# Chapter 2

# Review of Literature

## 2.1. Introduction

The literature on student academic performance was evaluated. Only a few research studies have been done on the factors that influence students' academic performance in high school/higher secondary schools, but also on the prediction of students' academic performance using different classification algorithms in data mining. The specific reviews of literature relevant to the current inquiry have been listed, with classifications on reviews related to factors that influence educational outcomes and evaluations with respect to performance models.

Figen Karaferye (2018) concluded that student mentoring approaches, which have a wide range of benefits, are used in a variety of settings, from K-12 to higher education. In summary, they facilitate the transition from university to work by connecting graduates and/or people from work-based settings into mentoring networks; they support students' self-improvement in social and cultural aspects; they support students' learning and academic work; they provide the guidance students need in setting their academic, professional, and career goals; and they facilitate the transition from university to work by connecting graduates and/or people from work-based settings into mentoring networks[1].

The study found that the students did best on the skills that required them to identify and describe objects and their properties. They did poorly on the skills that required them to explain how an object works or how it is used. The students in the study were different in terms of gender, grade level, and other factors. The study found that student performance varied depending on these factors. The findings showed that there was a good relationship between a student's academic performance and the school's environment [2].

Sunitha and Khadi (2007) looked at the impact of socioeconomic factors on the educational learning environment at home and at school. The study included 240 students in the 8th through 10th grades from eight co-educational schools in Dharwar, Karnataka, who were taught in both English and Kannada. The study found that there is a correlation between a child's home and school environment, their academic achievement, and their family's socio-economic status [3].

Hijazi and Naqvi (2006) chose 300 students (225 males, 75 females) from a collection of colleges associated with Pakistan's Punjab University to conduct a study on student performance. The hypothesis claimed that students' attitudes toward class attendance, hours spent studying on a regular basis beyond college, students' family income, students' mother's age, and mother's education are highly associated to student performance. The characteristics of mother's education and student's family income were found to be highly linked with student academic achievement using simple linear regression analysis [4].

David D. Law, Kim Hales and Don Busenbark has concluded in their research that, university-based mentorship programmes have become a popular solution for dealing with high student attrition and low graduation rates. While these mentorship programmes have grown in popularity, research on their effectiveness has lagged behind. We conclude that mentoring is significantly correlated with a wide variety of positive student outcomes, such as student behaviors, attitudes, and retention rates [5].

De Lange and Mavondo (2004) investigated the gender, motivational differences, and learning styles of pupils. The study used a structural equation model to construct a model that was tested on 246 business students in Australia through open learning. The model then shows that there are considerable disparities in learning techniques between males and girls [6].

Tho (1994) investigated the data on the factors that influence students' success in the University of Malaya's basic accounting course. Female students may exceed male students in accounting, according to reports, because they are thought to have more work needs. The study found that grades in accounting, mathematics, and economics are good predictors of how well a student will do in school [7].

Rineke Keijzer, Roeland van der Rijst, Erik van Schooten and Wilfried Admiraal has reported in their research that qualitative study took into account the variability of the at-risk student population. They were given a voice to express their thoughts and feelings about mentor qualities, and mentors' voices were also interpreted. As a result, information about students' and mentors' views of mentor traits, as well as the amount to which preferences and nuances were aligned, was gathered. These findings have added to their understanding of mentoring traits in the context of last-resort programmes for at-risk students who require extra help to graduate [8].

Maric and Petro (2004) looked at secondary school gender disparities in a variety of cognitive-motivational characteristics as well as performance in Language Arts and Mathematics. A total of 521 pupils aged 14 to 18 were selected from the province of Jeon's second cycle of compulsory secondary school (236 males and 285 females). As a result of conducting the 'T' test to find out the academic difference between male and female students, it was found that there was a gender difference in academic achievement [9].

Kristjansson, Sigfusdottir, and Allegrante (2010) conducted research to determine the association between health habits, BMI, and self-esteem, as well as teenage academic accomplishment. The researchers looked at survey data from 6,346 Icelandic adolescents in a cross-sectional sample. Lower BMI, increased physical activity, and healthy eating habits were all linked to improved academic attainment. Self-esteem and academic achievement were significantly influenced by poor food habits, and self-esteem was adversely impacted by rising BMI levels [10].

Christine Deasy, Barry Coughlan et. al. (2014) had stated about their research that “The work contributes to the body of knowledge by shedding light on the psychological suffering that undergraduate nursing/midwifery and teacher education students face. It also pinpoints their pain, dysfunctional coping, and the link to their lifestyle choices. The findings can be used to develop ways to reduce student discomfort and maladaptive coping throughout college and in the future” [11].

The journal Educational Leadership devoted an entire volume to kids in public schools and the importance of emphasizing the link between healthy bodies and minds. The theme of health includes scientific obstacles, ethical conflicts, and societal dilemmas. It is difficult to provide children with high-quality healthy-living training. This means that it is important for students to have access to good instruction, healthy food, and opportunities to exercise regularly if they want to stay healthy [12].

Grissom (2005) looked into the relationship between students' fitness levels and their intellectual achievement as measured by Stanford Achievement Test results. The study involved 884,715 California fifth, seventh, and ninth grade students who were enrolled in 2002. There is evidence that children who are physically fit do better in school than those who are not. Physical fitness levels have an impact on a child's health. This in turn promotes higher accomplishment. This study found that there is a link between health and ability, and that this link is larger for females than males, and for students with higher socioeconomic status than those with lower socioeconomic status [13].

The influence of sibling structure on educational attainment in the United States of America was investigated by Dalton, Kathryn, and Melissa (2007). For the period of January 1996 to December 1997, they used information from the Panel Study of Income Dynamics (PSID) and the Child Development Supplement (CDS) databases. The survey included 3563 black and white children aged 0 to 12 years old from 2380 households. It was discovered that children from two-parent families performed relatively equally on age-adjusted achievement exams than children from single-parent families. On age-adjusted achievement assessments, firstborn siblings often outperformed their younger siblings, according to findings from within-family sibling comparisons [14].

Muhammad Rashid Ali, Badar Nadeem Ashraf and Chuanmin Shuai(2019) had concluded in their research that overall, the study found that incivility among faculty members, as well as a lack of university resources, contribute to conflict-inducing attitudes among faculty members. Furthermore, teachers' uncivil behavior toward one another and a higher level of dissatisfaction with university resources are linked to unfavorable teacher–student interactions, which have a negative impact on students' scholastic and psychological outcomes [15].

This study looked at whether birth order (whether someone is the oldest, middle, or youngest child in their family) affects how well they do in school. The researchers found that children who are the oldest or the only child in their family tend to get better grades than those who are younger siblings. They think that 20 people, 9 men and 11 women, aged 13 to 39, all of whom had parents who had at least one sibling, were studied. Six people out of the twenty who were studied were firstborns, four were middleborns, and ten were lastborns. Every student who participated in the study completed the entire 2000-2001 academic school year and received a grade average. The researchers gathered information on the participants' basic demographics, as well as their birth order, how much attention they received from their parents, and their academic achievement. [16].

It was discovered that parental interest significantly reduces progressively with birth order – in other words, parents give their firstborn children the most attention, with less attention given to each subsequent child – and that as a consequence of this reduced parental attention, middle and last born children perform poorly academically. If parents don't pay attention to their kids, the kids might have to depend on each other. But if parents show favoritism, the kids might end up competing with each other. The study found that early childhood education has a positive influence on the educational outcomes of Botswana grade one kids in English language, mathematics, and science. A group of 120 students from four different schools in Botswana were chosen to be studied in the year 2000. According to the findings of a survey, kids with pre-school education experience outperformed their counterparts in all three school subject areas [17].

In their research Daniela Barni,Francesca Danioni  and Paula Benevene(2019) stated that "The findings revealed that, independent of the type or level of motivation for teaching, instructors' conservation values were positively connected with their sense of self-efficacy. More intriguingly, the associations between openness to change and self-efficacy on one hand, and self-transcendence and self-efficacy on the other, differed depending on the motivations of the teachers. Teachers' feelings of self-determination toward teaching were stronger when they felt less external pressure" [18].

In 1996, Johnson (1996) did some research with 100 third-grade students at May Metropolitan Academic Public School in Chicago to see how successful preschool education is in terms of academic achievement. This means that students who go to preschool do better in reading and math when they get to 3rd grade [19].

A research done in 2005 in Delhi found that children who attended low-budget, unrecognized private schools performed better on tests than public school children. The private school children had an average 72 percent higher score in arithmetic, 83 percent higher score in Hindi, and 246 percent higher score in English [20].

The study found that there were significant differences in the learning styles of upper secondary students depending on their class and type of school, but that there were no significant differences in the learning styles of higher secondary students in terms of class and type of school. In 2004, a study was done in the Coimbatore area of Tamil Nadu in selective aided and unaided schools. The study found that boys and girls have different learning styles in high school, and that better achievement scores are linked to better learning styles. [21].

Andrew S. Leavitt, Kari L. Nelson and Christine E. Cutucache (2022) concluded that “For future research on the influence of mentoring on mentors, we identified the some best practice suggestions: longitudinal and exploratory mixed methods designs, sequential collecting, and experimental descriptions nested inside a theoretical framework” [22].

Kamalamani (2001) performed a research of the attributes of high and low achievers in the Tamil Nadu state's Coimbatore district's Higher Secondary examination. One intriguing conclusion was that students from the Backward Class (BC) had a more favorable environment than students from the higher class. There are three groups of students in higher secondary education institutions: Most Backward Class (MBC), Scheduled Caste (SC), and Open Category (OC) [23].

Moriana, Alos, Alcala, Pino, Herruzo, and Ruiz (2006) investigated the impact of extracurricular activities such as study-related (tutoring or private courses, computers) and/or sports-related (indoor and outdoor games) on secondary school students' academic performance in Spain. A total of 222 students from 12 various schools were used as samples, and they were divided into two groups based on their extracurricular activities (both sports and academic). The influence of extracurricular activities on academic performance was investigated using analysis of variance (ANOVA), and it was discovered that students who participated in activities outside of school performed better academically [24].

Karen Aldrupa et. al (2018) had stated in their research that “The study's first result is that instructors' subjective assessments of classroom behavior problems are more closely related to their well-being than student ratings of misbehavior. Importantly, the suggested treatments for increasing teachers' abilities to regulate student conduct and develop positive teacher-student interactions may have a favorable impact on teachers' personal well-being as well. A calm, orderly learning environment, as well as a positive relationship with the teacher, are both beneficial to student growth [25].

Bray's study found that the percentage of students who received private tutoring was higher in India than in Malaysia, Singapore, Japan, China, and Sri Lanka. It was also discovered that the strength of private tutoring improves academic achievement, and that the level of private tutoring varies depending on a collective element, namely socioeconomic situations [26].

In 2007, Davis, Akers, Green, and Zartman did a study at Southwestern Agriculture University to identify student-related characteristics that potentially influence student performance in a soils introductory class (PSS 2432). They looked at the effects of SAT score, percentile position in high school class, high school chemistry background, major, gender, and academic semester on student performance in an introductory soil subject. They discovered that the SAT score, percentile rank in high school class, major, and gender were all highly connected to grade in PSS2432 [27].

Noe (1988) concluded that formal mentoring programmes in organizations are primarily used for training, employee socialization, personal and professional development, sponsorship or visibility/exposure, rather than inner-oriented psychosocial developmental functions, which is consistent with the findings of the following research studies [28].

Mentors and mentees share comparable ideas of mentoring functions, according to Fowler, L. Jane, and O'Gormans, John (2005). They devised a tool to assess individual mentoring functions in today's workplace. The instrument can be used to determine whether both parties' expectations and perceptions are in sync, as well as to diagnose and review their relationship [29].

According to Bragg (1989), use formal mentoring for professional growth. This connection is beneficial in attaining short-term objectives relevant to the protégé's current position [30].

Mentoring is a special kind of help that goes beyond just teaching someone how to do something. A mentor also helps the person grow and advance in their skills. This book is about how mentors can help protégés learn and grow. The person being mentored wants help with their career and social life. Mentoring functions were still employed over 25 years ago to predict protégés' career prospects and happiness with their mentor [31].

The study found that mentoring relationships and gender composition can have an effect on mentoring functions and career outcomes was investigated by Ragins, B.R., and Cotton, J.L. (1999). According to the findings, protégés in informal mentoring partnerships had better career outcomes than those in formal mentoring relationships. Mentoring roles and outcomes were similarly influenced by gender composition [32].

Mentorship, according to Jyothi Jeevan and Poonam Sharma (2015), is a significant resource for the protégé's learning that helps satisfy the needs of the business and the employee, allowing the protégé to cope with organizational changes. Using predictors such as mentoring culture and mentoring structure, Mentoring can help people in contact centers in India to move up in their careers. The study discovered that mentoring roles had a substantial impact on employee career growth [33].

Samei Hossein and Feyzbakhsh Alireza (2016) discussed the effect of mentoring duties on fostering successors in family enterprises. According to the study's findings, mentoring duties have been determined to be beneficial in the development of protégés' competences [34].

Ma, Liu, Wong, Yu, and Lee (2000) used a data mining technique on a real-life application for the Ministry of Education (MOE) of Singapore's Gifted Education Programme (GEP). GEP pupils were chosen while they were in their third year of primary school, and they were chosen through a series of tests. The GEP wanted to improve their pupils' A-level test outcomes by choosing the weak students for remedial lessons based on cut-off grades. Both traditional and data mining methods were used to investigate the impact of picking weak students. The cut-off marks for each subject of the O-level examination were thoroughly analyzed in the traditional way, and a subject drop level for attending the subject's remedial course was enforced [35].

Al-Radaideh, Al-Shawakfa, and Al-Najjar (2006) used a decision tree method to forecast students' final grades in the C++ course at Yarmouk University in Jordan in 2005. The model was built using 12 predictive factors and a 4-class response variable. There were three separate categorization algorithms used: ID3, C4.5, and the NaveBayes. Their findings revealed that the Decision Tree model predicted better than other models, with a forecast accuracy of 38.33% for a four-class response variable [36].

Kotsiantis, Pierrakeas, and Pintelas (2004) used a variety of data mining methods to predict the success of computer science students in the Hellenic Open University (HOUdistance )'s learning programme. For each of the most prevalent machine learning techniques, such as decision trees, bayesian networks, perceptron-based learning, instance-based learning, and rule-learning, a sample algorithm was employed. It was discovered that the effectiveness of machine-learning algorithms could accurately predict student performance before the final exam. They employed two types of attribute sets for model construction: socioeconomic and behavioral attributes [37].

Cortez and Silva (2008) sought to forecast high school student outcomes in two key subjects of mathematics and the Portuguese language who took the exam in 2006 in Portugal, Europe. Decision trees (DT), random forest (RF), neural networks (NN), and support vector machines were used to create prediction models for these two fundamental classes (SVM).The database was built using two main sources of data: school reports containing paper sheets with attributes such as three-period grades and number of school absences, and questionnaires containing closed-ended questions about several demographic characteristics such as mother's schooling, parental income, social/emotional (e.g. alcohol consumption) and other school-related variables that were expected to influence student performance. These two databases were combined into two datasets using final-grade (G3) as a class variable, one for Mathematics (395 cases) and the other for Portuguese language (649 records) [38].

The Bayesian technique was utilized to address this problem since it was discovered to be a clear and understandable language for expressing what was certain and certain. Eight features from a data set of high school students were used to conduct empirical tests on performance prediction. A number of variables should be taken into account, including sexual identity (male or female), team - work attitude (positive, neutral, negative), math interest (interested, indifferent, uninterested), student achievement (high, medium, low), self-confidence (high, medium, low), lack of self-confidence (extrovert, medium, introvert), Performance in mathematics and English was either above satisfactory or below satisfactory (above satisfactory, satisfactory, below satisfactory). Results showed that 172 out of 354 had been correctly classified, or 64%. The forecast may be related to the absence of true connection to two surveys and a sample. A closer look reveals that only 34% of satisfactory indicators and 54.2% of the best category of common estimate are accurate classifications, whereas 78% of the satisfactory activity team is. [39].

Rough set theory was utilized by Ramasubramanian, Iyakutti, and Thangavelu (2009) to analyze a student information system (SIS) database to forecast students' futures. They examined three categories of student characteristics: academic (A), nonacademic (NA), and relationships based on human behavior (HBR). The importance of education was evaluated based on how effectively students were exposed to theory, practical applications, participation, seminars, paper presentations, intestine, book reading, and departmental events. The number of students who excelled in social, athletic, NSC, and NCC activities was used to calculate the value of the non-academic quality. The relationships that students had with their teachers, peers, the broader public, their families, and their interests and leisure pursuits were also recognized as indicators of human behavior. On a fictitious SIS data set, they carried out elementary approximate set theory procedures like low and high approximation of all border decisions [40].

A model for forecasting student performance was created by Calles and Pierrakeas (2006) utilizing a combination of machine learning methods, such as decision trees and genetic algorithms. They created a population of tree representations using a fitness function, allowing them to adjust the size and precision of the trees in the training set. A specified number of decision trees (population) were produced and sorted according to fitness value at each time-point. Some modifications (genetic operators) were dependent on the line of chosen populations, leading to a continued rotation (or progression) until the new set was noticed with a predetermined number of preset generations. They constructed a brute force mechanism using the Calipa Library. They calculated the productivity of trees that were inspired by Katree for a regular classification in 2004, and they discovered that it was more effective in nature than a model than a conventional classification [41].

The research work of Figen Karaferye helped students to adjust easily to school or university life; support students' self-improvement in social and cultural aspects; support students' learning and academic work; provide the guidance students need in setting their academic, professional, and career goals; and ease the transition from school to work by putting graduates and/or people from work-based settings in contact with mentoring networks [42].

Ramakrishnan Ramachandran(2006) concluded in his research that “Young people in schools who receive mentoring can improve their interpersonal and communication skills, plan their careers, feel more motivated and confident, prepare for work experience, and achieve more. A mentor builds a relationship with her or his mentee on many levels, while a good adviser helps students learn about their discipline and the abilities required to do research or practice their vocation. A mentor is a reliable teacher” [43].

The research of Ya-Hui Kuo indicated that “How undergraduate students' experiences with research writing are influenced by mentoring and their expectations of a mentor using a qualitative research methodology” [44].

Peer mentoring has been described in higher education retention and enhancement strategy [45].

It has also been recognised as a valuable resource for new students in terms of social and academic support. In general, quality management techniques in higher education have shifted from objective outcomes like retention and grade point averages to subjective ones like satisfaction or stress reduction [46].

Köbis and Mehner discuss the relevant ethical issues associated with mentoring, raising awareness of the ethical development and use of future data-driven AI-supported mentoring environments in higher education. They have combined mentoring ethics and AI ethics with the goal of raising awareness in this interdisciplinary field [47].

Ruchi Mittal et. al. discussed in their research paper about the study of samples of undergraduate computer science students and used educational data mining to predict mentoring performance. A primary dataset was subjected to the WEKA machine learning linear regression technique. Academic subject knowledge support was found to be the most significant predictors of mentoring performance [48].

Crisp recognises the potential of mentoring as a guidance strategy in higher education, albeit not without challenges [49].

Other researchers emphasize the significance of e-mentoring as a strategy for improving academic performance and developing a tool to assess not only knowledge but also research and investigation ability, critical reasoning, logical-argumentative reasoning, and a variety of basic competencies required of modern learners [50, 51].

Mentoring, on the other hand, better learning processes and study skills [52,53].
Many of these studies have shown that e-mentoring programmes in higher education have been particularly created to assist vulnerable populations, including minority groups, gain access [54, 55].

Leah K. Hamilton et.al. concluded in their research that “As a whole, the findings show that undergraduate students benefit from mentoring programs designed to prepare them for the difficult transition from university to the workplace. Participating in a formal mentoring program during their postsecondary education may thus provide students with a competitive advantage when entering the job market” [56].

Mentoring is one of the best strategies for making exceptional students who are facing school underperformance or come from poor backgrounds aware of their own ability and incapable of using it without treatment strategies. Less vulnerable to sacrificing their potential and talents before graduating, within a mentorship program, talented students can also perform the role of the mentor in order to develop their management skills [57].

When Liu et al. (2020) used supervised learning models to predict the success of mentoring, they discovered that the best predictors were mentor-mentee compatibility and student involvement [58].

A machine learning-based mentorship recommendation system was created by Mishra et al. (2019) to match students with qualified mentors based on their goals, hobbies, and prior academic success [59].

Chen and Zhang (2021) used neural networks to identify which kids were likely to fail academically, allowing mentors to take preventative measures [60].

By spotting trends in student involvement, Kaur et al. (2020) used reinforcement learning to maximize e-mentoring engagements [61].

Zhang et al. (2019) showed how NLP techniques might evaluate mentor input for efficacy and sentiment, enhancing the caliber of advice given [62].

Alshammari et al. (2020) used machine learning (ML) to analyze behavioral data and forecast the effects of mentoring on students' academic and emotional health [63].

By incorporating machine learning models into gamified mentoring systems, Lim et al. (2021) showed improved student performance and motivation [64].

Predictive models by Kumar et al. (2022) identified students likely to drop out, prompting mentors to take corrective actions [65].

Personalized learning routes were suggested during mentoring sessions by Shaikh et al. (2018) using machine learning techniques [66].

Ament et al. (2019) created tools that help mentors make decisions by visualizing students' academic progress and areas that need attention [67].

Smith et al. (2020) investigated how mentoring relationships are impacted by cultural variations, highlighting the significance of cultural sensitivity [68].

Williams and Brown's (2021) study emphasized the value of mentorship in maintaining indigenous knowledge and enhancing native communities' educational results [69].

According to Chen et al. (2019), mentoring strategies and student outcomes were greatly impacted by hierarchical relationships, which are common in many Asian cultures [70].

Singh (2021) recommended culturally inclusive strategies after examining the difficulties of mentoring in different classes [71].

Language barriers between mentors and mentees frequently impeded communication, as demonstrated by Ahmed et al. (2022), who recommended the use of translation tools [72].

Johnson et al. (2020) examined the cultural challenges that first-generation students encounter and emphasized customized mentorship strategies [73].

Lee and Kim (2020) identified significant disparities in relationship dynamics between mentoring techniques in individualist cultures (like the US) and collectivist cultures (like Japan) [74].

The impact of religious values on students' academic aspirations and their involvement in mentoring were examined by Patel et al. in 2021[75].

Al-Mutairi (2020) examined the ways in which mentoring relationships were influenced by gender norms in conservative communities, highlighting the importance of culturally sensitive methods [76].

Nguyen et al. (2022) argued for different datasets to increase fairness after identifying cultural biases in mentorship machine learning models [77].

Park et al. (2021) improved mentoring outcomes by incorporating cultural preferences into adaptive learning models [78].

The ethical ramifications of implementing AI in culturally diverse educational environments were covered by Morales and Johnson (2022) [79].

Bhatia (2020) emphasized how the success of ML-driven mentoring programs was hampered by the lack of access to technology in disadvantaged communities [80].

Using clustering techniques, Sharma et al. (2021) created a framework for customizing mentorship programs to students' cultural backgrounds [81].

Lin et al. (2020) demonstrated how ML could improve students' learning experiences by giving them feedback that is sensitive to cultural differences [82].

Jacobsen et al. (2022) highlighted the importance of cultural insights in creating successful mentoring models by fusing sociology and machine learning [83].

Tanaka et al.'s studies from 2021 demonstrated the value of gamified mentoring techniques that are culturally appropriate [84].

In order to help mentors better grasp the requirements of their students, Ahmed and Farooq (2020) used machine learning to assess emotional indicators in varied classes [85].

Patel and Kumar (2021) addressed ethical concerns about bias in machine learning algorithms and argued for transparent AI systems [86].

Zhang and Wei (2022) used mentee behavioral data and teacher feedback to create an ML-based system that predicts student achievement in scientific courses. The study demonstrated how mentors could proactively assist failing students with the use of predictive analytics [87].

In order to promote more effective mentorship, Chen et al. (2021) used reinforcement learning to help teachers modify their lesson plans in response to real-time assessments of student involvement levels [88].

In order to improve compatibility, Wang et al. (2020) suggested a recommendation engine that was driven by collaborative filtering algorithms and matched mentors and mentees according to their academic backgrounds and preferred learning styles [89].

Using natural language processing (NLP) tools, Kumar et al. (2019) analyzed teacher comments to pinpoint areas where mentees' academic performance needed to improve while also helping mentors improve their approaches [90].

A 20% improvement in student retention and enhanced teacher-student collaboration were the outcomes of Lee et al.'s (2022) investigation into the use of gamification and machine learning algorithms to inspire mentees [91].

By using supervised learning models to identify early indicators of mentee disengagement through participation, attendance patterns, and assignment submissions, Ahmed and Santos (2023) enabled mentors to intervene in a timely manner [92].

After analyzing prejudice in machine learning systems intended for mentor-mentee matching, Morales and Zhao (2020) suggested fairness-aware algorithms that support equal opportunities for all students, irrespective of their socioeconomic status [93].

By creating a feedback loop driven by machine learning, Gupta and Patel (2021) increased mentee satisfaction by 35% by empowering mentors to offer tailored guidance in real-time [94].

Liu et al. (2021) used computer vision to analyze mentee emotions throughout sessions, which enabled mentors to modify their teaching methods to keep students engaged and lower stress levels [95].

By incorporating cultural information into an ML framework, Kim and Tanaka (2022) made it possible for mentors to offer culturally appropriate advice, which enhanced mentee performance in diverse classes [96].

A comparison research by Li and Zhao (2022) emphasized the distinctions between AI-assisted frameworks and conventional mentoring methods. Their study found that AI-enhanced technologies enable a more individualized approach to student coaching by giving mentors useful insights through real-time data analysis. Although they were successful in building interpersonal ties, traditional mentoring systems lacked the scalability and flexibility provided by AI solutions. The study underlined how crucial it is to incorporate AI techniques to supplement human mentoring experience [97].

The use of adaptive machine learning models in real-time mentoring interventions was investigated by Hernandez and Kumar (2023). Their results showed that by examining behavioral and performance indicators, AI-driven solutions might successfully identify kids who are at danger. By enabling mentors to offer prompt, focused assistance, these tools greatly increased student involvement and academic results. By automating repetitive tracking procedures, the study also demonstrated how real-time analytics may lessen mentor effort [98].

The application of AI to the analysis of mentor-mentee engagement was studied by Rao and Patel (2022). In order to shed light on the efficacy of mentoring relationships, their study concentrated on how AI algorithms identify trends in communication and activity data. The findings demonstrated that mentors' capacity to recognize disengaged students and proactively carry out remedial actions was improved by AI-based engagement analysis. The study demonstrated how AI tools may streamline mentoring procedures and promote deep relationships between mentors and mentees [99].

The function of cultural competency in AI-driven mentorship frameworks was examined by Fernandez and Gomez (2023). In order to meet the varied needs of pupils, their study underlined the necessity of including cultural understanding into AI models. Mentors could offer more effective and inclusive support if cultural considerations were incorporated into the algorithm design. In order to achieve equal mentorship outcomes, the study also emphasized problems including making sure datasets are objective and taking into account different cultural norms [100].

The predictive potential of AI in evaluating long-term student progress through teacher mentorship was investigated by Walker and Choi (2022). The study showed how predictive models could discover characteristics influencing student progress over long periods of time by merging mentor inputs with machine learning techniques. In order to improve student performance and retention rates, the study emphasized the value of mentors and AI systems working together to use both qualitative and quantitative insights [101].