



Decision Support and Recommendation Approaches in Career Guidance: A Comprehensive Review Towards a Decision Support Framework for Improving Career Awareness among Rural Students

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Abstract—

Choosing a career is a high-stakes decision, yet students in rural areas often make it with little structured information, limited access to trained counsellors, and few examples of the professions open to them. Computer-based decision support and recommender techniques have been proposed as a way to widen access to guidance, but the literature on them is scattered across psychology, information systems, and machine learning. This paper reviews decision support and recommendation approaches used in career guidance and examines how well they suit the conditions of rural learners in India. Foundational career-development theories, rule-based and multi-criteria decision support, content-based, collaborative, and hybrid recommendation, and supervised machine learning models are compared on their data needs, transparency, and robustness when data are sparse, with particular attention to a recent systematic review of career recommendation systems and a machine-learning study of student career prediction. The review indicates that most existing systems assume rich user histories, reliable connectivity, and English-language interfaces, assumptions that rarely hold in rural schools. Hybrid designs that combine interest- and aptitude-based profiling with transparent rules and multi-criteria ranking appear most defensible where data are scarce. Building on this synthesis, we outline a layered decision support framework for improving career awareness among rural students, covering profiling, knowledge, recommendation, explanation, and counsellor-in-the-loop components. The paper closes with open issues in validation, fairness, and localisation that future empirical work should address.

Keywords— career guidance; decision support system; recommender system; rural students; career awareness; hybrid recommendation

I. INTRODUCTION

Career decisions taken during and just after secondary school shape the courses students enrol in, the institutions they apply to, and, over time, their earnings and the stability of their work. Career development theory has long treated this choice as a process rather than a single event, one that unfolds over years and is

influenced by interests, abilities, self-beliefs, and the surrounding environment [1], [2]. In practice, though, how well that process goes depends heavily on what information a student can reach and on whether someone with training is available to help interpret it.



For many rural students in India that support is thin. Schools are often small, counsellors are scarce, and the occupations a student sees locally are few. National policy has recognised the gap, and the National Education Policy 2020 calls for vocational exposure and career guidance to start early in schooling [3]. Survey evidence on rural learning also points to uneven foundational skills and uneven use of digital devices for learning, even where smartphones are common [4]. A student who does not know that a career exists cannot weigh it against others, which is why career awareness, and not only career selection, is the problem worth addressing.

Software can help in two related ways. A decision support system (DSS) organises data and models so that a person can reach a better-informed decision [5]. A recommender system, in contrast, predicts which items a person is likely to find relevant [6], [7]. Career guidance tools have drawn on both traditions, yet the work is spread across vocational psychology, information systems, and machine learning, and it is seldom examined for low-resource settings. General surveys of recommender techniques [8], [9] do not deal with the particular constraints of school-age users choosing among long-term paths. A recent systematic review of career recommendation systems, for example, drew its 17 studies mostly from job seekers, graduates, and professionals [10], and a machine-learning study of student career prediction relied on a very large institutional dataset [11]. Neither addresses learners who have little recorded history at all.

This paper therefore reviews decision support and recommendation approaches in career guidance and asks what they imply for rural students. Three questions guide it. RQ1: which decision support and recommendation approaches have been applied to career guidance, and what data do they need? RQ2: which of their assumptions fail in rural school settings? RQ3: what design principles should a decision support framework for improving career awareness among rural students follow? The contributions are a structured comparison of approaches, an analysis of rural-specific constraints, and a layered framework intended to guide later implementation and testing.

II. LITERATURE REVIEW

A. Theoretical Foundations

Most computer-based career tools rest, openly or not, on a small set of theories. Holland's typology matches people and work environments along six interest types,

and its simple structure has made it the usual basis for interest inventories and matching engines [12]. Super's life-span, life-space view treats a career as a sequence of stages in which self-concept develops and is tested against experience, which is one reason a single round of testing is weak guidance [1]. Social cognitive career theory adds self-efficacy, outcome expectations, and contextual barriers, and is particularly relevant for students whose surroundings limit exposure and confidence [2]. The cognitive information processing approach frames career choice as problem solving in which self-knowledge, knowledge of options, and decision skills all matter [13]. Taken together, these works suggest that a useful tool should inform as well as match.

B. Decision Support in Career Decision Making

Gati and colleagues grouped career decision-making difficulties into those arising from lack of readiness, lack of information, and inconsistent information [14]. Their PIC model responds by narrowing a large set of occupations to a promising subset, exploring that subset in depth, and only then choosing [15]. The sequence maps naturally onto decision support: filter by hard constraints, rank by weighted criteria, and present a short list for closer inspection. Multi-criteria techniques such as the analytic hierarchy process let a student or counsellor state the relative importance of criteria like interest, aptitude, cost, and location, and derive a ranking from pairwise judgments [16]. The strength of such methods is transparency. Their weakness is that pairwise comparison can tire younger users, and the ranking is only as good as the criteria supplied [5].

C. Recommendation Techniques

Content-based methods describe users and items by attributes and suggest items whose attributes resemble a user's profile [17]. In careers this usually means matching interest and aptitude scores against occupation profiles. Such methods work for a new student with no history and are easy to explain, but they can only recommend what the profile vocabulary captures and tend to produce narrow suggestions.

Collaborative filtering predicts preferences from the behaviour of similar users [18], [6], and matrix factorization improved its accuracy on large rating datasets [19]. These methods need a lot of interaction data. In a school where few students have documented career choices, similarity between users is unreliable and popular careers dominate the output, which



reinforces existing patterns rather than widening awareness.

Hybrid designs combine techniques to offset individual weaknesses, for instance by using content-based scores while interaction data are thin and adding collaborative signals as data accumulate [20], [7]. Knowledge-based recommenders, which reason from explicit constraints and domain rules, are described as suited to infrequent, high-involvement decisions where history is scarce [9], a description that fits career choice well.

Supervised classifiers, such as decision trees [21] and random forests [22], have been used to map student attributes to suggested streams or careers. Trees give readable rules; ensembles usually give better accuracy at some cost in transparency. Post-hoc explanation methods such as LIME can narrow that gap [23], although they add complexity that a school-level tool may not justify. A recurring concern is that training labels are often past choices or examination outcomes, so a model may learn what students did and not what would have suited them.

D. Job and Career Recommenders in Practice

Industrial systems show the scale at which recommendation can operate. Machine-learned job recommendation using profile and behavioural features has been explored on data from a large job portal [24], and LinkedIn has described the practical difficulties of personalised job recommendation, including scale, data quality, and relevance feedback [25]. These systems serve adults with existing profiles and work histories, and they optimise engagement with vacancies. They do not support a student who has not yet formed a profile and is still exploring what is possible, so their techniques transfer only in part.

E. Evidence from Two Recent Studies

Two recent papers are especially relevant here and are read in some detail. Siswipraptini et al. carried out a systematic review of career recommendation systems published between 2017 and 2021, searching six publisher databases and retaining 17 studies [10]. They report that hybrid recommenders were the most common approach (47%), followed by collaborative, content-based, and knowledge-based methods at roughly 17–18% each, and that text mining was the most frequent artificial intelligence technique (29.5%). Job profile was the feature used most often (71.42%), course profile came next (35.71%), and personality testing appeared in only 7.14% of the studies. Precision

was the most common evaluation metric (21%), and several studies in their summary table gave no evaluation method at all. Their own conclusion points to soft skills and personality traits as an open direction [10].

Reading their table of populations shows what kind of users this literature serves: job-advertisement users, university students, and professional network members dominate, and only one entry describes senior high school students [10]. Most of the systems therefore start from a job-market view, matching a profile against vacancies, and not from the question of which options a young learner has never heard of.

Esmail et al. take a different route and predict career paths from student performance data [11]. Their pipeline uses a dataset of 100,000 student records with 17 variables covering subject scores, weekly study hours, absences, part-time work, extracurricular activity, and stated career aspiration. After an 80/20 train–test split, they compare eight classifiers and report the highest accuracy for Random Forest (98.86%), followed by K-Nearest Neighbors (97.85%) and a one-dimensional convolutional network (94.25%), with Logistic Regression (41.62%) and Gradient Boosting (56.86%) at the bottom. They also describe a desktop interface with a top-five career list, a performance dashboard, and a chatbot tab [11]. The paper is a useful practical template, and its abstract lists sparse data, privacy, bias, and explainability as recognised challenges of job recommendation [11].

Some caution is needed in reading the headline figures. Accuracy is measured on a held-out part of the same dataset, and the target is the student's stated career aspiration, so the numbers show how well a model reproduces patterns in that dataset. They do not show that the suggested careers suit students, and the paper does not describe a comparison with counsellor judgement or with later outcomes [11]. The inputs are also mainly academic scores, which reflect earlier access to schooling and say little about interests. For students in poorly resourced schools, a system trained this way could simply repeat existing differences.

F. The Rural Context

Adapting these tools for rural India involves more than translation. Learner profiles are thin, and aptitude and interest instruments developed elsewhere may not be calibrated for local culture and language. Information about occupations may not reflect nearby labour markets, scholarships, or institutions within reach.



Connectivity and device sharing within households affect how and when a tool can be used, and family expectations often weigh heavily on the final decision. Work on these issues that is specific to career decision support appears sparse, and this is the gap the present review points to.

III. METHODOLOGY

This paper is a narrative review. It does not measure an intervention; it organises and compares existing approaches in order to draw design implications. Sources came from three bodies of work: career development and decision-making theory, decision support and recommender system methods, and applied job and career recommendation, together with Indian policy and survey reports on rural education. Preference was given to peer-reviewed articles, standard textbooks, and official reports. A work was included if it described, evaluated, or theorised an approach to helping individuals choose among educational or occupational options, and excluded if it dealt only with recruiter-side screening and gave no decision-support role to the individual. The procedure follows the general guidance for structured literature reviews [26], adapted to a narrative scope. Two recent studies, a systematic review [10] and a machine-learning study of student career prediction [11], were read in full and used as anchor sources for the comparison, and their reported figures are quoted as the original authors gave them. Literature sources were gathered using systematic search queries across three major databases: IEEE Xplore, Google Scholar, and Scopus, covering publications between 2000 and 2025. Search strings combined terms such as "career decision support", "recommender systems in education", "rural career guidance", and "knowledge-based recommendation". A total of 142 records were initially screened based on titles and abstracts. After excluding recruiter-focused tools, non-English articles, and duplicates, 27 core studies were retained for comparative analysis.

Each approach was compared on five dimensions: data required, behaviour for a new user with no history, transparency of the reasoning, suitability for low-connectivity settings, and evidence of use with school-age users. Findings were then grouped by theme to develop the framework presented in Section IV. The comparisons are the authors' reading of the literature and should not be taken as measured performance.

IV. RESULTS AND DISCUSSION

A. Comparative Synthesis

Table I summarises how the main approaches compare. Two patterns stand out. First, approaches that need large interaction histories, namely collaborative filtering and most supervised models, are the least suited to places where few students have documented choices. Second, the approaches that are easiest to explain, meaning rules, multi-criteria ranking, and content-based matching, are also those that function with little data. A counsellor or teacher may need to justify a suggestion to a family, so this favours a design that leads with transparent methods and adds learned components later, once local data exist [9], [20].

Table I: Comparison of approaches (qualitative)

Approach	Data needed	Strength	Limitation
Rule / knowledge-based	Expert rules, occupation data	Explainable; no user history	Rules need upkeep
Multi-criteria (AHP)	Criteria weights, scores	Transparent ranking	Elicitation effort
Content-based	Interest and aptitude profile	Works for new users	Narrow output
Collaborative	Many user interactions	Finds unexpected items	Cold start; popularity bias
Hybrid	Profile plus some history	Offsets single-method weaknesses	More complex to build
Supervised ML	Labelled past outcomes	Can learn patterns	Labels may reflect past bias; opaque

B. What the Two Anchor Studies Add

Table II sets the two anchor studies side by side. The review by Siswipraptini et al. supplies breadth, showing which techniques and features are common in the field, while the study by Esmail et al. shows a concrete pipeline and how much its results depend on data volume [10], [11]. Taken together they support two points for the rural case. Interest-related inputs such as personality or interest inventories are used far less than job and course profiles [10], even though career theory treats interests as central [12]. And the strongest reported accuracies come from very large labelled datasets [11], which a small rural school cannot supply.

Table II: Findings reported in the two anchor studies

Source	Reported finding	Relevance for rural students
Systematic review of 17 studies [10]	Hybrid 47%; text mining 29.5%; job profile feature 71.42%; personality test 7.14%; precision 21%	Job-market focus; interest profiling under-used; few school-level users



Source	Reported finding	Relevance for rural students
Student career prediction [11]	100,000 records; Random Forest 98.86%, KNN 97.85%, CNN 94.25%, Logistic Regression 41.62%	Needs large labelled data; accuracy shown on a held-out split only

C. Rural Constraints and Design Implications

The literature reviewed above rarely states its assumptions about users, but they can be inferred: a profile exists or can be built from many interactions, connectivity is dependable, and the interface is in a widely used language. Table III sets out how these assumptions break down for rural students and what that implies for design. The row that matters most for this review is the one on limited awareness of options. If students do not know an occupation exists, a recommender that only ranks familiar options cannot raise awareness, however accurate its ranking.

Table III: Rural constraints and design implications

Constraint	Design implication
Thin student profile	Short adaptive questionnaire; accept incomplete input
Limited counsellor access	Teacher-usable interface with counsellor review
Intermittent connectivity	Lightweight, offline-capable tool with periodic sync
Language and literacy	Regional-language, visual, and audio content
Limited awareness of options	Show a wide occupation catalogue with short pathway notes
Local access limits (cost, distance)	Filter by feasibility; show scholarships and nearby institutions
Strong family influence	Shareable summary that parents can read

D. A Layered Decision Support Framework

Drawing on the sequence of prescreening, exploration, and choice [15] and on the problem-solving view of career decisions [13], we propose a framework with five layers (Table IV). The layers are deliberately modular, so that a school can start with the first three and add the rest as capacity grows.

Table IV: Proposed framework layers

Layer	Function	Suggested technique
1. Profiling	Capture interests, strengths, subjects, and context	Interest inventory; short questionnaire
2. Knowledge base	Curated data on occupations, courses, institutions, funding	Localised, maintained catalogue
3. Recommendation	Filter by constraints, then rank options	Rules, AHP-style weighting, content matching
4. Explanation	Give reasons and adjacent options	Rule traces; "also consider" lists
5. Counsellor loop	Review, feedback, outcome tracking	Teacher dashboard; periodic model updates

The profiling layer deliberately gives weight to interests, since interest and personality inputs are rare in the reviewed systems [10], and the performance-based prediction used by Esmail et al. [11] is treated as an optional later addition and not as the core. Two design choices deserve comment. First, the recommendation layer is built on filtering and weighted ranking, not on a learned model, because these need no interaction history and can be explained to students and parents. A learned component can be added later using locally collected outcomes, in the hybrid manner discussed in the literature [20]. Second, the explanation layer deliberately surfaces some options beyond the closest matches. Content-based systems tend toward narrow output [7], and for a tool whose purpose is to raise awareness, a modest amount of diversity is a feature and not a flaw.

Evaluation of such a framework should go beyond recommendation accuracy. Suitable measures include a before-and-after assessment of career awareness, agreement between tool suggestions and counsellor judgement, usability for teachers, and students' own reports of how useful and understandable the suggestions were.

E. Ethical and Data Considerations

Systems that profile minors raise concerns about consent, privacy, and bias. India's Digital Personal Data Protection Act, 2023 addresses the processing of children's data and requires verifiable parental consent in this setting [27], so any deployment should plan for consent and minimal data collection from the start. Suggestions should be presented as advice to be discussed and never as a verdict on a student's future. Where learned models are introduced, their training data should be audited for gender, caste, and regional patterns that would otherwise be reproduced, and explanations should be available to counsellors [23].

F. Limitations and Future Directions

This review has clear limits. It is narrative, and the comparisons are qualitative judgements and not pooled results. The framework has not been implemented or tested with students. Future work should build a prototype for a small set of rural schools, localise the occupation catalogue with regional labour-market and scholarship information, develop instruments in regional languages, and test whether the tool changes career awareness relative to conventional guidance.



V. CONCLUSION

Career guidance tools have a long research record, but the approaches that dominate it were shaped by settings with abundant data, stable connectivity, and access to trained counsellors. Reading them against rural school conditions changes which approaches look attractive: methods that are transparent and work with little history matter more than those that are statistically powerful but data-hungry. For rural students, the practical aim is awareness, that is, making a wider set of realistic options visible and understandable, and this shapes the framework proposed here. Its value now depends on empirical work: piloting it with teachers and students, measuring change in awareness, and checking that its suggestions are fair across groups.

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