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Comparative Analysis of Data Mining Methods in University Admissions

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Abstract

As higher education institutions increasingly adopt data-driven approaches to improve admissions outcomes, the role of Data Mining (DM) and Machine Learning (ML) in supporting equitable, efficient, and strategic decision-making has expanded significantly. This study presents a comprehensive comparative analysis of nineteen studies that applied DM techniques to university admissions. Through a structured literature review, the research categorizes the modeling approaches into six main types: classical classification and regression models, ensemble and stacked learning models, interpretable decision tree-based systems, SVM and hybrid SVM frameworks, deep learning models, and geodemographic or behavioral modeling. The analysis synthesizes model performance, feature relevance, interpretability, and fairness considerations across these categories. Findings indicate that while ensemble

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and deep learning models often achieve superior predictive accuracy, interpretable models such as decision trees and logistic regression remain essential in contexts demanding transparency and stakeholder trust. Furthermore, the integration of socio-demographic and behavioral data is gaining traction as a means of enhancing inclusivity, though it raises ethical concerns regarding fairness and bias. The study concludes with strategic recommendations for institutions and researchers, emphasizing the need for hybrid modeling, contextual alignment, fairness diagnostics, and validation across diverse educational settings.

Keywords: University Admissions, Data Mining, Machine Learning.

Introduction

University admissions play a critical role in shaping not only the academic and professional trajectories of students but also the strategic direction, diversity, and competitiveness of higher education institutions (HEIs). In the face of expanding global competition and increasingly complex enrollment dynamics, universities are under growing pressure to adopt data-informed strategies that enable more transparent, equitable, and efficient decision-making.

In response to these challenges, Educational Data Mining (EDM) has emerged as a promising interdisciplinary field that applies Machine Learning (ML), statistical modeling, and data science techniques to educational datasets. EDM facilitates a shift away from static, one-size-fits-all admission practices toward more dynamic, predictive, and personalized systems supporting improved student-program matching, retention forecasting, and long-term academic planning (Romero & Ventura, 2020).

However, many institutions still rely on conventional admissions frameworks that emphasize narrow academic metrics, often overlooking the complex and multifaceted nature of student potential. Persistent challenges such as high attrition rates, delayed graduation, and the underrepresentation of certain demographic groups underscore the limitations of traditional models (Dewantoro & Ardisa, 2020; Ujkani, Minkovska, & Stoyanova, 2021). In contrast, data-driven algorithms have demonstrated the capacity to uncover patterns in applicant profiles, enabling more context-sensitive and equitable admissions decisions (Jeganathan, Rajalakshmi, & Elango, 2021; Apoorva et al., 2020; Mengash, 2020).

Despite a growing body of research in this area, the literature remains fragmented. Studies differ widely in terms of modeling techniques, datasets, feature sets, and evaluation metrics making it difficult to derive generalizable insights or establish best practices (Acharya, Armaan, & Antony, 2019; Sridhar, Mootha, & Kolagati, 2023). Recent systematic reviews further highlight the absence of consensus regarding the most effective predictive models or features, especially across varied institutional and cultural contexts (Al-Alawi, Ali, Alfateh, & Alrayes, 2023).

This study addresses that gap by conducting a structured and comparative review of Data Mining (DM) methods applied to university admissions. It aims to synthesize methodological insights, evaluate model performance, and identify practices that can inform the development of future data-driven admissions systems.

Problem Definition

Although the application of DM and ML techniques in university admissions has expanded rapidly, much of the research remains fragmented, exploratory, and context specific. The field lacks a cohesive body of comparative studies that rigorously evaluate the performance of different algorithms under similar conditions or across diverse institutional datasets. This fragmentation not only hinders theoretical advancement but also impedes practical adoption.

Without a clear understanding of which models perform best, under what conditions and with which features, HEIs face significant uncertainty in deploying predictive analytics for admissions (Al-Alawi et al., 2023). Consequently, there is a pressing need for synthesis, evaluation, and critical comparison to inform evidence-based and equitable admissions strategies.

Research Objectives

This study aims to advance the field of EDM in university admissions by conducting a structured comparative analysis of existing work. The specific objectives are:

1. To systematically review and classify published studies that apply DM and ML techniques to university admissions, with attention to the models used, datasets employed, prediction targets, and evaluation metrics.
2. To compare the predictive performance and application scope of various modeling approaches including classification algorithms, regression techniques, ensemble methods, and Deep Learning (DL) models used in predicting admission decisions and student success.
3. To identify the most influential predictive features, such as academic records, demographic characteristics, and behavioral indicators, and evaluate their impact on model accuracy, fairness, and generalizability.
4. To synthesize methodological patterns, limitations, and research gaps across the reviewed literature, and to provide actionable recommendations for researchers and higher education institutions seeking to implement data-driven, context-sensitive, and equitable admissions systems.

Methodology

This study adopted a structured comparative literature review to analyze the application of DM and ML techniques in university admissions. The aim was to synthesize methodological trends, compare model performance, and extract actionable insights to support data-informed decision-making in higher education

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contexts. A targeted literature search was conducted across major academic databases, including IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar, covering studies published between 2018 and 2025. Additional sources were identified through backward citation tracking and expert consultation with domain specialists.

From an initial pool of over fifty articles, nineteen studies were selected based on clearly defined inclusion criteria. Eligible studies had to focus explicitly on university admission, enrollment, or student success modeling using DM or ML approaches, report empirical evaluation metrics such as accuracy, coefficient of determination (R^2), Area Under the Curve (AUC), or F1-score, and provide sufficient methodological transparency. Studies were excluded if they lacked quantitative results, focused exclusively on non-university contexts, or employed qualitative designs without predictive modeling components.

To support comparative synthesis, the selected studies were categorized according to their primary modeling strategy. These included (A) classical classification and regression models; (B) ensemble and stacked learning models; (C) interpretable and rule-based models; (D) support vector machines (SVM) and hybrid SVM systems; (E) DL and neural network (NN) models; and (F) geodemographic and behavioral modeling frameworks. This thematic classification enabled a focused analysis of performance trade-offs, model transparency, and contextual suitability across the reviewed literature.

Each study was examined in relation to algorithm type, dataset characteristics, feature diversity including academic, demographic, behavioral, and geographic inputs, evaluation techniques, and the integration of interpretability tools. Special emphasis was placed on fairness concerns, subgroup-specific outcomes, and the extent of external validation. To facilitate comparative insight, the findings were organized into summary tables (Tables 1–6) and visually represented using a radar chart (Figure 1), which maps the relative strengths of each modeling category across five dimensions:

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predictive accuracy, interpretability, fairness, feature diversity, and deployment readiness.

This structured methodological approach provided the foundation for the next section, which presents a detailed comparative analysis of the reviewed studies and their contributions to university admissions research.

Comparative Analyses of DM Methods in University Admissions

To assess the effectiveness of DM approaches in university admissions, this section reviews 19 studies, grouped into methodological categories based on the dominant modeling techniques used.

A. Core Classification and Regression Models:

This category encompasses foundational supervised learning techniques frequently utilized in university admissions research, including logistic regression (LR), k-nearest neighbors (KNN), naïve Bayes (NB), decision trees (DT), artificial neural networks (ANN), and support vector regression (SVR). These algorithms serve as standard baselines for predicting admission decisions, enrollment likelihood, or early academic outcomes.

Dewantoro and Ardisa (2020) developed a decision support system to identify students at risk of academic underperformance before enrollment. Motivated by persistent challenges in engineering programs such as low GPAs and extended graduation timelines, the study compared ANN, KNN, and NB models, representing neural, geometric, and probabilistic paradigms. Using a dataset of 145 students from Satya Wacana Christian University (2010–2014), the authors included features such as mathematics, physics, and English grades, along with school type and region. After normalization and duplicate removal, models were evaluated using 10-fold cross-validation. ANN achieved the highest accuracy (92.86%), outperforming KNN (~85%) and NB (~80%). Despite its small sample and lack of behavioral or demographic data, the study illustrated the ANN's capacity for capturing nonlinear relationships and outlier resilience, and recommended future use of unsupervised learning techniques.

Ujkani, Minkovska, and Stoyanova (2021) extended this foundational work by evaluating 16 algorithms across four model families (NB, LR, KNN, and DT) on a larger institutional dataset of 2,329 academic records from the University "Isa Boletini" (2018–2021). Preprocessing included normalization, removal of incomplete records, and internal reliability checks (Cronbach's alpha = 0.83). Reduced Error Pruning Tree (RepTree) achieved the highest True Positive Rate (TPR = 0.902), followed by Logistic Model Tree (LMT) and C4.5 DT (J48). NB variants such as NaiveMulti underperformed (TPR = 0.790), underscoring the limitations of strong independence assumptions. While tree-based models demonstrated flexibility with mixed data types, the study's omission of demographic or contextual variables limited its relevance to equity-focused modeling.

Jeganathan, Rajalakshmi, and Elango (2021) investigated graduate admission outcomes using a dataset of 500 anonymized applicants of the University of California Los Angeles (UCLA), incorporating Graduate Record Examination (GRE) and TOEFL scores, CGPA, Statement of Purpose (SOP) and Letter of Recommendation (LOR) strength, research experience, and institutional ranking. After normalization, six models were compared. LR achieved the highest accuracy (99%), followed by SVM and random forest (RF) (97%), NB (96%), and both DT and KNN (95%). The findings affirmed LR's suitability for structured and linearly separable data, though the study lacked a fairness audit and did not report on feature importance, limiting interpretability and transferability.

Apoorva et al. (2020) proposed the University Admission Prediction (UAP) model to support international graduate applicants, using data from Yocket, a university application platform. The dataset included GRE, TOEFL/IELTS, GPA, SOP, LOR, and research experience. After standardization and DT based feature analysis, four models were tested: KNN, LR, ridge regression, and RF. While RF achieved high training accuracy (95%), it overfit the data, resulting in lower test performance (77%). Ridge and LR demonstrated better generalization (78–79% test accuracy), illustrating the trade-off between complexity and robustness in moderate sized datasets.

Mengash (2020) applied multiple classifiers to predict first-year academic performance among 2,039 female students at Princess Nourah bint Abdulrahman University (PNU). Input features included Standardized Achievement Admission Test (SAAT), General Aptitude Test (GAT), and High School Grade Average (HSGA), used to classify cumulative GPA into five bands. After cleaning and scaling, ANN, DT, SVM, and NB were evaluated. ANN achieved the highest accuracy (79.22%) and precision (81.44%), while DT excelled in recall (80.24%) and F1-score (80.63%). The model's findings prompted a policy revision at PNU, increasing SAAT's weighting in admission scoring. Although the model lacked behavioral or demographic variables, its gender-specific scope highlighted the need for tailored admission frameworks.

Acharya, Armaan, and Antony (2019) adopted a regression perspective using 500 public graduate admission records with GRE, TOEFL, GPA, SOP, LOR, and research experience. They compared LR, SVR, DT regression, and RF regression. LR delivered the strongest results (R^2 = 0.7249), followed by RF (0.6602) and SVR (0.6440), while DT regression underperformed (0.5013) due to overfitting. Although the study reaffirmed the predictive utility of academic and experiential variables, it acknowledged the need for context-rich features and more advanced modeling approaches to capture subjective admission decisions.

Collectively, these studies confirm the predictive reliability of classical supervised learning methods in structured admissions contexts. LR and ANN frequently emerged as top-performing models, while DTs offered interpretable alternatives suitable for institutional use. Nevertheless, several limitations persist across the literature, including small sample sizes, absence of demographic or behavioral attributes, and limited analysis of fairness or bias. These gaps highlight key opportunities for future research aimed at building inclusive, explainable, and generalizable admission prediction systems. A comparative synthesis of these studies is presented in Table 1.

Table 1: Comparative Summary of Core Classification and Regression Models in University Admissions

Study	Models Compared	Best Performing Model	Key Predictors	Limitations
Dewantoro & Ardisa (2020)	ANN, KNN, NB	ANN (92.86% Accuracy)	Math, Physics, English Grades; School Type/Region	Small sample, single institution
Ujkani et al. (2021)	NB, LR, KNN, DT	RepTree (TPR = 0.902)	Academic Grades Only	Excluded demographic/contextual features
Jeganathan et al. (2021)	LR, SVM, RF, NB, KNN, DT	LR (99% Accuracy)	GRE, TOEFL, GPA, SOP, LOR, Research	Small dataset, no fairness or feature analysis
Apoorva et al. (2020)	KNN, LR, Ridge, RF	Ridge/LR (~78–79% Test Accuracy)	GRE, TOEFL/IELTS, GPA, SOP, LOR, Research	Overfitting in RF; no demographics
Mengash (2020)	ANN, DT, SVM, NB	ANN (79.22% Accuracy)	SAAT, GAT, HSGA	Female-only dataset; no behavioral data
Acharya et al. (2019)	LR, SVR, DT Regression, RF Regression	Linear Regression ($R^2 = 0.7249$)	GRE, TOEFL, GPA, SOP, LOR, Research	Small sample; lacks demographic nuance

B. Ensemble and Stacked Learning Models:

This category explores studies that apply ensemble and stacked learning models to enhance the predictive accuracy and robustness of university admissions modeling. Unlike single-model approaches, ensemble techniques combine multiple learners either in parallel (e.g., bagging) or sequentially (e.g., boosting) to better capture complex feature interactions, reduce overfitting, and improve generalizability. Methods such as RF, Gradient Boosting Decision Trees (GBDT), Extreme Gradient Boosting (XGBoost), Categorical Boosting (CatBoost), and stacked neural networks

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have demonstrated strong performance, particularly in high-dimensional and heterogeneous educational datasets.

Across varied institutional contexts, these methods consistently outperform traditional classifiers, especially when tasked with modeling decision patterns and incorporating diverse features, including academic, experiential, and socio-demographic variables. Six studies were reviewed under this category.

Sridhar, Mootha, and Kolagati (2023) proposed a University Admission Prediction System based on stacked ensemble learning for graduate program recommendations. Their architecture integrated five Multilayer Perceptron (MLP) sub-models (Level-0) with a meta-MLP (Level-1), trained on a large-scale dataset (n = 35,848) from Edulix. Features included GRE/GMAT, TOEFL/IELTS, CGPA, undergraduate institution, research experience, and program type. The stacked model outperformed baselines such as DT, RF, and SVM, with the best baseline achieving 65.5% accuracy. However, the model lacked reported precision/recall metrics and excluded demographic variables, limiting its transparency and generalizability. The authors called for real-time data integration and enhanced architecture in future work.

Sivasangari et al. (2021) evaluated CatBoost, RF, and LR using a dataset of 8,000 profiles from Occidental College. CatBoost achieved the highest accuracy (95%), outperforming RF (90%) and LR (88%). Key predictors included GPA, GRE, and LOR strength. Although the study demonstrated the strength of gradient boosting in handling categorical and non-linear patterns, it did not address fairness or subgroup disparities, and lacked model interpretability mechanisms which are important considerations in educational contexts.

Wang et al. (2024) employed boosting and bagging techniques including GBDT, XGBoost, RF, Ridge Regression, and SVR to optimize enrollment planning based on academic and employment data from a Chinese university (2020–2023, n > 3,000).

GBDT achieved the best performance ($R^2 = 0.922$), followed by XGBoost (0.865) and RF (0.863). Pearson correlation and feature ranking identified GPA, graduation rate, and employment outcomes as top predictors. While the study offered strong institutional planning support, its reliance on administrative-level data rather than applicant-level inputs reduced its adaptability to dynamic enrollment behavior.

Maulana et al. (2023) compared ensemble and non-ensemble models using a UCLA dataset that included CGPA, GRE/TOEFL, SOP/LOR ratings, and research experience. Among RF, XGBoost, KNN, and SVR, RF achieved the best performance ($R^2 = 0.816$; MAE = 0.050). CGPA, GRE, and TOEFL were the most influential features. Despite affirming ensemble models' strength in structured data settings, limitations included small sample size, static features, and the absence of demographic variables, restricting broader applicability.

Priulla et al. (2025) conducted a large-scale national study on Italian high school students (n = 138,656) to predict general and STEM-specific enrollment. Using Gradient Boosting Machines (GBM), the study outperformed LR by 18% AUC in general enrollment prediction and 1% in STEM prediction. Key predictors included mathematics and Italian scores, Socioeconomic Status (SES), and curriculum type. While the study revealed gender disparities in STEM choices, interpretability tools were not applied, and no intervention strategies were proposed to address observed inequities.

Overall, the studies in this category confirm that ensemble methods particularly GBDT, CatBoost, and stacked MLPs consistently achieve high predictive performance, especially in large, structured datasets. These models are well-suited for both applicant-level recommendations and institutional resource planning. However, common limitations include the underreporting of interpretability mechanisms, limited subgroup fairness analyses, and insufficient attention to ethical considerations factors such as bias mitigation, transparency, and responsible data use, all of which are critical for deploying models in equitable educational settings. A comparative summary of these studies and models is presented in Table 2.

Table 2. Summary of Studies Using Ensemble and Stacked Learning Models for University Admission

Study	Models Compared	Best Performing Model	Key Predictors	Limitations
Sridhar et al. (2023)	Stacked MLP, DT, RF, KNN, SVM, LR, NB, LDA, QDA	Stacked MLP (92% Accuracy)	GRE/GMAT, TOEFL/IELTS, CGPA, Research, Program, Institution	No demographic features; interpretability not discussed
Sivasangari et al. (2021)	LR, RF, CatBoost	CatBoost (95% Accuracy)	GRE, TOEFL, GPA, SOP, LOR, Research, University Ranking	No subgroup or fairness analysis
Wang et al. (2024)	Ridge, SVR, RF, GBDT, XGBoost	GBDT ($R^2 = 0.922$)	GPA, Grad Rate, Pass Rate, Employment Rate	Limited interpretability; local context
Maulana et al. (2023)	KNN, RF, SVR, XGBoost	RF ($R^2 = 0.816$, MAE = 0.050)	CGPA, GRE, TOEFL, SOP, LOR, Research	Weak performance of SVR; lacks fairness exploration
Priulla et al. (2025)	GBM, LR	GBM (AUC ↑18% over LR)	Math, Italian Scores, Curriculum Type, Gender, SES	Gender bias observed; no real-time data

C. Interpretable and Rule-Based Models:

This category highlights the use of interpretable models particularly DT based algorithms such as C4.5, CART, RepTree, and their variants in university admissions research. These models are especially valued in institutional settings where transparency, rule-based logic, and explainability are essential for stakeholder trust, policy justification, and academic advising. While often surpassed by ensemble and DL models in raw accuracy, DTs offer clear decision paths and human-readable rules, making them ideal for contexts where model outputs must be defensible and actionable. Five studies were reviewed in this category, focusing on the deployment of rule-based models either as standalone predictors or within hybrid decision-support systems.

Bhaskaran and Aali (2020) developed a decision support tool for Bahraini HEIs using the C4.5 algorithm. Trained on data from 430 students, the model incorporated variables such as study branch, GPA, and school system type. The DT generated interpretable rules that aligned applicant profiles with academic programs historically linked to higher success rates. Although the study did not report traditional evaluation metrics like accuracy or F1-score, it emphasized the clarity of its rules as a key asset for academic advising. The most influential features were study branch (100%) and GPA (75%). Despite its modest sample size and lack of performance benchmarks, the model's practical applicability positioned it as a promising foundation for future advisory tools.

Alothman et al. (2022) introduced a hybrid admissions evaluation system combining DT, RF, and KNN algorithms within a graphical interface for Kuwaiti universities. Using synthetic data on admission scores and equivalency percentages, the tool classified applicants into "Accepted," "Foundation," or "Rejected" categories. DT emerged as the most accurate model (~89%), outperforming RF, which showed signs of overfitting. The rule-based structure of the DT model was particularly useful in detecting anomalies and providing justifiable admission decisions highlighting its strength in regulated or high-stakes environments. However, inconsistent data quality and reliance on synthetic samples limited generalizability.

Revisited from Category A, the study by Ujkani et al. (2021) evaluated 16 algorithms on academic-only datasets from the University of Mitrovica. Among the models, RepTree (a variant of the decision tree) achieved the highest TPR (0.902), outperforming interpretable alternatives such as LMT and J48. Despite omitting demographic and behavioral features, the study demonstrated the value of tree-based logic in generating transparent predictions aligned with institutional admission practices.

Also revisited, Mengash (2020) compared four classifiers in predicting first-year academic performance at PNU. Although ANN achieved the highest overall accuracy, DT outperformed in recall (80.24%) and F1-score (80.63%), making it particularly effective in identifying both high- and low-performing students. The DT's interpretability enhanced its suitability for academic advising, though its findings were limited by the single-gender dataset and absence of behavioral data.

A comparative summary of these interpretable models is presented in Table 3. Collectively, the reviewed studies reinforce the value of rule-based classifiers particularly C4.5, CART, and RepTree in applications where transparency, stakeholder communication, and actionable insights are prioritized. Nonetheless, limitations such as lack of external validation, exclusion of sensitive attributes, and limited scalability remain important considerations when deploying these models in dynamic or high-volume institutional settings.

Table 3: Summary of Interpretable and Rule-Based Models in University Admissions,

Study	Models Compared	Best Performing Model	Key Predictors	Limitations
Bhaskaran & Aali (2020)	C4.5 Decision Tree	C4.5 (Interpretability-focused)	Study Branch, GPA, School System	No accuracy metrics; small sample
Alothman et al. (2022)	DT, RF, KNN	DT (~89% Accuracy)	Admission Scores, Grade Equivalents	Synthetic data; generalizability concerns
Ujkani et al. (2021)	RepTree, LMT, J48, others	RepTree (TPR = 0.902)	Cumulative Grades, Matura, Entrance Exams	Excluded demographics; limited fairness
Mengash (2020)	ANN, DT, SVM, NB	DT (F1 = 80.63%)	SAAT, GAT, HSGA	Female-only data; lacks behavioral features

D. SVM and Hybrid SVM Systems:

This category examines the application of SVM, both as standalone classifiers and within hybrid frameworks, for predicting university admission outcomes. SVMs are particularly effective in high-dimensional and non-linear feature spaces and have been widely used for binary and multiclass classification tasks. However, their utility in educational contexts is influenced by data characteristics, feature diversity, and ethical

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considerations. This section reviews three studies leveraging SVM to support graduate admissions decisions, assess policy shifts, and develop recommender systems.

Zhang (2023) conducted a comparative evaluation of ML models using a Kaggle dataset of 400 graduate applicants. Features included GRE, TOEFL, CGPA, SOP, LOR ratings, research experience, and university ranking. SVM achieved the highest accuracy (98%) among the models tested (LR, DT, KNN, and NB) particularly excelling due to its ability to model non-linear decision boundaries. CGPA and GRE were identified as the most influential predictors. Despite the high accuracy, the small sample size and lack of domain-specific features limit generalizability. Moreover, the SVM model underperformed in recall for high-likelihood applicants, potentially misclassifying top candidates which is a critical issue in high-stakes settings.

Fang (2023) applied linear SVM to evaluate the implications of test-optional admissions policies at a large urban U.S. university. Using approximately 7,700 records from the School of Science, the study analyzed GPA, SAT scores, race, gender, and first-generation college status. Models were tested under three configurations: GPA-only, test-score-only, and combined features. While SVM delivered consistently high accuracy, the analysis revealed notable disparities under-predicting admission for first-generation and non-white students, while over-predicting for white, non-first-gen applicants. The exclusion of standardized test scores increased the model's reliance on GPA, amplifying pre-existing subgroup inequities. This study emphasizes the importance of bias auditing and fairness-aware modeling in AI-assisted admissions.

Baskota and Ng (2018) introduced a hybrid graduate school recommendation system combining multi-class SVM and KNN. The system utilized two datasets: one containing 16,000 student profiles (e.g., CGPA, GRE) and another detailing institutional characteristic such as ranking, tuition, and acceptance rates. SVM was used to predict a primary university recommendation, while KNN identified

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additional alternatives based on proximity in feature space. The model was evaluated using Normalized Discounted Cumulative Gain (nDCG) metrics and user validation, outperforming baseline methods including NB, C4.5, and MLP. However, exact match accuracy remained modest (58%), and scalability for broader deployment remained a challenge.

In summary, SVM-based systems consistently show strong predictive power in admission-related tasks, especially when used in hybrid frameworks such as SVM and KNN. Their strength lies in identifying patterns in complex academic datasets, but concerns persist regarding fairness, subgroup accuracy, and interpretability. A comparative overview of these models is presented in Table 4.

Table 4. Summary of Studies Using SVM and Hybrid SVM Systems in University Admissions

Study	Models Compared	Best Performing Model	Key Predictors	Limitations
Zhang (2023)	SVM, DT, KNN, NB, Regression	SVM (98% Accuracy)	CGPA, GRE, TOEFL, SOP, LOR, Research	Small dataset; no discipline-specific features
Fang (2023)	Linear SVM (GPA-only, Test-only, Combined)	SVM (High Accuracy with Bias Audit)	GPA, SAT, Race, Gender, First-gen	Demographic bias in test-optional settings
Baskota & Ng (2018)	SVM, KNN, NB, C4.5, MLP	SVM + KNN (nDCG@5 = 0.59)	CGPA, GRE, Tuition, Ranking	Moderate exact-match accuracy; scalability concerns

E. DL and NN Models for Interpretability and Accuracy:

This category explores the application of DL models in university admissions, with a focus on balancing predictive performance and interpretability. Techniques such as Feedforward Neural Networks (FFNN), Input Convex Neural Networks (ICNN), and traditional ANN provide flexible architectures capable of capturing complex, nonlinear relationships among academic, experiential, and behavioral features. When combined with interpretability tools like Local Interpretable Model-agnostic

Explanations (LIME) or gradient-based sensitivity analysis, these models become more suitable for use in high-stakes, ethically sensitive admission decisions.

Raftopoulos et al. (2024) proposed an interpretable DL framework for predicting undergraduate admissions to the University of California, Irvine's Computer Science program. The dataset included 4,442 applications with both quantitative (e.g., GPA, Advanced Placement (AP) scores) and qualitative (e.g., Personal Insight Questions (PIQs)) components. Two architectures were compared FFNN and ICNN both achieving 80.67% accuracy. However, ICNN demonstrated superior AUROC, precision, and recall, attributed to its convex optimization properties and ability to define more reliable decision boundaries. The authors used LIME and gradient sensitivity analysis to identify GPA, AP scores, and PIQ writing style as key drivers of admission predictions. The study emphasized the importance of embedding anomaly detection mechanisms and ethical constraints in future DL-based admissions systems.

As discussed earlier in Category A, Dewantoro and Ardisa (2020) utilized a standard ANN to predict students at risk of underperformance before university entry. Despite being trained on a small institutional dataset (n = 145), the ANN achieved 92.86% accuracy outperforming KNN and NB. While the model demonstrated strong predictive capability for academic variables, its limited sample size and absence of interpretability tools restricted broader applicability.

Bansode (2024) introduced a system-level admission prediction framework that integrated ANN with DT and LR models. The system leveraged a diverse set of features, including academic records, extracurricular involvement, LOR, and admission essays. Though exact model performance metrics were not reported, the framework prioritized ethical AI principles namely fairness, transparency, and privacy. The combination of ANN's ability to handle complex, heterogeneous data and DT's interpretability formed a hybrid pipeline aligned with institutional requirements. The study also recommended incorporating Natural Language Processing (NLP) techniques for future handling of unstructured textual data.

Overall, DL-based models show strong potential for accurately modeling admissions outcomes, particularly in settings involving diverse input types. Importantly, the incorporation of interpretability-enhancing components such as LIME and ICNN convexity constraints addresses longstanding concerns about DL model transparency. However, common limitations persist, including limited external validation, dataset-specific modeling, and a lack of fairness auditing. These issues must be addressed before such models can be widely deployed in equitable and trustworthy admission systems. A comparative summary of these studies is provided in Table 5.

Table 5. Summary of Deep Learning and Neural Network Models in University Admissions

Study	Models Compared	Best Performing Model	Key Predictors	Limitations
Raftopoulos et al. (2024)	FFNN, ICNN	ICNN (80.67% Accuracy; Highest AUROC)	GPA, AP Scores, PIQ Writing Style	No external validation; limited to one department; interpretability still complex
Dewantoro & Ardisa (2020)	ANN, KNN, Naive Bayes	ANN (92.86% Accuracy)	Math, Physics, English Grades; School Type	Small dataset; single institution; lacks cross-validation
Bansode (2024)	ANN, DT, LR (in deployment pipeline)	ANN likely contributed most (no separate metrics)	Academic records, Essays, Extracurriculars, Recommenders	No empirical results; mostly conceptual; lacks separate model benchmarks

F. Geodemographic and Behavioral Modeling in Admissions:

This category examines studies that integrate geospatial, socio-demographic, and behavioral variables into university admissions and enrollment prediction models. Unlike traditional approaches that rely primarily on academic indicators, these models incorporate factors such as ZIP-code-level attributes, travel distance, household income, Internet access, ethnicity, gender, and prior outreach behaviors (e.g., campus visits, application inquiries). Such approaches are particularly valuable for institutions

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seeking to enhance diversity, promote regional equity, and design data-informed recruitment strategies.

Pawar (2020) conducted a comprehensive geospatial and statistical analysis of engineering college enrollment trends in the United States by merging institutional enrollment data (n = 9,034) with ZIP-code-level U.S. Census indicators. Key features included household income, educational attainment, broadband access, minority population share, and travel distance to campus. The study employed Lasso regression and Negative Binomial Regression for feature selection, alongside QGIS for spatial mapping and clustering. Findings revealed that socioeconomic status and physical proximity significantly influenced enrollment patterns, with greater travel distances associated with lower likelihood of enrollment. Notably, gender and race analyses showed that underrepresented students were more likely to attend institutions close to home, often due to cultural or financial constraints. Although classification metrics were not reported, the study provided critical policy insights relevant to equity-focused outreach. However, the reliance on geographic proxies may mask individual variability and poses fairness challenges.

Priulla et al. (2025) investigated socio-demographic and academic predictors of university and STEM program enrollment across Italy, with a specific focus on gender disparities. Using a nationally representative dataset of 138,656 high school students, the study applied GBM, which outperformed LR by 18% in general enrollment prediction and by 1% in STEM-specific prediction (AUC metric). Important predictors included mathematics and Italian proficiency, curriculum track, school-level SES, and gender. The applied science curriculum emerged as the most influential predictor of STEM enrollment (relative importance = 40.7%). Male students with strong math scores were more likely to choose STEM fields than similarly performing female students, pointing to sociocultural factors and self-efficacy as mediators of

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gendered decision-making. Despite robust methodology, the study was limited by the absence of behavioral variables such as career motivation or outreach engagement.

Fang (2023), previously discussed in Category D, further emphasized the role of socio-demographic factors in admissions modeling under test-optional policies. Using linear SVM on approximately 7,700 records from a U.S. urban university, the study revealed systematic prediction disparities disadvantaging first-generation, female, and non-white applicants especially when test scores were omitted. These findings reinforce the importance of fairness auditing and subgroup impact analysis when incorporating demographic or proxy features in predictive models.

Collectively, these studies underscore the value of geodemographic and behavioral modeling for building more inclusive and context-aware admissions systems. While these variables enable a richer understanding of enrollment drivers, they also demand careful handling to avoid reinforcing structural inequalities. Future work should combine such features with rigorous fairness metrics and transparency frameworks. A comparative summary of the studies is presented in Table 6.

Table 6. Summary of Geodemographic and Behavioral Models in University Admissions

Study	Models Used	Best Performing Model	Key Predictors	Limitations
Pawar (2020)	Lasso, Negative Binomial Regression, K-Means	No accuracy metric; inferential results only	Household Income, Educational Attainment, Internet Access, Travel Distance	No predictive accuracy reported; risk of fairness issues from proxy variables
Priulla et al. (2025)	GBM, Logistic Regression	GBM (AUC ↑18% overall; ↑1% STEM)	Math & Italian Proficiency, Curriculum Type, Gender, SES	Limited behavioral data; potential for unobserved confounders
Fang (2023)	Linear SVM	SVM (High accuracy; fairness flagged)	GPA, Race, Gender, First-Gen Status, Test Scores	Demographic bias in test-optional settings; requires fairness diagnostics

The comparative analysis of diverse DM approaches underscores that no single modeling technique universally outperforms others in predicting university admissions outcomes. Instead, each category from interpretable rule-based models and classical regression techniques to advanced ensemble frameworks and DL architectures brings unique advantages and inherent trade-offs. Model selection must be context-driven, guided by factors such as predictive accuracy, interpretability, fairness, data characteristics, and institutional objectives.

This multi-perspective synthesis highlights the importance of balancing methodological rigor with ethical and operational considerations when designing predictive systems for higher education. The following section builds upon these findings, synthesizing cross-study themes, methodological patterns, and practical implications to guide future applications and research directions in educational data mining.

Findings and Discussion

The comparative analysis of nineteen studies reveals key patterns in how DM and ML techniques are applied in university admissions. Synthesized across five thematic dimensions: model performance, feature relevance, modeling purpose, interpretability, and fairness, these findings illustrate both methodological diversity and emerging trends shaping the field.

A. Model Performance and Predictive Accuracy:

Ensemble and DL models consistently outperformed traditional single-algorithm methods in both accuracy and robustness. GBDT achieved the highest R^2 (0.922) for enrollment prediction (Wang et al., 2024), while CatBoost and RF also delivered strong results across varied datasets (Sivasangari et al., 2021; Maulana et al., 2023). Stacked NN further demonstrated effectiveness, reaching 92% accuracy through meta-MLP architectures (Sridhar et al., 2023).

Despite their simplicity, LR models remained reliable for structured, academic-only datasets, often offering competitive performance with high interpretability (Acharya et al., 2019; Apoorva et al., 2020). SVM also performed well, particularly in high-dimensional feature spaces (Zhang, 2023; Fang, 2023), though their generalization capacity was occasionally surpassed by ensembles. DT, while not top-performing in accuracy, provided rule-based transparency valuable for decision support (Bhaskaran & Aali, 2020; Ujkani et al., 2021).

B. Feature Relevance and Selection:

Academic features such as GPA, CGPA, GRE, and standardized test scores were consistently among the strongest predictors across models (Mengash, 2020; Maulana et al., 2023). In graduate-focused studies, qualitative variables such as SOP, LOR, and research experience contributed significantly to model performance when used with ensemble or neural methods (Zhang, 2023; Baskota & Ng, 2018).

Non-academic and contextual features are increasingly integrated into predictive frameworks. Geodemographic factors such as ZIP code, income level, and travel distance were shown to influence enrollment decisions, especially in underserved or rural regions (Pawar, 2020). Behavioral signals like campus visits and application inquiries added predictive value in dynamic, real-time recommendation systems (Bansode, 2024), reflecting a broader shift toward modeling student intent and experience.

C. Modeling Purpose and Scope:

The reviewed studies varied in scope, reflecting different institutional objectives and phases of the admissions process. Some focused on early-stage risk detection and applicant screening (Dewantoro & Ardisa, 2020; Mengash, 2020), while others addressed program matching and final admission decisions (Baskota & Ng, 2018; Bhaskaran & Aali, 2020).

Graduate-level applications prioritized personalized recommendations and program fit, whereas undergraduate models often supported yield prediction and strategic planning (Wang et al., 2024; Priulla et al., 2025). Regression models estimating

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likelihood of admission or performance provided nuanced insights beyond binary classifications, especially in contexts demanding prediction and optimization (Acharya et al., 2019; Zhang, 2023).

D. Interpretability and Institutional Use:

While ensemble and DL models dominated in predictive metrics, their lack of inherent interpretability limited direct deployment in many institutional contexts. Several studies incorporated post hoc interpretability tools such as LIME and gradient sensitivity analysis to increase transparency in NN outputs (Raftopoulos et al., 2024; Bansode, 2024).

Rule-based models such as C4.5 and RepTree continued to deliver value through explainable, traceable decision logic (Bhaskaran & Aali, 2020; Ujkani et al., 2021). These interpretable systems are especially relevant in regulated or high-stakes environments where stakeholder trust and ethical accountability are critical. Hybrid frameworks combining accuracy and explainability offer a promising middle ground for deployment.

E. Fairness, Bias, and Generalizability:

Despite growing awareness, fairness considerations remain underreported. Only a few studies explicitly examined subgroup bias or equity impact. Fang (2023) demonstrated that test-optional SVM models exacerbated disparities among non-white and first-generation applicants, illustrating how model assumptions can amplify systemic bias. Priulla et al. (2025) and Pawar (2020) further documented inequalities based on gender, curriculum track, and SES.

Concerns about generalizability were also common. Several models were developed on localized or demographically restricted samples without external validation (Dewantoro & Ardisa, 2020; Raftopoulos et al., 2024), limiting scalability and applicability to broader institutional settings. These findings reinforce the need for rigorous fairness auditing and cross-context evaluation in future work.

Cross-Model Synthesis:

Taken together, the comparative synthesis reveals that each modeling category offers distinct advantages aligned with specific institutional priorities. Ensemble and DL models deliver high predictive performance and adaptability for large-scale or complex datasets. Yet interpretable techniques such as LR and DT remain essential for transparent advising and operational deployment, especially where human oversight is required.

The integration of behavioral and geodemographic data marks a shift toward more inclusive, equity-aware models, though ethical safeguards must be in place to avoid proxy discrimination. Importantly, no single modeling technique universally excels across all evaluation criteria. As illustrated in the comparative radar chart (Figure 1), each modeling category presents a distinct trade-off across key dimensions (accuracy, interpretability, fairness, feature diversity, and purpose alignment) underscoring the importance of context-driven model selection in institutional settings.

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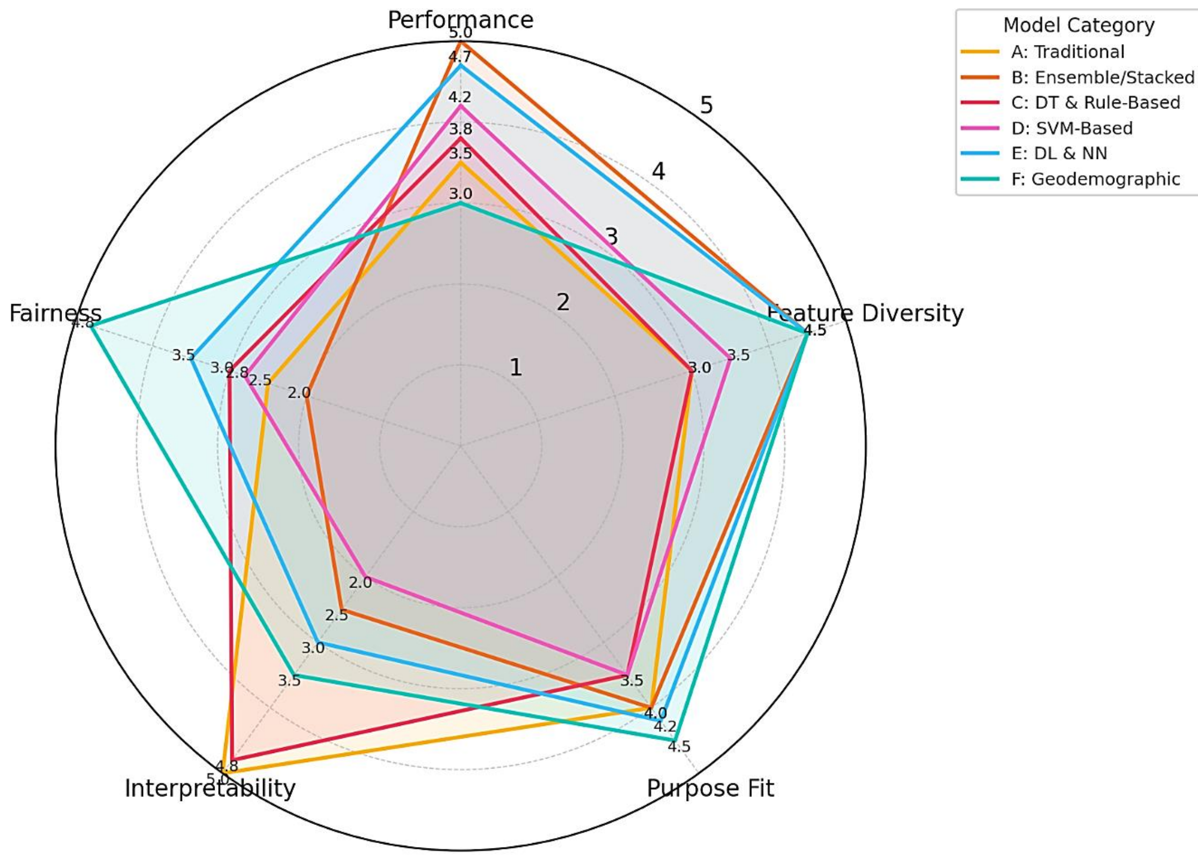

Figure 1. Comparative Evaluation of Modeling Categories in University Admissions

Conclusion and Recommendations

As HEIs face mounting pressures to optimize enrollment, improve student retention, and promote equitable access, data-driven decision-making has become an essential strategic tool. This review synthesized findings from nineteen studies applying DM and ML techniques within university admissions. Through a comparative lens, it examined model performance, interpretability, feature diversity, and fairness considerations across six major modeling categories.

The findings confirm that no single model universally excels across all evaluation dimensions. Classical methods such as LR and DT remain valuable for their interpretability and usability in structured academic contexts. Ensemble techniques particularly RF, GBM, and CatBoost consistently deliver superior predictive accuracy, especially when incorporating heterogeneous features such as behavioral or contextual data. DL and NN demonstrate scalability and strong performance on complex or unstructured inputs, yet their limited transparency and ethical concerns pose deployment challenges.

A notable shift is evident toward hybrid and stacked architectures that combine the strengths of multiple approaches. Additionally, the increasing integration of geodemographic and behavioral features reflects a growing commitment to equity-aware admissions modeling. However, these advancements necessitate careful validation and fairness auditing to avoid unintended bias through proxy variables.

Recommendations for Practice and Research

Based on the synthesis of literature, several key recommendations emerge for both institutional practitioners and researchers. First, model selection should be contextually grounded. Institutions are encouraged to align their choice of DM techniques with specific operational goals prioritizing transparency and interpretability in applicant-facing scenarios and favoring higher predictive accuracy for internal planning and strategic analytics.

Second, fairness and explainability must be strengthened in the development and deployment of predictive models. Incorporating diagnostic tools such as LIME, and sensitivity analysis can help uncover potential algorithmic bias and increase trust in black-box methods, particularly when used in high-stakes decision environments.

Third, while the inclusion of non-academic features such as geodemographic and behavioral data can enrich model accuracy and support more inclusive strategies, their use must be ethically grounded. Institutions should apply fairness audits and consider the implications of proxy variables to avoid reinforcing systemic biases.

Fourth, the adoption of hybrid modeling approaches offers a promising direction. Combining interpretable models (such as DT and LR) with ensemble or DL frameworks can yield both explainability and performance, enabling real-world deployment without compromising transparency.

Fifth, validation and replicability must be prioritized in future research. Cross-institutional studies and testing on diverse student populations are essential to ensure generalizability and equity of findings beyond specific datasets or contexts.

Finally, institutions should move toward integrating predictive analytics into real-time decision systems. Embedding models into admissions platforms, academic advising tools, and institutional dashboards can foster proactive, data-informed strategies that enhance recruitment, retention, and equity.

In summary, this review underscores the need for context-aware, multifactorial, and ethically grounded approaches to predictive modeling in university admissions. When thoughtfully applied, such models can help HEIs design smarter, fairer, and more inclusive admission systems aligned with 21st-century educational priorities.

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