**Topic: A Dynamic Recommender System for Improved Academic Mentorship Based on Attribute Pattern Matching**

**Review of Related Literature**

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| **S/N** | **Author(s) / Year** | **Title** | **Methodology** | **Major Findings / Recommendations** | **Limitations** |
| 1 | Somavarapu and Shrivastav (2025) | A Data-Driven Approach to Improving Mentor-Mentee Matching Using Machine Learning Models | Experimental study using real-world and synthetic datasets; employed clustering (K-means), classification (SVM, RF, NN), and recommendation systems (collaborative, content-based, hybrid). | Data-driven mentor matching improves compatibility, satisfaction, and engagement. Neural networks and random forests showed highest performance. Integration of demographic, personality, and behavioral data improves pairing outcomes | Feedback integration and real-time matching still underdeveloped. Most findings based on simulations. Limited deployment case studies in large-scale systems. |
| 2 | Gupta *et al.* (2024) | Brace: A Pairing Algorithm for Mentorship Using Compatibility Score | Algorithm computes compatibility scores across dimensions (tools/tech, time zone, availability) and uses matrix computation. Secure data handling via Ethereum blockchain. | Improved compatibility and accuracy over manual pairing; ensures security and transparency through blockchain; practical implementation for real-world mentorship cycles. | Limited adaptability due to fixed compatibility metrics; lacks machine learning or feedback loops; tested in a single organizational context only. |
| 3 | Varghese and Mohaghegh (2023) | Personality-Based Hybrid Machine Learning Model for Mentor-Mentee Matching Using Collaborative and Content Filtering Methods | Developed a hybrid ML model combining CNN-based collaborative filtering with content-based filtering; used a dataset from a NZ-based company including MBTI personality data. | Inclusion of personality traits, skills, and goals in a hybrid ML model enhances match quality. CNN and content filtering proved effective in predicting compatible matches. Proposed a scalable, personality-aware algorithm. | Lacked long-term follow-up or generalizability to other domains. Focused on a single organization; no external validation. No real-time feedback loop implemented. |
| 4 | Zhang *et al.* (2022) | Learning Path Optimization Based on Multi-Attribute Matching and Variable Length Continuous Representation | Developed a differential evolution-based model with floating-point representation to optimize multi-attribute learning paths. Attributes like ability, objectives, learning style, and time were matched to course elements. | Outperformed binary/integer models in scalability and efficiency; well-suited for personalized education; demonstrated strong optimization of path quality. | Not specific to mentor-mentee pairing; lacks real-world deployment and user feedback integration. |
| 5 | Weimer (2020) | Mentor Identification, Selection, Preparation, and Development: A Literature Review | Qualitative literature review covering mentor selection, training, and mentorship effectiveness, with a focus on music education. | A clearly defined mentor selection process based on competencies, along with structured and flexible training, improves mentorship outcomes. Preparation boosts mentor self-efficacy, effectiveness, and novice teacher retention. | Focused largely on music education. Did not employ or test algorithmic or data-driven matching systems. No quantitative model validation. |
| 6 | Haas *et al.* (2018) | Finding Optimal Mentor-Mentee Matches: A Case Study in Applied Two-Sided Matching | Applied Two-Sided Matching using the Deferred Acceptance algorithm; compared with approximation algorithms (Shift, Király, McDermid, GSModified) and heuristics (GATA, LocalSearchSMTI) on real-world preference data. | Evolutionary heuristics combined with local search (GATA) provided the best results in matching quality and closeness to ideal preferences. | No real-world deployment or behavioral validation; results based solely on algorithmic output. |

Somavarapu and Shrivastav (2025) employed a range of machine learning techniques spanning three primary categories in their study.

1. Clustering Models:

* K-means
* Hierarchical Clustering
* DBSCAN

1. Classification Models:

* Support Vector Machines (SVM)
* Random Forest (RF)
* Neural Networks (NN)
* Logistic Regression
* Decision Trees

1. Recommendation Systems:

* Collaborative Filtering
* Content-Based Filtering
* Hybrid Recommendation Systems

The study simulated mentorship cycles, evaluated match success with metrics such as accuracy, precision, recall, F1-score, and satisfaction scores, and comparing model performance.

**Study Limitations**

Despite its contributions, the study presents several limitations. Firstly, the integration of feedback mechanisms and real-time matching capabilities remains underdeveloped, limiting the system's adaptability and responsiveness in dynamic environments. Additionally, much of the analysis is based on simulation data, with minimal real-world deployment or large-scale case studies to validate the model’s practical effectiveness.

The use of real-world datarather than synthetic datasets would enhance the reliability and generalizability of the findings, potentially leading to improved accuracy. However, the study does not explicitly describe the neural network (NN) model utilized; key details such as the architecture, training parameters, and performance metrics are omitted, hindering reproducibility and comparative evaluation.

Moreover, the model considers only a minimal set of attributes for both mentors and mentees, which may oversimplify the matching process. The absence of detailed quantitative data—such as the ratio of mentees per mentor or vice versa further limits insights into scalability and resource allocation efficiency.

**Proposed work**

The improved work will incorporate Multi-Objective Optimization to enhance the supervisor-supervisee matching process. This addition is suggested to address the reality that effective matching often involves navigating trade-offs among multiple factors such as skills, goals, availability, and diversity. This enhancement will enable the system to consider and balance several competing priorities simultaneously.

According to Haas *et al.* (2018), Genetic Algorithms model can identify optimal trade-off solutions rather than relying on one-dimensional matching criteria. This approach ensures a more nuanced and balanced pairing process, where matches are not only technically aligned but also practically sustainable, accounting for supervisors’ capacity and program diversity goals.

While several studies have applied machine learning to mentor-mentee matching, most rely on static, predefined attributes and lack dynamic adaptability or real-time feedback integration. Existing models often fail to capture evolving user behavior, multi-attribute compatibility, and institutional context.

This research addresses these gaps by developing a dynamic, attribute-based academic mentorship system using Artificial Neural Networks and distributed clustering. It will continuously be learned from behavioral patterns and feedback, enabling personalized, flexible, and scalable mentor-mentee matching. Designed with synthetic dataset of 80 supervisees and 15 supervisors with academic, sociological, economic and psychological attributes,this aligns with institutional goals of improving student support, retention, and academic outcomes through intelligent automation has been generated.

**References**

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