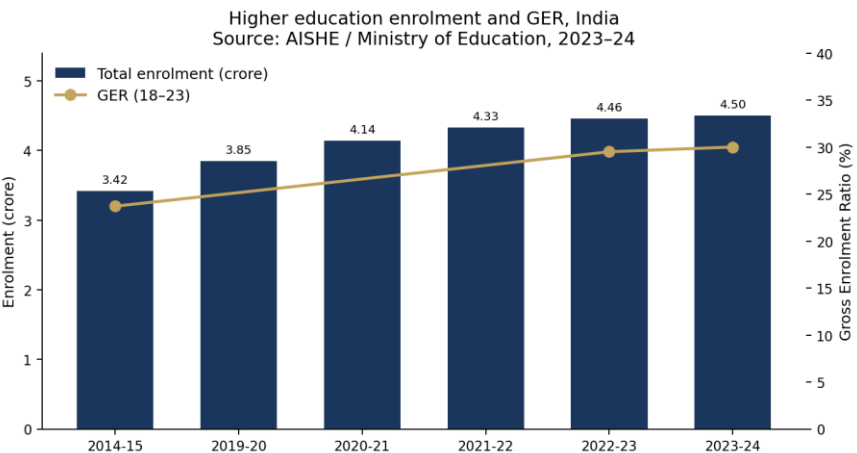


Figure 1. Higher-education enrolment and GER, India. Source: AISHE / Ministry of Education [12], [13]

B. Enrollment level in Education

Figure 2 shows programme mix in 2023–24. Undergraduate programmes hold 76.8 per cent of enrolment. Postgraduate programme hold 12.9 per cent and diploma or certificate programme 7.4 per cent. STEM enrolment is 22.5 per cent of the total on actual institutional response [13]. A recommendation platform limited to a few professional degrees omits most feasible next steps.

Share of higher-education enrolment by level, 2023–24
Source: AISHE 2023–24, Ministry of Education

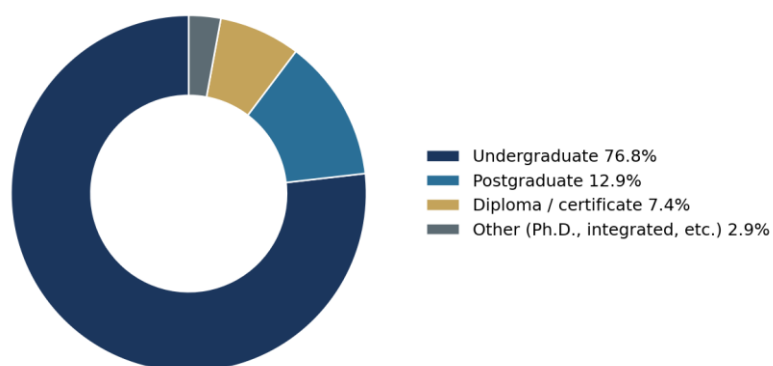


Figure 2. Enrolment by programme level, India, 2023–24. Source: AISHE 2023–24 [13]

Figure 3 reports social-group shares in the same year: Other Backward Classes 40.1 per cent, other communities 38.0 per cent, Scheduled Castes 15.5 per cent, Scheduled Tribes 6.4 per cent [13]. Fairness cuts in Layer 5 should follow these official groupings.

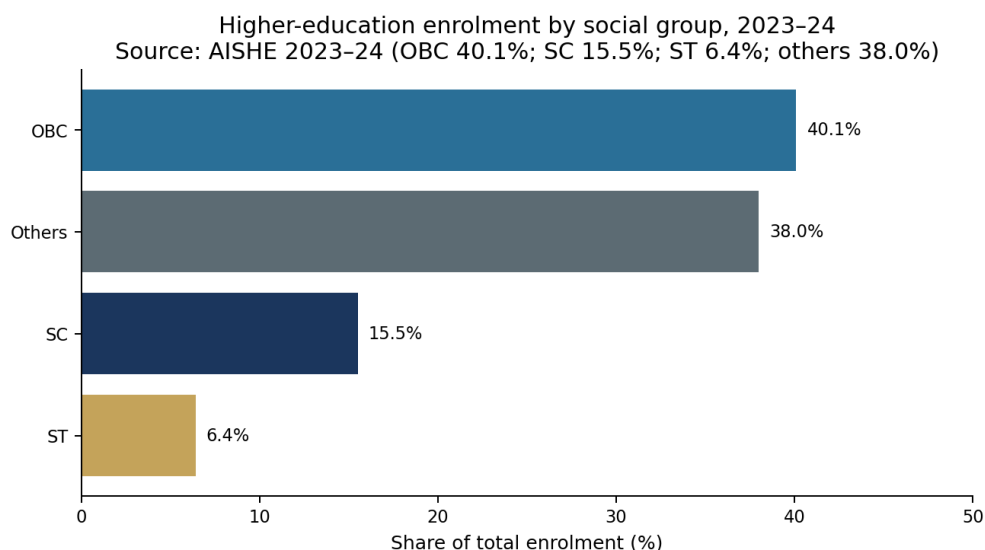


Figure 3. Enrolment by social group, India, 2023–24. Source: AISHE 2023–24 [13].

Figure 4 places students in the labour market. PLFS usual-status unemployment for July 2023–June 2024 was 3.2 per cent at ages 15 and above and 10.2 per cent at ages 15–29 (8.5 per cent rural, 14.7 per cent urban) [14], [15]. That gap is why Layer 3 must emit vocational and enterprise pathways with wide confidence bands [16].

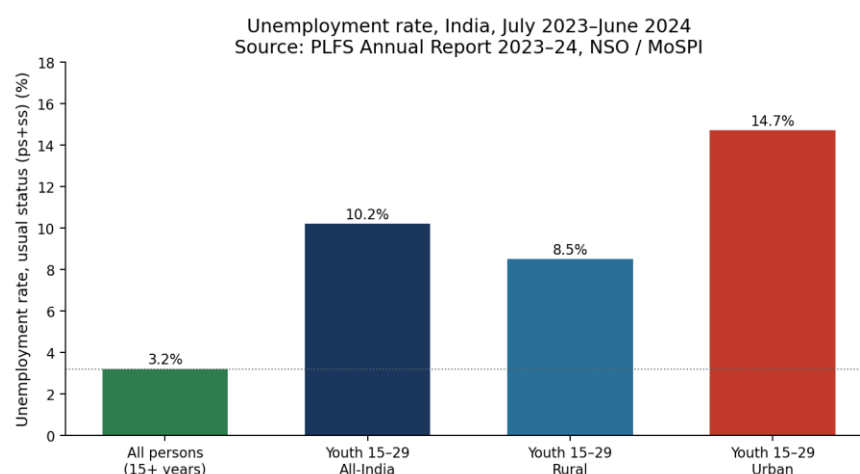


Figure 4. Unemployment rate, usual status, India, July 2023–June 2024. Source: PLFS / MoSPI [14], [15].

Methodology

The method is a design framework where Table 2 shows layers, functions, method & control. Layer 1 assembles a jurisdiction graph from administrative enrolment, public employment fragments and a national skills taxonomy. Student records enter only with consent. A missing internship field is stored as coverage failure, not as low aptitude.

Layer 2 builds a versioned profile: subject strengths, locally adapted interests, mobility and language constraints, and a skill vector. Layer 3 scores pathways with three modules. A gradient-boosted tree is used where labeled graduate outcomes exist because TreeSHAP can attribute that model exactly [7]. A graph matcher is used where labels are scarce [10]. Rules block illegal or ineligible options. Fusion returns K pathways, each with a fit score, a confidence band that widens when local labels are thin, and a pathway type (academic, TVET, apprenticeship, enterprise).

Layer 4 attaches three explanations to every shortlisted pathway: global SHAP summaries for ministry audit; local SHAP and LIME for the case [7], [8]; and a counterfactual that may change only mutable features [9]. If the three methods disagree on the leading feature, the interface reports the disagreement [11]. Layer 5 gives the student a narrative in the language of instruction and gives the counsellor confidence, fairness flags and an override log. A printed one-pager carries the top three pathways, two mutable reasons and one dated next step.

Table 2. Framework layers, methods and controls

Layer	Function	Method	Control
1 Data	Labour and student evidence	AISHE, PLFS, skills graph	Missingness flags
2 Profile	Structured student object	Local instruments, NLP	Granular consent
3 Match	Ranked pathways	Trees, graph, rules	Wide confidence if labels are scarce
4 Explain	Why and what-if	SHAP, LIME, counterfactuals	Show disagreement; mutable features
5 Deliver	Decision support	Dual interface; print summary	Counsellor override; offline cache

Results and Discussions

A. Machine learning and XAI in career and education systems

Figures 5 and 6 report the NCRB occupational category “students” in Accidental Deaths and Suicides in India. Recorded student suicides rose from 8,032 in 2014 to 13,892 in 2023, or 8.1 per cent of all recorded suicides that year [17], [18]. Maharashtra, Madhya Pradesh, Uttar Pradesh and Tamil Nadu have the largest counts; these are large-population states, so Figure 6 is a count, not a rate. NCRB does not show that an assessment tool causes these deaths. The series is used only as a duty-of-care constraint: Layer 5 keeps a human in authority and forbids a single irreversible score.

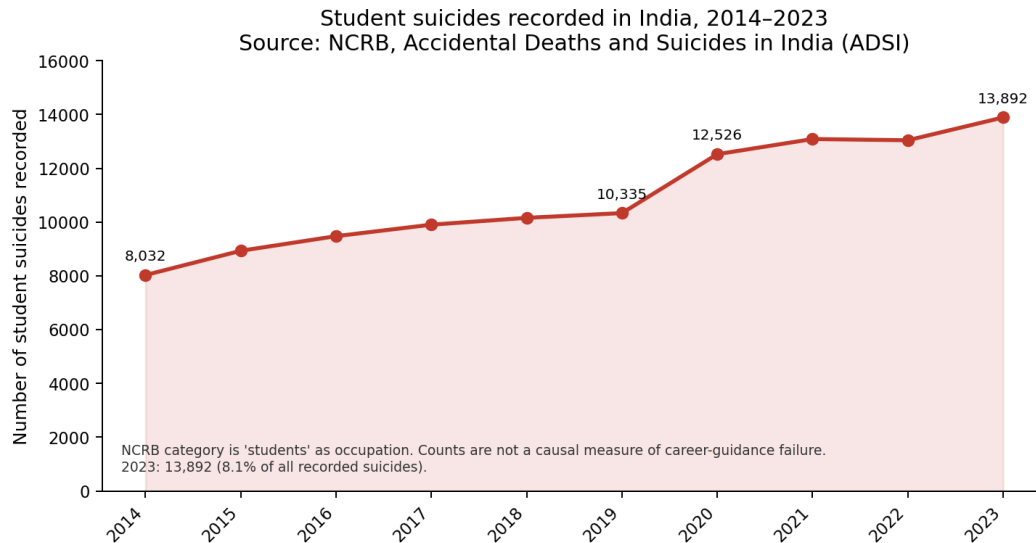


Figure 5. Student suicides recorded in India, 2014–2023. Source: NCRB, Accidental Deaths and Suicides

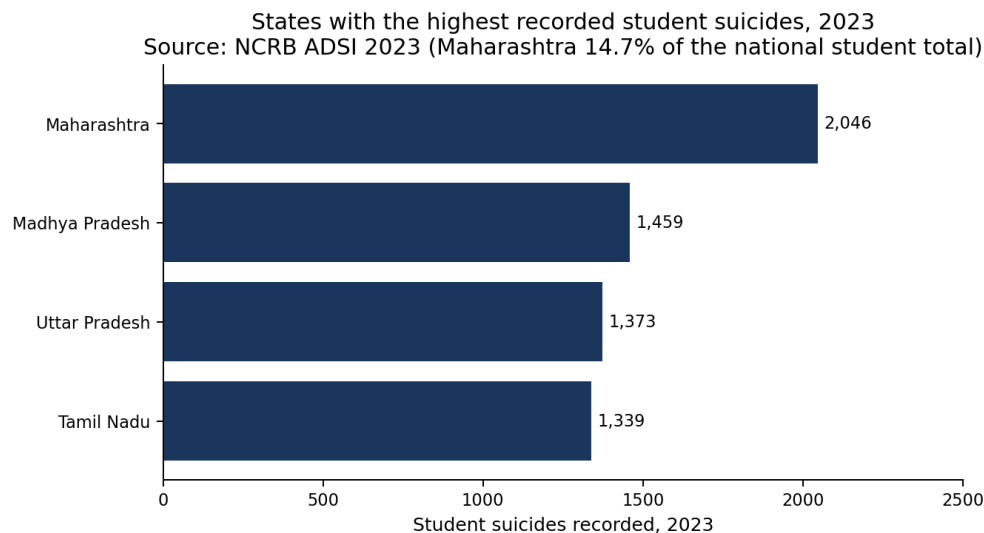


Figure 6. Highest state counts of recorded student suicides, 2023. Source: NCRB ADSI 2023

B. Modular conceptual architecture of the proposed career decision-support framework

Proposed architecture for career decision support including Student data, psychometric assessment and labor-market signals are integrated, matched and aligned, then passed through an explainable recommendation engine with fairness checking and counsellor review, producing a career recommendation with explanation.

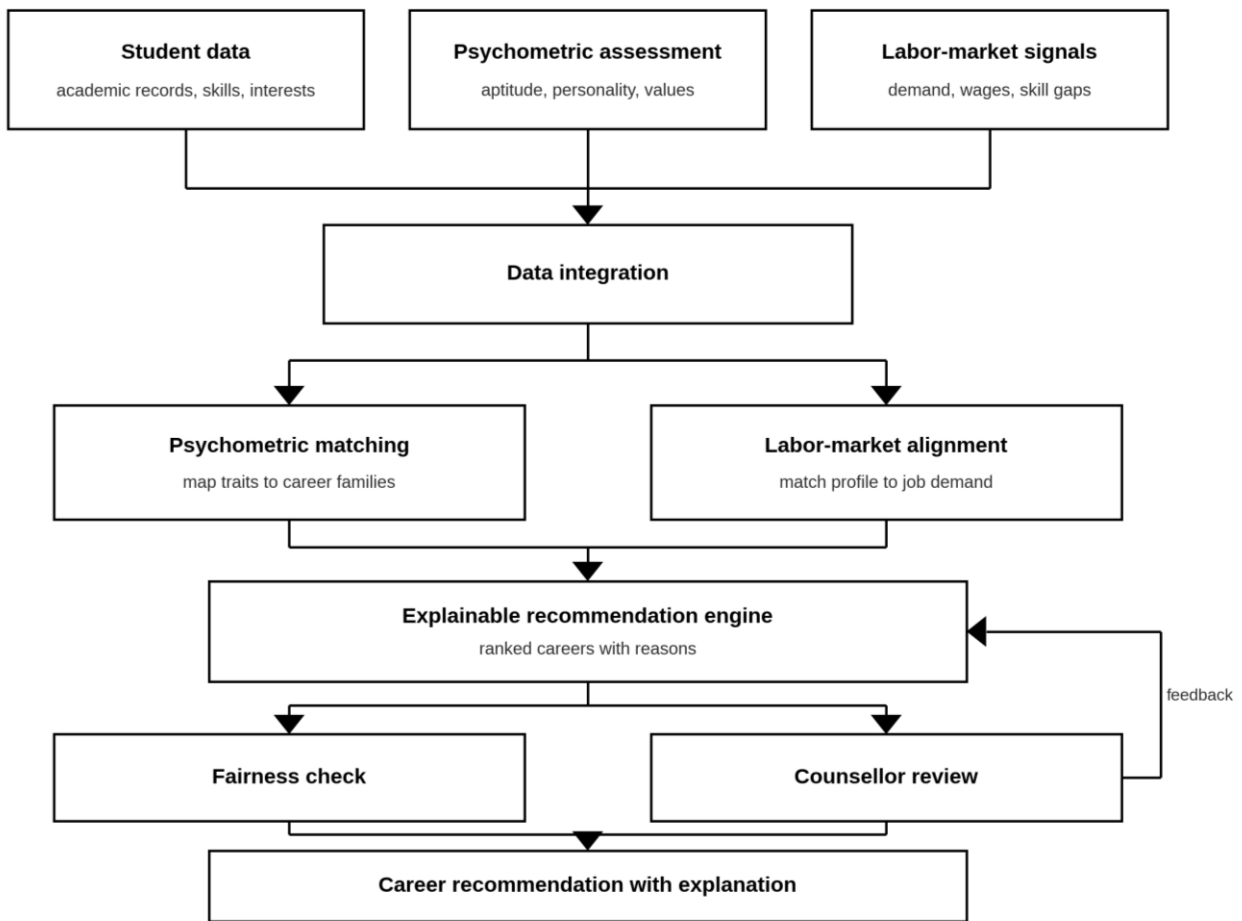


Figure 7. Proposed architecture for career decision support

Conclusion

Choosing a career remains one of the most consequential and poorly supported decisions facing students in emerging countries. Limited access to professional counseling, scattered digital resources and a weak alignment between personal traits and labor-market realities continue to produce mismatched choices and lost opportunity. Existing responses are incomplete: most AI recommenders lack a psychometric foundation and offer little transparency, while traditional counseling is personalized but cannot be scaled. This study addressed that gap by proposing an integrated explainable AI framework that combines psychometric intelligence, multimodal student data, transparent recommendation mechanisms and labor-market signals, governed by principles of fairness and human supervision. The work contributes a modular conceptual architecture for career assessment, identifies key fragmentation gaps in current practice, and synthesizes existing methodologies into a coherent design. Future work should train and test the interface with students, in a fixed order, so that this gap is closed before any live ranking.

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