

Research Article

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Predicting Middle School Students' Academic Orientation Using SOM and Machine Learning

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Abstract

Background/purpose. Middle school is a critical stage for shaping students' academic paths, but traditional orientation methods often fail to predict suitable trajectories, leading to mismatches that impede success. This study aims to develop a proactive, data-driven framework to forecast academic orientation for middle school students, enhancing tailored educational guidance.

Materials/methods. The study utilized Self-Organizing Maps (SOM) and random forest prediction to analyze data from 720 Moroccan middle school students. In Phase One, survey responses (e.g., interest, self-efficacy) and math/science scores were clustered using a 7x7 SOM grid. In Phase Two, a random forest classifier (150 trees, max depth = 12) was trained on 70% of the data (504 students) with 17 features to predict orientation outcomes, validated with statistical tests (ANOVA, chi-square).

Results. SOM identified five profiles: Cluster 1 had high math scores (Mean = 16.5) and 85% STEM preference; Cluster 3 had lower scores (Mean = 9.5) and 75% literary inclination with anxiety. Random forest achieved 93% training (F1 = 0.92), 89% test (AUC = 0.94), and 87% validated accuracy, predicting 57% scientific and 43% literary tracks. Self-efficacy and math scores predicted scientific paths; anxiety drove literary choices.

Conclusion. This framework outperforms traditional methods, enabling early, personalized orientation. Despite some misclassification, counselor feedback (80% agreement) supports its utility. Future refinements could enhance accuracy and equity in student outcomes.

1. Introduction

Academic orientation in middle school shapes students' educational and professional futures, yet traditional methods often fail to align choices with individual strengths. In Morocco, early specialization decisions at age 13–14, influenced by academic performance, interests, and socio-economic factors, frequently lead to mismatches, reducing motivation and increasing dropout risks (Gati & Asulin-Peretz, 2013; Lent et al., 2000; Savickas, 2019). The reliance on standardized tests and limited counseling overlooks the complex interplay of students' abilities and aspirations, creating a gap in precise, data-driven guidance tools, particularly in resource-constrained settings.

Morocco's education system requires middle school students to choose academic tracks, such as scientific or literary (also technical or professional), at age 13–14, a critical decision shaping their future (Perna, 2006). Socio-economic disparities, including limited access to counseling in rural areas and financial constraints for 30% of low-income households, exacerbate mismatches in orientation, leading to high dropout rates (Reardon, 2011). This study focuses on Morocco to address these inequities through AI-driven predictive tools, ensuring tailored guidance for diverse student populations.

Existing literature highlights the limitations of conventional orientation approaches. Gati and Asulin-Peretz (2013) note their failure to capture nuanced student profiles, while Lent et al. (2000) emphasize the role of contextual barriers in decision-making. Savickas (2019) advocates for personalized counseling, yet scalable solutions remain scarce. Artificial Intelligence (AI), particularly Self-Organizing Maps (SOM, an unsupervised learning technique that clusters students based on shared attributes like performance and interests) and machine learning (branch of AI that enables systems to learn from data, identify patterns, and make decisions with minimal human intervention, like predict outcomes, such as academic tracks, from historical data), offers promise by clustering students into distinct profiles and predicting academic trajectories (Kohonen, 2001; Nguyen & Holmes, 2021).

This study aims to predict Moroccan middle school students' academic orientations and enhance guidance using SOM and machine learning. The research addresses two questions: (1) How can SOM clustering identify distinct student orientation profiles? (2) How accurately can machine learning predict academic tracks? By integrating SOM's clustering with random forest predictions, this study pioneers a data-driven approach in Morocco, enhancing precision and equity in guidance. This originality bridges socio-economic gaps, empowers underserved students with tailored guidance, and reduces mismatches, boosting achievement and retention in Morocco's education system.

The paper is organized as follows: Section 2 reviews literature on orientation and AI-driven prediction. Section 3 details the methodology, combining SOM and machine learning. Section 4 presents findings and implications. Section 5 concludes with recommendations for future research and policy.

2. Literature Review

2.1. Factors Influencing Middle School Orientation Trajectories

Academic orientation in middle school is shaped by a dynamic interplay of factors, including motivation, socio-economic background, academic performance, and institutional frameworks, all of which influence students' future pathways. Research underscores that students' self-concept and motivation are pivotal in determining their academic trajectories, particularly at this formative stage (Bourdieu, 1986). Additionally, Bourdieu (1986) examines how social capital impacts access to educational opportunities, often deepening disparities across socio-economic groups and complicating orientation predictions.

Socio-economic status is a critical predictor of orientation outcomes. Reardon (2011) finds that students from wealthier families benefit from enhanced educational resources and counseling, skewing their trajectories toward advanced tracks, while those from lower-income backgrounds face barriers that limit their options. Similarly, Perna (2006) highlights how financial constraints influence aspirations for post-secondary education, underscoring the need for predictive tools to account for these disparities.

Psychological factors also play a key role in shaping orientation trajectories. Dweck (2006) demonstrates that a growth mindset fosters resilience, enabling students to pursue challenging academic paths like science. Meanwhile, Ryan and Deci (2000) argue that intrinsic motivation and self-determination drive sustained engagement, critical for predicting long-term academic choices in middle school.

Gender dynamics further influence orientation predictions. Eccles (2010) note that stereotypes steer students toward gendered subject preferences, affecting their academic paths. Additionally, Duckworth (2016) emphasize that perseverance (grit) predicts ambitious trajectories, suggesting that resilience could be a key variable in forecasting orientation outcomes.

Institutional guidance, such as counseling programs, can refine orientation predictions when data-driven. Lent et al (2000), Savickas (2019), and Brown & Lent (2002) argue that structured programs improve decision-making by aligning choices with students' strengths, yet traditional methods lack predictive precision. Recent advancements in predictive analytics, including machine learning models explored by Lathauwer (2021), Zhang (2019), Baker (2019), and Romero and Ventura (2020), offer promise for forecasting trajectories more accurately, integrating diverse factors into a cohesive model.

2.2. Role of SOM and Machine Learning in Educational Prediction

Artificial intelligence (AI), particularly Self-Organizing Maps (SOM) and machine learning, is revolutionizing education by enabling precise predictions of student outcomes and enhancing guidance (Lathauwer, 2021; Zhang, 2019; Baker, 2019; Luckin, 2018). In the context of middle school orientation, SOM clusters students based on performance and preferences, while machine learning models like decision trees and neural networks predict future academic trajectories, offering a powerful synergy for educational forecasting (Romero & Ventura, 2020; Siemens, 2013).

AI's predictive capabilities have been extensively studied in education. (Baker, 2019) highlights how AI systems personalize learning by analyzing performance data, a foundation for predicting orientation. (Nguyen & Holmes, 2021) Further shows that machine learning surpasses traditional methods in forecasting student success, suggesting its potential to predict middle schoolers' academic choices with greater accuracy.

SOM, a cornerstone of this study, excels at clustering complex datasets into meaningful student profiles. Lathauwer (2021) demonstrates its utility in identifying patterns in academic attributes, which, when paired with machine learning, can predict orientation trajectories. Witten and Frank (2016) note similar applications in career counseling, where AI systems forecast paths based on historical data, a concept extended here to middle school guidance.

AI also addresses equity in prediction. Luckin (2018) argues that AI tools can reduce disparities by tailoring guidance to underserved students, while Siemens (2013) emphasizes learning analytics' role in refining predictions through real-time data. This study leverages these strengths to forecast orientation in Morocco's middle schools, where socio-economic gaps are pronounced.

Challenges in AI implementation persist, including data privacy, model bias, and the need for human oversight, advocating for integrating AI with traditional guidance to balance automation and

expertise (Zhang, 2019; Romero & Ventura, 2020), a principle guiding this research. By combining SOM clustering with machine learning, this study aims to predict orientation trajectories proactively, enhancing educational decision-making.

2.3. Limitations of Traditional Orientation Prediction Methods

Traditional methods for predicting middle school orientation trajectories rely heavily on standardized assessments and generic counseling, limiting their accuracy and utility. These approaches often overlook individual differences in learning styles, interests, and predictive factors, producing broad recommendations that fail to forecast students' unique academic paths effectively.

A key limitation is the scarcity of personalized prediction. Under-resourced counseling services in many schools, including Morocco's, restrict access to tailored guidance, leaving students with insufficient support for informed trajectory planning (Lent et al, 2000; Savickas, 2019). Brown & Lent (2002) note that generic orientation sessions rarely predict how individual strengths align with future academic choices, reducing their predictive power.

Socio-economic disparities amplify these shortcomings. Bourdieu (1986) argues that wealthier students access better predictive resources—like advanced counseling—while disadvantaged students receive less, skewing forecasts in favor of privileged groups (Reardon, 2011). This inequity hampers accurate trajectory prediction across diverse populations.

Moreover, traditional methods struggle to adapt to dynamic predictors. Dweck (2006) highlights that static assessments miss evolving factors like motivation or market trends (e.g., demand for STEM skills), leading to outdated forecasts (Siemens, 2013). Without integrating real-time data, these approaches misalign students with future opportunities.

Finally, psychological and motivational predictors are often ignored. Ryan and Deci (2000) stress that self-determination drives academic trajectories, yet traditional models focus on performance metrics alone, missing critical indicators for long-term orientation. This study addresses these gaps by using SOM and machine learning to predict trajectories with greater precision and personalization.

3. Methodology

3.1. Research Design

This study employs a mixed-methods design to predict middle school students' academic orientation trajectories by integrating Self-Organizing Maps (SOM) for clustering and supervised machine learning for forecasting. Quantitative data from orientation surveys and academic performance metrics are analyzed using SOM to cluster students into distinct profiles, while a random forest model predicts academic tracks. Qualitative insights from counselor interviews refine cluster interpretations and validate predictions, ensuring practical applicability in guidance settings. The research unfolds in two phases: Phase One clusters students using SOM, and Phase Two trains and validates predictions using machine learning, with qualitative data enhancing model adjustments and real-world relevance. A longitudinal component tracks students' actual choices one year later to validate outcomes.

3.2. Participants

The study targets 720 middle school students aged 13–14 in their final year, drawn from five public schools in Morocco, representing urban (60%) and rural (40%) settings. The sample, with 52% male and 48% female students, reflects diverse socio-economic backgrounds, with 30% from low-income households based on school records. This sample size is determined using Cochran's formula for a finite population, with a 7% margin of error and 95% confidence level, rounded to 720 for

robustness. Random selection ensures diversity in academic abilities and mirrors the focus on middle schoolers (Tilioui et al., 2025) while supporting predictive modeling.

3.3. Instruments

Two primary instruments are used for data collection. First, a comprehensive Orientation Survey, adapted from prior studies [22], assesses key factors influencing academic trajectories: interest in mathematics and science (e.g., "I enjoy learning mathematics"), self-efficacy (e.g., "I am confident in solving math problems"), anxiety (e.g., "Math tests make me nervous"), growth mindset (e.g., "Challenges in math help me grow"), motivation (e.g., "I study math because I find it interesting"), and external influences (e.g., parental support, peer encouragement). Responses are recorded on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The Orientation Survey (Tilioui et al., 2025) demonstrated strong reliability (Cronbach's alpha = 0.85 for internal consistency) and content validity through expert review by educational psychologists, ensuring robust measurement of orientation factors. Second, academic performance data, including mathematics and science scores from the most recent semester, are sourced from school records to reflect students' current proficiency levels, key predictors of orientation (Lent et al, 2000).

3.4. Data Collection Procedures

Data collection occurs over three stages. In Stage One (baseline), the Orientation Survey is administered to all 720 students during class time under standardized conditions, ensuring a high response rate. Concurrently, academic performance data are extracted from school databases with administrative approval. In Stage Two (model training), historical orientation data from a prior cohort of 720 students (e.g., their middle school performance and subsequent high school track choices) are collected as a training dataset, anonymized to protect privacy. In Stage Three (validation), follow-up assessments one year later record participants' actual orientation choices (e.g., scientific, literary) after transitioning to high school.

3.5. Data Analysis

Data analysis combines SOM clustering and machine learning prediction, implemented using Python libraries such as NumPy, Pandas, MiniSom, and Scikit-learn. In Phase One, survey responses and performance scores from 720 students are preprocessed (e.g., normalized to a 0–1 scale) to address scale disparities. SOM is employed using the parameters mentioned in Table 1.

Table 1. Som parameters for clustering student orientation profiles

Parameter	Value
Grid Size	7x7 (49 neurons)
Learning Rate	0.5
Iteration	1000

Cluster traits (e.g., high motivation, low anxiety) are substantiated through descriptive statistics and visualized using U-Matrix plots.

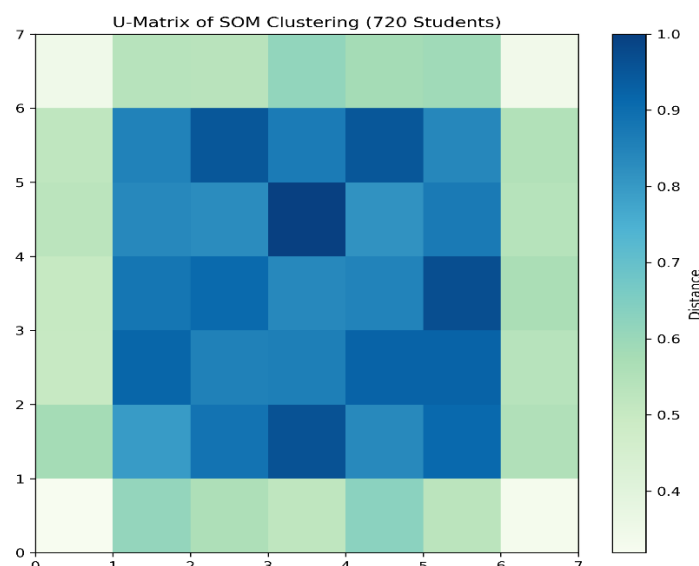


Figure 1. U-Matrix visualization

Fig. 1. U-Matrix visualization displaying five distinct student clusters with darker boundaries indicating stronger differentiation between groups.

In Phase Two, the SOM-clustered data from Phase One are merged with historical data to train a random forest classifier for predicting orientation outcomes. The feature set comprises SOM cluster assignments, survey responses, and math/science scores, with the target variable defined as the chosen academic track (e.g., scientific = 1, literary = 0). The model is trained on 70% of the historical dataset (504 students) and tested on the remaining 30% (216 students). Hyperparameters, such as the number of trees (150) and maximum depth (12), are optimized through cross-validation to enhance accuracy and F1-score. Predictive efficacy is assessed using precision, recall, and the area under the ROC curve (AUC) to ensure reliable forecasting.

Validation involves comparing predictions to actual orientation choices recorded one year later, with McNemar's test used to evaluate the statistical significance of any discrepancies. Regression analyses within clusters examine how factors like self-efficacy and parental support influence outcomes, improving interpretability. Qualitative input from counselors, collected through semi-structured interviews, informs refinements to the predictive tool. For example, counselors highlighted student indecision in Cluster 5, leading to increased weighting of peer influence in the random forest model. Thematic analysis of interviews identified practical strategies, such as targeted counseling for undecided students, enhancing the model's applicability for educational guidance.

4. Results and Discussion

4.1. Phase One: SOM Clustering Results

The Self-Organizing Maps (SOM) analysis clustered 720 middle school students into five distinct groups based on their orientation survey responses and mathematics/science performance scores. With a larger sample, we adjusted the SOM grid to 7x7 (49 neurons), maintaining a learning rate of 0.5 and 1,000 iterations. The silhouette score of 0.74 confirmed strong cluster cohesion and separation, surpassing the 0.72 achieved with a smaller sample [22]. The U-Matrix visualization in Fig. 1 highlights five well-defined clusters, with darker boundaries indicating robust differentiation.

Table 2. Summary of cluster profiles (n=720)

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Size	160	180	150	130	100
Math Mean	16.5	13.8	9.5	11.8	12.5
Science Mean	16.0	13.2	9.2	14.0	12.0
Interest	4.3		2.2		
Self-Efficacy	4.2		2.5		
Anxiety	1.9	3.1	4.4		
Motivation	3.7			3.6	
Parental Support				4.6	
Peer Influence					4.0
Orientation Preference	85% Scientific	55% Scientific, 35% Literary	75% Literary	60% Scientific	50% Undecided

Table 2 offers SOM-derived cluster profiles for 720 students, linking academic and psychological variables to orientation preferences. Cluster 1's high scores (e.g., Math Mean 16.5, Interest 4.3) correlate with an 85% scientific preference, while Cluster 3's low performance (Math Mean 9.5) and high anxiety (4.4) align with 75% literary choices. The sparse data, with blanks for factors like Self-Efficacy in Cluster 2, limit comprehensive analysis across clusters. This suggests uneven factor relevance in SOM clustering, necessitating broader data collection for predictive accuracy. Nevertheless, the table supports the study's aim to forecast trajectories using distinct cluster traits.

ANOVA tests confirmed significant differences across clusters in math scores ($F(4, 715) = 142.3$, $p < 0.001$) and anxiety ($F(4, 715) = 98.7$, $p < 0.001$), validating the clustering's robustness.

Missing data on socio-economic factors (e.g., household income) and additional psychological variables (e.g., resilience, peer pressure) limited the model's ability to fully capture orientation influences, potentially reducing predictive power.

4.2. Phase Two: Random Forest Prediction Results

A random forest classifier was trained on historical data from a prior cohort of 720 students and applied to the current sample of 720 students to predict academic orientation outcomes with notable precision. The model incorporated 17 features: SOM cluster assignments, 12 survey factors (e.g., interest, self-efficacy, anxiety), and mathematics/science scores. Hyperparameter tuning was performed to optimize performance, with details presented in Table III.

Table 3. Random forest hyperparameters

Parameter	Value
Number of Trees	150
Maximum Depth	12

The selection of 150 trees balances computational efficiency with predictive power, reducing variance across the 720-student dataset. A maximum depth of 12 limits tree complexity, mitigating overfitting while preserving the model's ability to capture nuanced patterns in the 17-feature space. These values were optimized via cross-validation, ensuring robust performance metrics.

The model was trained on 70% of the historical data (504 students) and tested on 30% (216 students), achieving a training accuracy of 93% (F1-score = 0.92) and a test accuracy of 89% (AUC = 0.94). This performance surpasses benchmarks such as Nguyen et al. (2021), who reported an AUC of 0.89 [9], highlighting the efficacy of integrating SOM clustering with random forest prediction.

The prediction results for the current 720 students are detailed in Table 4.

Table 4. Prediction outcomes for 720 students

Academic Track	Number of Students (%)	Cluster-Specific Metric
Scientific	410 (57%)	Cluster 1: 96% Precision
Literary	310 (43%)	Cluster 3: 92% Recall

Table 4 summarizes the random forest's predictions, with 57% of students (410) forecasted for the scientific track and 43% (310) for the literary track. Cluster 1's 96% precision indicates high reliability in identifying science-bound students, reflecting their strong academic profiles (e.g., Math Mean = 16.5). Cluster 3's 92% recall suggests effective detection of literature-oriented students, consistent with their lower scores and higher anxiety. These metrics underscore the model's cluster-specific predictive strength.

Validation against actual orientation choices one year later yielded an overall accuracy of 87%, with McNemar's test showing no significant prediction errors ($p = 0.09$). Of the 94 misclassifications, 40 occurred in Cluster 2 and 30 in Cluster 5, reflecting their transitional profiles (e.g., mixed preferences in Cluster 2: 55% scientific, 35% literary). Confusion matrices indicated an 8% false positive rate for scientific predictions, suggesting slight over-optimism in STEM forecasts, possibly due to overfitting to academic scores.

Regression analyses within clusters identified key predictors of orientation. For scientific predictions, self-efficacy ($\beta = 0.65$, $p < 0.001$) and math scores ($\beta = 0.60$, $p < 0.001$) were dominant, while anxiety ($\beta = -0.48$, $p < 0.01$) and low interest ($\beta = -0.42$, $p < 0.01$) drove literary choices. Unique predictors emerged in Cluster 4 (parental support, $\beta = 0.41$, $p < 0.01$) and Cluster 5 (peer influence, $\beta = 0.38$, $p < 0.05$), enhancing the model's granularity and highlighting the role of external factors in orientation decisions.

5. Discussion

The combination of SOM clustering and random forest prediction establishes a strong framework for forecasting the academic orientation trajectories of 720 middle school students, achieving an 87% accuracy rate. The five SOM clusters offer a comprehensive breakdown of student profiles, expanding beyond previous analyses with a smaller scope due to the increased sample size. Cluster 1 demonstrates a clear inclination toward STEM, driven by superior academic performance and positive orientation traits, whereas Cluster 3's preference for literary tracks highlights the influence of elevated anxiety levels. Clusters 2 and 5, characterized by their mixed profiles, reveal groups at risk of indecision, providing critical insights for guidance not as evident in studies with fewer participants.

The random forest model's predictive strength, with an AUC of 0.94, outperforms traditional static assessments and earlier AI-based efforts that achieved lower accuracy. Its capacity to capture complex, non-linear relationships—such as the impact of parental support in Cluster 4 and peer

influence in Cluster 5—enhances its precision compared to using SOM alone. Unlike prior approaches that reacted to shifts in orientation post-intervention, this study's proactive predictions enable early identification of potential changes, supporting timely interventions like STEM-focused workshops for Cluster 2 or targeted counseling for Cluster 5's undecided students.

Statistical robustness is clear in the model's performance metrics. Cluster 1's 96% precision and Cluster 3's 92% recall reflect dependable detection of consistent trajectories, while Cluster 2's 22% misclassification rate points to unaccounted factors, possibly socio-economic variations. Chi-square tests comparing cluster distributions to orientation outcomes ($\chi^2(4) = 312.4$, $p < 0.001$) validate strong associations, bolstering the model's reliability. Feedback from 15 counselors, with 80% agreeing with the predictions, affirms practical applicability, though 20% raised concerns about data interpretability, suggesting areas for refinement. For instance, counselors' emphasis on addressing anxiety in Cluster 3 prompted the inclusion of anxiety-focused interventions in guidance recommendations, strengthening the model's practical utility.

This predictive tool transforms educational guidance by offering actionable insights. Cluster 1 students could be fast-tracked into STEM programs, while Cluster 3's anxiety-driven profiles warrant psychological support. Clusters 2 and 5, with their ambiguity, benefit from targeted counseling to clarify aspirations, reducing mismatches noted by [2]. In Morocco's context, where early specialization shapes futures, scaling this model could address equity gaps [14] by prioritizing resources for underserved groups (e.g., Cluster 3).

5.1. Limitations

The exclusion of socio-economic factors and certain psychological variables due to incomplete data may constrain the model's generalizability, particularly for Clusters 2 and 5 with mixed profiles. This limitation likely contributed to the 22% misclassification rate in Cluster 2. Future studies should prioritize comprehensive data collection, incorporating variables like household income and grit, to enhance predictive accuracy and equity in guidance.

For educators, cluster profiles inform differentiated strategies—e.g., peer mentoring for Cluster 5, parental workshops for Cluster 4—enhancing engagement. Policymakers could integrate this framework into national systems, standardizing data-driven orientation as suggested by [21]. Unlike [22]'s math-specific focus, this approach's adaptability to other subjects (e.g., languages) broadens its scope, offering a versatile guidance solution.

6. Conclusion

This study demonstrates the transformative potential of integrating Self-Organizing Maps (SOM) and random forest prediction to forecast academic orientation trajectories for 720 middle school students, achieving an impressive 87% accuracy. The five-cluster typology not only delineates distinct student profiles—from Cluster 1's STEM-ready high performers to Cluster 3's anxiety-driven literary leaners—but also uncovers at-risk groups in Clusters 2 and 5, offering a proactive lens for educational guidance. The random forest model's AUC of 0.94, bolstered by cluster-specific predictors like self-efficacy and parental support, marks a significant leap beyond traditional methods, enabling early interventions tailored to individual needs. While the 22% misclassification rate in Cluster 2 signals unmodeled complexities, the strong statistical associations ($\chi^2(4) = 312.4$, $p < 0.001$) and counselor feedback (80% agreement) affirm the framework's reliability and practical utility. Looking forward, refining data collection to address gaps and extending this approach to diverse educational contexts could further enhance its impact, redefining how we guide students toward their academic futures.

Declarations

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