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Article

AI-Driven Mentorship in Education: A Systematic Review of Educational Chatbots, Stress Detection Systems, and Career Guidance Platforms

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Abstract: Artificial Intelligence (AI) has emerged as a promising enabler of scalable and personalized mentorship in education, addressing limitations of traditional human-centric mentoring models such as restricted availability, inconsistent quality, and high student-to-mentor ratios. This systematic review synthesizes 134 peer-reviewed studies published between 2018 and 2025, selected using PRISMA 2020 guidelines from IEEE Xplore, ACM Digital Library, SpringerLink, Scopus, and PubMed. The review critically examines three dominant application domains: (i) educational chatbots and intelligent tutoring systems, (ii) AI-based stress and well-being detection mechanisms, and (iii) AI-powered career guidance platforms. Findings indicate that educational chatbots effectively support cognitive learning outcomes but rarely incorporate emotional awareness or long-term mentoring functions. Stress-detection systems demonstrate high predictive accuracy in controlled or laboratory settings but lack deployment within authentic educational environments and rarely trigger mentoring interventions. Career guidance platforms offer scalable and structured pathway recommendations but operate independently of students' emotional states and academic performance. Across all domains, research remains fragmented, pilot-driven, and weakly integrated, with limited longitudinal validation, minimal focus on transferable skill development, and insufficient ethical governance. This review consolidates existing evidence, identifies systemic research gaps, and outlines future research directions necessary for advancing holistic, ethical, and student-centered AI-driven mentorship in education.

Keywords: Artificial Intelligence in Education, Digital Mentorship, Educational Chatbots, Student Stress Detection, Career Guidance Systems, Systematic Review

1. INTRODUCTION

Mentorship plays a critical role in shaping students' academic success, emotional resilience, and career readiness. Empirical studies consistently demonstrate that effective mentoring contributes to improved academic performance, higher retention rates, reduced stress levels, and clearer career trajectories [1], [2]. Despite its importance, traditional mentorship models face structural limitations, including limited faculty availability, uneven mentor expertise, and increasing student populations, particularly in higher-secondary and tertiary education contexts [3].

As educational systems scale, students increasingly report unmanaged academic stress, disengagement, and uncertainty regarding career choices [4]. These challenges have motivated the adoption of AI-driven solutions capable of providing personalized, data-informed, and scalable support [5]. Advances in natural language processing, machine learning, learning analytics, and recommender systems have enabled the development of educational chatbots, stress-detection tools, and AI-powered career guidance platforms [6], [7].

However, existing literature indicates that these systems are predominantly designed for single-purpose objectives, such as tutoring, stress prediction, or career planning, rather than holistic mentorship [8]. This fragmentation undermines the core value of mentorship, which traditionally integrates academic, emotional, and professional guidance.

The purpose of this systematic review is to critically analyze existing AI-driven mentorship research, identify methodological trends and limitations, and synthesize cross-domain insights. Importantly, this paper does not propose any new model or framework, maintaining the scholarly neutrality required of a standard review paper.

2. METHODOLOGY

This review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure transparency, reproducibility, and rigor [9].

A. Databases and Search Strategy

Five academic databases were systematically searched:

- IEEE Xplore
- ACM Digital Library
- SpringerLink
- Scopus
- PubMed

Search strings combined keywords related to AI, mentorship, education, stress, and career guidance using Boolean operators. Representative terms included ("educational chatbot" OR "intelligent tutoring system" OR "AI tutor") AND

("student stress detection" OR "emotion recognition" OR "well-being analytics") AND ("AI career guidance" OR "career recommender system" OR "digital mentoring") AND ("higher education" OR "university students" OR "secondary education") AND (2018–2025)

B. Inclusion and Exclusion Criteria

TABLE I. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Population	Higher-secondary & university students	Employees, patients, non-student groups
Context	Educational mentoring, tutoring, stress detection, career guidance	Clinical-only or enterprise-only systems
Study Type	Peer-reviewed journals & conferences	Blogs, theses, patents
Language	English	Non-English
Publication Period	2018–2025	Pre-2018

C. Screening and Selection

A total of 412 records were initially identified. After removing 54 duplicates, 358 studies were screened by title and abstract. Of these, 180 were excluded for irrelevance. Full-text assessment of 178 studies resulted in the exclusion of 44 papers due to methodological weaknesses or non-educational focus. The final synthesis included 134 studies.

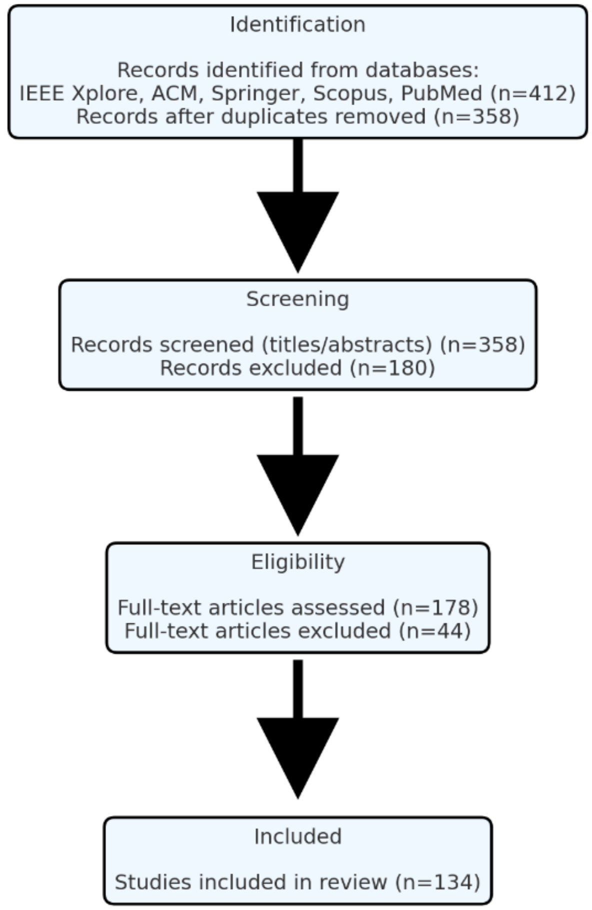

Fig. 1. The PRISMA flow diagram.

D. Quality Assessment

Studies were evaluated based on methodological clarity, dataset transparency, educational relevance, evaluation rigor, and replicability. Each study was categorized as low, moderate, or high risk of bias.

3. QUANTITATIVE OVERVIEW OF INCLUDED STUDIES

To complement the qualitative synthesis, the 134 included studies were categorized according to primary application domain, methodological approach, and evaluation design. This distribution provides structural insight into the current research landscape.

A. Distribution by Application Domain

TABLE II. Distribution of Included Studies by Domain

Domain	**Number of Studies**	**Percentage (%)**
Educational Chatbots & Tutoring Systems	56	41.8%
Stress Detection & Well-being Systems	44	32.8%
AI Career Guidance Platforms	26	19.4%
Transferable Skill-Focused Systems	8	6.0%

Total	134	100%

This distribution indicates that chatbot-based tutoring dominates the literature, while transferable skill development remains substantially underexplored.

B. Distribution by Evaluation Design

TABLE III. Distribution by Evaluation Design

Evaluation Type	Frequency	Percentage
Pilot Studies (Single Course)	61	45.5%
Controlled Experiments / RCT	18	13.4%
Observational Studies	27	20.1%
Dataset-Based Model Validation	22	16.4%
Longitudinal Studies (>1 Semester)	6	4.6%

The predominance of short-term pilot studies confirms the limited longitudinal validation identified in the qualitative synthesis.

4. LITERATURE REVIEW

A. Educational Chatbots and Intelligent Tutoring Systems

Educational chatbots represent one of the most mature applications of AI in education. Systematic reviews report that chatbots improve learner engagement, motivation, and conceptual understanding, particularly in large or online learning environments [10], [11]. GPT-based tutoring systems demonstrate learning outcomes comparable to human tutors in language and computing education [12], [13].

However, most tutoring chatbots remain cognitively focused, providing explanations, quizzes, or feedback without accounting for emotional states or long-term mentoring needs [8]. Mental-health-oriented chatbots such as Woebot and MISHA demonstrate short-term reductions in anxiety and perceived stress [14], [15], yet remain disconnected from academic tutoring or career planning [16]

TABLE IV. Comparative Summary of Educational Chatbots

System	Purpose	Learners	Outcomes	Reviewer Gap
GPT-4 Tutor	Adaptive tutoring	STEM & language	Human-comparable results	No stress or skill awareness
61A Bot	CS tutoring	Undergraduates	Higher engagement	Domain-locked
Woebot	Emotional support	Students & adults	Reduced anxiety	No academic or career role
MISHA	Stress micro-coaching	Students	Improved coping	Lacks academic alignment
ICCC	Career chatbot	IT/CSE	Personalized pathways	Narrow scope
Review (2023)	Synthesis of 80+ chatbots	Higher education	Overall learning improvement	No integrated frameworks

Reviewer Synthesis:

Chatbots deliver strong cognitive benefits but do not incorporate real-time stress detection, long-term mentoring, or transferable skill development.

B. Stress Detection and Well-Being Systems

Student stress has been extensively studied using AI-based detection methods. Algorithmic prediction frameworks leveraging machine learning models have demonstrated robust diagnostic capabilities in mapping college student mental stress and identifying critical public well-being trends [17], [18].Survey-based machine learning models employing validated instruments like GAD-7 and PHQ-9 also demonstrate strong predictive performance [19].

Recent studies apply NLP techniques to detect stress from discussion forums, chat logs, and learning management systems [20], [21]. Despite high technical accuracy, most stress-detection systems remain laboratory-bound or predictive in nature, rarely deployed in real classrooms or linked to mentoring interventions [22].

TABLE V. Stress Detection Methods in Education

Category	Techniques	Data	Performance	Reviewer Gap
Physiological	EEG, ECG, HRV, CNN-LSTM	Wearables	Up to 99.53%	Lab-restricted; not classroom-tested
Survey-Based	GAD-7, PHQ-9, workload ML	Self-report	>93%	No intervention mapping
NLP/Behavioral	Sentiment, Transformers	Text-based	High accuracy	Limited contextualization
Predictive ML	Socio-demographic	Large datasets	High prediction	No mentorship linkage
Stress Chatbots	CBT-based	Conversations	Improved perception	No academic/career support

Reviewer Synthesis:

These systems detect stress effectively but seldom connect detection with actionable educational interventions—resulting in incomplete mentoring processes.

C. AI-Powered Career Guidance Platforms

AI-driven career guidance systems employ recommender algorithms, analytics, and labor-market data to assist students in career decision-making [23], [24]. Platforms such as Naviance and Advisor.AI are widely adopted and provide structured pathway planning and milestone tracking [25], [26].

Nevertheless, prior research highlights concerns related to algorithmic bias, transparency, and limited consideration of students' emotional readiness or academic context [27]. Administrative platforms such as AdvisorTrac and MentorcliQ emphasize workflow efficiency rather than student mentoring [28].

TABLE VI. AI-Powered Career Guidance Platforms

Platform	Features	Outcomes	Reviewer Gap
Advisor.AI	Pathway planning, analytics	High adoption	No emotional or academic linkage
Naviance	College/career readiness	Strong institutional use	Limited personalization
AdvisorTrac	Scheduling & advising	Efficiency gains	Administrative focus only
MentorcliQ	Corporate mentoring	Retention outcomes	Non-student oriented
Qooper	Matching & guidance	Scalable	Lacks skills integration

ITCareerBot	IT-specific guidance	Improved clarity	Domain-restricted

Reviewer Synthesis:

Career systems remain siloed and do not consider stress, psychological readiness, or academic performance in their recommendations.

D. Transferable Skill Development

Transferable skills such as communication, adaptability, teamwork, and leadership significantly influence employability and stress resilience [29]. However, AI-based mentorship systems rarely target these skills explicitly. Existing work relies primarily on human-led peer mentoring or limited chatbot-based soft-skill training, which shows modest outcomes and poor scalability [30].

Reviewer Synthesis:

This is one of the most underdeveloped areas in AI mentorship research.

5. COMPARATIVE CROSS-DOMAIN ANALYSIS

Synthesizing findings across domains reveals several consistent patterns:

- Strong but Narrow Capabilities:

Each domain performs well in isolation but fails to address holistic mentorship needs [8].

- Fragmentation:

Academic tutoring, stress detection, and career guidance systems are rarely integrated [31].

- Detection Without Action:

Stress-detection systems often stop at prediction without triggering mentoring interventions [22].

- Limited Ethical Governance:

Few studies report bias audits, explainability mechanisms, or privacy safeguards [27], [32].

- Short-Term Evaluation:

Most studies are pilot-based, lacking longitudinal validation across semesters or institutions [33].

6. RESEARCH GAPS IDENTIFIED

TABLE VII. Summary of Research Gaps

Gap	**Evidence**	**Implication**
Lack of Integration	Tools operate independently	Fragmented student experience
Stress Detection Not Educationally Grounded	Mostly lab datasets	Weak generalizability
Minimal Empathy Modeling	Limited affective cues	Reduced engagement
Bias & Fairness Concerns	Stereotype reinforcement	Inequitable outcomes
Lack of Longitudinal Studies	Mostly pilots	Unclear long-term impact
Weak Soft-Skill Support	Few tools target skills	Students lack career readiness
Ethical Weaknesses	Sparse governance models	Low trust & adoption barrier

7. LIMITATIONS OF THIS REVIEW

While this review adhered to PRISMA 2020 guidelines and synthesized 134 peer-reviewed studies, several limitations should be acknowledged.

First, the review was restricted to English-language publications, potentially excluding relevant research from non-English-speaking regions. Second, although five major academic databases were searched, additional studies indexed in specialized or regional repositories may not have been captured. Third, due to methodological heterogeneity across studies, formal meta-analysis was not feasible, and findings are therefore primarily narrative and comparative. Finally, given the rapid evolution of large language models and AI technologies, emerging systems developed after early 2025 may not be reflected in this synthesis.

Recognizing these limitations strengthens transparency and contextualizes the conclusions drawn.

8. FUTURE RESEARCH DIRECTIONS

The synthesis of 134 studies across educational chatbots, stress-detection systems, and AI-driven career guidance platforms reveals a rapidly evolving yet structurally fragmented research landscape. While technological capabilities have advanced considerably, future investigations must move beyond isolated task optimization toward integrated, ethically grounded, and educationally validated mentorship ecosystems.

1) Cross-Domain Integration of Mentorship Functions

A consistent pattern across the literature is the separation of academic tutoring, affective monitoring, and career guidance functionalities. Future research should examine architectures and evaluation frameworks capable of integrating these domains within unified learning environments. Rather than optimizing performance within single dimensions (e.g., tutoring accuracy or stress prediction rate), studies should investigate how multi-dimensional support systems influence learner progression, engagement, persistence, and resilience over time.

2) Real-World Deployment of Stress-Aware Systems

Although stress-detection models demonstrate high predictive performance on benchmark datasets and controlled laboratory environments, their ecological validity in authentic classroom and institutional settings remains limited. Future research should prioritize deployment within learning management systems (LMS), advising platforms, and classroom workflows. Importantly, evaluation should extend beyond detection accuracy to examine the downstream effects of stress-informed interventions on academic outcomes, coping behavior, and sustained well-being.

3) Linking Predictive Analytics to Actionable Mentorship Interventions

A recurring limitation across studies is the disconnection between predictive analytics and mentoring action. Future work should investigate mechanisms through which AI systems translate stress signals, motivational decline, or performance fluctuations into structured mentoring responses. Evaluation metrics should prioritize behavioral change, coping improvement, and longitudinal academic stability rather than predictive performance alone.

4) Integration of Transferable Skill Development

Transferable competencies—including communication, collaboration, adaptability, leadership, and digital literacy—remain significantly underrepresented in AI-driven mentorship research, despite their central role in employability and psychological resilience. Future investigations should explore how conversational agents, simulation-based environments, and feedback-driven learning systems can scaffold these skills in measurable and scalable ways. Standardized assessment rubrics and longitudinal tracking mechanisms are essential for evaluating meaningful skill development beyond cognitive gains.

5) Longitudinal and Multi-Institutional Validation

The current evidence base is dominated by short-term pilot implementations, often limited to a single course or semester. To establish sustained impact, future research should conduct longitudinal studies spanning multiple academic terms and diverse institutional contexts. Cross-cultural validation is particularly important to ensure generalizability, inclusivity, and equitable system performance across varied learner populations.

6) Ethical Governance, Fairness, and Explainability

As AI-driven mentorship systems increasingly influence academic and career decisions, concerns regarding algorithmic bias, privacy, and transparency become more consequential. Future research should incorporate fairness-aware modeling, bias auditing procedures, explainability techniques, and privacy-preserving approaches such as federated learning and consent-based data governance. Empirical investigation of student trust, perceived fairness, and ethical acceptability will be essential for responsible large-scale adoption.

7) Interoperability and Institutional Alignment

For AI mentorship systems to transition from experimental prototypes to institutional infrastructure, interoperability with existing educational technologies—including LMS, Student Information Systems (SIS), and career services platforms—is critical. Future research should examine scalable deployment strategies, modular system design, and sustainable maintenance models to ensure long-term viability and equitable access.

9. CONCLUSION

This systematic review synthesized evidence from 134 peer-reviewed studies investigating AI-driven mentorship technologies across educational chatbots, stress-detection systems, and AI-supported career guidance platforms. The evidence demonstrates that artificial intelligence has made substantial progress in addressing specific educational challenges. Educational chatbots have enhanced learner engagement and academic support, stress-detection models have achieved high predictive performance, and AI-driven career guidance systems have improved personalized educational and professional planning. Despite these advances, most existing solutions have been developed independently, with each addressing only a limited aspect of the mentoring process rather than the broader and interconnected needs of students.

A consistent finding across the reviewed literature is the fragmented nature of current AI-driven mentorship research. Academic tutoring, emotional well-being, career guidance, and transferable skill development are typically investigated as separate application domains, with relatively few studies attempting to integrate these dimensions into a unified mentoring experience. Furthermore, the existing evidence is dominated by short-term pilot implementations, leaving important questions regarding long-term educational impact, fairness across diverse learner populations, explainability of AI-driven decisions, and ethical governance only partially addressed. Transferable competencies—including communication, collaboration, adaptability, leadership, and lifelong learning skills—also receive comparatively limited attention, despite their recognized importance in supporting student success, employability, and resilience.

By bringing together evidence from intelligent tutoring systems, affective computing, and AI-enabled career guidance research, this review provides a comprehensive synthesis of the current landscape of AI-driven mentorship in education. Beyond summarizing existing knowledge, it identifies the principal methodological limitations and emerging research priorities that are shaping the future direction of this field. The collective evidence consistently suggests that future research should move beyond isolated AI applications toward integrated mentorship ecosystems capable of combining academic support, emotional well-being, career development, and transferable skill enhancement within a unified, ethical, transparent, and learner-centered environment.

Rather than identifying or advocating a single technological solution, this review establishes the conceptual and empirical foundation upon which future integrated AI-driven mentorship research can be systematically designed, implemented, and rigorously evaluated. Advancing research in this direction will require longitudinal validation in authentic educational settings, fairness-aware and explainable AI methodologies, responsible data governance, and interdisciplinary collaboration between education, artificial intelligence, psychology, and learning sciences. Such efforts have the potential to transform AI from a collection of specialized educational tools into a comprehensive mentoring partner capable of supporting learners throughout their academic, personal, and professional development.

References

1. G. Crisp and I. Cruz, “Mentoring college students: A critical review of the literature between 1990 and 2007,” Res. Higher Educ., vol. 50, no. 6, pp. 525–545, 2009, doi: 10.1007/s11162-009-9130-2.
2. National Academies of Sciences, Engineering, and Medicine, The Science of Effective Mentorship in STEMM. Washington, DC, USA: National Academies Press, 2019, doi: 10.17226/25568.
3. Organisation for Economic Co-operation and Development (OECD), Artificial Intelligence and the Future of Skills. Paris, France: OECD Publishing, 2021.
4. R. Beiter et al., “The prevalence and correlates of depression, anxiety, and stress in a sample of college students,” J. Affect. Disord., vol. 173, pp. 90–96, 2015, doi: 10.1016/j.jad.2014.10.054.

5. W. Holmes, M. Bialik, and C. Fadel, Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Boston, MA, USA: Center for Curriculum Redesign, 2019.
6. O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, “Systematic review of research on artificial intelligence applications in higher education,” Int. J. Educ. Technol. Higher Educ., vol. 16, no. 1, pp. 1–27, 2019, doi: 10.1186/s41239-019-0171-0.
7. L. Chen, P. Chen, and Z. Lin, “Artificial intelligence in education: A review,” IEEE Access, vol. 8, pp. 75264–75278, 2020, doi: 10.1109/ACCESS.2020.2988510.
8. Roll and R. Wylie, “Evolution and revolution in artificial intelligence in education,” Int. J. Artif. Intell. Educ., vol. 26, no. 2, pp. 582–599, 2016, doi: 10.1007/s40593-016-0110-3.
9. M. J. Page et al., “The PRISMA 2020 statement: An updated guideline for reporting systematic reviews,” BMJ, vol. 372, p. n71, 2021, doi: 10.1136/bmj.n71.
10. S. Wollny et al., “Are we there yet? A systematic literature review on chatbots in education,” Comput. Educ., vol. 179, p. 104399, 2021, doi: 10.1016/j.compedu.2021.104399.
11. C. Okonkwo and A. Ade-Ibijola, “Chatbots applications in education: A systematic review,” Comput. Educ.: Artif. Intell., vol. 2, p. 100033, 2021, doi: 10.1016/j.caeai.2021.100033.
12. S. Kesarwani, Titiksha, and S. Juneja, “Student chatbot system: A review on educational chatbot,” in Proc. 7th Int. Conf. Trends Electron. Informatics (ICOEI 2023), Ghaziabad, India, 2023, pp. 1201–1207, doi: 10.1109/ICOEI56765.2023.10125876.
13. B. D. Nye, “Intelligent tutoring systems by and for the developing world: A review of trends and approaches,” Int. J. Artif. Intell. Educ., vol. 25, no. 2, pp. 177–203, 2015, doi: 10.1007/s40593-014-0028-6.
14. K. K. Fitzpatrick, A. Darcy, and M. Vierhile, “Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent,” JMIR Ment. Health, vol. 4, no. 2, p. e19, 2017, doi: 10.2196/mental.7785.
15. B. Inkster, S. Sarda, and V. Subramanian, “An empathy-driven, conversational artificial intelligence agent (Wysa) for digital mental well-being: Real-world data evaluation,” JMIR mHealth uHealth, vol. 6, no. 11, p. e12106, 2018, doi: 10.2196/12106.
16. R. A. Calvo and D. Peters, Positive Computing: Technology for Wellbeing and Human Potential. Cambridge, MA, USA: MIT Press, 2014.
17. G. Mahalakshmi and G. Sujatha, “Predictions of college students' mental stress using machine learning algorithms,” in Proc. 7th Int. Conf. Intell. Comput. Control Syst. (ICICCS-2023), Madurai, India, 2023, pp. 412–417, doi: 10.1109/ICICCS56967.2023.10142672.
18. R. Walambe, A. Nayak, and K. Kotecha, “Multimodal stress detection using deep learning and wearable sensors,” IEEE Access, vol. 10, pp. 14725–14737, 2022, doi: 10.1109/ACCESS.2022.3148084.
19. R. L. Spitzer, K. Kroenke, J. B. W. Williams, and B. Löwe, “A brief measure for assessing generalized anxiety disorder: The GAD-7,” Arch. Intern. Med., vol. 166, no. 10, pp. 1092–1097, 2006, doi: 10.1001/archinte.166.10.1092.
20. M. Wen, D. Yang, and C. Rosé, “Sentiment analysis in massive open online courses,” in Proc. 7th Int. Conf. Educ. Data Mining (EDM), London, U.K., 2014, pp. 130–137.
21. Sarker et al., “Utilizing social media data for detecting mental health signals,” J. Biomed. Inform., vol. 94, p. 103187, 2019, doi: 10.1016/j.jbi.2019.103187.
22. S. K. D’Mello and A. Graesser, “Dynamics of affective states during complex learning,” Learn. Instr., vol. 22, no. 2, pp. 145–157, 2012, doi: 10.1016/j.learninstruc.2011.10.001.
23. R. Goyal, N. Chaudhary, and M. Singh, “Machine learning based intelligent career counselling chatbot (ICCC),” in Proc. 2023 Int. Conf. Comput. Commun. Informatics (ICCCI), Coimbatore, India, 2023, pp. 1–6, doi: 10.1109/ICCCI56745.2023.10128305.
24. M. Sharma and A. Kumari, “AI-based deep learning chatbot for career and personal mentorship,” in Proc. IEEE 3rd Int. Conf. Technol. Eng. Manage. Societal Impact using Marketing, Entrepreneurship Talent (TEMSMET), Greater Noida, India, 2023, pp. 1–6, doi: 10.1109/TEMSMET56707.2023.10149907.
25. PowerSchool, Naviance College and Career Readiness Platform: Technical Product Overview. Folsom, CA, USA: PowerSchool Group LLC, 2024. [Online]. Available: https://www.powerschool.com/classroom/naviance/
26. K. Sumathy and R. Surendran, “AI-driven mentor service advising application for timely course completion using RNN/LSTM,” in Proc. Int. Conf. Sustainable Expert Syst. (ICSES), Chennai, India, 2024, pp. 1–8.
27. H. Khosravi et al., “Explainable AI in education: A systematic review,” Comput. Educ. Artif. Intell., vol. 3, p. 100074, 2022, doi: 10.1016/j.caeai.2022.100074.
28. MentorcliQ, MentorcliQ Platform Documentation. MentorcliQ Inc., 2023.
29. World Economic Forum, The Future of Jobs Report 2020. Geneva, Switzerland: WEF, 2020.
30. J. A. Ballesteros, M. D. Fernandez, and J. L. González-Geraldo, “Peer-mentoring program for the individual attention of engineering students,” IEEE Trans. Educ., vol. 67, no. 5, pp. 786–795, Oct. 2024, doi: 10.1109/TE.2024.3432830.
31. N. Selwyn, Should Robots Replace Teachers? AI and the Future of Education. Cambridge, U.K.: Polity Press, 2019.
32. IEEE Standards Association, Ethically Aligned Design: A Vision for Prioritizing Human Well-being with Autonomous and Intelligent Systems, 1st ed., 2019.
33. O. Viberg, M. Hatakka, O. Bälter, and A. Mavroudi, “The current landscape of learning analytics in higher education: A systematic review,” Comput. Educ., vol. 124, pp. 98–110, Sep. 2018, doi: 10.1016/j.compedu.2018.05.010.