# A Systematic Literature Review of Prediction of Career Readiness among Undergraduate Students Using Explainable AI and Machine Learning Techniques

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## ABSTRACT

Career readiness is an increasingly important concern in higher education, as good grades alone do not guarantee that a student is ready for the workplace. Being career-ready typically involves a mix of academic knowledge, technical skills, communication, teamwork, problem-solving, practical experience, and genuine engagement with career planning. With more student data available than ever, Machine Learning (ML), Deep Learning (DL), and Explainable AI (XAI) are increasingly used to predict how ready students are for this transition. This paper reviews recent literature on ML, DL, and XAI approaches used to predict student career readiness and closely related outcomes such as employability and placement. The reviewed studies are grouped by technique into traditional ML, Deep Learning, hybrid/ensemble methods, explainable AI, and supporting measurement work, and by the types of variables used as predictors. The review finds that traditional ML models such as Random Forest and SVM remain the most widely used; Deep Learning is applied mainly to larger and more complex datasets; and Explainable AI, though important for trust and transparency, is still used sparingly. The literature also tends to treat career readiness, employability, and placement as interchangeable, even though they are not quite the same thing. Employment and placement outcomes are shaped by the job market and institutional opportunities, while career readiness reflects how prepared a student actually feels for that transition. A consistent gap is identified across the literature: psychological attributes such as self-efficacy, and the impact of student–teacher relationship quality, are largely missing from current prediction models.

**Keywords:** Career Readiness, Machine Learning, Deep Learning, Explainable AI, Student Employability, Self-Efficacy, Student–Teacher Relationship Quality, Higher Education

## INTRODUCTION

Higher education is an important stage in the transition from academic learning to the workforce. During this period, students are expected to apply their knowledge, communicate effectively, work with others, solve problems, adapt to new situations, and be mentally prepared to face workplace demands. Therefore, academic performance alone does not fully indicate whether a student is prepared for employment. Career readiness refers to this overall preparation and includes academic knowledge, technical skills, communication, teamwork, problem-solving ability, practical experience, career engagement, and mental preparedness for the transition from education into employment.

Career readiness is different from employment or placement. Employment and placement refer to whether a student obtains a job, and these outcomes can be influenced by factors such as the job market and the availability of companies recruiting students. Career readiness, in contrast, focuses on the student's own level of preparation for entering the workforce. A student may be well prepared for a career but may not get placed immediately because of external factors. Similarly, getting a job does not necessarily mean that the student is

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fully prepared for workplace demands. Therefore, this distinction is important when reviewing studies on career readiness and related outcomes.

Traditionally, teachers and counsellors have assessed students' career readiness using grades, internships, and interviews. Although these methods can provide useful information, they can be time-consuming and may depend on personal judgment, which can lead to differences in assessment. With the growing availability of student data, researchers have increasingly explored Machine Learning (ML) and Deep Learning (DL) for predicting career readiness. These techniques can analyse different types of student information, such as academic performance, skills, and activity records, and use these data to identify patterns and predict students' readiness for employment.

Many ML and DL models can be difficult to interpret because they provide predictions without clearly explaining how the results were reached. For example, if a model predicts that a student is not career-ready, it may not be clear which factors contributed to that prediction. Explainable Artificial Intelligence (XAI) can help address this issue by identifying the factors that influence the model's prediction, such as academic performance, communication skills, or project experience. This is particularly important in education, where unclear or inaccurate predictions may affect decisions related to students' future careers.

In recent years, several studies have explored ML and DL for predicting career-related outcomes. Some focus on employability, while others examine career readiness directly. A smaller number of studies have also incorporated XAI to make their predictions more understandable. However, the existing research is spread across different methods, variables, and outcomes. A comprehensive review is therefore needed to bring together what has been studied, the approaches that have been used, and the areas that remain underexplored.

In this review, recent studies that use ML, DL, and XAI to predict student career readiness and employability are examined. The methods, data, results, strengths, and limitations of these studies are organized to provide a clear overview of the existing research and a useful starting point for future studies in this area.

One important gap identified in the reviewed literature is the limited attention given to the human side of career readiness. Factors such as how students perceive their own abilities, particularly self-efficacy, and how their relationships with teachers may influence their confidence and preparation are rarely considered in existing prediction models. Most models rely mainly on measurable variables such as scores, grades, and skill-related measures, while psychological and relational factors receive much less attention. This highlights an important area for further research on student career readiness.

The rest of the paper is organized as follows. Section 2 explains how papers were selected and reviewed. Section 3 classifies the techniques used across the literature. Section 4 looks at the variables used to predict career readiness and related outcomes. Section 5 discusses the studies in detail, grouped by theme. Section 6 compares the studies in a summary table. Section 7 covers key findings, challenges, and the gap identified. Section 8 concludes the paper.

## REVIEW METHODOLOGY

To keep this review organized and fair, a clear process was followed instead of picking papers at random.

**Search process:**

A structured Boolean search string was developed to capture the intersection of three core concept groups: (1) the outcome of interest, (2) the target population, and (3) the analytical approach. The search string applied was:

> *("career readiness" OR "work readiness" OR "employability" OR "career adaptability" OR "job readiness") AND ("undergraduate" OR "college student" OR "university student" OR "higher education") AND ("explainable AI" OR "machine learning" OR "artificial intelligence" OR "predictive model" OR "classification" OR "regression")*

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Searches covered major academic sources, including IEEE, Elsevier, Springer Nature, and MDPI platforms.

**Inclusion criteria:**

Papers were kept if they: use ML, DL, or XAI methods; predict student career readiness, employability, related academic performance, or placement outcomes; were mostly published between 2020 and 2026, to keep the review current; and are written in English and publicly accessible.

**Exclusion criteria:**

Papers were left out if they: had no real connection to education or student outcomes; didn't use any ML/DL/XAI method; or appeared in journals with a clear subject mismatch, unless the paper was too relevant to skip.

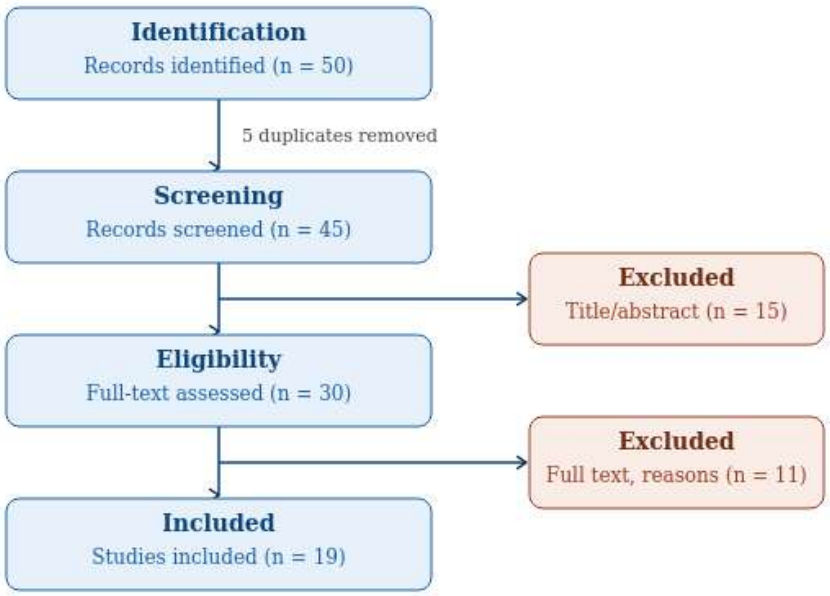
**Screening:**

Titles and abstracts were first checked to drop papers that did not fit. The remaining papers were read in full to confirm relevance. This process left a core set of papers, which form the basis of this review.

**Data extraction:**

For each selected paper, the following was recorded: the technique(s) used (e.g., Random Forest, Deep Neural Networks, SHAP, LIME); the dataset type (academic records, behavioral data, survey data, etc.); the main outcome predicted (career readiness, employability, placement, performance); the reported accuracy or performance metric; and strengths and limitations noted by the authors.

***Figure 1. PRISMA-style flow diagram of the study selection process.***




## CLASSIFICATION OF TECHNIQUES

Before looking at individual studies, it helps to see the bigger picture ,how the different techniques used in this field relate to each other. Based on the papers reviewed, the methods generally fall into four groups.

Traditional Machine Learning models — These are the most commonly used techniques. They include Random Forest, Decision Trees, Logistic Regression, Support Vector Machines (SVM), Naive Bayes, and various ensemble methods (like bagging and boosting). Most of the reviewed papers rely on these models because they work well with smaller, structured datasets and are relatively easy to train and interpret.

Deep Learning models — A smaller but growing number of studies use neural network-based approaches, such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). These models tend to perform better with larger, more complex datasets, but they need more data and computing power, and are harder to interpret without extra tools.

Hybrid and Ensemble approaches — Some studies combine multiple models together — for example, mixing Random Forest with Gradient Boosting, or combining Deep Learning with Reinforcement Learning (as seen in CareerNet). These hybrid setups usually aim to balance accuracy with robustness, picking up the strengths of each individual method.

Explainable AI (XAI) techniques — This is the newest and least common category. Techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are used to open up the "black box" of ML/DL models. Instead of just giving a prediction, these tools show which input features mattered most and by how much. Only a few of the reviewed papers apply these methods, which itself points to a gap in the field.

## VARIABLES USED IN CAREER READINESS AND RELATED PREDICTION

Looking across the reviewed literature, the predictors used to build these models generally fall into four broad categories: academic, skill-based, practical, and engagement-related.

Academic variables — GPA, semester scores, and academic progression are the most common predictors, used in studies predicting employability [5, 7], placement [9], and career readiness directly [8]. They dominate because they are easy to collect, though strong grades alone do not guarantee a student feels prepared for their career.

Technical and soft skills — Some studies move beyond grades to include competencies like communication, teamwork, and problem-solving. Urs and Sudharshan [13] combined behavioral data with academic and financial variables, while Vo et al. [15] built their model around competency gaps rather than grades alone.

Practical experience — Internships and hands-on exposure appear as predictors in Pathak et al. [9], Muhammad et al. [7], and Chen et al. [2], reflecting real-world readiness rather than classroom performance.

Career engagement and other factors — A smaller group of studies, including Pachouly and Bormane [8] and Zheng et al. [19], add demographic, socioeconomic, and organizational engagement data for a fuller picture of the student.

Even with this range, one category is consistently missing: relational and psychological factors. No reviewed study includes student–teacher relationship quality and self-efficacy together as a predictor , the gap this review builds toward.

## LITERATURE REVIEW

The selected studies were examined based on the prediction technique, variables used, target outcome, and reported performance measures. The literature mainly covers machine learning (ML), deep learning (DL), ensemble approaches, explainable artificial intelligence (XAI), and studies related to career readiness and student performance.

### Machine Learning, Deep Learning and Ensemble Approaches

Traditional ML is the most frequently used approach for predicting student career-related outcomes. VidyaShreeram and Muthukumaravel [14] applied ML techniques for student career prediction, demonstrating the use of computational methods for identifying suitable career outcomes. Muhammad et al. [7] predicted student employability using variables including CGPA, industrial experience, and co-curricular participation. Random Forest achieved 98% accuracy and an F1-score of 0.99. Vo et al. [15] proposed OPT-BAG, an

optimised Bagging model based on Random Forest for student employability prediction and evaluated the model using accuracy, precision, recall, and F1-score.

Mansor and Othman [5] developed an ML-based employability prediction model for Malaysian Community College graduates. Haque et al. [4] compared different classification techniques for graduate employability prediction. Chen et al. [2] used the CART algorithm to predict early employability among 610 Vietnamese graduates using demographic and academic variables and achieved 93.6% accuracy. Pathak et al. [9] investigated student placement prediction using different ML classifiers. XGBoost achieved 89.23% accuracy, 89.81% F1-score, and 0.945 AUC.

DL has been applied less frequently than conventional ML. Wang [16] proposed a DL-based approach for college graduate employment prediction. Raja and Priya [11] developed CareerNet by combining DL and Reinforcement Learning for student career recommendation. Qiang et al. [10] incorporated educational domain knowledge into a DL model for student performance prediction. Zheng et al. [19] developed an explainable hybrid DL framework using multi-source student data for employment prediction and evaluated it using accuracy, macro-F1, AUC, and Cohen's kappa.

Ensemble and hybrid approaches have also been explored. Vo et al. [15] used optimised Bagging, while Raja and Priya [11] combined DL with Reinforcement Learning. Zha [18] proposed a hybrid ML approach for predicting students' employment and entrepreneurship choices. Pathak et al. [9] also compared individual classifiers with a Voting Classifier. These studies indicate that combining algorithms can provide competitive predictive performance, particularly when different types of student information are considered.

**Career Readiness, Employability and Related Student Outcomes**

The reviewed studies address several career-related outcomes, including career readiness, employability, placement, employment, career prediction, and entrepreneurship. These outcomes are related but represent different aspects of students' transition from education to work.

Pachouly and Bormane [8] directly investigated student career-readiness prediction using ML, DL, and XAI. Logistic Regression achieved 98.55% accuracy, 98.55% F1-score, and 0.9995 ROC-AUC, with 98.37% accuracy in five-fold cross-validation. This study is particularly relevant because it directly addresses career readiness rather than using employment or placement as the prediction target.

Several other studies focus on employability. Muhammad et al. [7], Vo et al. [15], Mansor and Othman [5], Haque et al. [4], and Chen et al. [2] examined employability prediction using academic, demographic, experience, and other student-related variables. Pathak et al. [9] focused on placement outcomes, while Wang [16] investigated graduate employment. Zha [18] examined employment and entrepreneurship choices. Agustin-Cera et al. [1] considered student startup readiness, while Maulana et al. [6] and Urs and Sudharshan [13] focused primarily on academic performance.

Wang et al. [17] examined career readiness as a multidimensional construct using multidimensional Item Response Theory and text mining. This study is important for establishing that career readiness involves multiple dimensions rather than a single academic or employment indicator. Haque et al. [3] examined LLM-based feature selection for graduate employment classification, while Syed Mustapha [12] compared feature-selection methods for student learning-performance prediction.

**Psychosocial, Interpersonal and Explainable AI Factors**

Career-related outcomes are also associated with psychological and interpersonal factors. Zhou et al. [20] examined career decision-making self-efficacy and employability and reported a positive relationship between the two. Petruzziello et al. [21] examined teaching-staff support and perceived employability, demonstrating the relevance of students' interactions with teaching staff to career-related outcomes. Das et al. [22] investigated career self-efficacy and highlighted the role of career courses, coaching, and peer learning in supporting students' career development.

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Although these studies are not ML-based career-readiness prediction studies, they provide supporting evidence for considering psychological and interpersonal variables in computational models.

XAI has also received increasing attention in educational prediction. Pachouly and Bormane [8] incorporated XAI into direct career-readiness prediction. Qiang et al. [10] integrated educational domain knowledge into DL-based prediction, while Zheng et al. [19] used SHAP to examine feature contributions in employment pre-

diction. Tiukhova et al. [23] investigated the stability of XAI explanations in student-success prediction. Kesgin et al. [24] combined ML, XAI, and fairness assessment using SHAP and LIME. Ayanwale et al. [25] further incorporated psychological variables into a transparent ML framework while considering explainability and fairness.

**Synthesis and Research Gap**

The reviewed literature shows that traditional ML remains the dominant technique, while DL, hybrid approaches, and XAI are less frequently used. Academic performance, technical and soft skills, practical experience, demographic characteristics, behavioural factors, and career engagement are among the commonly used predictors. The studies also demonstrate strong predictive performance in several cases, including Random Forest with 98% accuracy [7], CART with 93.6% accuracy [2], XGBoost with 89.23% accuracy and 0.945 AUC [9], and Logistic Regression with 98.55% accuracy and 0.9995 ROC-AUC [8].

The literature also indicates that career readiness, employability, placement, employment, and entrepreneurship should not be treated as identical outcomes. Although psychosocial studies identify self-efficacy and teaching-staff support as relevant career-related factors, these variables have been less consistently integrated with academic, skill-based, behavioural, and engagement variables in computational models that directly predict career readiness. In addition, the use of XAI and fairness evaluation remains limited. These observations establish the basis for examining a more multidimensional and interpretable approach to student career-readiness prediction.

## COMPARATIVE SUMMARY OF REVIEWED STUDIES

The table 1 below summarizes the algorithm used, main predictor(s), advantages, and disadvantages reported across the reviewed studies.

**Table 1: summarization of algorithm used, main predictor(s), advantages, and disadvantages**

| Author(s), Year | Algorithm Used | Main Predictor(s) | Advantage | Disadvantage |
|---|---|---|---|---|
| Pachouly & Bormane, 2026 [8] | ML + DL + XAI | Academic, demographic, behavioral, career engagement | Directly predicts career readiness with explainability | Limited generalizability due to the specific student dataset |
| Vo et al., 2023 [15] | Random Forest (OPT-BAG) | Competency and skill gaps | Strong, stable accuracy for employability prediction | No explainability included |
| Mansor & Othman, 2024 [5] | ML classifiers | Academic and institutional attributes | Tailored to a specific student population (community college) | Small, regionally limited dataset |
| Haque et al., 2024 [4] | ML classification (comparative) | Structured academic/employment data | Compares multiple classifiers for best fit | No explainability included |

| | | | | |
|---|---|---|---|---|
| Muhammad et al., 2023 [7] | ML classifiers | CGPA, industrial experience, co-curricular | Simple, easy to implement | Limited generalizability beyond region studied |
| Pathak et al., 2025 [9] | ML framework | CGPA, internships | Useful proxy for readiness via placement outcomes | Placement is not the same as full career readiness |
| Wang, 2026 [16] | Deep Learning | Individual and employment-related data | Handles large, complex employment datasets well | Requires high computational resources |
| Chen et al., 2025 [2] | ML (data-driven) | Entrance score, academic performance | Captures early-stage employability signals | Regionally limited sample (Vietnam only) |
| Raja & Priya, 2025 [11] | DL + Reinforcement Learning | Career and behavioral data | Novel hybrid approach, adapts recommendations dynamically | Complex model, harder to interpret |
| Zha, 2025 [18] | Hybrid ML | Employment/entrepreneurship decision factors | Combines strengths of multiple models | Narrow outcome (employment vs. entrepreneurship only) |
| Qiang et al., 2026 [10] | DL + domain knowledge (XAI) | Academic + domain-knowledge features | Domain knowledge improves interpretability | Focused on performance, not career readiness directly |
| Zheng et al., 2026 [19] | Hybrid DL + XAI | Academic, demographic, financial, engagement | Explains predictions using multi-source data | Explanation limited to structured features only |
| Wang et al., 2024 [17] | IRT + text mining | Career readiness constructs (survey/text) | Strong for measuring career readiness as a construct | Measurement-focused, not a predictive model |
| Haque et al., 2025 [3] | LLM-based feature selection | Demographic, academic, graduate-tracer data | Cutting-edge, improves feature quality | Depends on LLM reliability and bias |
| Syed Mustapha, 2023 [12] | Feature selection (comparative) | Learning performance features | Useful methodological reference | Focused on learning performance, not readiness |
| Maulana et al., 2023 [6] | ML (comparative) | Academic and behavioral variables | Identifies best-performing algorithm across models | Predicts performance, not career readiness |
| Agustin-Cera et al., 2026 [1] | ML classifiers | Startup readiness indicators | Extends readiness prediction to startup context | Narrow focus on entrepreneurship only |
| Urs & Sudharshan, 2025 [13] | Multi-factor ML | Behavioral, financial, wearable data | Combines behavioral, financial, and wearable data | No relational/psychological data included |
| VidyaShreeram & Muthukumaravel, 2021 [14] | ML | Career-related attributes | Early, foundational work on career prediction | Limited technique diversity |

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## DISCUSSION AND RESEARCH GAPS

The reviewed studies show several patterns in the use of machine learning for student career-related prediction.

Traditional ML remains the most widely used approach. Random Forest, SVM, Decision Trees, Logistic Regression, and other classification methods are frequently applied to employability, placement, and related outcomes. These approaches are particularly common with structured educational datasets. Ensemble methods are also widely used because of their predictive performance.

Deep Learning is used less frequently. The reviewed studies applying Deep Learning generally involve larger or more complex datasets and, in some cases, combine Deep Learning with other techniques. These approaches can capture complex patterns but are generally more computationally demanding and less interpretable than conventional ML methods.

Explainable AI remains limited. Only a small number of reviewed studies incorporate XAI, including Pachouly and Bormane [8], Qiang et al. [10], and Zheng et al. [19]. These studies demonstrate the value of explaining model predictions, particularly by identifying important features. However, the use of XAI is still limited compared with conventional predictive approaches.

The predictor variables are mainly structured and measurable student characteristics. Academic performance, skills, behavioural information, internships, work experience, financial characteristics, and career engagement are among the commonly used variables. Despite this wide range, psychological and relational factors receive very limited attention. In particular, the reviewed studies do not include student–teacher relationship quality or self-efficacy as predictive variables.

Studies also measure career readiness inconsistently. Several studies focus on employability, placement, employment, or startup readiness rather than career readiness directly. Although these outcomes are related, they represent different aspects of students' transition from education to work. This distinction matters because placement and employment can also be influenced by external factors such as job-market conditions and institutional opportunities.

## IDENTIFIED GAP

Existing ML/DL/XAI studies mainly predict career readiness and related outcomes using academic, technical, soft-skill, and other structured student variables. Student–teacher relationship quality and self-efficacy have received limited attention as predictive factors, while career readiness is not always clearly distinguished from employability and placement outcomes. In addition, further comparison of multiple XAI techniques is needed to determine which methods provide more reliable and interpretable explanations of career-readiness predictions. Therefore, an integrated model incorporating academic, competency-related, and psychosocial factors, along with comparative XAI analysis, is needed

## CONCLUSION

This review examined the use of Machine Learning, Deep Learning, and Explainable AI for predicting student career readiness and related outcomes. The reviewed studies show that academic performance is the most commonly used predictor, while technical skills, soft skills, internships, work experience, behavioural factors, and career engagement are also used. Traditional ML methods, particularly Random Forest and other ensemble approaches, are widely applied, while Deep Learning is used in relatively fewer studies. XAI is still less commonly applied, with SHAP being one of the approaches used to explain important predictors.

The review also shows that career readiness, employability, placement, and employment are often used as closely related outcomes, although they are not identical. Most existing studies rely on structured academic, skill-based, behavioural, and career-related data. Psychological and relational factors, particularly self-efficacy and student–teacher relationship quality, are largely less explored in the reviewed prediction studies. This

suggests a shift from simple academic-based prediction towards multidimensional and increasingly explainable approaches to understanding students' career-related outcomes

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